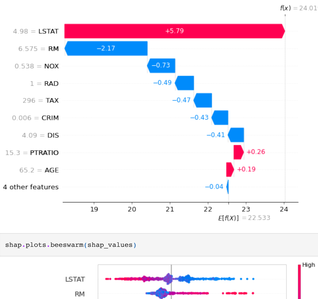
In [1]:
```
import pandas as pd
```

In [2]:
```
import xgboost
import shap
```

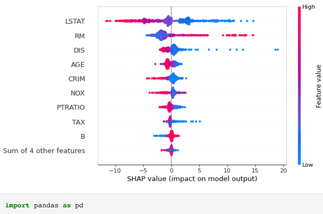
In [3]:
```
X, y = shap.datasets.boston()
model = xgboost.XGBRegressor().fit(X, y)
```

In [4]:
```
explainer = shap.Explainer(model)
shap_values = explainer(X)
```

In [5]:
```
shap.plots.waterfall(shap_values[0])
```



In [6]:
```
shap.plots.beeswarm(shap_values)
```



In [7]:
```
import pandas as pd

shaps_df = pd.DataFrame(shap_values.values)
```

In [8]:
```
shaps_df.columns=['SHAP_' + x for x in X.columns]
```

In [9]:
```
shaps_df
```

Out[9]:

	SHAP_CRIM	SHAP_ZN	SHAP_INDUS	SHAP_CHAS	SHAP_NOX	SHAP_RM	SHAP_AGE	SHAP_DIS	SHAP_RAD	SHAP_TAX	SHAP_PTRATIO	SHAP_B	SHAP_LSTAT
0	-0.428502	-0.066637	-0.481867	-0.001530	-0.729227	-2.170028	0.192134	-0.414259	-0.491561	-0.472966	0.256695	-0.053907	5.788325
1	-0.159478	-0.039209	-0.227837	-0.000803	0.180373	-1.750252	-0.246799	-0.948719	-0.091274	0.210134	0.460189	0.001291	1.547877
2	-0.062259	-0.039241	-0.270554	-0.002156	0.627054	3.956776	0.289584	-0.936786	-0.065633	0.409528	0.036114	0.209845	7.915174
3	0.252239	-0.007029	0.252571	-0.003503	0.543809	1.614911	0.197332	-1.169711	-0.060547	1.086732	-0.138008	0.192880	8.041687
4	0.642628	-0.005839	0.277436	-0.006831	0.367894	4.457727	0.441548	-0.360033	-0.049200	2.044360	-0.134221	0.256531	5.662515
...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.311293	-0.030525	-0.662102	0.012181	0.090738	-0.524010	-0.291097	0.526536	-0.597070	0.062571	-1.423389	-0.052292	1.847324
502	-0.069905	0.014419	-0.183791	-0.005589	-0.025346	-2.323497	-0.368136	1.272306	-0.159295	-0.224204	-1.457388	-0.035109	1.411655
503	-0.346926	-0.001135	-0.508748	-0.004978	0.178337	2.970993	-1.281448	0.712909	-0.403885	-0.187878	-2.105958	-0.086937	2.020948
504	0.354983	-0.014469	-0.727385	0.003881	0.041460	0.119506	-1.245963	0.283501	-0.632829	-0.155977	-1.670154	0.094823	2.354920
505	-0.926841	-0.002582	-0.841228	-0.015234	-0.225415	-4.432957	-1.702593	0.049425	-0.563556	-0.343111	-1.926649	-0.310639	0.066318

506 rows × 13 columns

In [10]:
```
#shap positivi contribuiscono positivamente all'output -> di interesse
#creo matrice binaria dove si ha 1 se quella persona ha shap positivo per quella feature, 0 altrimenti
positive_shaps_df = shaps_df.apply(lambda x: x>0).astype(int)
```

In [11]:
```
positive_shaps_df
```

Out[11]:

	SHAP_CRIM	SHAP_ZN	SHAP_INDUS	SHAP_CHAS	SHAP_NOX	SHAP_RM	SHAP_AGE	SHAP_DIS	SHAP_RAD	SHAP_TAX	SHAP_PTRATIO	SHAP_B	SHAP_LSTAT
0	0	0	0	0	0	0	1	0	0	0	1	0	1
1	0	0	0	0	1	0	0	0	0	1	1	1	1
2	0	0	0	0	1	1	1	0	0	1	1	1	1
3	1	0	1	0	1	1	1	0	0	1	0	1	1
4	1	0	1	0	1	1	1	0	0	1	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	1	0	0	1	1	0	0	1	0	1	0	0	1
502	0	1	0	0	0	0	0	1	0	0	0	0	1
503	0	0	0	0	1	1	0	1	0	0	0	0	1
504	1	0	0	1	1	1	0	1	0	0	0	1	1
505	0	0	0	0	0	0	0	1	0	0	0	0	1

506 rows × 13 columns

In [ ]:
```
#utilizzo apriori per generarmi itemset comuni -> insiemi di baskets composti da pattern comuni di shap positivi
```

In [12]:
```
from mlxtend.frequent_patterns import apriori
```

In [14]:
```
frequent_itemsets = apriori(positive_shaps_df, min_support=0.01, use_colnames=True)
```

In [15]:
```
frequent_itemsets
frequent_itemsets['length'] = frequent_itemsets['itemsets'].apply(lambda x: len(x))
```

In [16]:
```
frequent_itemsets[frequent_itemsets['length'] > 1].sort_values("support", ascending=False)
```

Out[16]:

	support	itemsets	length
16	0.577075	(SHAP_CRIM, SHAP_NOX)	2
61	0.509881	(SHAP_B, SHAP_NOX)	2
23	0.458498	(SHAP_CRIM, SHAP_B)	2
76	0.452569	(SHAP_DIS, SHAP_RAD)	2
19	0.413043	(SHAP_CRIM, SHAP_DIS)	2
...	...	...	...
2861	0.011858	(SHAP_LSTAT, SHAP_PTRATIO, SHAP_DIS, SHAP_RM, ...	6
2865	0.011858	(SHAP_B, SHAP_TAX, SHAP_PTRATIO, SHAP_RM, SHAP...	6
3320	0.011858	(SHAP_NOX, SHAP_TAX, SHAP_PTRATIO, SHAP_INDUS,...	7
2866	0.011858	(SHAP_LSTAT, SHAP_TAX, SHAP_PTRATIO, SHAP_RM, ...	6
3645	0.011858	(SHAP_B, SHAP_CRIM, SHAP_LSTAT, SHAP_NOX, SHAP...	10

3633 rows × 3 columns

In [17]:
```
mask = frequent_itemsets['itemsets'].map(lambda x: 'SHAP_LSTAT' in set(x))
```

In [47]:
```
#come primo step di un ipotetico algoritmo, prendo gli itemset (rules) che contengono la feature più importante
#secondo lo shap e che contengono più di un solo itemset (il solo shap della prima feature)

frequent_itemsets[mask & (frequent_itemsets['length'] > 1)].sort_values('support',ascending=False)
```

Out[47]:

	support	itemsets	length
62	0.389328	(SHAP_LSTAT, SHAP_NOX)	2
24	0.316206	(SHAP_CRIM, SHAP_LSTAT)	2
75	0.302372	(SHAP_LSTAT, SHAP_AGE)	2
90	0.288538	(SHAP_B, SHAP_LSTAT)	2
128	0.286561	(SHAP_CRIM, SHAP_LSTAT, SHAP_NOX)	3
...	...	...	...
1546	0.011858	(SHAP_ZN, SHAP_B, SHAP_CHAS, SHAP_LSTAT, SHAP_...	5
1564	0.011858	(SHAP_ZN, SHAP_LSTAT, SHAP_NOX, SHAP_DIS, SHAP...	5
1576	0.011858	(SHAP_ZN, SHAP_LSTAT, SHAP_NOX, SHAP_DIS, SHAP...	5
3136	0.011858	(SHAP_CRIM, SHAP_LSTAT, SHAP_TAX, SHAP_PTRATIO...	7
3645	0.011858	(SHAP_B, SHAP_CRIM, SHAP_LSTAT, SHAP_NOX, SHAP...	10

1715 rows × 3 columns

In [ ]:
```
#prendo il primo itemset in termini di frequenza nel database, quindi SHAP_LSTAT, SHAP_NOX
```

In [49]:
```
import numpy as np
```

In [34]:
```
#seleziono le osservazioni che corrispondono a quell'itemset
lstat_nox_index = positive_shaps_df[(positive_shaps_df['SHAP_LSTAT']==1) & (positive_shaps_df['SHAP_NOX']==1)].index
```

In [50]:
```
#ricontrollo la media del target del dataset
np.mean(y)
```

Out[50]:
```
22.532806324110673
```

In [51]:
```
np.mean(y[lstat_nox_index])
```

Out[51]:
```
30.13147208121828
```

In [52]:
```
(30.13-22.53)/22.53
```

Out[52]:
```
0.3373280071016421
```

In [ ]:
```
#l'itemset selezionato porta la media del target al 30% in più rispetto alla media
#
# si può pensare a diverse strategie, come itemset disgiunti ma con supporto alto (pattern frequenti ma che
# corrispondono a feature completamente diverse) o pattern più complessi con più elementi in ogni itemset per
# azione più chirurgica
```

In [ ]:
```
#Si possono selezionare
feat3_max = X.loc[lstat_nox_index,"LSTAT"].max()
feat3_min = X.loc[lstat_nox_index,"LSTAT"].min()
feat4_max = X.loc[lstat_nox_index,"NOX"].max()
feat4_min = X.loc[lstat_nox_index,"NOX"].min()
```

In [42]:
```
feat4_min
```

Out[42]:
```
0.389
```

In [43]:
```
feat2_min
```

Out[43]:
```
0.394
```

In [45]:
```
#Filtro per visualizzare le osservazioni che soddisfano la rule

X.loc[lstat_nox_index]
```

Out[45]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3.0	222.0	18.7	394.12	5.21
...	...	...	...	...	...	...	...	...	...	...	...	...	...
464	7.83932	0.0	18.10	0.0	0.655	6.209	65.4	2.9634	24.0	666.0	20.2	396.90	13.22
483	2.81838	0.0	18.10	0.0	0.532	5.762	40.3	4.0983	24.0	666.0	20.2	392.92	10.42
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48

197 rows × 13 columns

In [ ]:
```

```