```
import sys
in_colab = 'google.colab' in sys.modules
if in_colab:
    # Install packages in Colab
    !pip install category_encoders==2.0.0
    !pip install pandas-profiling==2.3.0
    !pip install plotly==4.1.1
```

```
Collecting category_encoders==2.0.0
  Downloading https://files.pythonhosted.org/packages/6e/a1/f7a22f144f33be78afeb06bfa78478e8284a64263a3c09b1ef5
     |████████████████████████████████| 92kB 5.7MB/s
Requirement already satisfied: pandas>=0.21.1 in /usr/local/lib/python3.6/dist-packages (from category_encoders
Requirement already satisfied: scipy>=0.19.0 in /usr/local/lib/python3.6/dist-packages (from category_encoders=
Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-packages (from category_encoders=
Requirement already satisfied: patsy>=0.4.1 in /usr/local/lib/python3.6/dist-packages (from category_encoders==
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.6/dist-packages (from category_er
Requirement already satisfied: statsmodels>=0.6.1 in /usr/local/lib/python3.6/dist-packages (from category_encc
Requirement already satisfied: python-dateutil>=2.5.0 in /usr/local/lib/python3.6/dist-packages (from pandas>=0
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas>=0.21.1->cate
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from patsy>=0.4.1->category_encoc
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.20.
Installing collected packages: category-encoders
Successfully installed category-encoders-2.0.0
Collecting pandas-profiling==2.3.0
  Downloading https://files.pythonhosted.org/packages/2c/2f/aae19e2173c10a9bb7fee5f5cad35dbe53a393960fc91abc477
     |████████████████████████████████| 133kB 4.8MB/s
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.6/dist-packages (from pandas-profiling==2
Requirement already satisfied: matplotlib>=1.4 in /usr/local/lib/python3.6/dist-packages (from pandas-profiling
Requirement already satisfied: jinja2>=2.8 in /usr/local/lib/python3.6/dist-packages (from pandas-profiling==2.
Requirement already satisfied: missingno>=0.4.2 in /usr/local/lib/python3.6/dist-packages (from pandas-profilir
Collecting htmlmin>=0.1.12 (from pandas-profiling==2.3.0)
  Downloading https://files.pythonhosted.org/packages/b3/e7/fcd59e12169de19f0131ff2812077f964c6b960e7c09804d30a
Collecting phik>=0.9.8 (from pandas-profiling==2.3.0)
  Downloading https://files.pythonhosted.org/packages/45/ad/24a16fa4ba612fb96a3c4bb115a5b9741483f53b66d3d3afd98
     |████████████████████████████████| 614kB 15.2MB/s
Collecting confuse>=1.0.0 (from pandas-profiling==2.3.0)
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Requirement already satisfied: astropy in /usr/local/lib/python3.6/dist-packages (from pandas-profiling==2.3.0)
Requirement already satisfied: numpy>=1.12.0 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19->panc
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Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.6/dist-packages (from jinja2>=2.8->pa
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Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from missingno>=0.4.2->pandas-p
Requirement already satisfied: jupyter-client>=5.2.3 in /usr/local/lib/python3.6/dist-packages (from phik>=0.9.
Collecting pytest-pylint>=0.13.0 (from phik>=0.9.8->pandas-profiling==2.3.0)
  Downloading https://files.pythonhosted.org/packages/64/dc/6f35f114844fb12e38d60c4f3d2441a55baff7043ad4e013777
Requirement already satisfied: numba>=0.38.1 in /usr/local/lib/python3.6/dist-packages (from phik>=0.9.8->panda
Collecting pytest>=4.0.2 (from phik>=0.9.8->pandas-profiling==2.3.0)
  Downloading https://files.pythonhosted.org/packages/0c/91/d68f68ce54cd3e8afa1ef73ea1ad44df2438521b64c0820e5fc
     |████████████████████████████████| 235kB 30.0MB/s
Requirement already satisfied: nbconvert>=5.3.1 in /usr/local/lib/python3.6/dist-packages (from phik>=0.9.8->pa
Requirement already satisfied: pyyaml in /usr/local/lib/python3.6/dist-packages (from confuse>=1.0.0->pandas-pr
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.5.0-
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Requirement already satisfied: pyzmq>=13 in /usr/local/lib/python3.6/dist-packages (from jupyter-client>=5.2.3-
Requirement already satisfied: tornado>=4.1 in /usr/local/lib/python3.6/dist-packages (from jupyter-client>=5.2
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Requirement already satisfied: jupyter-core>=4.6.0 in /usr/local/lib/python3.6/dist-packages (from jupyter-clie
Collecting pylint>=1.4.5 (from pytest-pylint>=0.13.0->phik>=0.9.8->pandas-profiling==2.3.0)
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     |████████████████████████████████| 307kB 28.7MB/s
Requirement already satisfied: llvmlite>=0.25.0dev0 in /usr/local/lib/python3.6/dist-packages (from numba>=0.38
Requirement already satisfied: atomicwrites>=1.0 in /usr/local/lib/python3.6/dist-packages (from pytest>=4.0.2-
Collecting pluggy<1.0,>=0.12 (from pytest>=4.0.2->phik>=0.9.8->pandas-profiling==2.3.0)
  Downloading https://files.pythonhosted.org/packages/92/c7/48439f7d5fd6bddb4c04b850bb862b42e3e2b98570040dfaf68
Requirement already satisfied: wcwidth in /usr/local/lib/python3.6/dist-packages (from pytest>=4.0.2->phik>=0.9
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.6/dist-packages (from pytest>=4.0.2->phi
Requirement already satisfied: py>=1.5.0 in /usr/local/lib/python3.6/dist-packages (from pytest>=4.0.2->phik>=0
Requirement already satisfied: more-itertools>=4.0.0 in /usr/local/lib/python3.6/dist-packages (from pytest>=4.
Requirement already satisfied: importlib-metadata>=0.12; python_version < "3.8" in /usr/local/lib/python3.6/dis
Requirement already satisfied: packaging in /usr/local/lib/python3.6/dist-packages (from pytest>=4.0.2->phik>=0
Requirement already satisfied: pygments in /usr/local/lib/python3.6/dist-packages (from nbconvert>=5.3.1->phik>
Requirement already satisfied: pandocfilters>=1.4.1 in /usr/local/lib/python3.6/dist-packages (from nbconvert>=
Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/python3.6/dist-packages (from nbconvert>=5.3
Requirement already satisfied: nbformat>=4.4 in /usr/local/lib/python3.6/dist-packages (from nbconvert>=5.3.1->
```

```
Requirement already satisfied: bleach in /usr/local/lib/python3.6/dist-packages (from nbconvert>=5.3.1->phik>=0
Requirement already satisfied: testpath in /usr/local/lib/python3.6/dist-packages (from nbconvert>=5.3.1->phik>
Requirement already satisfied: entrypoints>=0.2.2 in /usr/local/lib/python3.6/dist-packages (from nbconvert>=5.
Requirement already satisfied: defusedxml in /usr/local/lib/python3.6/dist-packages (from nbconvert>=5.3.1->phi
Requirement already satisfied: decorator in /usr/local/lib/python3.6/dist-packages (from traitlets->jupyter-cli
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Collecting astroid<2.4,>=2.3.0 (from pylint>=1.4.5->pytest-pylint>=0.13.0->phik>=0.9.8->pandas-profiling==2.3.0
  Downloading https://files.pythonhosted.org/packages/64/d3/4ba68bd56297556c9c2e5072d71d1664feaa86d9726c237a9fe
     |████████████████████████████████| 215kB 48.0MB/s
Collecting isort<5,>=4.2.5 (from pylint>=1.4.5->pytest-pylint>=0.13.0->phik>=0.9.8->pandas-profiling==2.3.0)
  Downloading https://files.pythonhosted.org/packages/e5/b0/c121fd1fa3419ea9bfd55c7f9c4fedfec5143208d8c7ad3ce3c
     |████████████████████████████████| 51kB 22.1MB/s
Collecting mccabe<0.7,>=0.6 (from pylint>=1.4.5->pytest-pylint>=0.13.0->phik>=0.9.8->pandas-profiling==2.3.0)
  Downloading https://files.pythonhosted.org/packages/87/89/479dc97e18549e21354893e4ee4ef36db1d237534982482c368
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.6/dist-packages (from importlib-metadata>=0.
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in /usr/local/lib/python3.6/dist-packages (from nbformat
Requirement already satisfied: webencodings in /usr/local/lib/python3.6/dist-packages (from bleach->nbconvert>=
Collecting lazy-object-proxy==1.4.* (from astroid<2.4,>=2.3.0->pylint>=1.4.5->pytest-pylint>=0.13.0->phik>=0.9.
  Downloading https://files.pythonhosted.org/packages/0e/26/534a6d32572a9dbca11619321535c0a7ab34688545d9d67c2c2
     |████████████████████████████████| 51kB 21.4MB/s
Requirement already satisfied: wrapt==1.11.* in /usr/local/lib/python3.6/dist-packages (from astroid<2.4,>=2.3.
Collecting typed-ast<1.5,>=1.4.0; implementation_name == "cpython" and python_version < "3.8" (from astroid<2.4
  Downloading https://files.pythonhosted.org/packages/31/d3/9d1802c161626d0278bafb1ffb32f76b9d01e123881bbf9d91e
     |████████████████████████████████| 737kB 31.8MB/s
Building wheels for collected packages: pandas-profiling, htmlmin, confuse
  Building wheel for pandas-profiling (setup.py) ... done
  Created wheel for pandas-profiling: filename=pandas_profiling-2.3.0-py2.py3-none-any.whl size=145035 sha256=4
  Stored in directory: /root/.cache/pip/wheels/ce/c7/f1/dbfef4848ebb048cb1d4a22d1ed0c62d8ff2523747235e19fe
  Building wheel for htmlmin (setup.py) ... done
  Created wheel for htmlmin: filename=htmlmin-0.1.12-cp36-none-any.whl size=27084 sha256=eb4a5fec6c889189912a57
  Stored in directory: /root/.cache/pip/wheels/43/07/ac/7c5a9d708d65247ac1f94066cf1db075540b85716c30255459
  Building wheel for confuse (setup.py) ... done
  Created wheel for confuse: filename=confuse-1.0.0-cp36-none-any.whl size=17486 sha256=d79b314f3a96d6e9a60ef55
  Stored in directory: /root/.cache/pip/wheels/b0/b2/96/2074eee7dbf7b7df69d004c9b6ac4e32dad04fb7666cf943bd
Successfully built pandas-profiling htmlmin confuse
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have folium 0.8.3 which is incompatible.
Installing collected packages: htmlmin, pluggy, pytest, lazy-object-proxy, typed-ast, astroid, isort, mccabe, p
  Found existing installation: pluggy 0.7.1
    Uninstalling pluggy-0.7.1:
      Successfully uninstalled pluggy-0.7.1
  Found existing installation: pytest 3.6.4
    Uninstalling pytest-3.6.4:
      Successfully uninstalled pytest-3.6.4
  Found existing installation: pandas-profiling 1.4.1
    Uninstalling pandas-profiling-1.4.1:
      Successfully uninstalled pandas-profiling-1.4.1
Successfully installed astroid-2.3.2 confuse-1.0.0 htmlmin-0.1.12 isort-4.3.21 lazy-object-proxy-1.4.2 mccabe-0
Requirement already satisfied: plotly==4.1.1 in /usr/local/lib/python3.6/dist-packages (4.1.1)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from plotly==4.1.1) (1.12.0)
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.6/dist-packages (from plotly==4.1.1) (
```

```python
#Fetch smoking data file
from google.colab import files
uploaded = files.upload()
```

Choose Files cancerxx - for_import.csv

- **cancerxx - for_import.csv**(application/vnd.ms-excel) - 6137717 bytes, last modified: 9/18/2019 - 100% done

```
Saving cancerxx - for_import.csv to cancerxx - for_import.csv
```

```python
# Load smoking data
import pandas as pd
import io
df_smoking = pd.read_csv(io.StringIO(uploaded['cancerxx - for_import.csv'].decode('utf-8')))
df_smoking.head()
```

	language	cereal_serve_per_month	cereal_times_per_month	more_than_one_cereal_type	milk_serve_per_month
0	5	3	2	2.0	3
1	4	0	0	NaN	0
2	5	5	2	2.0	5
3	3	1	1	2.0	4
4	5	2	2	1.0	0

5 rows × 92 columns

```
# We assess the contents of df_smoking
df_smoking_shape = df_smoking.shape
print ('df_smoking Shape')
print (df_smoking_shape, '\n')
print ('df_smoking Count')
print (df_smoking.count(), '\n')
print ('df_smoking NaN Count')
print (df_smoking.isna().sum(), '\n')
print ('df_smoking Describe')
print (df_smoking.describe())
```

```
df_smoking Shape
(33672, 92)

df_smoking Count
language                         33672
cereal_serve_per_month           33672
cereal_times_per_month           33672
more_than_one_cereal_type        22858
milk_serve_per_month             33672
milk_times_per_month             33672
milk_type                        24044
soda_serve_per_month             33672
soda_times_per_month             33672
juice_serve_per_month            33672
juice_times_per_month            33672
coffee_serve_per_month           33672
coffee_times_per_month           33672
sports_drink_serve_per_month     33672
sports_drink_times_per_month     33672
fruit_drink_serve_per_month      33672
fruit_drink_times_per_month      33672
fruit_eat_serve_per_month        33672
fruit_eat_times_per_month        33672
salad_eat_serve_per_month        33672
salad_eat_times_per_month        33672
fries_eat_serve_per_month        33672
fries_eat_times_per_month        33672
potatoe_eat_serve_per_month      33672
potatoe_eat_times_per_month      33672
beans_eat_serve_per_month        33672
beans_eat_times_per_month        33672
grains_eat_serve_per_month       33672
grains_eat_times_per_month       33672
vegies_eat_serve_per_month       33672
                                 ...
vitD_reason                       6906
1st_kind_cereal_eaten            22858
2nd_kind_cereal_eaten             9958
walk_past_wk                     33672
walk_number_wk                   10246
single_walk_distance             10229
single_walk_time                 10229
walk_leisure_past_wk             32778
walk_leisure_number_wk           16074
walk_leisure_ distance           16055
walk_leisure_ time               16055
see_walking_from_home            33672
weather_discourages_walk         33672
walkway_existence                33672
walkable_retail                  33672
walkable_bus_stop                33672
walkable_entertainment           33672
walkable_relaxation              33672
streets_have_walkways            33672
traffic_discourages_walking      33672
crime_discourages_walking        33672
animals_discourage_walking       33672
cigarette_even_once              33672
cigar_even_once                  33672
pipe_even_once                   33672
smokeless_even_once              33672
had_genetic_counseling           33672
genetic_counseling_with_MD       33672
genetic_counseling_for_cancer    33672
cigarettes_per_day                7602
Length: 92, dtype: int64

df_smoking NaN Count
language                             0
cereal_serve_per_month               0
cereal_times_per_month               0
```

```
cereal_times_per_month               0
more_than_one_cereal_type        10814
milk_serve_per_month                 0
milk_times_per_month                 0
milk_type                         9628
soda_serve_per_month                 0
soda_times_per_month                 0
juice_serve_per_month                0
juice_times_per_month                0
coffee_serve_per_month               0
coffee_times_per_month               0
sports_drink_serve_per_month         0
sports_drink_times_per_month         0
fruit_drink_serve_per_month          0
fruit_drink_times_per_month          0
fruit_eat_serve_per_month            0
fruit_eat_times_per_month            0
salad_eat_serve_per_month            0
salad_eat_times_per_month            0
fries_eat_serve_per_month            0
fries_eat_times_per_month            0
potatoe_eat_serve_per_month          0
potatoe_eat_times_per_month          0
beans_eat_serve_per_month            0
beans_eat_times_per_month            0
grains_eat_serve_per_month           0
grains_eat_times_per_month           0
vegies_eat_serve_per_month           0
                                 ...
vitD_reason                      26766
1st_kind_cereal_eaten            10814
2nd_kind_cereal_eaten            23714
walk_past_wk                         0
walk_number_wk                   23426
single_walk_distance             23443
single_walk_time                 23443
walk_leisure_past_wk               894
walk_leisure_number_wk           17598
walk_leisure_ distance           17617
walk_leisure_ time               17617
see_walking_from_home                0
weather_discourages_walk             0
walkway_existence                    0
walkable_retail                      0
walkable_bus_stop                    0
walkable_entertainment               0
walkable_relaxation                  0
streets_have_walkways                0
traffic_discourages_walking          0
crime_discourages_walking            0
animals_discourage_walking           0
cigarette_even_once                  0
cigar_even_once                      0
pipe_even_once                       0
smokeless_even_once                  0
had_genetic_counseling               0
genetic_counseling_with_MD           0
genetic_counseling_for_cancer        0
cigarettes_per_day               26070
Length: 92, dtype: int64

df_smoking Describe
           language  ...  cigarettes_per_day
count  33672.000000  ...         7602.000000
mean       4.670587  ...           22.540647
std        1.191156  ...           26.525465
min        1.000000  ...            1.000000
25%        4.000000  ...            6.000000
50%        5.000000  ...           15.000000
75%        5.000000  ...           20.000000
max        9.000000  ...           99.000000
```

```
[8 rows x 92 columns]
```

```
# Replace NaN to improve data format
import numpy as np
df_smoking1 = df_smoking.replace ({np.NaN: 0})
df_smoking1.head()
```

	language	cereal_serve_per_month	cereal_times_per_month	more_than_one_cereal_type	milk_serve_per_month
0	5	3	2	2.0	3
1	4	0	0	0.0	0
2	5	5	2	2.0	5
3	3	1	1	2.0	4
4	5	2	2	1.0	0

5 rows × 92 columns

```
# Set up boolean columns such that yes = 1 and no = 0
features1 = {'more_than_one_cereal_type', 'vitamin_past_month', 'multivitamin_past_month', 'calcium_past_month', 'vitD_past_
            'walkway_existence', 'walkable_retail', 'walkable_bus_stop', 'walkable_entertainment', 'walkable_relaxation', 's
            'crime_discourages_walking', 'animals_discourage_walking', 'cigarette_even_once', 'cigar_even_once', 'pipe_even_
            'had_genetic_counseling', 'genetic_counseling_with_MD', 'genetic_counseling_for_cancer'}

replacements1 = {
  2: 0,
  3: 0,
  4: 0,
  5: 0,
  6: 0,
  7: 0,
  8: 0,
  9: 0
}

df_smoking2 = df_smoking1[features1].replace(replacements1)

df_smoking2.head()
```

	traffic_discourages_walking	walkable_bus_stop	walkable_retail	walkable_relaxation	vitamin_past_month
0	1	1	1	1	0
1	0	1	1	1	1
2	0	1	1	1	1
3	1	1	1	0	0
4	0	1	1	0	1

```
df_smoking1['number'] = df_smoking1.index
df_smoking2['number'] = df_smoking2.index

df_smoking1.loc[df_smoking1.number.isin(df_smoking2.number), features1] = df_smoking2[features1]
df_smoking1.head()
```

	language	cereal_serve_per_month	cereal_times_per_month	more_than_one_cereal_type	milk_serve_per_month
0	5	3	2	0.0	3
1	4	0	0	0.0	0
2	5	5	2	0.0	5
3	3	1	1	0.0	4
4	5	2	2	1.0	0

5 rows × 93 columns

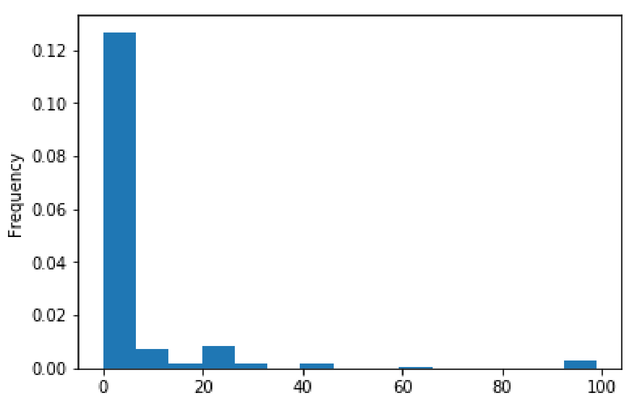
```
df_smoking1 = df_smoking1.drop('number', axis = 1)
df_smoking1.head()
```

	language	cereal_serve_per_month	cereal_times_per_month	more_than_one_cereal_type	milk_serve_per_month
0	5	3	2	0.0	3
1	4	0	0	0.0	0
2	5	5	2	0.0	5
3	3	1	1	0.0	4
4	5	2	2	1.0	0

5 rows × 92 columns

```
# Freqeuncy plot for cigarettes_per_day
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

d = df_smoking1['cigarettes_per_day']
plt.hist(df_smoking1['cigarettes_per_day'], normed=True, bins=15)
plt.ylabel('Frequency');
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/axes/_axes.py:6521: MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.
  alternative="'density'", removal="3.1")
```

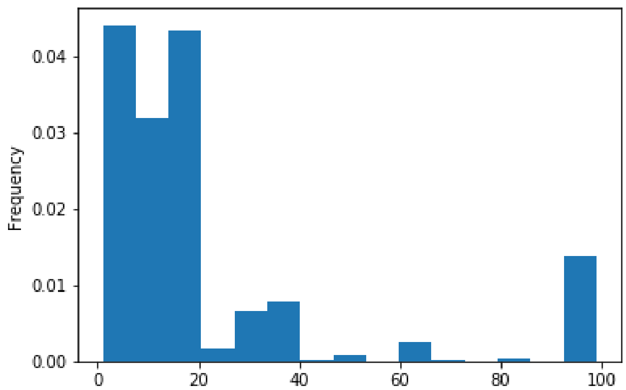



```
# Drop rows where cigarettes_per_day = 0
df_smoking1['cigarettes_per_day'] =  df_smoking1['cigarettes_per_day'].replace ({np.NaN: 0})
df_smoking1 = df_smoking1[df_smoking1['cigarettes_per_day'] > 0]
df_smoking1.shape
```

```
(7602, 92)
```

```
# Create frequency plot of cigarettes per day
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

d = df_smoking1['cigarettes_per_day']
plt.hist(df_smoking1['cigarettes_per_day'], normed=True, bins=15)
plt.ylabel('Frequency');
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/axes/_axes.py:6521: MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.
  alternative="'density'", removal="3.1")
```



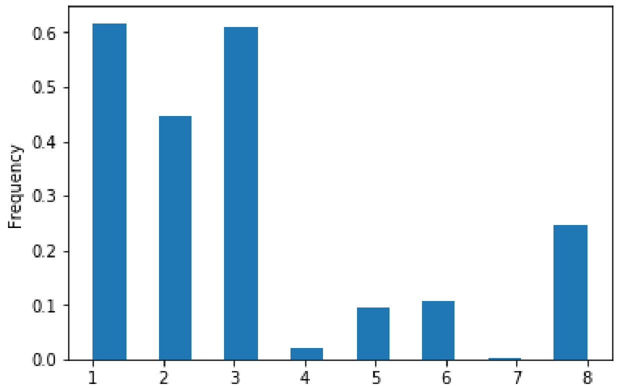

```
# Create a column in which cigarettes per day are sorted into 8 bins
df_smoking1['cigarettes_per_day_bins'] = pd.cut(x=df_smoking1['cigarettes_per_day'], bins=[0, 7, 14, 21, 28, 35, 42, 49, 100
df_smoking1 = df_smoking1.drop('cigarettes_per_day', axis = 1)
df_smoking1['cigarettes_per_day_bins'] =  df_smoking1['cigarettes_per_day_bins'].replace ({np.NaN: 0})
df_smoking1.head()
```

	language	cereal_serve_per_month	cereal_times_per_month	more_than_one_cereal_type	milk_serve_per_month
4	5	2	2	1.0	0
9	1	3	2	0.0	1
11	5	0	0	0.0	0
13	5	0	0	0.0	0
14	2	0	0	0.0	0

5 rows × 92 columns

```
# Looking at the frequency distribution of cigarettes per day bins
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

d_bin = df_smoking1['cigarettes_per_day_bins']
plt.hist(d_bin, normed=True, bins=15)
plt.ylabel('Frequency')
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/axes/_axes.py:6521: MatplotlibDeprecationWarning:
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.
  alternative="'density'", removal="3.1")
Text(0, 0.5, 'Frequency')
```




```
# Train/validate split: random 80/20% train/validate split.
from sklearn.model_selection import train_test_split
XTrain, XVal, yTrain, yVal = train_test_split(df_smoking1.drop('cigarettes_per_day_bins', axis = 1), df_smoking1['cigarettes_

XTrain.shape, yTrain.shape, XVal.shape, yVal.shape
```

```
((6081, 91), (6081,), (1521, 91), (1521,))
```

```
# Look at correlation coefficients
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 1000)
XTrain.corr()
```

	language	cereal_serve_per_month	cereal_times_per_month	more_than_one_ce
language	1.000000	0.436982	0.351576	
cereal_serve_per_month	0.436982	1.000000	0.760684	
cereal_times_per_month	0.351576	0.760684	1.000000	
more_than_one_cereal_type	-0.035361	-0.138573	0.103886	
milk_serve_per_month	0.433675	0.972695	0.735602	
milk_times_per_month	0.349838	0.769347	0.739144	
milk_type	-0.096036	-0.232121	-0.007578	
soda_serve_per_month	0.431958	0.959336	0.721514	
soda_times_per_month	0.342304	0.734191	0.595590	
juice_serve_per_month	0.428804	0.956040	0.720313	
juice_times_per_month	0.332304	0.727421	0.597924	
coffee_serve_per_month	0.426747	0.951691	0.714146	
coffee_times_per_month	0.333119	0.801064	0.622032	
sports_drink_serve_per_month	0.432197	0.957457	0.718121	
sports_drink_times_per_month	0.359200	0.808602	0.625149	
fruit_drink_serve_per_month	0.431355	0.952001	0.713791	
fruit_drink_times_per_month	0.358626	0.798001	0.620712	
fruit_eat_serve_per_month	0.425964	0.957833	0.721305	
fruit_eat_times_per_month	0.384347	0.806646	0.658352	
salad_eat_serve_per_month	0.427673	0.950363	0.713253	
salad_eat_times_per_month	0.382662	0.789765	0.644858	
fries_eat_serve_per_month	0.425416	0.950622	0.710713	
fries_eat_times_per_month	0.361141	0.706499	0.579918	
potatoe_eat_serve_per_month	0.422435	0.936681	0.699211	
potatoe_eat_times_per_month	0.375218	0.743602	0.606211	
beans_eat_serve_per_month	0.421520	0.935026	0.698968	
beans_eat_times_per_month	0.334060	0.704172	0.577761	
grains_eat_serve_per_month	0.422670	0.940141	0.701947	
grains_eat_times_per_month	0.352108	0.698946	0.547232	
vegies_eat_serve_per_month	0.415677	0.928090	0.693861	
vegies_eat_times_per_month	0.359752	0.801514	0.632530	
salsa_eat_serve_per_month	0.421930	0.932706	0.695506	
salsa_eat_times_per_month	0.332938	0.678452	0.541066	
pizza_eat_serve_per_month	0.422585	0.938145	0.699300	
pizza_eat_times_per_month	0.358019	0.679303	0.546140	
tomatoe_eat_serve_per_month	0.418889	0.930008	0.692785	
tomatoe_eat_times_per_month	0.360487	0.700663	0.569326	

cheese_eat_serve_per_month	0.417031	0.926477	0.691735
cheese_eat_times_per_month	0.363737	0.769202	0.610668
red_meat_eat_serve_per_month	0.419657	0.929806	0.694151
red_meat_eat_times_per_month	0.376608	0.780559	0.615793
processed_meat_eat_serve_per_month	0.418972	0.928255	0.692179
processed_meat_eat_times_per_month	0.373554	0.707912	0.571415
bread_eat_serve_per_month	0.417267	0.923150	0.689785
bread_eat_times_per_month	0.339279	0.735331	0.595573
candy_eat_serve_per_month	0.411998	0.922073	0.689743
candy_eat_times_per_month	0.372756	0.707072	0.583550
donut_eat_serve_per_month	0.416284	0.926723	0.690687
donut_eat_times_per_month	0.334741	0.680731	0.556009
cookie_eat_serve_per_month	0.409480	0.912101	0.677290
cookie_eat_times_per_month	0.355908	0.682247	0.559441
ice_cream_eat_serve_per_month	0.414443	0.918537	0.683445
ice_cream_eat_times_per_month	0.350857	0.677407	0.552084
pop_corn_eat_serve_per_month	0.415217	0.921843	0.687277
pop_corn_eat_times_per_month	0.354492	0.669004	0.529327
vitamin_past_month	-0.050629	-0.243404	-0.157238
multivitamin_past_month	-0.037872	-0.162842	-0.096123
multivitamin_days_in_month	-0.029406	-0.150437	-0.089361
calcium_past_month	-0.040267	-0.096730	-0.061498
calcium_days_in_month	-0.034379	-0.086469	-0.060933
vitD_past_month	-0.016192	-0.122617	-0.076643
vitD_days_in_month	-0.013972	-0.111407	-0.068578
vitD_reason	-0.011984	-0.099275	-0.061147
1st_kind_cereal_eaten	-0.066491	-0.213615	0.202229
2nd_kind_cereal_eaten	-0.021112	-0.118378	0.093967
walk_past_wk	-0.100718	-0.114823	-0.085251
walk_number_wk	-0.049873	-0.039521	-0.041604
single_walk_distance	-0.015167	-0.034909	-0.037080
single_walk_time	-0.075258	-0.097345	-0.084728
walk_leisure_past_wk	-0.077325	-0.188538	-0.135776
walk_leisure_number_wk	-0.026543	-0.105001	-0.087298
walk_leisure_ distance	-0.026035	-0.067584	-0.044969
walk_leisure_ time	-0.061651	-0.163052	-0.120797
see_walking_from_home	0.322965	0.612504	0.441254
weather_discourages_walk	0.214795	0.481079	0.334835
walkway_existence	-0.203418	-0.385381	-0.283120

walkable_retail	-0.159764	-0.199678	-0.134860
walkable_bus_stop	-0.188837	-0.181334	-0.142217
walkable_entertainment	-0.150265	-0.176244	-0.124428
walkable_relaxation	-0.141028	-0.274859	-0.193180
streets_have_walkways	-0.188904	-0.217642	-0.159778
traffic_discourages_walking	-0.093775	-0.097254	-0.076176
crime_discourages_walking	-0.096958	-0.069252	-0.066612
animals_discourage_walking	-0.069518	-0.061819	-0.047632
cigarette_even_once	-0.014661	-0.082766	-0.060123
cigar_even_once	0.017100	-0.156603	-0.099829
pipe_even_once	0.021861	-0.104214	-0.052365
smokeless_even_once	0.036964	-0.087348	-0.057695
had_genetic_counseling	-0.011091	-0.026606	-0.011029
genetic_counseling_with_MD	-0.021622	-0.039074	-0.013490
genetic_counseling_for_cancer	-0.015048	-0.023971	-0.022560

```
# Dropping highly corrlated columns
def correlation(dataset, validation_dataset, threshold):
    col_corr = set() # Set of all the names of deleted columns
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if (corr_matrix.iloc[i, j] >= threshold) and (corr_matrix.columns[j] not in col_corr):
                colname = corr_matrix.columns[i] # getting the name of column
                col_corr.add(colname)
                if colname in dataset.columns:
                    del dataset[colname] # deleting the column from the dataset
                    del validation_dataset[colname] # deleting the column from the validation dataset

correlation(XTrain, XVal, 0.98)

XTrain.shape
XVal.shape
```

```
(1521, 78)
```

```
# Begin with baselines for classification.
# The baseline accuracy, if the majority class is guessed for every prediction?
# option with pandas function:
yTrain.value_counts(normalize=True)
```

```
3    0.286466
1    0.285644
2    0.208847
8    0.113633
6    0.049663
5    0.044565
4    0.009702
7    0.001480
Name: cigarettes_per_day_bins, dtype: float64
```

```
# option with scikit-learn function
from sklearn.metrics import accuracy_score
y = yTrain
majority_class = y.mode()[0]
y_pred = [majority_class] * len(y)
accuracy_score(y, y_pred)
```

```
0.2864660417694458
```

```
# Thus, baseline accuracy, if you guessed the majority class for every prediction is 0.286
```

```
# Optimizing Hyperparameters
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

# Define classifier
forest = RandomForestClassifier(random_state = 1)

# Input
X_train = XTrain
y_train = yTrain
X_val = XVal
y_val = yVal

# Parameters to fit
n_estimators = [5, 10, 45, 46, 152, 205, 358, 393, 1000]
max_depth = [3, 5, 7, 10, 15]
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 5, 10, 15]
max_leaf_nodes = [None, 10, 52]
max_features = [0.11373956383989692, 0.14621091571560108, 0.17046743865886782, 0.17281968473284381, 0.5545636480509806, 0.61

hyperF = dict(n_estimators = n_estimators, max_depth = max_depth,
              min_samples_split = min_samples_split,
             min_samples_leaf = min_samples_leaf,
             max_leaf_nodes = max_leaf_nodes,
             max_features = max_features)

gridF = GridSearchCV(forest, hyperF, cv = 3, verbose = 10,
                     scoring='accuracy', return_train_score=True,
                     n_jobs = -1)
bestF = gridF.fit(X_train, y_train)
```

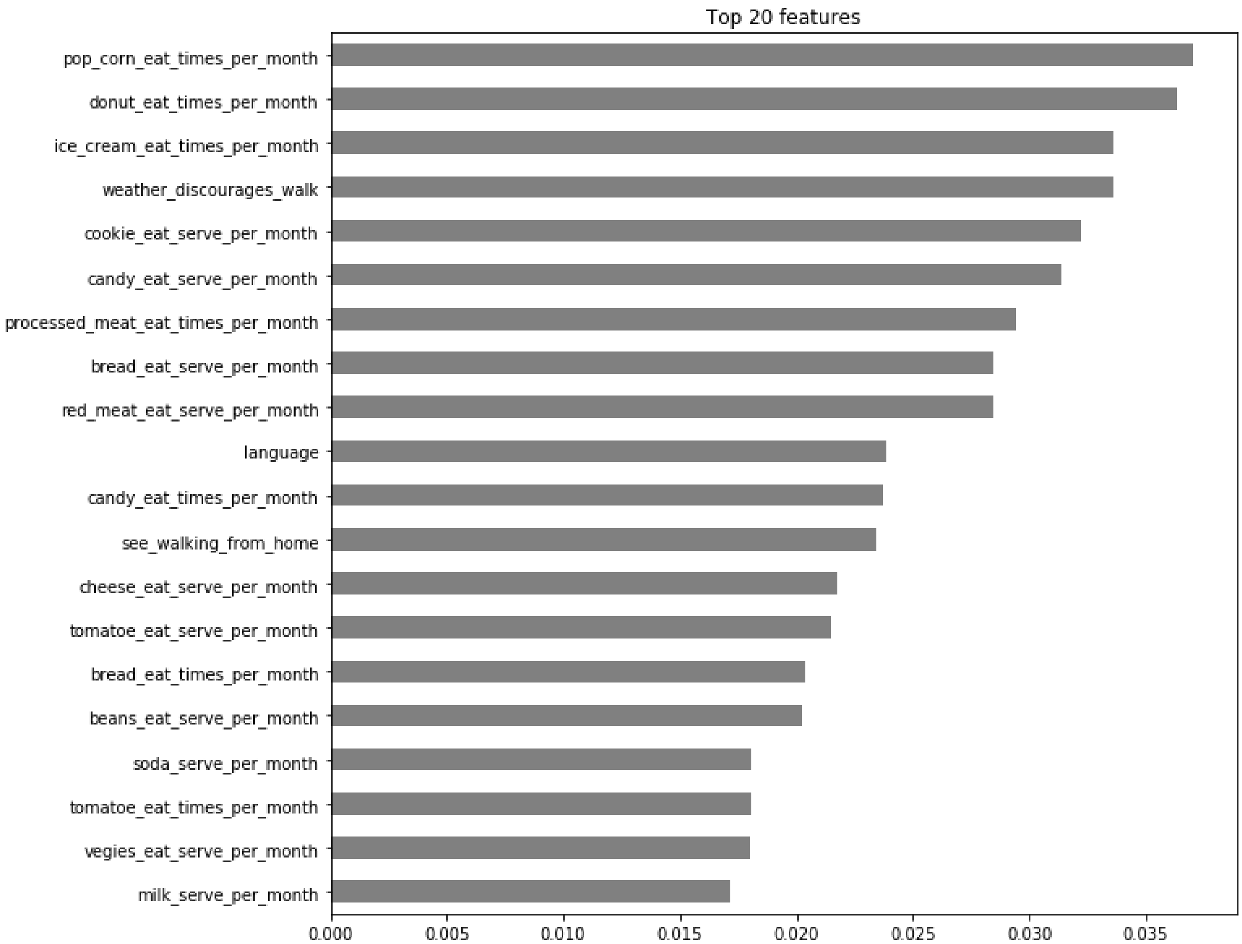
```
# Output best accuracy and best parameters
print('The score achieved with the best parameters = ', gridF.best_score_, '\n')
print('The parameters are:', gridF.best_params_)
```

```
# Use a scikit-learn pipeline to encode categoricals and fit a Random Forest Classifier model.

X_train = XTrain
y_train = yTrain
X_val = XVal
y_val = yVal

from sklearn.pipeline import make_pipeline
import category_encoders as ce
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier

pipeline = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy='mean'),
    RandomForestClassifier(random_state = 42, max_depth = 10,
                               max_features = 0.11373956383989692,
                               max_leaf_nodes = None,
                               min_samples_leaf = 1,
                               min_samples_split = 10,
                               n_estimators = 205))
pipeline.fit(X_train, y_train)

# Get the model's validation accuracy
ce.OneHotEncoder(use_cat_names=True),
print('Validation Accuracy', pipeline.score(X_val, y_val))
```

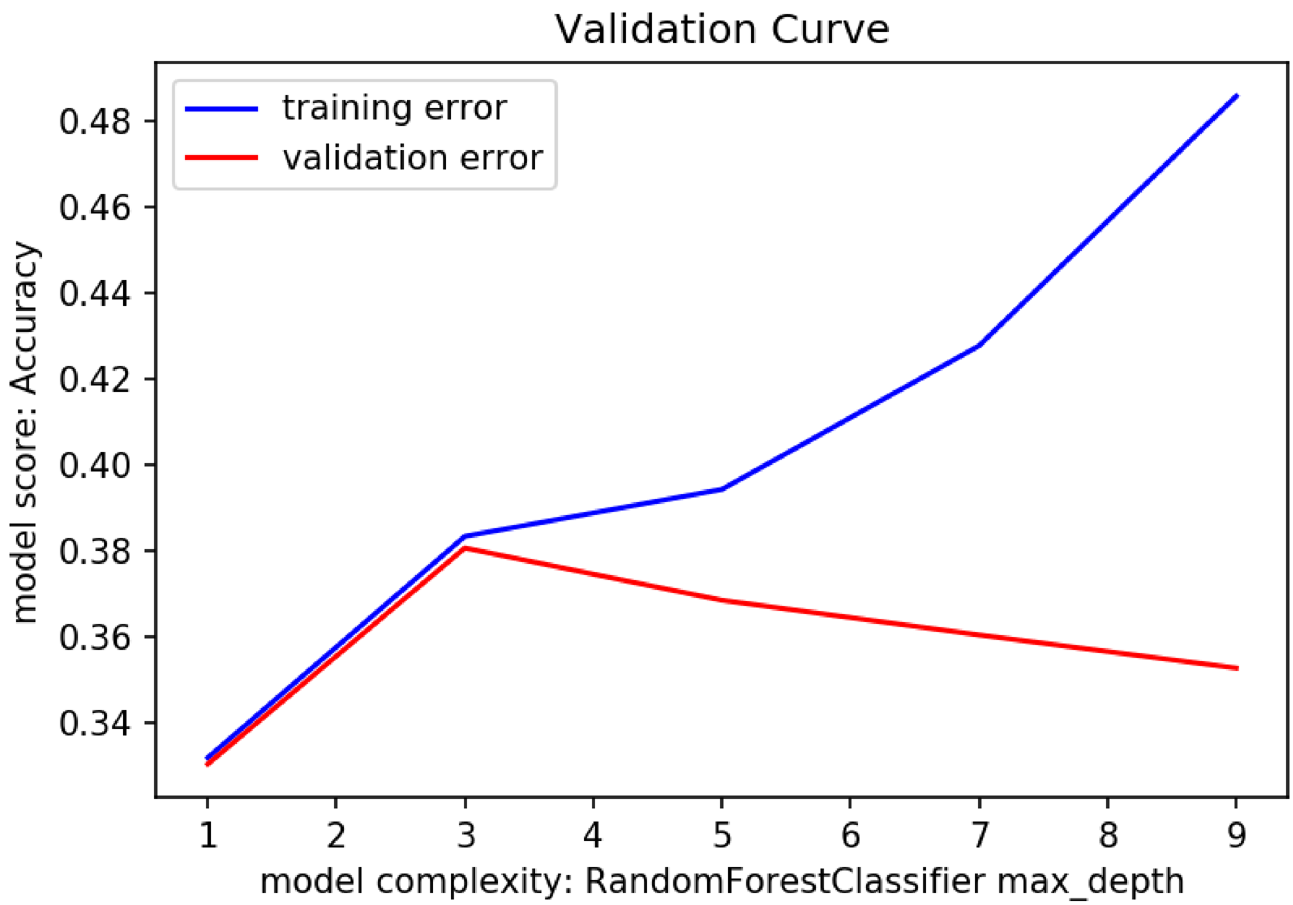
```
Validation Accuracy 0.398422090729783
```

```
# Plot of features
%matplotlib inline
import matplotlib.pyplot as plt
# Get feature importances
encoder = pipeline.named_steps['onehotencoder']
encoded = encoder.transform(X_train)
rf = pipeline.named_steps['randomforestclassifier']
```

```
importances1 = pd.Series(rf.feature_importances_, encoded.columns)
# Plot feature importances
n = 20
plt.figure(figsize=(10,n/2))
plt.title(f'Top {n} features')
importances1.sort_values()[-n:].plot.barh(color='grey');
```




```
# Generate validation curves
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import validation_curve
from sklearn.tree import DecisionTreeClassifier
pipeline = make_pipeline(
    ce.OrdinalEncoder(),
    SimpleImputer(),
    DecisionTreeClassifier()
)

depth = range(1, 10, 2)
train_scores, val_scores = validation_curve(
    pipeline, X_train, y_train,
    param_name='decisiontreeclassifier__max_depth',
    param_range=depth, scoring='accuracy',
    cv=3,
    n_jobs=-1
)

plt.figure(dpi=150)
plt.plot(depth, np.mean(train_scores, axis=1), color='blue', label='training error')
plt.plot(depth, np.mean(val_scores, axis=1), color='red', label='validation error')
plt.title('Validation Curve')
plt.xlabel('model complexity: RandomForestClassifier max_depth')
plt.ylabel('model score: Accuracy')
plt.legend();
```




```
# Tuning the hyper-parameters for a Random Forrest Classifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from scipy.stats import randint, uniform
from sklearn.pipeline import make_pipeline
import category_encoders as ce
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier

pipeline = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(),
    RandomForestClassifier(random_state = 42, max_depth = 10,
                           max_features = 0.11373956383989692,
                           max_leaf_nodes = None,
                           min_samples_leaf = 1,
                           min_samples_split = 10,
                           n_estimators = 205)
)

param_distributions = {'simpleimputer__strategy': ['mean', 'median', 'most_frequent']}
search = RandomizedSearchCV( pipeline, param_distributions=param_distributions, n_iter=10, cv=3, scoring='accuracy', verbose

search.fit(X_train, y_train);
```

```
Fitting 3 folds for each of 3 candidates, totalling 9 fits
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:266: UserWarning: The total space of
  % (grid_size, self.n_iter, grid_size), UserWarning)
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:    3.5s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:    5.3s
[Parallel(n_jobs=-1)]: Done   7 out of   9 | elapsed:    8.9s remaining:    2.5s
[Parallel(n_jobs=-1)]: Done   9 out of   9 | elapsed:   10.1s remaining:    0.0s
[Parallel(n_jobs=-1)]: Done   9 out of   9 | elapsed:   10.1s finished
```

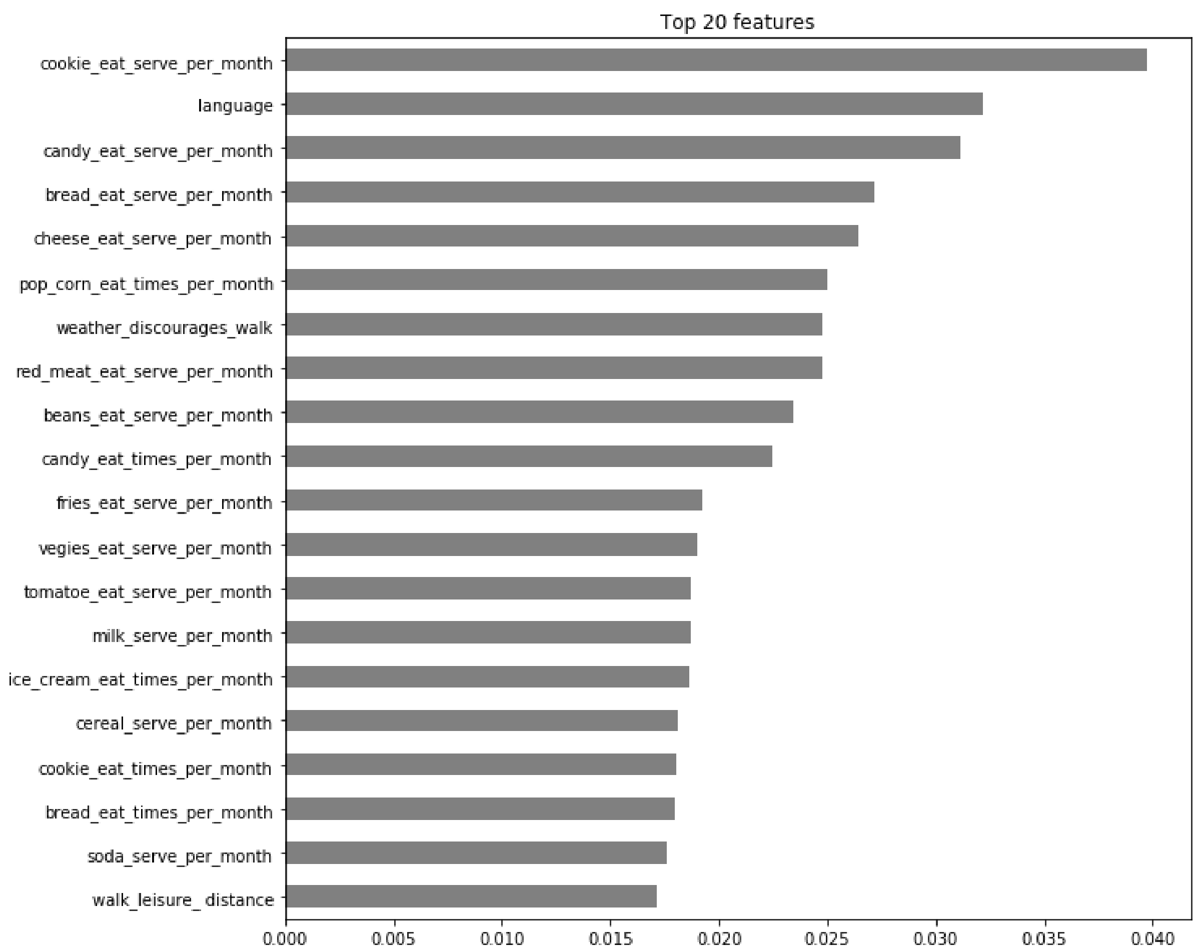
```
from sklearn.model_selection import cross_val_score
k = 3
scores = cross_val_score(pipeline, X_val, y_val, cv=k,
scoring='accuracy')
print(f'Validation Accuracy for {k} folds:', scores);
```

```
Validation Accuracy for 3 folds: [0.38235294 0.40631164 0.38690476]
```

```
print('Best hyperparameters', search.best_params_)
print('Cross-validation Accuracy', search.best_score_)
```

```
Best hyperparameters {'simpleimputer__strategy': 'mean'}
Cross-validation Accuracy 0.3945074823219865
```

```
pipeline.fit(X_val, y_val)
# Plot of features
%matplotlib inline
import matplotlib.pyplot as plt

# Get feature importances
encoder = pipeline.named_steps['onehotencoder']
encoded = encoder.transform(X_val)
rf = pipeline.named_steps['randomforestclassifier']
importances2 = pd.Series(rf.feature_importances_, encoded.columns)

# Plot feature importances
n = 20
plt.figure(figsize=(10,n/2))
plt.title(f'Top {n} features')
importances2.sort_values()[-n:].plot.barh(color='grey');
```




```
# Demonstrate the relatively high cardinatlity of candy_eat_times_per_month

XTrain['cookie_eat_serve_per_month'].value_counts()
```

```
1      1730
0      1502
2      1138
3       507
4       265
998     254
5       185
10      120
15       62
7        58
6        57
20       45
8        33
997      32
30       23
999      20
12       17
25       14
18        5
14        4
9         3
203       1
13        1
28        1
24        1
22        1
16        1
31        1
Name: cookie_eat_serve_per_month, dtype: int64
```

```
# Get drop-column importances
column = 'cookie_eat_serve_per_month'

# # Fit without column
pipeline = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy = 'mean'),
    RandomForestClassifier(random_state = 42, max_depth = 10,
                           max_features = 0.11373956383989692,
                           max_leaf_nodes = None,
                           min_samples_leaf = 1,
                           min_samples_split = 10,
                           n_estimators = 205)
)

pipeline.fit(X_train.drop(columns=column), y_train)
score_without = pipeline.score(X_val.drop(columns=column), y_val)
print(f'Validation Accuracy without {column}: {score_without}')

# Fit with column
pipeline = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy = 'mean'),
    RandomForestClassifier(random_state = 42, max_depth = 10,
                           max_features = 0.11373956383989692,
                           max_leaf_nodes = None,
                           min_samples_leaf = 1,
                           min_samples_split = 10,
                           n_estimators = 205)
)

pipeline.fit(X_train, y_train)
score_with = pipeline.score(X_val, y_val)
print(f'Validation Accuracy with {column}: {score_with}')

# Compare the error with & without column
print(f'Drop-Column Importance for {column}: {score_with - score_without}')
```

```
Validation Accuracy without cookie_eat_serve_per_month: 0.40039447731755423
Validation Accuracy with cookie_eat_serve_per_month: 0.398422090729783
Drop-Column Importance for cookie_eat_serve_per_month: -0.0019723865877712132
```

```
# Rerun the permutation importance process, but for a different feature
```

```
feature = 'language'
X_val_permuted = X_val.copy()
X_val_permuted[feature] = np.random.permutation(X_val[feature])
score_permuted = pipeline.score(X_val_permuted, y_val)

print(f'Validation Accuracy without {feature} permuted: {score_permuted}')
print(f'Validation Accuracy with {feature}: {score_with}')
print(f'Permutation Importance: {score_with - score_permuted}')
```

```
Validation Accuracy without language permuted: 0.3806706114398422
Validation Accuracy with language: 0.398422090729783
Permutation Importance: 0.017751479289940808
```

```
# Using Eli5 library which does not work with pipelines
transformers = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy='mean')
)

X_train_transformed = transformers.fit_transform(X_train)
X_val_transformed = transformers.transform(X_val)

model = RandomForestClassifier(random_state = 42, max_depth = 10,
                               max_features = 0.11373956383989692,
                               max_leaf_nodes = None,
                               min_samples_leaf = 1,
                               min_samples_split = 10,
                               n_estimators = 205)

model.fit(X_train_transformed, y_train)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=10, max_features=0.11373956383989692,
                       max_leaf_nodes=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=1,
                       min_samples_split=10, min_weight_fraction_leaf=0.0,
                       n_estimators=205, n_jobs=None, oob_score=False,
                       random_state=42, verbose=0, warm_start=False)
```

```
# Get permutation importances
! pip install eli5
from eli5.sklearn import PermutationImportance
import eli5

permuter = PermutationImportance(
    model,
    scoring='accuracy',
    n_iter=2,
    random_state=42
)

permuter.fit(X_val_transformed, y_val)
feature_names = X_val.columns.tolist()

eli5.show_weights(
    permuter,
    top=None, # show permutation importances for all features
    feature_names=feature_names
)
```

```
Collecting eli5
  Downloading https://files.pythonhosted.org/packages/97/2f/c85c7d8f8548e460829971785347e14e45fa5c6617da374711c
     |████████████████████████████████| 112kB 5.1MB/s
Requirement already satisfied: jinja2 in /usr/local/lib/python3.6/dist-packages (from eli5) (2.10.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from eli5) (1.3.1)
Requirement already satisfied: tabulate>=0.7.7 in /usr/local/lib/python3.6/dist-packages (from eli5) (0.8.5)
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (from eli5) (0.10.1)
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from eli5) (1.16.5)
Requirement already satisfied: attrs>16.0.0 in /usr/local/lib/python3.6/dist-packages (from eli5) (19.3.0)
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.6/dist-packages (from eli5) (0.21.3
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from eli5) (1.12.0)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.6/dist-packages (from jinja2->eli5) (
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.18-
Installing collected packages: eli5
Successfully installed eli5-0.10.1
Using TensorFlow backend.
```

Weight	Feature
0.0079 ± 0.0026	language
0.0059 ± 0.0000	walk_leisure_ distance
0.0039 ± 0.0013	smokeless_even_once
0.0030 ± 0.0007	red_meat_eat_serve_per_month
0.0030 ± 0.0059	coffee_times_per_month
0.0026 ± 0.0039	walk_number_wk
0.0023 ± 0.0033	red_meat_eat_times_per_month
0.0023 ± 0.0007	cigarette_even_once
0.0020 ± 0.0066	walk_leisure_number_wk
0.0016 ± 0.0020	calcium_past_month
0.0016 ± 0.0020	fries_eat_serve_per_month
0.0016 ± 0.0059	cigar_even_once
0.0016 ± 0.0046	single_walk_distance
0.0016 ± 0.0007	bread_eat_times_per_month
0.0013 ± 0.0079	walkable_bus_stop
0.0010 ± 0.0033	cheese_eat_serve_per_month
0.0010 ± 0.0046	fruit_eat_times_per_month
0.0010 ± 0.0033	weather_discourages_walk
0.0010 ± 0.0007	sports_drink_times_per_month
0.0007 ± 0.0013	walkable_relaxation
0.0007 ± 0.0039	milk_serve_per_month
0.0007 ± 0.0013	vitD_days_in_month
0.0007 ± 0.0026	milk_type
0.0003 ± 0.0059	bread_eat_serve_per_month
0.0003 ± 0.0007	vitamin_past_month
0.0003 ± 0.0046	cheese_eat_times_per_month
0.0003 ± 0.0020	walk_leisure_ time
0 ± 0.0000	vegies_eat_serve_per_month
0 ± 0.0000	genetic_counseling_with_MD
0 ± 0.0000	walkway_existence
0 ± 0.0000	calcium_days_in_month
-0.0000 ± 0.0026	vegies_eat_times_per_month
-0.0003 ± 0.0020	cereal_serve_per_month
-0.0003 ± 0.0059	walkable_entertainment
-0.0007 ± 0.0013	pizza_eat_times_per_month
-0.0007 ± 0.0000	multivitamin_past_month
-0.0007 ± 0.0000	single_walk_time
-0.0007 ± 0.0053	milk_times_per_month
-0.0010 ± 0.0033	candy_eat_serve_per_month
-0.0010 ± 0.0033	cookie_eat_serve_per_month
-0.0010 ± 0.0033	cookie_eat_times_per_month
-0.0010 ± 0.0020	had_genetic_counseling
-0.0010 ± 0.0033	vitD_reason
-0.0010 ± 0.0059	donut_eat_times_per_month
-0.0010 ± 0.0007	1st_kind_cereal_eaten
-0.0010 ± 0.0007	animals_discourage_walking
-0.0010 ± 0.0007	crime_discourages_walking
-0.0010 ± 0.0085	soda_times_per_month
-0.0010 ± 0.0046	juice_times_per_month
-0.0010 ± 0.0007	genetic_counseling_for_cancer
-0.0013 ± 0.0026	ice_cream_eat_times_per_month
-0.0013 ± 0.0000	fruit_drink_times_per_month
-0.0013 ± 0.0039	pop_corn_eat_times_per_month
-0.0013 ± 0.0053	processed_meat_eat_times_per_month

-0.0016 ± 0.0033 grains_eat_times_per_month
-0.0016 ± 0.0007 more_than_one_cereal_type
-0.0016 ± 0.0020 vitD_past_month
-0.0016 ± 0.0007 traffic_discourages_walking
-0.0020 ± 0.0000 walk_past_wk
-0.0020 ± 0.0013 fries_eat_times_per_month
-0.0020 ± 0.0026 beans_eat_times_per_month
-0.0023 ± 0.0007 beans_eat_serve_per_month
-0.0023 ± 0.0007 salsa_eat_times_per_month
-0.0023 ± 0.0007 walk_leisure_past_wk
-0.0023 ± 0.0033 soda_serve_per_month
-0.0026 ± 0.0000 tomatoe_eat_times_per_month
-0.0026 ± 0.0013 grains_eat_serve_per_month
-0.0030 ± 0.0020 tomatoe_eat_serve_per_month
-0.0030 ± 0.0033 pipe_even_once
-0.0030 ± 0.0059 walkable_retail
-0.0033 ± 0.0026 2nd_kind_cereal_eaten
-0.0033 ± 0.0000 potatoe_eat_times_per_month
-0.0036 ± 0.0072 see_walking_from_home
-0.0036 ± 0.0007 cereal_times_per_month
-0.0039 ± 0.0066 streets_have_walkways
-0.0043 ± 0.0007 salad_eat_times_per_month
-0.0043 ± 0.0020 candy_eat_times_per_month
-0.0046 ± 0.0026 multivitamin_days_in_month

```
# Thus, language is way more important according to feature permutation than according to feature importance in the Random Fo
# Use importances for feature selection
print('Shape before removing features:', X_train.shape)
```

```
Shape before removing features: (6081, 78)
```

```
# Remove features of 0 importance
zero_importance = 0.0003
mask = permuter.feature_importances_ > zero_importance
features = X_train.columns[mask]
X_train = X_train[features]
print('Shape after removing features:', X_train.shape)
```

```
Shape after removing features: (6081, 27)
```

```
# Random Forest with reduced features to 27
X_val = X_val[features]

pipeline = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy = 'mean'),
    RandomForestClassifier(random_state = 42, max_depth = 10,
                           max_features = 0.11373956383989692,
                           max_leaf_nodes = None,
                           min_samples_leaf = 1,
                           min_samples_split = 10,
                           n_estimators = 205)
)

# Fit on train, score on val
pipeline.fit(X_train, y_train)
print('Validation Accuracy', pipeline.score(X_val, y_val))
```

```
Validation Accuracy 0.4076265614727153
```

```
# Validation Accuracy History
# 0.2864660417694458- baseline guessing the majority class
# 0.4010853478046374- initial fit with optimal hyperparameters
# 0.398422090729783 - use pipeline with random forest
# 0.3945074823219865- from cross validation
# 0.398422090729783 - doing permutation importance
# 0.4076265614727153- after removing features of zero importance
```

```
# Gradient boosting using XGboost
encoder = ce.OrdinalEncoder()
X_train_encoded = encoder.fit_transform(X_train)
X_val_encoded = encoder.transform(X_val)
X_train.shape, X_val.shape, X_train_encoded.shape, X_val_encoded.shape
```

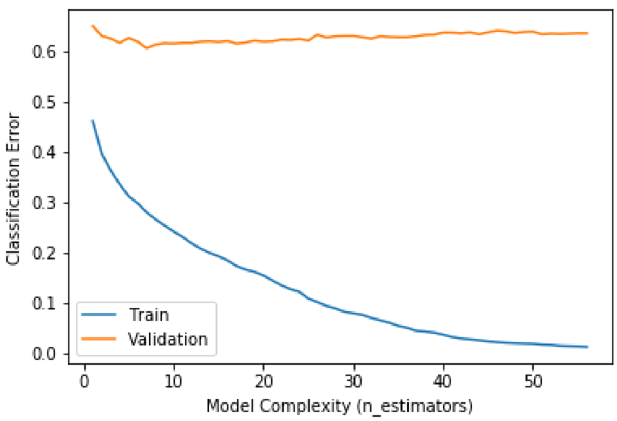
```
((6081, 27), (1521, 27), (6081, 27), (1521, 27))
```

```
#XGboost with learning_rate=0.25
from xgboost import XGBClassifier

eval_set = [(X_train_encoded, y_train),
            (X_val_encoded, y_val)]

model = XGBClassifier(
    random_state = 42,
    max_depth = 10,
    max_features = 0.11373956383989692,
    max_leaf_nodes = None,
    min_samples_leaf = 1,
    min_samples_split = 10,
    n_estimators = 205,
    learning_rate=0.25,
    n_jobs=-1
)

model.fit(X_train_encoded, y_train, eval_set=eval_set, eval_metric='merror',
    early_stopping_rounds=50)
```

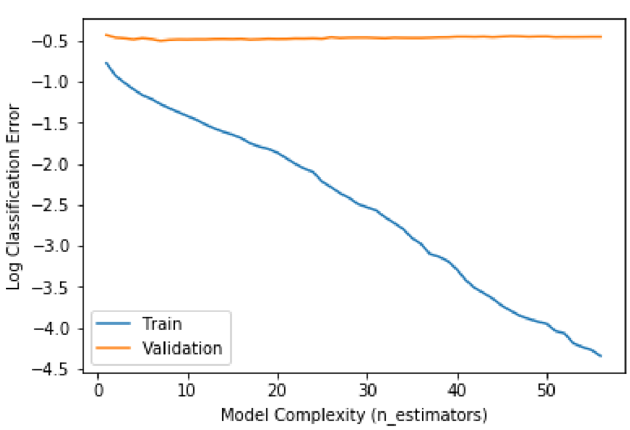
```
[0]	validation_0-merror:0.460615	validation_1-merror:0.649573
Multiple eval metrics have been passed: 'validation_1-merror' will be used for early stopping.

Will train until validation_1-merror hasn't improved in 50 rounds.
[1]	validation_0-merror:0.396152	validation_1-merror:0.629849
[2]	validation_0-merror:0.362769	validation_1-merror:0.624589
[3]	validation_0-merror:0.335636	validation_1-merror:0.616042
[4]	validation_0-merror:0.311955	validation_1-merror:0.625904
[5]	validation_0-merror:0.298142	validation_1-merror:0.618672
[6]	validation_0-merror:0.280053	validation_1-merror:0.605523
[7]	validation_0-merror:0.266075	validation_1-merror:0.612755
[8]	validation_0-merror:0.253741	validation_1-merror:0.615385
[9]	validation_0-merror:0.242065	validation_1-merror:0.614727
[10]	validation_0-merror:0.231376	validation_1-merror:0.616042
[11]	validation_0-merror:0.21855	validation_1-merror:0.616042
[12]	validation_0-merror:0.208189	validation_1-merror:0.618672
[13]	validation_0-merror:0.199638	validation_1-merror:0.619329
[14]	validation_0-merror:0.192896	validation_1-merror:0.618014
[15]	validation_0-merror:0.184838	validation_1-merror:0.619987
[16]	validation_0-merror:0.173491	validation_1-merror:0.614727
[17]	validation_0-merror:0.166584	validation_1-merror:0.6167
[18]	validation_0-merror:0.162144	validation_1-merror:0.620644
[19]	validation_0-merror:0.154909	validation_1-merror:0.618672
[20]	validation_0-merror:0.144877	validation_1-merror:0.619329
[21]	validation_0-merror:0.135175	validation_1-merror:0.622617
[22]	validation_0-merror:0.127611	validation_1-merror:0.621959
[23]	validation_0-merror:0.122348	validation_1-merror:0.623932
[24]	validation_0-merror:0.108864	validation_1-merror:0.620644
[25]	validation_0-merror:0.101792	validation_1-merror:0.632479
[26]	validation_0-merror:0.094392	validation_1-merror:0.626561
[27]	validation_0-merror:0.089295	validation_1-merror:0.629191
[28]	validation_0-merror:0.082717	validation_1-merror:0.629849
[29]	validation_0-merror:0.079592	validation_1-merror:0.629849
[30]	validation_0-merror:0.076632	validation_1-merror:0.627219
[31]	validation_0-merror:0.070548	validation_1-merror:0.624589
[32]	validation_0-merror:0.065779	validation_1-merror:0.629191
[33]	validation_0-merror:0.061174	validation_1-merror:0.627876
[34]	validation_0-merror:0.054761	validation_1-merror:0.627219
[35]	validation_0-merror:0.050978	validation_1-merror:0.627219
[36]	validation_0-merror:0.045058	validation_1-merror:0.629191
[37]	validation_0-merror:0.043578	validation_1-merror:0.631821
[38]	validation_0-merror:0.041276	validation_1-merror:0.632479
[39]	validation_0-merror:0.037329	validation_1-merror:0.636423
[40]	validation_0-merror:0.032725	validation_1-merror:0.636423
[41]	validation_0-merror:0.029765	validation_1-merror:0.635108
[42]	validation_0-merror:0.027956	validation_1-merror:0.637081
[43]	validation_0-merror:0.026147	validation_1-merror:0.633136
[44]	validation_0-merror:0.024009	validation_1-merror:0.637081
[45]	validation_0-merror:0.022529	validation_1-merror:0.640368
[46]	validation_0-merror:0.021214	validation_1-merror:0.639053
[47]	validation_0-merror:0.020391	validation_1-merror:0.635766
[48]	validation_0-merror:0.019734	validation_1-merror:0.637738
[49]	validation_0-merror:0.01924	validation_1-merror:0.638396
[50]	validation_0-merror:0.017596	validation_1-merror:0.633136
[51]	validation_0-merror:0.017102	validation_1-merror:0.634451
[52]	validation_0-merror:0.015129	validation_1-merror:0.633794
[53]	validation_0-merror:0.014471	validation_1-merror:0.634451
[54]	validation_0-merror:0.013978	validation_1-merror:0.635108
[55]	validation_0-merror:0.012991	validation_1-merror:0.635108
[56]	validation_0-merror:0.01184	validation_1-merror:0.635108
Stopping. Best iteration:
[6]	validation_0-merror:0.280053	validation_1-merror:0.605523

XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.25, max_delta_step=0, max_depth=10,
              max_features=0.11373956383989692, max_leaf_nodes=None,
              min_child_weight=1, min_samples_leaf=1, min_samples_split=10,
              missing=None, n_estimators=205, n_jobs=-1, nthread=None,
              objective='multi:softprob', random_state=42, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
```

```
                 reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
                 subsample=1, verbosity=1)
```

```
# Plot the results
results = model.evals_result()
train_error = results['validation_0']['merror']
val_error = results['validation_1']['merror']
epoch = range(1, len(train_error)+1)
plt.plot(epoch, train_error, label='Train')
plt.plot(epoch, val_error, label='Validation')
plt.ylabel('Classification Error')
plt.xlabel('Model Complexity (n_estimators)')
# plt.ylim((0.5, 0.7)) # Zoom in
plt.legend();
```




```
# Plot log classification error versus model complexity
import numpy as np
results = model.evals_result()
log_train_error = np.log(results['validation_0']['merror'])
log_val_error = np.log(results['validation_1']['merror'])
epoch = range(1, len(train_error)+1)
plt.plot(epoch, log_train_error, label='Train')
plt.plot(epoch, log_val_error, label='Validation')
plt.ylabel('Log Classification Error')
plt.xlabel('Model Complexity (n_estimators)')
# plt.ylim((-0.75, -0.4)) # Zoom in
plt.legend();
```




```
# Note the Classification Error is minimum at n_estimators = 6 in the above
# This is best scene when using the Zoom In scaling

#Gradient Boosting R^2
from sklearn.metrics import r2_score
from xgboost import XGBRegressor

gb = make_pipeline(
    ce.OrdinalEncoder(),
    XGBRegressor(n_estimators=46, objective='reg:squarederror', n_jobs=-1)
```

```
)

gb.fit(X_train, y_train)
y_pred = gb.predict(X_val)
from sklearn.metrics import r2_score
from xgboost import XGBRegressor
print('Gradient Boosting R^2', r2_score(y_val, y_pred))
```

```
Gradient Boosting R^2 0.2737135437482129
/usr/local/lib/python3.6/dist-packages/xgboost/core.py:587: FutureWarning: Series.base is deprecated and will b
  if getattr(data, 'base', None) is not None and \
```

```
# Getting the value distribution for the language feature
df_smoking1['language'].value_counts()
```

```
5    5713
4    1031
8     213
3     203
1     169
2     138
6     134
9       1
Name: language, dtype: int64
```

```
# Define function to vary the language feature while holding all other features constant
import numpy as np

def vary_language(model, example):
    print('Vary language, hold other features constant', '\n')
    example = example.copy()
    preds = []
    for lang in range(1, 9, 1):
        example['language'] = lang
        pred = model.predict(example)[0]
        print(f'Predicted cigarettes_per_day_bin: {pred:.3f}%')
        print(example.to_string(), '\n')
        preds.append(pred)
    print('Difference between predictions')
    print(np.diff(preds))
```

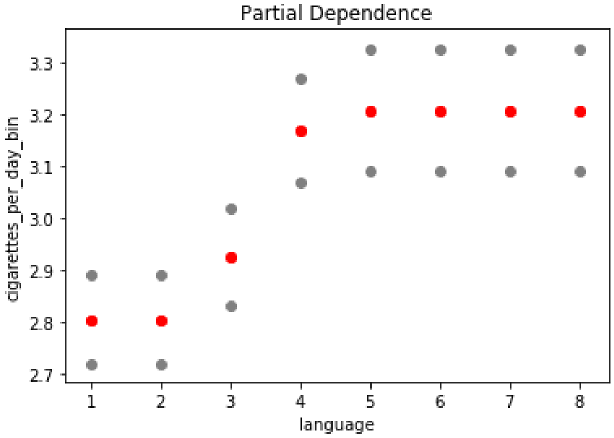
```
# Vary the language feature while holding all other features constant for the first row
example1 = X_val.iloc[[0]]
vary_language(gb, example1)
```

```
Vary language, hold other features constant

Predicted cigarettes_per_day_bin: 2.890%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         1                     3        2.0                       0                            0

Predicted cigarettes_per_day_bin: 2.890%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         2                     3        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.017%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         3                     3        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.268%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         4                     3        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.323%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         5                     3        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.323%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         6                     3        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.323%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         7                     3        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.323%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
31502         8                     3        2.0                       0                            0

Difference between predictions
[0.         0.12740803 0.25086045 0.05542064 0.         0.
 0.        ]
```

```
# Vary the language feature while holding all other features constant for the second row
example2 = X_val.iloc[[2]]
vary_language(gb, example2)
```

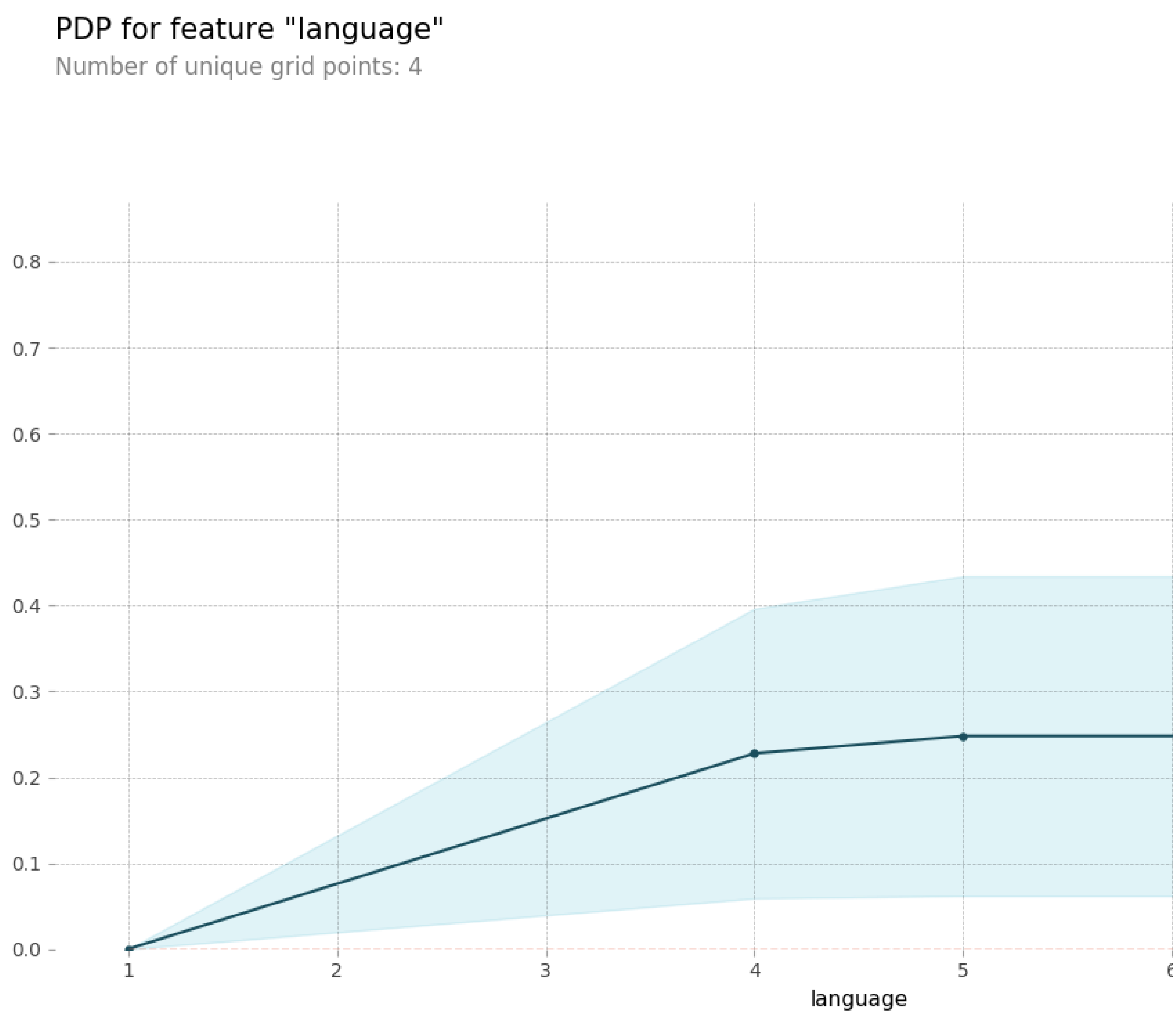
```
Vary language, hold other features constant

Predicted cigarettes_per_day_bin: 2.719%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         1                     2        2.0                       0                            0

Predicted cigarettes_per_day_bin: 2.719%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         2                     2        2.0                       0                            0

Predicted cigarettes_per_day_bin: 2.832%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         3                     2        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.069%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         4                     2        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.090%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         5                     2        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.090%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         6                     2        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.090%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         7                     2        2.0                       0                            0

Predicted cigarettes_per_day_bin: 3.090%
       language  milk_serve_per_month  milk_type  coffee_times_per_month  sports_drink_times_per_month  fruit_e
27082         8                     2        2.0                       0                            0

Difference between predictions
[0.         0.11254644 0.23789716 0.02041197 0.         0.
 0.        ]
```

```python
# Plot pair dependency of the language feature for rows 1 and 2
%matplotlib inline
import matplotlib.pyplot as plt

examples = pd.concat([example1, example2])
for lang in range(1, 9, 1):
    examples['language'] = lang
    preds = gb.predict(examples)
    for pred in preds:
        plt.scatter(lang, pred, color='grey')
        plt.scatter(lang, np.mean(preds), color='red')
    plt.title('Partial Dependence')
    plt.xlabel('language')
    plt.ylabel('cigarettes_per_day_bin')
```

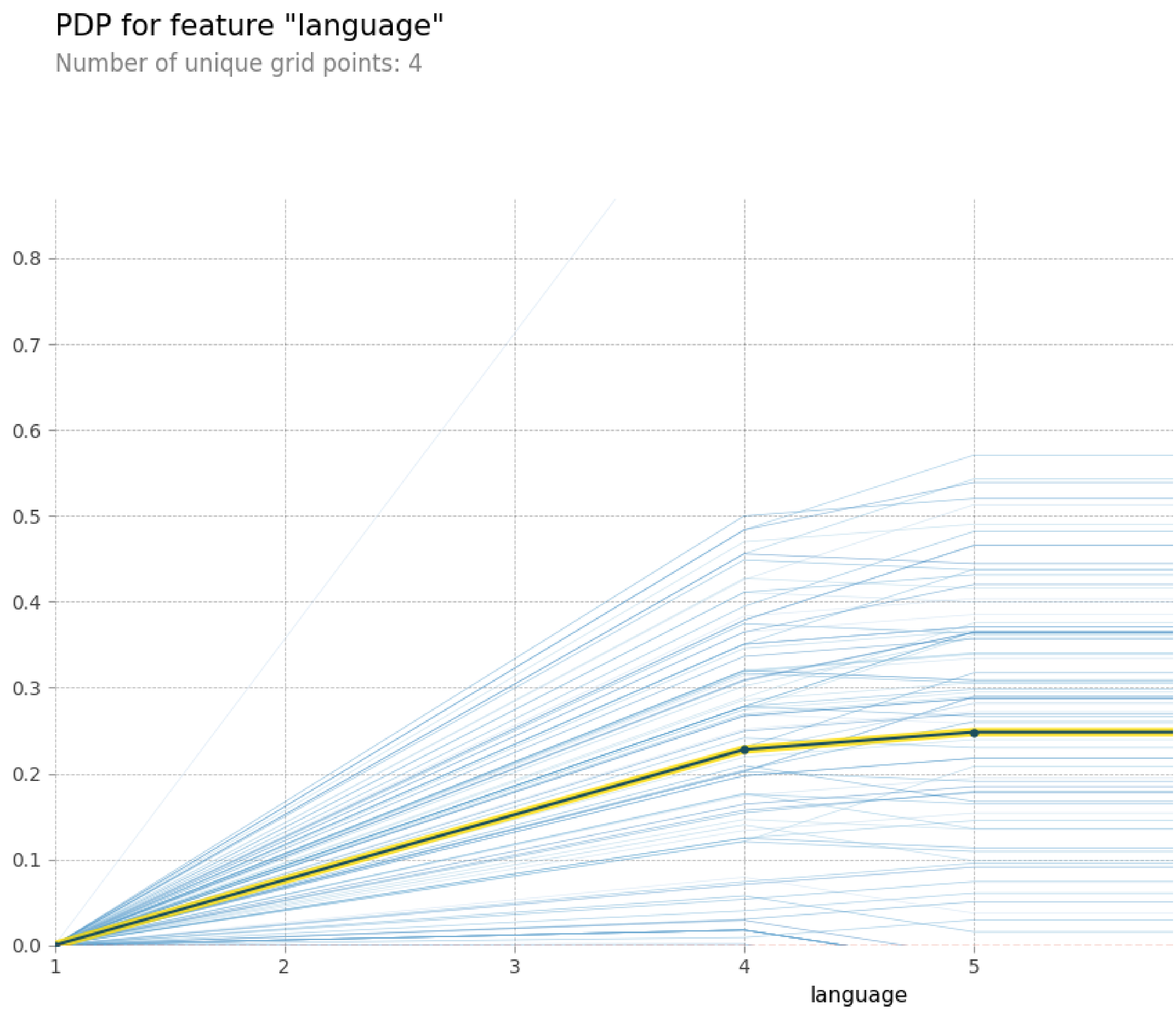



```
# Create patrial dependence plots with one feature
import matplotlib.pyplot as plt
! pip install PDPbox

# First for the language feature
plt.rcParams['figure.dpi'] = 100
from pdpbox.pdp import pdp_isolate, pdp_plot
feature = 'language'
isolated = pdp_isolate(
    model=gb,
    dataset=X_val,
    model_features=X_val.columns,
    feature=feature
)

pdp_plot(isolated, feature_name=feature);
```

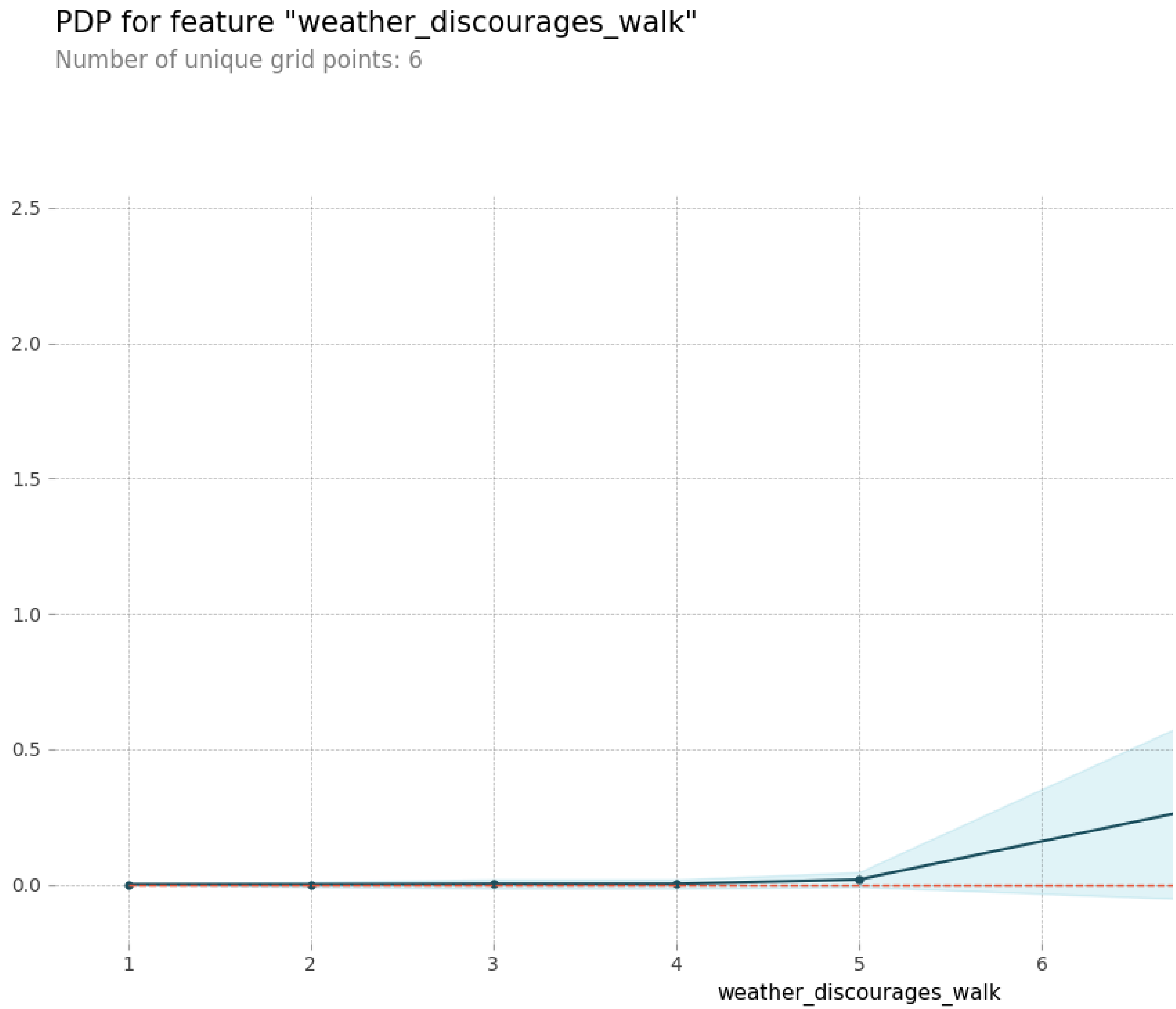
```
Collecting PDPbox
  Downloading https://files.pythonhosted.org/packages/87/23/ac7da5ba1c6c03a87c412e7e7b6e91a10d6ecf4474906c3e736
     |████████████████████████████████| 57.7MB 1.5MB/s
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from PDPbox) (0.24.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from PDPbox) (1.16.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from PDPbox) (1.3.1)
Requirement already satisfied: matplotlib>=2.1.2 in /usr/local/lib/python3.6/dist-packages (from PDPbox) (3.0.3
Requirement already satisfied: joblib in /usr/local/lib/python3.6/dist-packages (from PDPbox) (0.14.0)
Requirement already satisfied: psutil in /usr/local/lib/python3.6/dist-packages (from PDPbox) (5.4.8)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from PDPbox) (0.21.3)
Requirement already satisfied: python-dateutil>=2.5.0 in /usr/local/lib/python3.6/dist-packages (from pandas->P
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas->PDPbox) (201
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib>=2.1.2->
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib>=2.
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.5.0-
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-packages (from kiwisolver>=1.0.1->ma
Building wheels for collected packages: PDPbox
  Building wheel for PDPbox (setup.py) ... done
  Created wheel for PDPbox: filename=PDPbox-0.2.0-cp36-none-any.whl size=57690723 sha256=a05ce886e84ab8fdcc23ba
  Stored in directory: /root/.cache/pip/wheels/7d/08/51/63fd122b04a2c87d780464eeffb94867c75bd96a64d500a3fe
Successfully built PDPbox
Installing collected packages: PDPbox
Successfully installed PDPbox-0.2.0
```



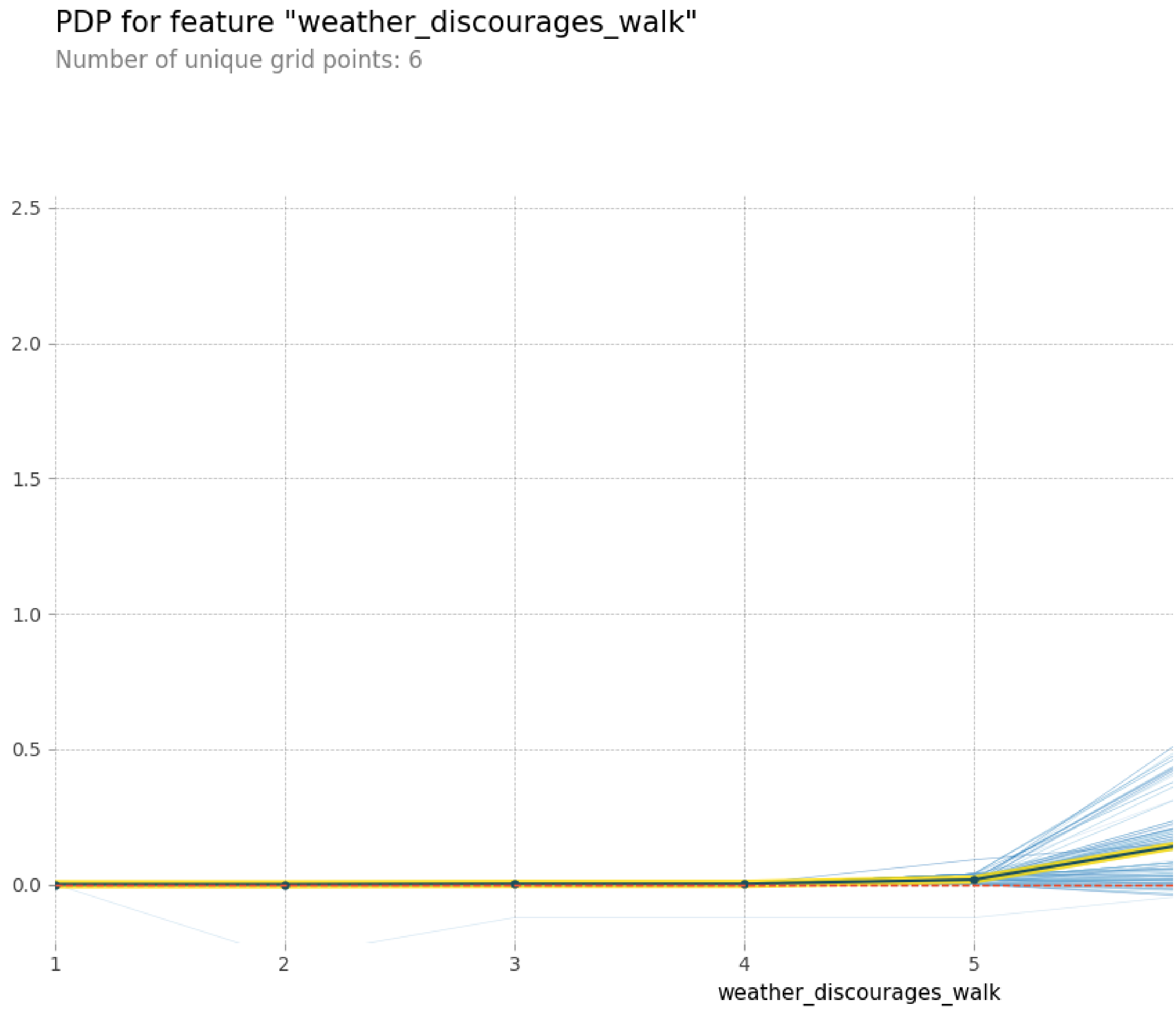
```
# Plot partial dependence plot with ICE lines for the language feature
pdp_plot(isolated, feature_name=feature, plot_lines=True, frac_to_plot=100) # Plot 100 ICE lines
plt.xlim(1,8);
```



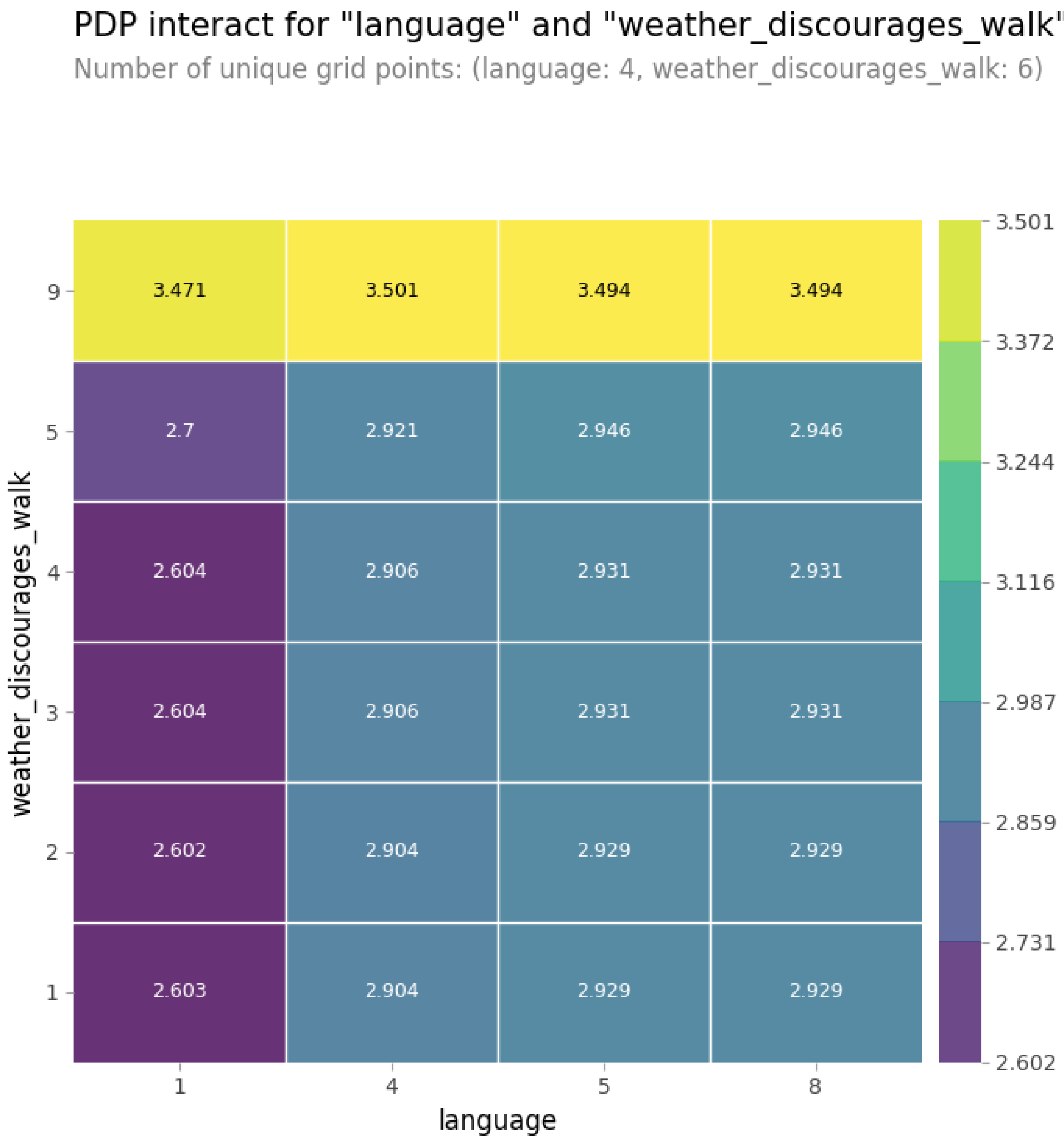

```
# First for the weather_discourages_walk feature
plt.rcParams['figure.dpi'] = 100
from pdpbox.pdp import pdp_isolate, pdp_plot
feature = 'weather_discourages_walk'
isolated = pdp_isolate(
    model=gb,
    dataset=X_val,
    model_features=X_val.columns,
    feature=feature
)

pdp_plot(isolated, feature_name=feature);
```



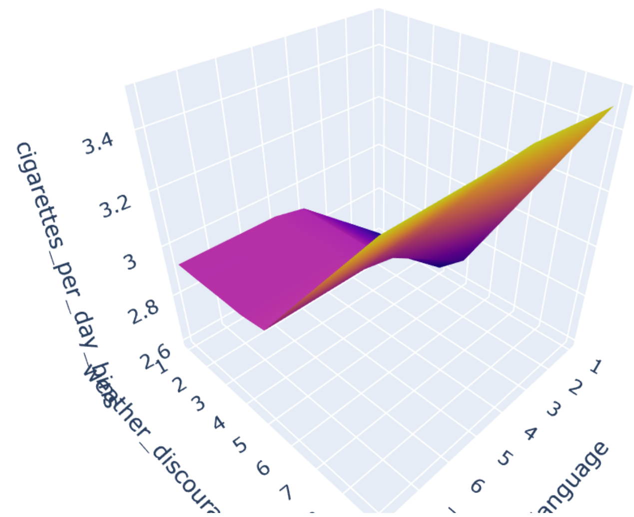

```
# Plot partial dependence plot with ICE lines for the weather_discourages_walk feature
pdp_plot(isolated, feature_name=feature, plot_lines=True, frac_to_plot=100) # Plot 100 ICE lines
plt.xlim(1,8);
```




```
# Partial Dependence Plots with 2 features
from pdpbox.pdp import pdp_interact, pdp_interact_plot

features = ['language', 'weather_discourages_walk']
interaction = pdp_interact(
    model=gb,
    dataset=X_val,
    model_features=X_val.columns,
    features=features
)

pdp_interact_plot(interaction, plot_type='grid', feature_names=features);
```




```
# A two feature partical dependence plot in 3D
pdp = interaction.pdp.pivot_table(
    values='preds',
    columns=features[0],
    index=features[1]
)[::-1] # Slice notation to reverse index order so y axis is ascending

import plotly.graph_objs as go

target = 'cigarettes_per_day_bins'

surface = go.Surface(x=pdp.columns,
                     y=pdp.index,
                     z=pdp.values)

layout = go.Layout(
    scene=dict(
    xaxis=dict(title=features[0]),
    yaxis=dict(title=features[1]),
    zaxis=dict(title=target)
    )
)
fig = go.Figure(surface, layout)
fig.show()
```



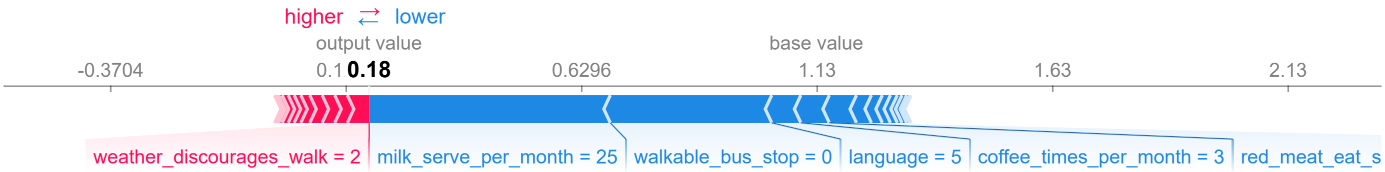

```
# Test ROC AUC
from sklearn.metrics import roc_auc_score
from sklearn.impute import SimpleImputer
from sklearn.pipeline import make_pipeline
from xgboost import XGBClassifier
import category_encoders as ce

processor = make_pipeline(
    ce.OrdinalEncoder(),
    SimpleImputer(strategy='mean')
)

# Note ROC AUC ranges from 0 - 1, the higher the better
X_val_processed = processor.fit_transform(X_val)
```

```
# Contributrions to making bin 1 (1 - 7 cigarettes per day) for sample 170
! pip install shap==0.23.0
! pip install -I shap

import shap

row = X_val.iloc[[170]]

explainer = shap.TreeExplainer(model)
row_processed = processor.transform(row)
shap_values_input = explainer.shap_values(row_processed)

shap.initjs()
shap.force_plot(
    base_value=explainer.expected_value[0],
    shap_values=shap_values_input[0],
    features=row
)
```

```
Collecting shap==0.23.0
  Downloading https://files.pythonhosted.org/packages/60/0d/8bd076821f7230edb2892ad982ea91ca25f2f925466563272e6
     |████████████████████████████████| 184kB 5.0MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (1.16.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (1.3.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (0.21
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (3.0.3)
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (0.24.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (4.28.1)
Requirement already satisfied: ipython in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (5.5.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn->shap=
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib->shap==0
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib-
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->sh
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas->shap==0.23.0
Requirement already satisfied: prompt-toolkit<2.0.0,>=1.0.4 in /usr/local/lib/python3.6/dist-packages (from ipy
Requirement already satisfied: pygments in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0)
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.6/dist-packages (from ipython->shap==
Requirement already satisfied: decorator in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/python3.6/dist-packages (from ipython->shap=
Requirement already satisfied: pexpect; sys_platform != "win32" in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from cycler>=0.10->matplotlib->sh
Requirement already satisfied: wcwidth in /usr/local/lib/python3.6/dist-packages (from prompt-toolkit<2.0.0,>=1
Requirement already satisfied: ipython-genutils in /usr/local/lib/python3.6/dist-packages (from traitlets>=4.2-
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.6/dist-packages (from pexpect; sys_pla
Building wheels for collected packages: shap
  Building wheel for shap (setup.py) ... done
  Created wheel for shap: filename=shap-0.23.0-cp36-cp36m-linux_x86_64.whl size=235663 sha256=97cab79745da68842
  Stored in directory: /root/.cache/pip/wheels/c1/2c/aa/10d1782fe066536fcd564a2f8adea4dd05f57768236038855b
Successfully built shap
Installing collected packages: shap
Successfully installed shap-0.23.0
Collecting shap
  Downloading https://files.pythonhosted.org/packages/2b/4b/5944c379c94f8f6335dd36b9316292236e3da0dee8da806f60a
     |████████████████████████████████| 266kB 4.1MB/s
Collecting numpy (from shap)
  Downloading https://files.pythonhosted.org/packages/0e/46/ae6773894f7eacf53308086287897ec568eac9768918d913d5b
     |████████████████████████████████| 20.0MB 40.6MB/s
Collecting scipy (from shap)
  Downloading https://files.pythonhosted.org/packages/29/50/a552a5aff252ae915f522e44642bb49a7b7b31677f9580cfd11
     |████████████████████████████████| 25.2MB 59.4MB/s
Collecting scikit-learn (from shap)
  Downloading https://files.pythonhosted.org/packages/a0/c5/d2238762d780dde84a20b8c761f563fe882b88c5a5fb03c0565
     |████████████████████████████████| 6.7MB 23.3MB/s
Collecting pandas (from shap)
  Downloading https://files.pythonhosted.org/packages/86/12/08b092f6fc9e4c2552e37add0861d0e0e0d743f78f1318973ca
     |████████████████████████████████| 10.4MB 39.0MB/s
Collecting tqdm>4.25.0 (from shap)
  Downloading https://files.pythonhosted.org/packages/e1/c1/bc1dba38b48f4ae3c4428aea669c5e27bd5a7642a74c8348451
     |████████████████████████████████| 61kB 23.7MB/s
Collecting joblib>=0.11 (from scikit-learn->shap)
  Downloading https://files.pythonhosted.org/packages/8f/42/155696f85f344c066e17af287359c9786b436b1bf86029bb341
     |████████████████████████████████| 296kB 41.5MB/s
Collecting python-dateutil>=2.6.1 (from pandas->shap)
  Downloading https://files.pythonhosted.org/packages/41/17/c62faccbfbd163c7f57f3844689e3a78bae1f403648a6afb1d0
     |████████████████████████████████| 235kB 42.9MB/s
Collecting pytz>=2017.2 (from pandas->shap)
  Downloading https://files.pythonhosted.org/packages/e7/f9/f0b53f88060247251bf481fa6ea62cd0d25bf1b11a87888e53c
     |████████████████████████████████| 512kB 35.2MB/s
Collecting six>=1.5 (from python-dateutil>=2.6.1->pandas->shap)
  Downloading https://files.pythonhosted.org/packages/73/fb/00a976f728d0d1fecfe898238ce23f502a721c0ac0ecfedb80e
Building wheels for collected packages: shap
  Building wheel for shap (setup.py) ... done
  Created wheel for shap: filename=shap-0.31.0-cp36-cp36m-linux_x86_64.whl size=375012 sha256=f2f79a7d3d05ebf26
  Stored in directory: /root/.cache/pip/wheels/7b/2d/46/ff8959add2e4e99a18a6e90b82f47508bf52fdf7e7d806f7df
Successfully built shap
ERROR: google-colab 1.0.0 has requirement pandas~=0.24.0, but you'll have pandas 0.25.2 which is incompatible.
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have folium 0.8.3 which is incompatible.
```

```
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have folium 0.8.3 which is incompatible.
ERROR: albumentations 0.1.12 has requirement imgaug<0.2.7,>=0.2.5, but you'll have imgaug 0.2.9 which is incomp
Installing collected packages: numpy, scipy, joblib, scikit-learn, six, python-dateutil, pytz, pandas, tqdm, sh
Successfully installed joblib-0.14.0 numpy-1.17.3 pandas-0.25.2 python-dateutil-2.8.0 pytz-2019.3 scikit-learn-
WARNING: The following packages were previously imported in this runtime:
  [dateutil,joblib,numpy,pandas,pytz,scipy,six,sklearn,tqdm]
You must restart the runtime in order to use newly installed versions.
```

RESTART RUNTIME




```python
# Contributrions to making bin 8 (49 - more cigarettes per day) for sample 170
import shap

row = X_val.iloc[[170]]

explainer = shap.TreeExplainer(model)
row_processed = processor.transform(row)
shap_values_input = explainer.shap_values(row_processed)

shap.initjs()
shap.force_plot(
    base_value=explainer.expected_value[7],
    shap_values=shap_values_input[7],
    features=row
)
```

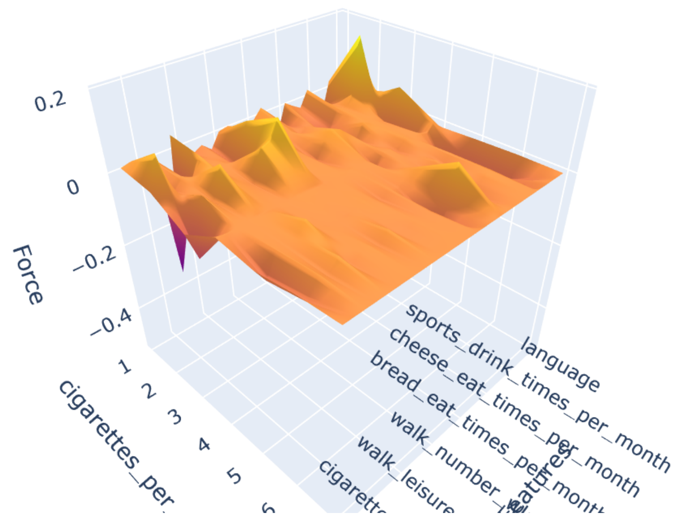

```python
# Featues importances for sample 170

feature_names = row.columns
feature_values = row.values[0]
shap_values_array = np.asarray(shap_values_input)
shaps = pd.Series(shap_values_array[0,0,:], zip(feature_names, feature_values))
shaps.sort_values().plot.barh(color='grey', figsize=(10,15));
```


(weather_discourages_walk, 2.0)
(fruit_eat_times_per_month, 2.0)
(bread_eat_serve_per_month, 3.0)
(milk_type, 3.0)
(cigar_even_once, 0.0)
(cheese_eat_times_per_month, 2.0)
(vitD_days_in_month, 0.0)
(smokeless_even_once, 0.0)
(walk_number_wk, 4.0)
(walkable_relaxation, 1.0)
(red_meat_eat_times_per_month, 3.0)
(bread_eat_times_per_month, 2.0)
(cigarette_even_once, 0.0)
(walk_leisure_ time, 0.0)
(cheese_eat_serve_per_month, 4.0)
(vitamin_past_month, 1.0)
(walk_leisure_number_wk, 0.0)
(calcium_past_month, 0.0)
(sports_drink_times_per_month, 0.0)
(fries_eat_serve_per_month, 3.0)
(walk_leisure_ distance, 0.0)
(single_walk_distance, 30.0)
(red_meat_eat_serve_per_month, 6.0)
(coffee_times_per_month, 3.0)
(language, 5.0)
(walkable_bus_stop, 0.0)
(milk_serve_per_month, 25.0)
−0.5
−0.4
−0.3
−0.2

```
# Create a dataframe for sample 170
# bin versus feature

my_python_list = [shap_values_array[0, 0, :], shap_values_array[1, 0, :], shap_values_array[2, 0, :], shap_values_array[3, 0
df_bins = pd.DataFrame(columns=np.array(feature_names), data=my_python_list)

df_bins.head(8)
```

	language	milk_serve_per_month	milk_type	coffee_times_per_month	sports_drink_times_per_month	fruit_eat_
0	-0.061779	-0.511992	0.026290	-0.060509	-0.014543	
1	0.019009	0.010580	0.184655	0.035340	0.003004	
2	0.047818	0.071849	-0.129440	-0.005469	0.004459	
3	-0.007261	0.016940	-0.002746	0.002019	-0.000090	
4	-0.002535	-0.072378	-0.148577	-0.052950	0.003131	
5	0.000696	-0.067148	-0.039820	-0.126848	0.003957	
6	0.000000	0.000000	0.000000	0.000000	0.000000	

```
# Create a 3D plot of force as a function of cigarettes_per_day_bin and feature for sample 170
# A two feature partical dependence plot in 3D
import plotly.graph_objs as go

surface = go.Surface(x=df_bins.columns,
                     y=df_bins.index + 1,
                     z=df_bins.values)

layout = go.Layout(
    scene=dict(
    xaxis=dict(title= 'Features'),
    yaxis=dict(title= 'cigarettes_per_day_bin'),
    zaxis=dict(title= 'Force')
    )
)
fig = go.Figure(surface, layout)
fig.show()
```

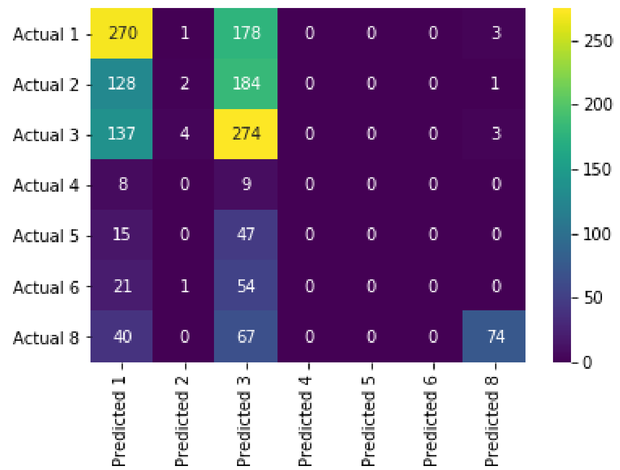



```
pros = shaps.sort_values(ascending=False)[:3].index
cons = shaps.sort_values(ascending=True)[:3].index

print('Pros:')
for i, pro in enumerate(pros, start=1):
    feature_name, feature_value = pro
    print(f'{i}. {feature_name} is {feature_value}')
print('\n')

print('Cons:')
for i, con in enumerate(cons, start=1):
    feature_name, feature_value = con
    print(f'{i}. {feature_name} is {feature_value}')
```

```
Pros:
1. weather_discourages_walk is 2.0
2. fruit_eat_times_per_month is 2.0
3. bread_eat_serve_per_month is 3.0


Cons:
1. milk_serve_per_month is 25.0
2. walkable_bus_stop is 0.0
3. language is 5.0
```

```
# Create function for constructing confusion matrix
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix
from sklearn.utils.multiclass import unique_labels
def plot_confusion_matrix(y_true, y_pred):
    labels = unique_labels(y_true)
    columns = [f'Predicted {label}' for label in labels]
    index = [f'Actual {label}' for label in labels]
    table = pd.DataFrame(confusion_matrix(y_true, y_pred),
    columns=columns, index=index)
    return sns.heatmap(table, annot=True, fmt='d', cmap='viridis')
```

```
y_pred = pipeline.predict(X_val)
plot_confusion_matrix(y_val, y_pred);
```




```
# Get precision & recall for majority class baseline
from sklearn.metrics import classification_report
print(classification_report(y_val, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.44      0.60      0.50       452
           2       0.25      0.01      0.01       315
           3       0.34      0.66      0.45       418
           4       0.00      0.00      0.00        17
           5       0.00      0.00      0.00        62
           6       0.00      0.00      0.00        76
           8       0.91      0.41      0.56       181

    accuracy                           0.41      1521
   macro avg       0.28      0.24      0.22      1521
weighted avg       0.38      0.41      0.34      1521
```

```
# Another way to get a classification report using an ROC_AUC approach (https://stackoverflow.com/questions/39685740/calcula
import pandas as pd
import numpy as np
from scipy import interp

from  sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import LabelBinarizer

def class_report(y_true, y_pred, y_score=None, average='micro'):
    if y_true.shape != y_pred.shape:
        print("Error! y_true %s is not the same shape as y_pred %s" % (
              y_true.shape,
              y_pred.shape)
        )
        return

    lb = LabelBinarizer()

    if len(y_true.shape) == 1:
        lb.fit(y_true)

    #Value counts of predictions
    labels, cnt = np.unique(
        y_pred,
        return_counts=True)
    n_classes = len(labels)
    pred_cnt = pd.Series(cnt, index=labels)

    metrics_summary = precision_recall_fscore_support(
            y_true=y_true,
            y_pred=y_pred,
            labels=labels)
```

```
    avg = list(precision_recall_fscore_support(
            y_true=y_true,
            y_pred=y_pred,
            average='weighted'))

    metrics_sum_index = ['precision', 'recall', 'f1-score', 'support']
    class_report_df = pd.DataFrame(
        list(metrics_summary),
        index=metrics_sum_index,
        columns=labels)

    support = class_report_df.loc['support']
    total = support.sum()
    class_report_df['avg / total'] = avg[:-1] + [total]

    class_report_df = class_report_df.T
    class_report_df['pred'] = pred_cnt
    class_report_df['pred'].iloc[-1] = total

    if not (y_score is None):
        fpr = dict()
        tpr = dict()
        roc_auc = dict()
        for label_it, label in enumerate(labels):
            fpr[label], tpr[label], _ = roc_curve(
                (y_true == label).astype(int),
                y_score[:, label_it])

            roc_auc[label] = auc(fpr[label], tpr[label])

        if average == 'micro':
            if n_classes <= 2:
                fpr["avg / total"], tpr["avg / total"], _ = roc_curve(
                    lb.transform(y_true).ravel(),
                    y_score[:, 1].ravel())
            else:
                fpr["avg / total"], tpr["avg / total"], _ = roc_curve(
                        lb.transform(y_true).ravel(),
                        y_score.ravel())

            roc_auc["avg / total"] = auc(
                fpr["avg / total"],
                tpr["avg / total"])

        elif average == 'macro':
            # First aggregate all false positive rates
            all_fpr = np.unique(np.concatenate([
                fpr[i] for i in labels]
            ))

            # Then interpolate all ROC curves at this points
            mean_tpr = np.zeros_like(all_fpr)
            for i in labels:
                mean_tpr += interp(all_fpr, fpr[i], tpr[i])

            # Finally average it and compute AUC
            mean_tpr /= n_classes

            fpr["macro"] = all_fpr
            tpr["macro"] = mean_tpr

            roc_auc["avg / total"] = auc(fpr["macro"], tpr["macro"])

        class_report_df['AUC'] = pd.Series(roc_auc)

    return class_report_df
```

```
# The above function provides the predicted values for each class.
class_report(y_val, y_pred, y_score=None, average='micro')
```

```
              precision    recall  f1-score   support     pred
```

```python
# Deriving an ROC curve for each class in cigarettes_per_day_bins
# Transform y_val and y_pred to arrays that are 1521 by 8 with bins as the columns

y_val_trans = pd.DataFrame(columns=['1','2','3','4','5','6','7', '8'])
y_val_trans['1']=y_val.map(lambda x : 1 if x==1 else 0)
y_val_trans['2']=y_val.map(lambda x : 1 if x==2 else 0)
y_val_trans['3']=y_val.map(lambda x : 1 if x==3 else 0)
y_val_trans['4']=y_val.map(lambda x : 1 if x==4 else 0)
y_val_trans['5']=y_val.map(lambda x : 1 if x==5 else 0)
y_val_trans['6']=y_val.map(lambda x : 1 if x==6 else 0)
y_val_trans['7']=y_val.map(lambda x : 1 if x==7 else 0)
y_val_trans['8']=y_val.map(lambda x : 1 if x==8 else 0)
print ('y_val_trans =')
print (y_val_trans.head(), '\n')

y_pred_proba = model.predict_proba(X_val)

y_pred_trans = pd.DataFrame(y_pred_proba)

print ('y_pred_trans')
print (y_pred_trans.head(), '\n')
```

```
y_val_trans =
       1  2  3  4  5  6  7  8
31502  0  0  1  0  0  0  0  0
4439   1  0  0  0  0  0  0  0
27082  0  1  0  0  0  0  0  0
19317  0  1  0  0  0  0  0  0
2063   0  0  0  0  1  0  0  0

y_pred_trans
          0         1         2         3         4         5         6  \
0  0.178043  0.130463  0.289964  0.049230  0.100498  0.109930  0.047515
1  0.335150  0.190683  0.208097  0.055982  0.050956  0.061312  0.048803
2  0.162726  0.170873  0.269222  0.054843  0.082429  0.077854  0.053092
3  0.042685  0.109349  0.096257  0.042840  0.042537  0.042914  0.042197
4  0.339703  0.140684  0.228627  0.040287  0.058948  0.087655  0.038745

          7
0  0.094356
1  0.049017
2  0.128961
3  0.581220
4  0.065351
```

```python
# Learn to predict each class against the other
print(__doc__)

import numpy as np

from sklearn import svm, datasets
from sklearn.metrics import roc_curve, auc

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(8):
    fpr[i], tpr[i], _ = roc_curve(y_val_trans.iloc[:, i], y_pred_trans.iloc[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_val_trans.values.ravel(), y_pred_trans.values.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
```

```
Automatically created module for IPython interactive environment
```

```python
# Compute macro-average ROC curve and ROC area
import matplotlib.pyplot as plt
from itertools import cycle
from scipy import interp
n_classes = 8
```

```
lw = 2

# First aggregate all false positive rates
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
    mean_tpr += interp(all_fpr, fpr[i], tpr[i])

# Finally average it and compute AUC
mean_tpr /= n_classes

fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure()
plt.plot(fpr["micro"], tpr["micro"],
         label='micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc["micro"]),
         color='deeppink', linestyle=':', linewidth=4)

plt.plot(fpr["macro"], tpr["macro"],
         label='macro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc["macro"]),
         color='navy', linestyle=':', linewidth=4)

colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'blue', 'green'])
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=lw,
             label='ROC curve of class {0} (area = {1:0.2f})'
             ''.format(i + 1, roc_auc[i]))

plt.plot([0, 1], [0, 1], 'k--', lw=lw)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Some extension of Receiver operating characteristic to multi-class')
plt.legend(loc="lower right")
plt.show()
```