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Course Name: Topics in Data Science

Assignment No-03(Lab)

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List of the work:

-Example-1-‘student-mat.csv’- code and output (jupyter notebook is attached).

-Example-2-‘compass-score-two-years’ dataset is analyzed following the instruction given in the PDF. (jupyter notebook is attached).

-Overall conclusions about effectiveness of explainability techniques used as of the instruction given in the PDF. (attached in the next page).

References:

-Class Lecture and PDF.

-https://lime-ml.readthedocs.io/en/latest/lime.html

-https://analyticsindiamag.com/how-to-explain-ml-models-and-feature-importance-with-lime/

-https://www.justintodata.com/explainable-machine-learning-with-python/

An introduction of explainability techniques of machine learning:

Name of the Dataset: ‘compass-score-two-years’.

Target variable and Purpose of the Analysis: ‘two_year_recid‘ is the target variable of my analysis in the dataset. The target variable indicates the probability of going jail in the next two years for a person by doing any new crime. The model will make prediction of the probability of target variable.

Variable used to predict: There was 53 features in the dataset, I have considered 9 features to predict my target variable. I drop many features in this analysis as I feel these have few and almost no impact in the target variable. Later, I have created some dummy variables for the need of my analysis. In total, I have worked with 17 features.

Explainability techniques of machine learning:

To complete the overall analysis I have used some **explainability techniques** of machine learning. **Explainable machine learning** includes methods to extract and interpret information from ‘black box’ models, in a humanly understandable way so that we can explain how the model makes predictions.

With the help of these explainable ML methods, we can answer questions such as:

- What are the critical features for the predictions?
- How much did this particular feature contribute to the prediction?
- Why was this specific instance classified as positive?

The explainable machine learning methods can be of two main categories:

- **Summary-based**: explain the average behavior of the model
- **Instance-based**: explain individual instance’s prediction

In general, when we try to understand the overall picture or debug the model, the summary-based methods are more appropriate. In contrast, instance-based methods help us focus on one prediction at a time.

In my analysis I will use explainable machine learning methods of both types:

- **SHAP**: both summary and instance-based
- **LIME**: instance-based

Overall conclusions about effectiveness of explainability techniques used:

- I have used **XGBoost model** that predicts individuals’ chances of going to jail in the next two years with doing a new crime throughout the analysis based on df_c_features. This model has provided excellent prediction results. I have used **XGBRegressor**. My goal is to fit a model that I can explain instead of a good one. So I have omitted processes like train-test split and hyperparameter tuning.

- **SHAP values** interpret the impact of having a certain value for a given feature in comparison to the prediction we'd make if that feature took some baseline value. To display the SHAP value of each feature, I have use **TreeExplainer**. It is an implementation of Tree SHAP, a fast and exact algorithm to compute SHAP values for trees and ensembles of trees. **From this tree, I have observed which features are more influencing my model's target variable.**

- I also have used **Partial Dependence Plots (PDP)**. It visualizes the effect of one or two features of interest on the prediction results while marginalizing the rest of the other features. More specifically, partial dependence is the expected target response as a function of those one or two features of interest. PDP is a summary-based explainable machine learning method because it includes all instances and summarizes the relationship of the features of interest with the model's predictions. **Through this plot, I have clearly observed how much individual variable influencing prediction of the target variable.**

- I have used used **SHAP between summary plot** in the analysis. By using this plot, we can see both feature importance and the effects on the predictions. **From this summary plot, I have observed which features and how these are influencing my model's target variable either positively or negatively.**

- I have also used **scatter plot** to focus on one feature's effect across the entire dataset through scatter plot. **Through this plot, I have analysed some features strong and lowest impact on the target variable.**

- I also have used **waterfall char**t. A waterfall chart is a form of data visualization that helps in understanding the cumulative effect of sequentially introduced positive or negative values. **From this plot, I have get to know how much either positively or negatively features are influencing the target variable.**

-I have used **Lame packages**. LIME takes an individual sample and generates fake dataset based on it. It then permutes the fake dataset. It then calculates distance metrics (or similarity metric) between permuted fake data and original observations. This helps to understand how similar permuted fake data is compared to original data. **From this, I have get to know the difference between the local prediction and actual prediction of the dataset. Before applying constrain the local prediction result was low.**

- I have applied monotonicity constrain-t to retrain the dataset to get a better prediction result.

- After that, I have applied all the techniques again in the dataset and get clear and more acceptable output.

-I have applied the lime packages again and get the better prediction result than before. At the end the local prediction result improved to 1, which indicates a perfect prediction.

In [1]:

```
#Install xgboost and line, I already have instatted this package
#!pip install xgboost
#!pip install lime
```

Example-1

In [2]:

```
import pandas as pd
import xgboost as xgb
import shap
import lime
import lime.lime_tabular
#
# read the dataset
df = pd.read_csv('student-mat.csv', delimiter=',')
# drop columns that are less related to the target based on my judgement
cols_to_drop = ['school', 'address', 'Medu', 'Fedu', 'Mjob', 'Fjob', 'reason', 'guardian', 'famsup',
                'romantic', 'goout', 'Dalc', 'Walc', 'health', 'G1', 'G2']
# at the same time, rename the columns so that they are understandable
df = df.drop(columns=cols_to_drop).rename(columns={'famsize': 'family_size', 'Pstatus': 'parent_cohab_status',
                                                    'traveltime': 'travel_time_school', 'studytime': 'study_time',
                                                    'failures': 'past_failures', 'schoolsup': 'extra_support',
                                                    'paid': 'extra_paid_classes', 'activities': 'extra_curricular',
                                                    'nursery': 'nursery_school', 'higher': 'want_higher_edu',
                                                    'internet': 'internet_access', 'famrel': 'family_relationships',
                                                    'freetime': 'free_time', 'absences': 'number_absences',
                                                    'G3': 'score'})
df.head()
```

```
C:\Users\Taslima Akter\anaconda3\lib\site-packages\xgboost\compat.py:36: FutureWarning: pandas.Int64Index is deprecated an
d will be removed from pandas in a future version. Use pandas.Index with the appropriate dtype instead.
  from pandas import MultiIndex, Int64Index
```

Out[2]:

	sex	age	family_size	parent_cohab_status	travel_time_school	study_time	past_failures	extra_support	extra_paid_classes	extra_curricular	nur
0	F	18	GT3	A	2	2	0	yes	no	no	
1	F	17	GT3	T	1	2	0	no	no	no	
2	F	15	LE3	T	1	2	3	yes	yes	no	
3	F	15	GT3	T	1	3	0	no	yes	yes	
4	F	16	GT3	T	1	2	0	no	yes	no	

In [3]:

```
# convert categorical variables into dummy variables
df = pd.get_dummies(df, drop_first=True)
# define the features
df_features = df.drop(columns='score')
df_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   age                    395 non-null    int64
 1   travel_time_school     395 non-null    int64
 2   study_time             395 non-null    int64
 3   past_failures          395 non-null    int64
 4   family_relationships   395 non-null    int64
 5   free_time              395 non-null    int64
 6   number_absences        395 non-null    int64
 7   sex_M                  395 non-null    uint8
 8   family_size_LE3        395 non-null    uint8
 9   parent_cohab_status_T  395 non-null    uint8
 10  extra_support_yes      395 non-null    uint8
 11  extra_paid_classes_yes 395 non-null    uint8
 12  extra_curricular_yes   395 non-null    uint8
 13  nursery_school_yes     395 non-null    uint8
 14  want_higher_edu_yes    395 non-null    uint8
 15  internet_access_yes    395 non-null    uint8
dtypes: int64(7), uint8(9)
memory usage: 25.2 KB
```

In [4]:

```
#build XGBoost model using all data available
# set some parameters to make the model more complicated
model = xgb.XGBRegressor(n_estimators=500, max_depth=20, learning_rate=0.1, subsample=0.8, random_state=33)
model.fit(df_features, df['score'])
```

```
pandas.Int64Index is deprecated and will be removed from pandas in a future version. Use pandas.Index with the appropriate dtype instead.
```

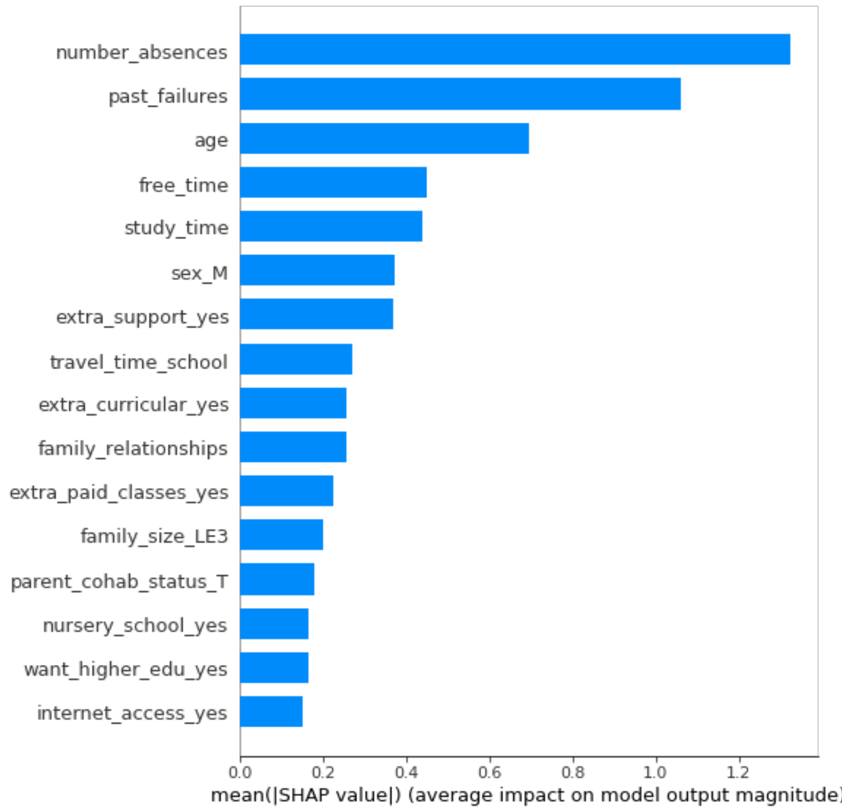
Out[4]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=20, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=500, n_jobs=8,
             num_parallel_tree=1, predictor='auto', random_state=33,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=0.8,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

In [5]:

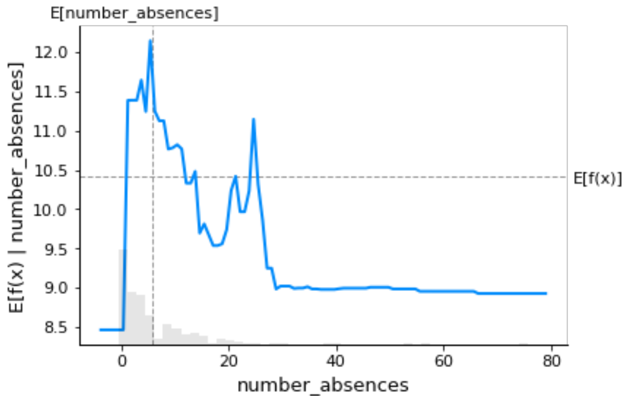
```
# feature importance
#The target variable is score; the number of absence, past_failure, age are affecting much compared to score.
#If the number of absence is more the number of score is goint to reduce
explainer = shap.TreeExplainer(model)
shap_values = explainer.shap_values(df_features)
shap.summary_plot(shap_values, df_features, plot_type="bar")
```

```
ntree_limit is deprecated, use `iteration_range` or model slicing instead.
```



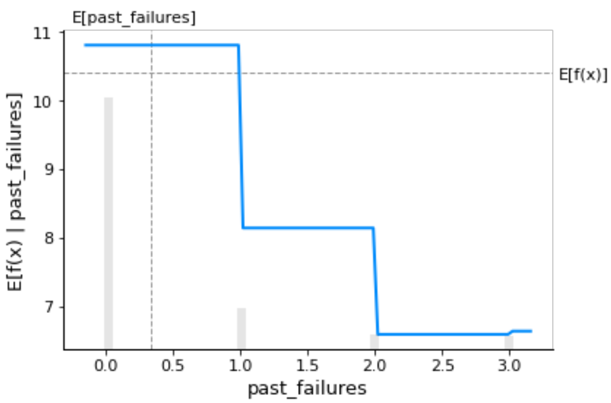
In [6]:

```
#vertical line-avg value of absence
#Horizental line is avg value of score
#E[f(x)]=expected value of score
shap.plots.partial_dependence(
    'number_absences', model.predict, df_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



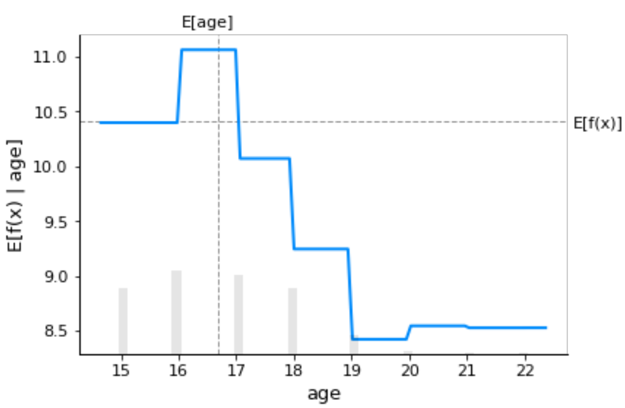
In [7]:

```
shap.plots.partial_dependence(
    'past_failures', model.predict, df_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



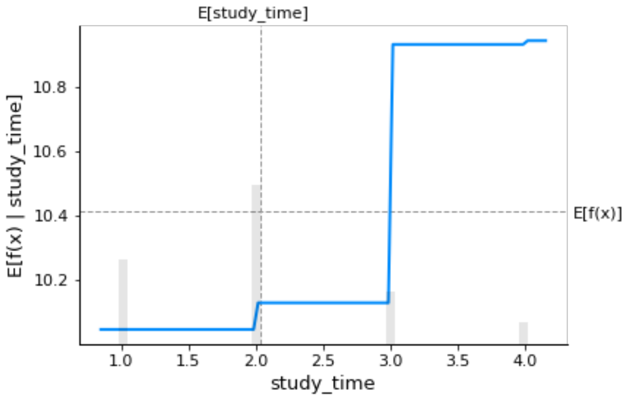
In [8]:

```
shap.plots.partial_dependence(
    'age', model.predict, df_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



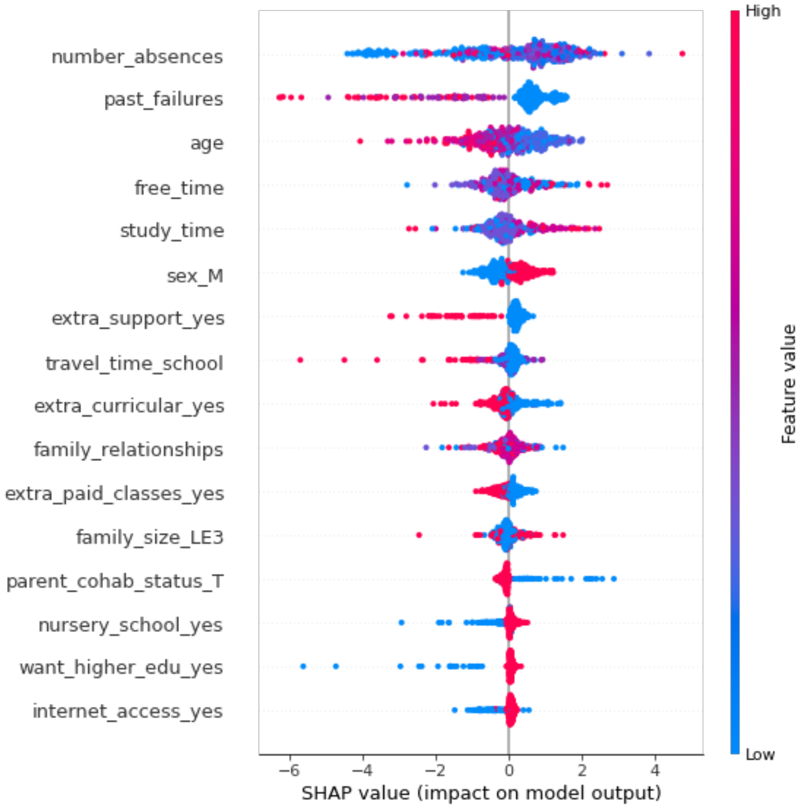
In [9]:

```
shap.plots.partial_dependence(
    'study_time', model.predict, df_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



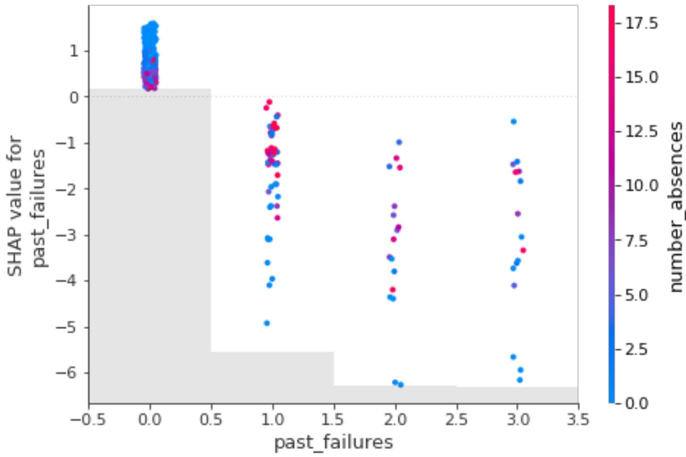
In [10]:

```
#Created TreeExplainer
explainer = shap.TreeExplainer(model)
shap_values = explainer(df_features)
shap.summary_plot(shap_values, df_features)
```

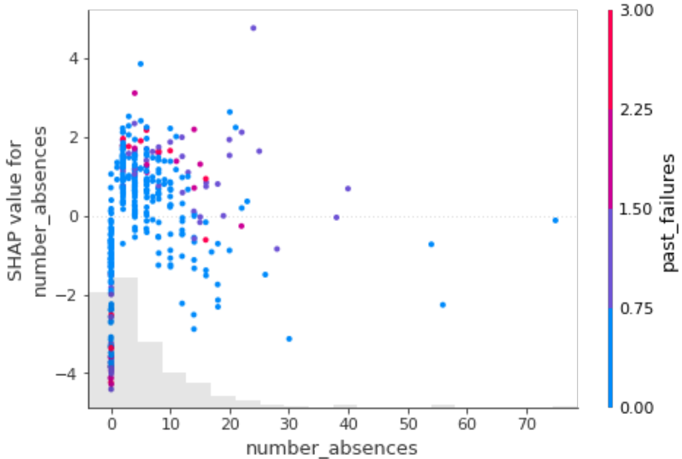


In [11]:

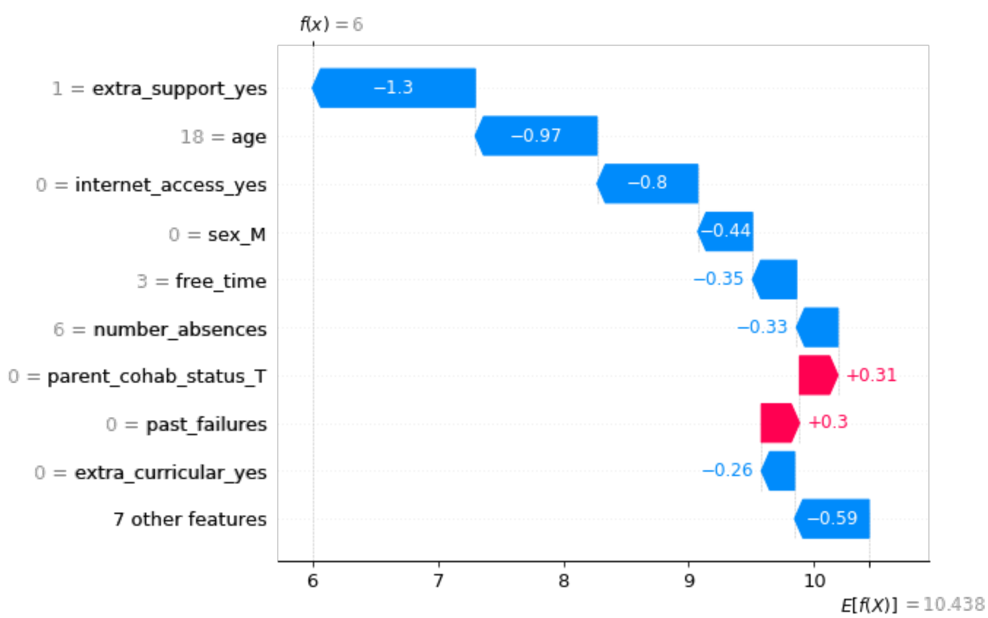
```
#Creating Scatter Plot
shap.plots.scatter(shap_values[:,'past_failures'], color=shap_values)
```



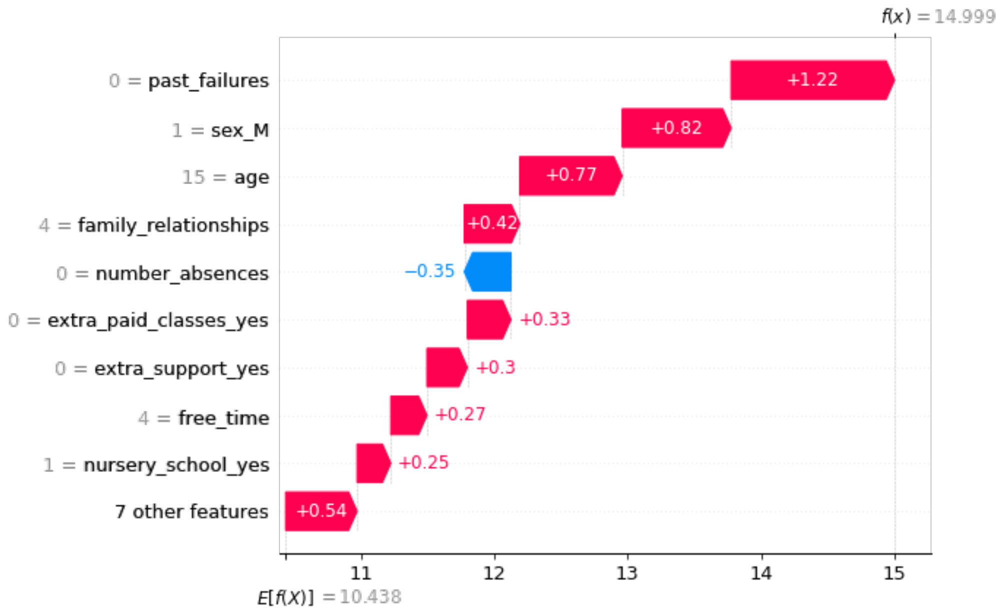
In [12]:
```
shap.plots.scatter(shap_values[:,'number_absences'], color=shap_values)
```



In [13]:
```
#Creating Waterfall Plot
shap.plots.waterfall(shap_values[0])
```



In [14]:
```
#Creating Waterfall Plot in other way
shap.plots.waterfall(shap_values[20])
```



In [15]:

```
#LimeTabularExplainer class and reshapes the training data and feature names
explainer = lime.lime_tabular.LimeTabularExplainer(
    df_features.to_numpy(), feature_names=df_features.columns, class_names=['score'],
    verbose=True, mode='regression', random_state=33)
```

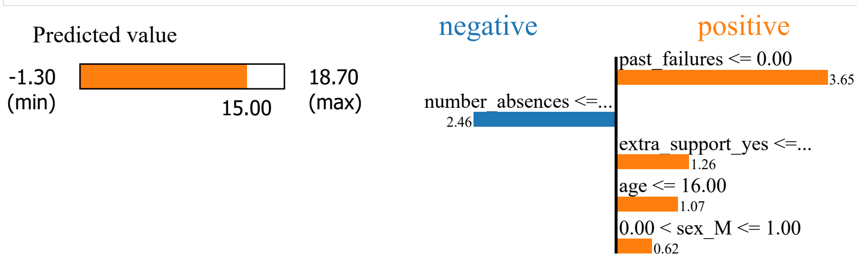
In [16]:

```
exp = explainer.explain_instance(df_features.iloc[20], model.predict, num_features=5)
```

```
Intercept 5.8006425125931775
Prediction_local [9.94061039]
Right: 14.999445
```

In [17]:

```
exp.show_in_notebook(show_table=True)
```



Feature	Value
past_failures	0.00
number_absences	0.00
extra_support_yes	0.00
age	15.00
sex_M	1.00

In [18]:

```
df_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   age                   395 non-null    int64
 1   travel_time_school    395 non-null    int64
 2   study_time            395 non-null    int64
 3   past_failures         395 non-null    int64
 4   family_relationships  395 non-null    int64
 5   free_time             395 non-null    int64
 6   number_absences       395 non-null    int64
 7   sex_M                 395 non-null    uint8
```

```
 8   family_size_LE3         395 non-null    uint8
 9   parent_cohab_status_T   395 non-null    uint8
 10  extra_support_yes       395 non-null    uint8
 11  extra_paid_classes_yes  395 non-null    uint8
 12  extra_curricular_yes    395 non-null    uint8
 13  nursery_school_yes      395 non-null    uint8
 14  want_higher_edu_yes     395 non-null    uint8
 15  internet_access_yes     395 non-null    uint8
dtypes: int64(7), uint8(9)
memory usage: 25.2 KB
```

In [19]:

```
# retrain with monotonicity constrain
params = {
    'monotone_constraints':'(0,0,1,-1,0,0,-1)'
}
model_constrained = xgb.XGBRegressor(**params, n_estimators=500, max_depth=20, learning_rate=0.1, subsample=0.8, random_st
model_constrained.fit(df_features, df['score'])
```

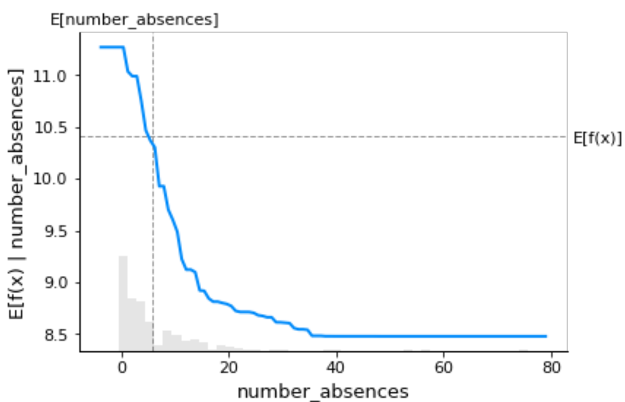
```
pandas.Int64Index is deprecated and will be removed from pandas in a future version. Use pandas.Index with the appropriate
dtype instead.
```

Out[19]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=20, min_child_weight=1, missing=nan,
             monotone_constraints='(0,0,1,-1,0,0,-1)', n_estimators=500,
             n_jobs=8, num_parallel_tree=1, predictor='auto', random_state=33,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=0.8,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

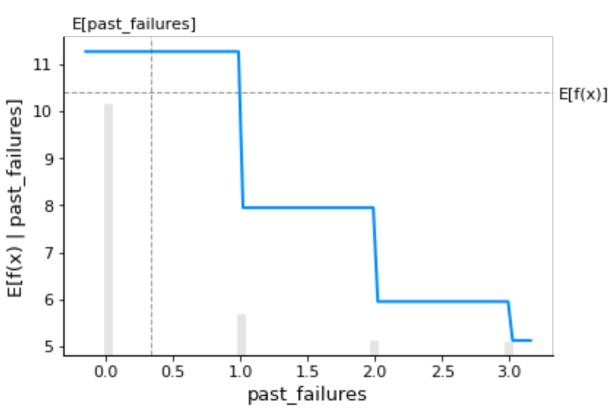
In [20]:

```
import shap
shap.plots.partial_dependence(
    'number_absences', model_constrained.predict, df_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```

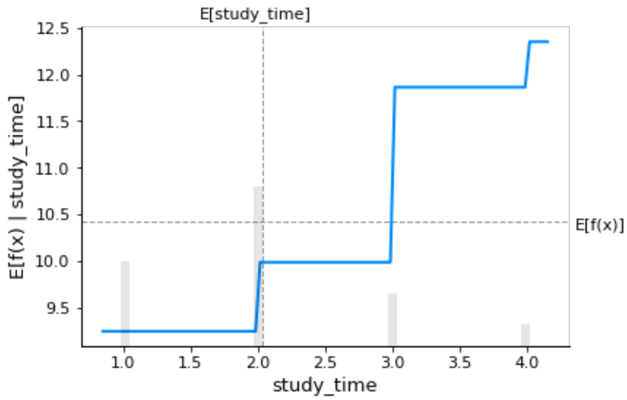


In [21]:

```
shap.plots.partial_dependence(
    'past_failures', model_constrained.predict, df_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```

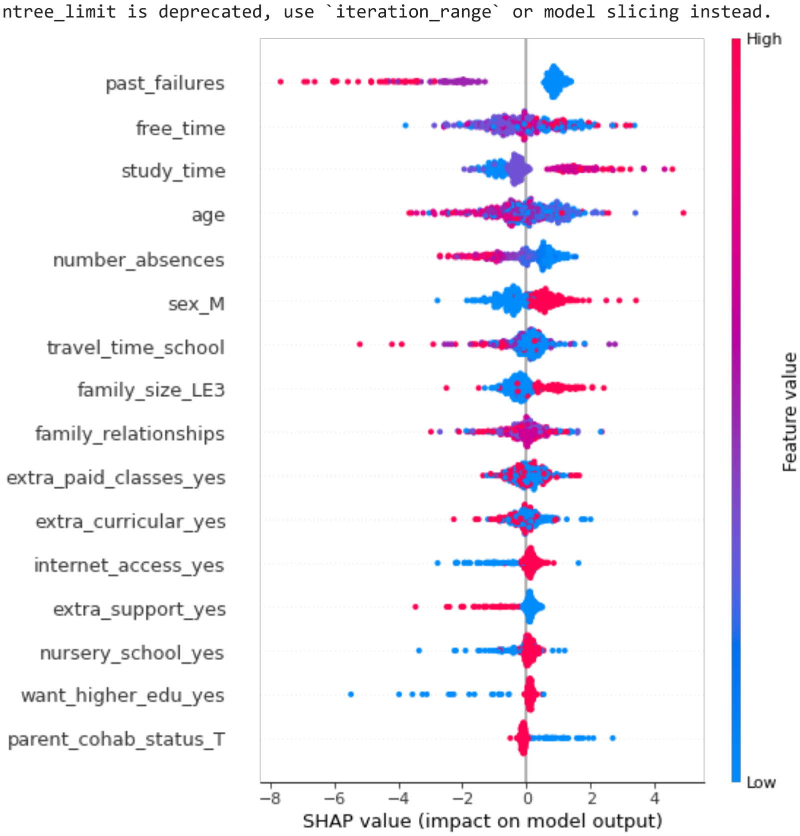


In [22]:
```
shap.plots.partial_dependence(
    'study_time', model_constrained.predict, df_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```

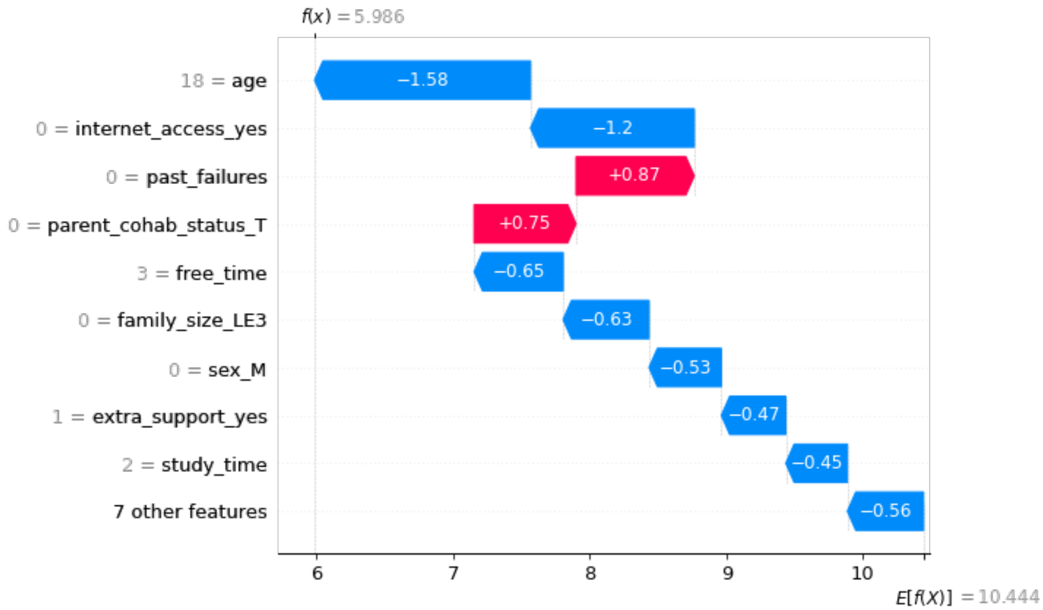


In [23]:
```
#Re-created TreeExplainer
explainer = shap.TreeExplainer(model_constrained)
shap_values = explainer(df_features)
shap.summary_plot(shap_values, df_features)
```

```
ntree_limit is deprecated, use `iteration_range` or model slicing instead.
```

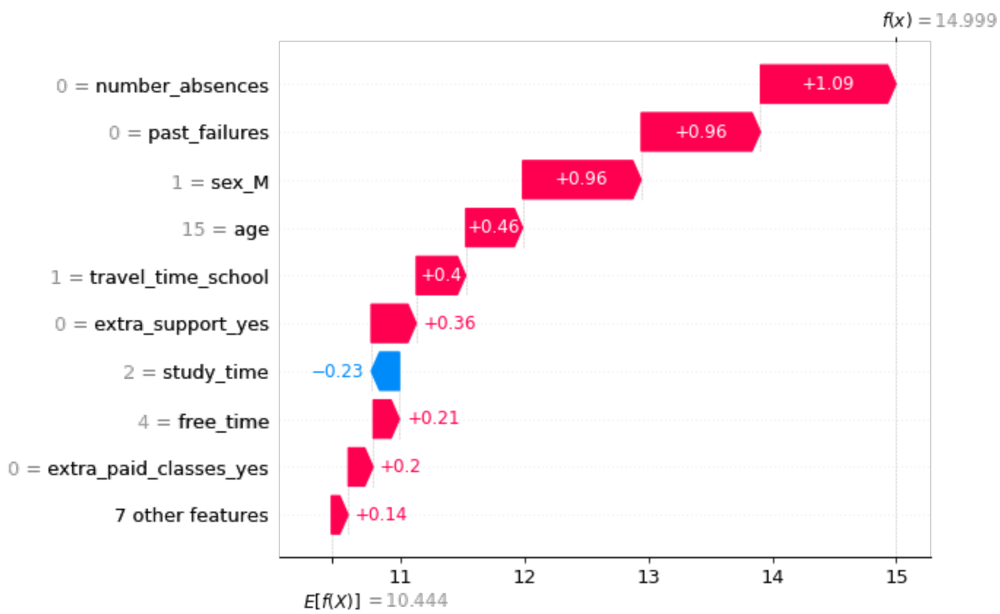


In [24]:
```
shap.plots.waterfall(shap_values[0])
```



In [25]:

```
shap.plots.waterfall(shap_values[20])
```



In [26]:

```
explainer = lime.lime_tabular.LimeTabularExplainer(
    df_features.to_numpy(), feature_names=df_features.columns, class_names=['score'],
    verbose=True, mode='regression', random_state=33)
```

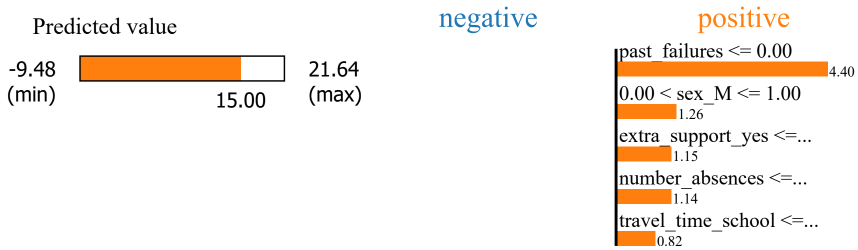
In [27]:

```
exp = explainer.explain_instance(df_features.iloc[20], model_constrained.predict, num_features=5)
```

```
Intercept 4.160316689146363
Prediction_local [12.93215198]
Right: 14.998528
```

In [28]:

```
exp.show_in_notebook(show_table=True)
```



Feature	Value
past_failures	0.00
sex_M	1.00
extra_support_yes	0.00
number_absences	0.00
travel_time_school	1.00

Example-2, Lab-3 Assignment

Data Loading, Preparation and Feature Engineering Part:

In [29]:

```
#Load the dataset
df_c = pd.read_csv('compas-scores-two-years.csv')
```

In [30]:

```
#Display data of the dataset
df_c.head()
```

Out[30]:

	id	name	first	last	compas_screening_date	sex	dob	age	age_cat	race	...	v_decile_score	v_score_text	v_screeni
0	1	miguel hernandez	miguel	hernandez	2013-08-14	Male	1947-04-18	69	Greater than 45	Other	...	1	Low	201
1	3	kevon dixon	kevon	dixon	2013-01-27	Male	1982-01-22	34	25 - 45	African-American	...	1	Low	201
2	4	ed philo	ed	philo	2013-04-14	Male	1991-05-14	24	Less than 25	African-American	...	3	Low	201
3	5	marcu brown	marcu	brown	2013-01-13	Male	1993-01-21	23	Less than 25	African-American	...	6	Medium	201
4	6	bouthy pierrelouis	bouthy	pierrelouis	2013-03-26	Male	1973-01-22	43	25 - 45	Other	...	1	Low	201

5 rows × 53 columns

In [31]:

```
#Display info of the dataset
df_c.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7214 entries, 0 to 7213
Data columns (total 53 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       7214 non-null   int64
 1   name                     7214 non-null   object
 2   first                    7214 non-null   object
 3   last                     7214 non-null   object
 4   compas_screening_date    7214 non-null   object
 5   sex                      7214 non-null   object
 6   dob                      7214 non-null   object
 7   age                      7214 non-null   int64
 8   age_cat                  7214 non-null   object
 9   race                     7214 non-null   object
 10  juv_fel_count            7214 non-null   int64
 11  decile_score             7214 non-null   int64
 12  juv_misd_count           7214 non-null   int64
 13  juv_other_count          7214 non-null   int64
 14  priors_count             7214 non-null   int64
```

```
 15  days_b_screening_arrest  6907 non-null   float64
 16  c_jail_in                6907 non-null   object
 17  c_jail_out               6907 non-null   object
 18  c_case_number            7192 non-null   object
 19  c_offense_date           6055 non-null   object
 20  c_arrest_date            1137 non-null   object
 21  c_days_from_compas       7192 non-null   float64
 22  c_charge_degree          7214 non-null   object
 23  c_charge_desc            7185 non-null   object
 24  is_recid                 7214 non-null   int64
 25  r_case_number            3471 non-null   object
 26  r_charge_degree          3471 non-null   object
 27  r_days_from_arrest       2316 non-null   float64
 28  r_offense_date           3471 non-null   object
 29  r_charge_desc            3413 non-null   object
 30  r_jail_in                2316 non-null   object
 31  r_jail_out               2316 non-null   object
 32  violent_recid            0 non-null      float64
 33  is_violent_recid         7214 non-null   int64
 34  vr_case_number           819 non-null    object
 35  vr_charge_degree         819 non-null    object
 36  vr_offense_date          819 non-null    object
 37  vr_charge_desc           819 non-null    object
 38  type_of_assessment       7214 non-null   object
 39  decile_score.1           7214 non-null   int64
 40  score_text               7214 non-null   object
 41  screening_date           7214 non-null   object
 42  v_type_of_assessment     7214 non-null   object
 43  v_decile_score           7214 non-null   int64
 44  v_score_text             7214 non-null   object
 45  v_screening_date         7214 non-null   object
 46  in_custody               6978 non-null   object
 47  out_custody              6978 non-null   object
 48  priors_count.1           7214 non-null   int64
 49  start                    7214 non-null   int64
 50  end                      7214 non-null   int64
 51  event                    7214 non-null   int64
 52  two_year_recid           7214 non-null   int64
dtypes: float64(4), int64(16), object(33)
```

Note about Target variable:

two_year_recid->in the next two years the person is going to do wrong and come into jail

Data Preparation:

-I have deleted many of the features of the dataset, which I think have less impact on the target variable. -I also have changed a column name to make it more understandable.

In [32]:

```
# Droping the columns, which I found have no such mentionable impact to the target variable

cols_to_drop = ['id','name','first','last','compas_screening_date','dob','juv_fel_count', 'juv_misd_count','juv_other_cour
                'c_jail_in', 'c_jail_out','c_case_number','c_offense_date','c_days_from_compas','c_charge_desc','c_arrest_
                'c_charge_degree','r_case_number','r_charge_degree','r_days_from_arrest','r_offense_date','r_jail_in', 'r_
                'violent_recid','vr_case_number','vr_charge_degree','vr_offense_date','vr_charge_desc','type_of_assessment
                'screening_date','v_type_of_assessment','v_screening_date','in_custody','out_custody','start','end','event
                'r_charge_desc', 'is_violent_recid','priors_count.1']
# at the same time, rename the columns so that they are understandable
df_c = df_c.drop(columns=cols_to_drop).rename(columns={'score_text': 'crime_level'})
df_c
```

Out[32]:

	sex	age	age_cat	race	decile_score	priors_count	crime_level	v_decile_score	two_year_recid
0	Male	69	Greater than 45	Other	1	0	Low	1	0
1	Male	34	25 - 45	African-American	3	0	Low	1	1
2	Male	24	Less than 25	African-American	4	4	Low	3	1
3	Male	23	Less than 25	African-American	8	1	High	6	0
4	Male	43	25 - 45	Other	1	2	Low	1	0
...	...	...	...	...	...	...	...	...	...
7209	Male	23	Less than 25	African-American	7	0	Medium	5	0

	sex	age	age_cat	race	decile_score	priors_count	crime_level	v_decile_score	two_year_recid
7210	Male	23	Less than 25	African-American	3	0	Low	5	0
7211	Male	57	Greater than 45	Other	1	0	Low	1	0
7212	Female	33	25 - 45	African-American	2	3	Low	2	0
7213	Female	23	Less than 25	Hispanic	4	2	Low	4	1

Feature Engineering:

In this part I have created some dummy variables to clearny know the feature impacts of the target variable.

In [33]:

```
# convert categorical variables into dummy variables
#df_c = pd.get_dummies(df_c, columns=['sex','age_cat','race','crime_level'])
df_c = pd.get_dummies(df_c)
# define the features
df_c_features = df_c.drop(columns='two_year_recid')
df_c_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7214 entries, 0 to 7213
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   age                     7214 non-null   int64
 1   decile_score            7214 non-null   int64
 2   priors_count            7214 non-null   int64
 3   v_decile_score          7214 non-null   int64
 4   sex_Female              7214 non-null   uint8
 5   sex_Male                7214 non-null   uint8
 6   age_cat_25 - 45         7214 non-null   uint8
 7   age_cat_Greater than 45 7214 non-null   uint8
 8   age_cat_Less than 25    7214 non-null   uint8
 9   race_African-American   7214 non-null   uint8
 10  race_Asian              7214 non-null   uint8
 11  race_Caucasian          7214 non-null   uint8
 12  race_Hispanic           7214 non-null   uint8
 13  race_Native American    7214 non-null   uint8
 14  race_Other              7214 non-null   uint8
 15  crime_level_High        7214 non-null   uint8
 16  crime_level_Low         7214 non-null   uint8
 17  crime_level_Medium      7214 non-null   uint8
dtypes: int64(4), uint8(14)
memory usage: 324.2 KB
```

Display of the Dataset after Data Wrangling:

In [34]:

```
df_c.head()
```

Out[34]:

	age	decile_score	priors_count	v_decile_score	two_year_recid	sex_Female	sex_Male	age_cat_25 - 45	age_cat_Greater than 45	age_cat_Less than 25	race_African-American
0	69	1	0	1	0	0	1	0	1	0	0
1	34	3	0	1	1	0	1	1	0	0	1
2	24	4	4	3	1	0	1	0	0	1	1
3	23	8	1	6	0	0	1	0	0	1	1
4	43	1	2	1	0	0	1	1	0	0	0

Using XGBoost:

-Throughout the analysis based on df_c_features. This model has provided excellent prediction results.

-XGBoost package and other relevant packages are installed at the top of the code while completing the Example-1.

In [35]:
```
#Build XGBoost model using all data available
#Set some parameters to make the model more complicated
model = xgb.XGBRegressor(n_estimators=500, max_depth=20, learning_rate=0.1, subsample=0.8, random_state=33)
model.fit(df_c_features, df_c['two_year_recid'])
```

```
pandas.Int64Index is deprecated and will be removed from pandas in a future version. Use pandas.Index with the appropriate dtype instead.
```

Out[35]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=20, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=500, n_jobs=8,
             num_parallel_tree=1, predictor='auto', random_state=33,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=0.8,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

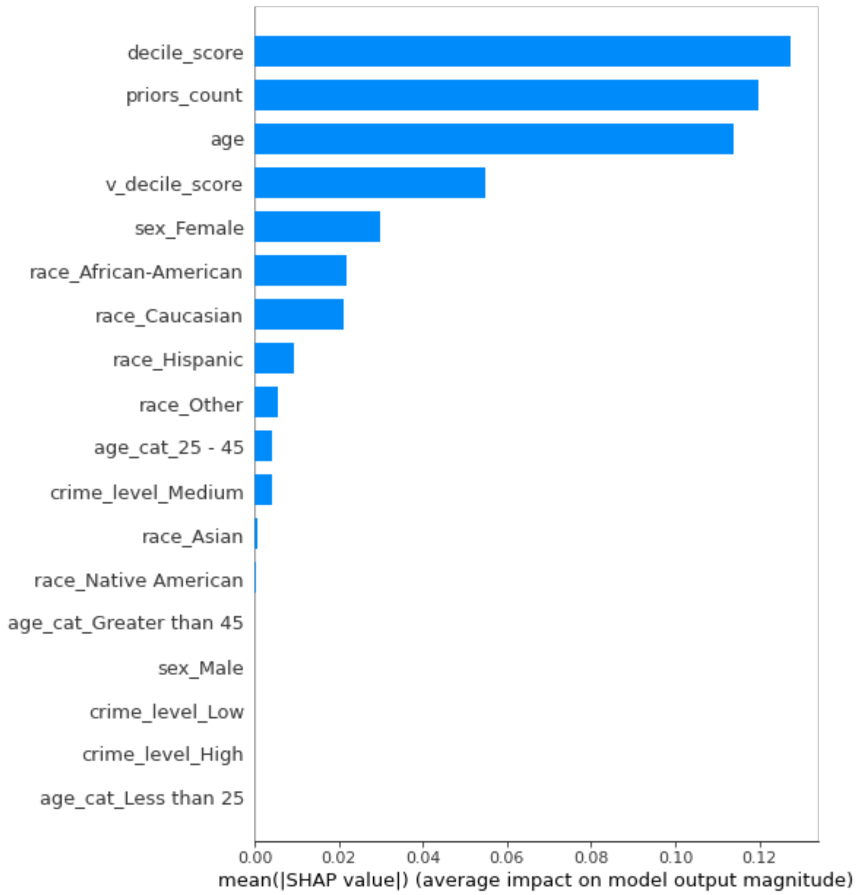
Using TreeExplainer to Display Shap Value:

-SHAP values interpret the impact of having a certain value for a given feature in comparison to the prediction we'd make if that feature took some baseline value.

-To display the shap value of each feature I have use TreeExplainer.It is an implementation of Tree SHAP, a fast and exact algorithm to compute SHAP values for trees and ensembles of trees.

In [36]:
```
explainer = shap.TreeExplainer(model)
shap_values = explainer.shap_values(df_c_features)
shap.summary_plot(shap_values, df_c_features, plot_type="bar")
```

```
ntree_limit is deprecated, use `iteration_range` or model slicing instead.
```



Observation Based on Shap Value (TreeExplainer):

-From the plot it is analyzed that the whether the individual had been jailed for a new crime in next two years (target value:two_year_recid)is greatly influenced by the decile_score. Here, decile_score indicates general minor crime rate.

-The target variable also highly influenced by priors_count and age of individuals; here, priors_count means number of previous arrests.

-The target variable also notibly influenced by v_decile_score; here, v_decile_score = violate crime rate.

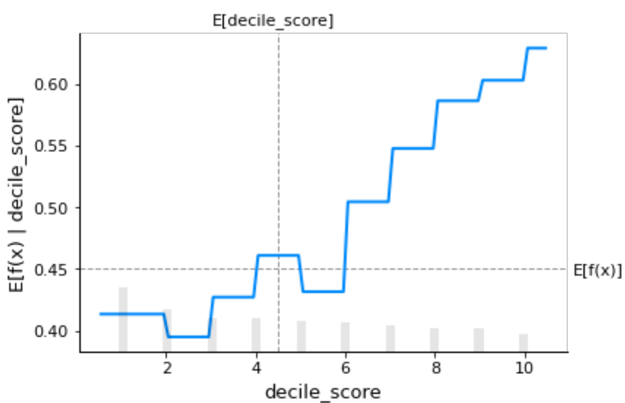
-According to the barchart, female, race(african-American, Caucacian, Hispanic) have a little influence to the target variable. -Others variables have no influence to the target variable

Using Partial Dependence Plots (PDP):

-It visualizes the effect of one or two features of interest on the prediction results while marginalizing the rest of the other features. More specifically, partial dependence is the expected target response as a function of those one or two features of interest. PDP is a summary-based explainable machine learning method because it includes all instances and summarizes the relationship of the features of interest with the model's predictions.

In [37]:

```
#vertical line-avg value of absence
#Horizental line is avg value of score
#E[f(x)]=expected value of score
shap.plots.partial_dependence(
    'decile_score', model.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



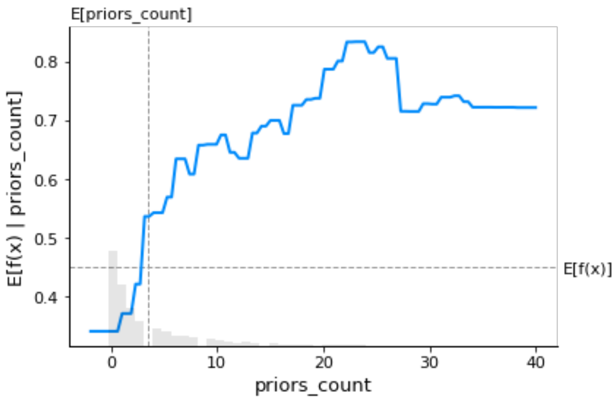
Observation of the impact of 'decile_score' to the target variable:

-The grey bars on the plot indicate its data distribution. The target variable is gradually increased whith the increased if decile_score. However, two local down are seen in the plot at the decile_score 2-3 and 5-6, that might be because of data deficiency at these points.

-From the blue line it has been seen that while the number of decile_score iscrease the chances of the individual had been jailed for a new crime in next two years (target variable:two_year_recid) also increases.

In [38]:

```
shap.plots.partial_dependence(
    'priors_count', model.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```

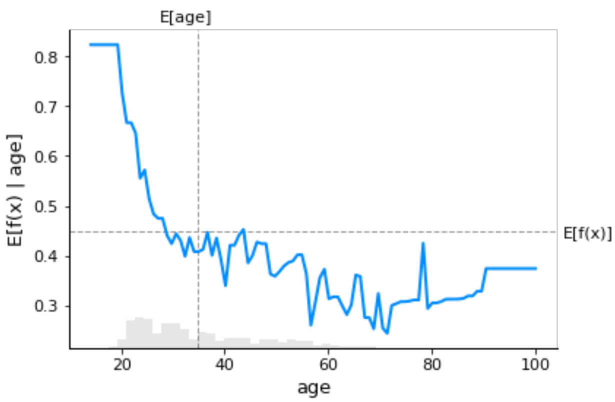


Observation of the impact of 'priors_count' to the target variable:

-It is clearly visible that the the target variable is increases with the increase of priors_count; that means,the chances of the individual had been jailed for a new crime in next two years is high while that person's number of previous arrests is also high.

In [39]:

```
shap.plots.partial_dependence(
    'age', model.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



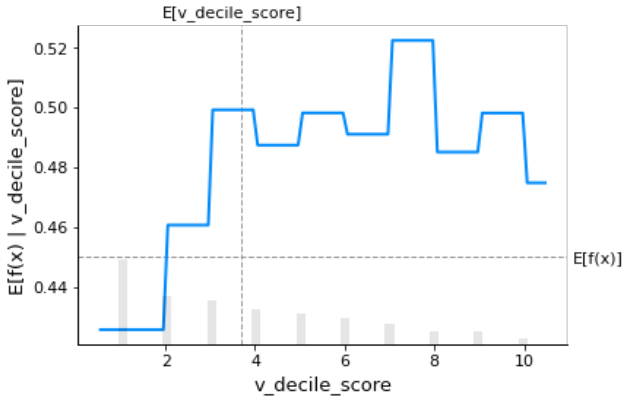
Observation of the impact of 'age' to the target variable:

-From the graph it is seen that at the age between 18 to 25 the target variable reaches at high point; after 25 the the target variable score gradually decreased and it reaches at the lowest point at the age 70; a local peak of towards target variable is shown at the age 80, that might be because of small amount of data.

-That means, the chances of the individual had been jailed for a new crime in next two years is high at the age between 18 to 25.

In [40]:

```
shap.plots.partial_dependence(
    'v_decile_score', model.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



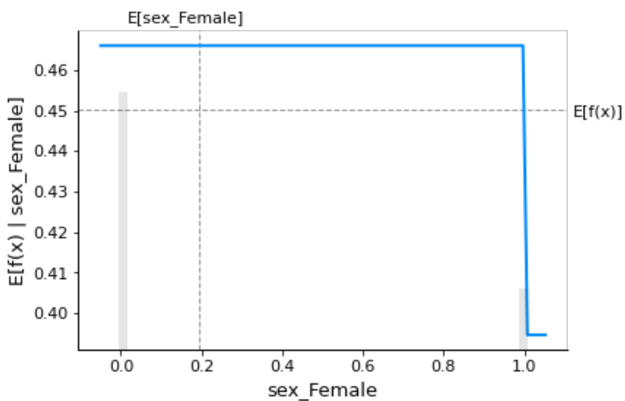
Observation of the impact of 'v_decile_score' to the target variable:

-The target variable is gradually increased whith the increased if v_decile_score.

-From the blue line it has been seen that while the violent crime score iscreases of a person, the chances of that person have been jailed for a new crime in next two years also increases. At the v_decile_score 7-8 the, chancees of reaching the target variable is showing maximum.

In [41]:

```
shap.plots.partial_dependence(
    'sex_Female', model.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



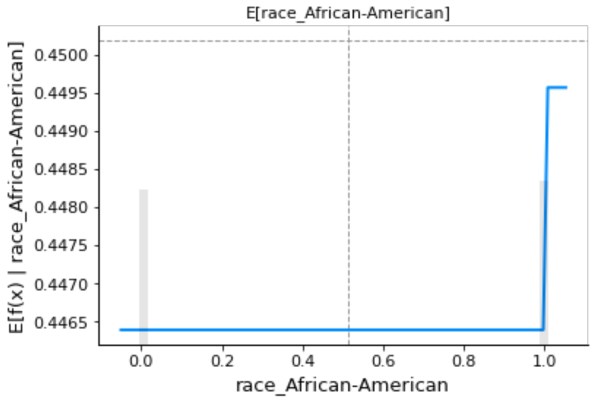
Observation of the impact of 'sex_Female' to the target variable:

-sex_Female is a dummy variable with values of 0 and 1. The grey bars on the plot indicate its data distribution.

-At the blue line, we can see the expected score is higher when this feature has a value of 1 versus 0. This makes sense female sex have higher chance of back to jail in next two years with a new crime.

In [42]:

```
shap.plots.partial_dependence(
    'race_African-American', model.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



Observation of the impact of 'race_African-American' to the target variable:

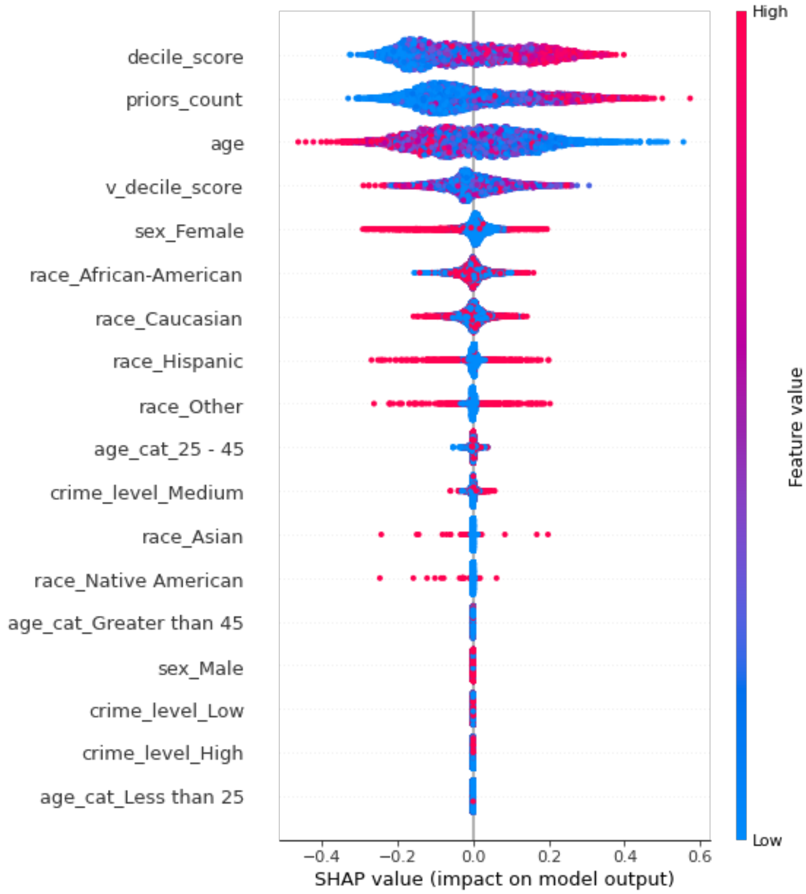
-Graphs shows that African-American have higher chance of back to jail in next two years with a new crime compared to other races.

Using SHapley Additive exPlanations (SHAP):

It is a practical method based on Shapley values. So, on the below SHAP between summary plot, we can see both feature importance and the effects on the predictions. As the number of features increases, the number of possible coalitions increases exponentially, resulting in a computation increase. So we usually approximate the Shapley values, rather than applying the exact calculations. And that's why here I will apply SHAP. SHAP includes an estimation approach of Shapley values, but more than that. Besides being an instance-based method to explain one instance, SHAP also contains methods of combining the Shapley values of all instances to summarize the model predictions.

In [43]:

```
#Let’s use the TreeExplainer function from shap and make a summary plot
#Along the y-axis, the features are sorted from top to down by the sum of SHAP value magnitudes of all instances
#Along the x-axis, for each feature, you can also see the distribution of the impacts each feature has on the model’s pred
#The color of dots represents the values of the features: red high and blue low
explainer = shap.TreeExplainer(model)
shap_values = explainer(df_c_features)
shap.summary_plot(shap_values, df_c_features)
```



Comments about Shap Summary Plot(TreeExplainer):

-We can see that 'decile_score' is the first most important feature for our model. The higher values of decile_score (red dots) tend to contribute positively to the prediction. In comparison, the lower values (blue dots) have negative contributions. This makes sense since the more decile_score a person have, the more likely that person will be in been jail for a new crime in next two years. The same observation is true form the variable 'priors_count'.

-The oposite scenerio is shown in the variable'age'. The higher lower value of age (blue dots) tend to contribute positively to the prediction and vice versa.

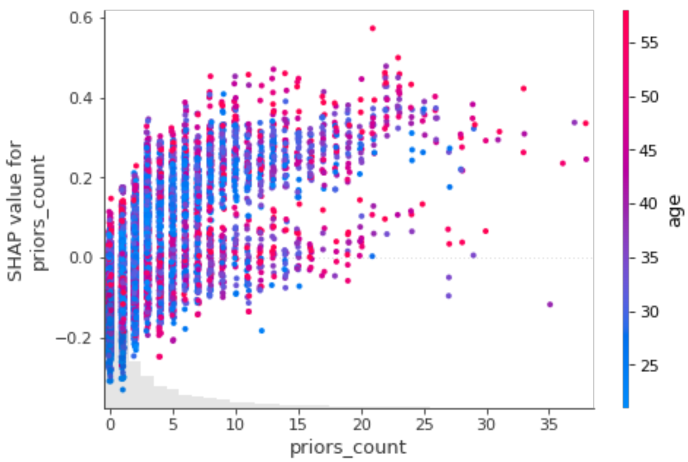
-We can see that 'v_decile_score' impact is showing little bit confusing in the plot.

Using scatter plot:

I Have used this to focus on one feature’s effect across the entire dataset through scatter plot

In [44]:

```
#We can also focus on one feature’s effect across the entire dataset through scatter plot
shap.plots.scatter(shap_values[:,'priors_count'], color=shap_values)
```



Comment about scatter plot:

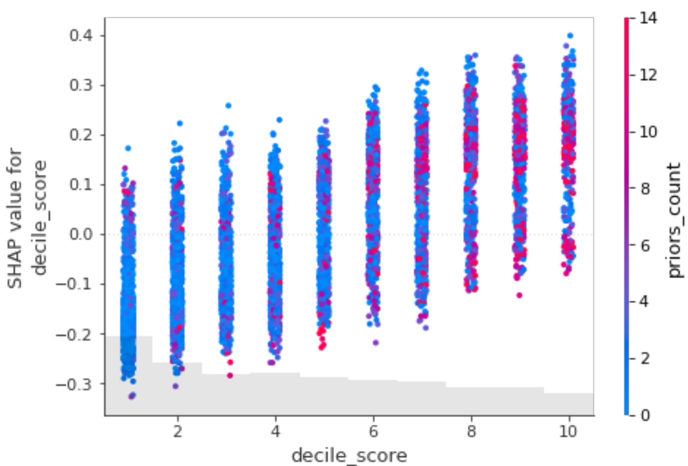
-The grey bars represent the distribution of the feature, while the dots show the SHAP values.

-The vertical dispersion at a single value of 'priors_count' shows interaction effects with other features. Using the color=shap_values argument, the scatter plot picked the best feature to color by to reveal the interactions.

-Here, we can see that the feature 'priors_count' has a no such clear impact on scores (higher SHAPs) with high or low age value.

In [45]:

```
#We can also focus on one feature’s effect across the entire dataset through scatter plot
shap.plots.scatter(shap_values[:,'decile_score'], color=shap_values)
```

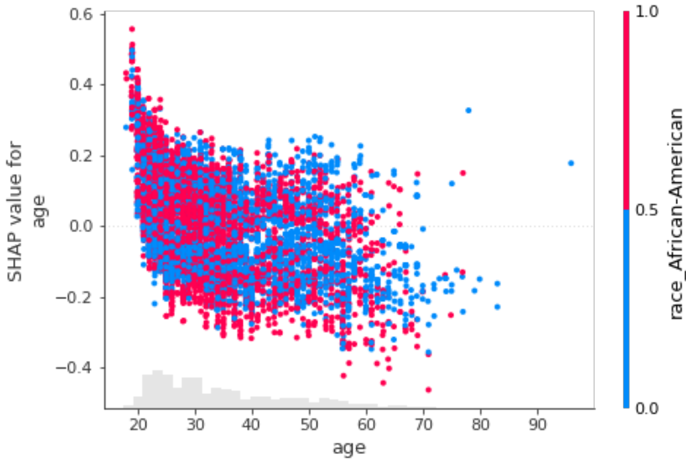


Comment about scatter plot:

-We can see that the feature 'decile_score' has a moderate impact on scores (higher SHAPs) with higher 'priors_count' values.

In [46]:

```
shap.plots.scatter(shap_values[:,'age'], color=shap_values)
```



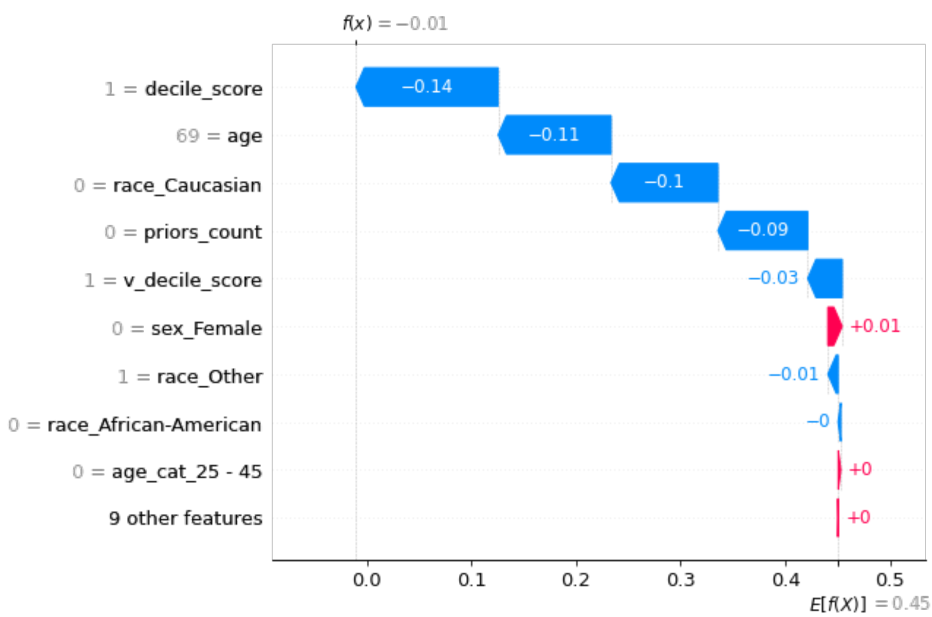
Comment about scatter plot:

-We can see that the feature 'age' has higher impact on target variable(higher SHAPs) with higher race_African-American values. When the age is lower and race_African-American value is higher, the Shap value is also seeing higher.

Using Water Fall Chart:

-A waterfall chart is a form of data visualization that helps in understanding the cumulative effect of sequentially introduced positive or negative values.

In [47]:
```
#A waterfall chart is a form of data visualization that helps in understanding the cumulative effect of sequentially intro
#positive or negative values.
shap.plots.waterfall(shap_values[0])
```

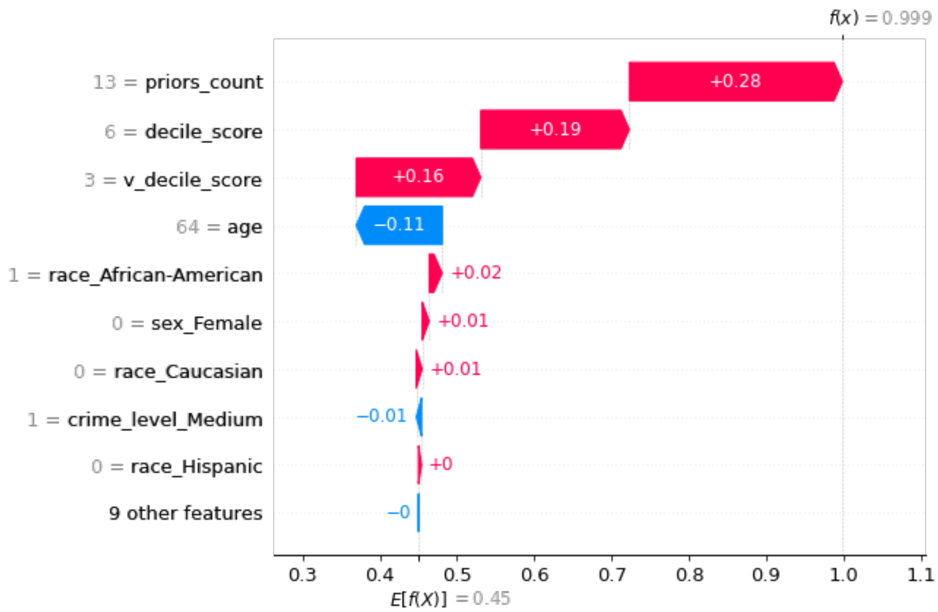


Comment about Waterfall Plot:

On this plot, we are seeing two values. At the bottom of the plot, E(f(x)), the average predicted score of the dataset is 0.45. At the top of the plot, f(x), the predicted score for the sample is, is -01. Between these two values, the waterfall plots how each feature contributes to the changes of prediction from E(f(x)) to f(x).

Here, the 'decile_score', age, race_caucasian has the most impact. It pulled the prediction down, while the sex_female value has increased the prediction.

In [48]:
```
#Another instance's waterfall plot
shap.plots.waterfall(shap_values[20])
```



Comment About Waterfall Plot

-On this plot, we are seeing two values. At the bottom of the plot, E(f(x)), the average predicted score of the dataset is 0.45. At the top of the plot, f(x), the predicted score for the sample is, is .99. Between these two values, the waterfall plots how each feature contributes to the changes of prediction from E(f(x)) to f(x).

-Here we can see the result is completely changed; the priors_count, decile_score, v_decile_score at the value of 13, 6, 3 consequently have strong positive influence to increase the sample prediction; the age at the value 64 has oposite influence.

Using Local Interpretable Model-agnostic Explanations (LIME):

-Local Interpretable Model-Agnostic Explanations (LIME) is another popular method to explain one instance. Unlike SHAP, LIME suggests learning interpretable local surrogate models around the prediction to estimate features' effects.

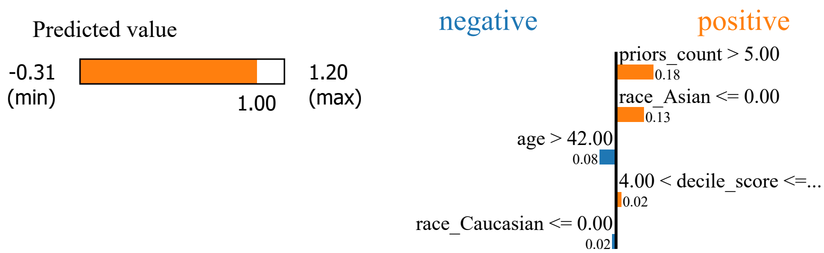
Suppose you want to explain how a 'black box' model makes a specific prediction on one instance. Here are the general steps of LIME: perturb the dataset, and get the 'black box' model predictions for the new points, weight the new samples based on their proximity to the instance of interest, train a weighted, interpretable model on the dataset with the variations, i.e., learn a local surrogate model, this local surrogate model should approximate the 'black box' model's prediction locally, the common local surrogate models include linear regression, decision tree, interpret the local model to explain the prediction

In [49]:
```
#Here we use the lime_tabular module from lime since our data is tabular
explainer = lime.lime_tabular.LimeTabularExplainer(
    df_c_features.to_numpy(), feature_names=df_c_features.columns, class_names=['two_year_recid'],
    verbose=True, mode='regression', random_state=33)
```

In [50]:
```
#Here we generate explanations for one instance and set the maximum number of features to include in the explanation to be
exp = explainer.explain_instance(df_c_features.iloc[20], model.predict, num_features=5)
```

```
Intercept 0.3239313594970047
Prediction_local [0.5604325]
Right: 0.99864966
```

In [51]:
```
exp.show_in_notebook(show_table=True)
```



Feature	Value
priors_count	13.00
race_Asian	0.00
age	64.00
decile_score	6.00
race_Caucasian	0.00

Observation about LIME Output:

The intercept of the linear model created by LIME is presented, followed by the local prediction generated by the linear model, and the actual prediction from our model. We can see that the predicted score for this sample is 0.99864966, whereas the local prediction result is only 0.5604325. The features and their contributions (blue being negative, orange being positive) to this prediction are shown, as well as their feature values for this sample. Here, the feature 'priors_count', 'race_asian', decile_score has positive effects on the prediction at the certain values, while 'age' and 'race_Caucasian' has oposite impact.

In [52]:

```
#Display of the information of the dataset
df_c_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7214 entries, 0 to 7213
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   age                     7214 non-null   int64
 1   decile_score            7214 non-null   int64
 2   priors_count            7214 non-null   int64
 3   v_decile_score          7214 non-null   int64
 4   sex_Female              7214 non-null   uint8
 5   sex_Male                7214 non-null   uint8
 6   age_cat_25 - 45         7214 non-null   uint8
 7   age_cat_Greater than 45 7214 non-null   uint8
 8   age_cat_Less than 25    7214 non-null   uint8
 9   race_African-American   7214 non-null   uint8
 10  race_Asian              7214 non-null   uint8
 11  race_Caucasian          7214 non-null   uint8
 12  race_Hispanic           7214 non-null   uint8
 13  race_Native American    7214 non-null   uint8
 14  race_Other              7214 non-null   uint8
 15  crime_level_High        7214 non-null   uint8
 16  crime_level_Low         7214 non-null   uint8
 17  crime_level_Medium      7214 non-null   uint8
dtypes: int64(4), uint8(14)
memory usage: 324.2 KB
```

Applying Constraints in the Dataset:

retrain dataset with monotonicity constrain-t is often the case in a modeling problem or project that the functional form of an acceptable model is constrained in some way.

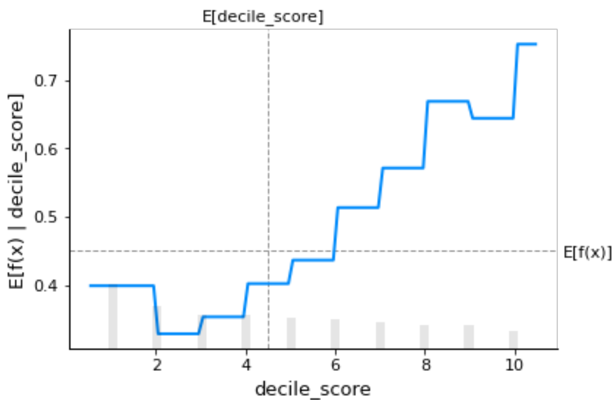
The term monotonic relationship is a statistical definition that is used to describe a scenario in which the size of one variable increases as the other variables also increases, or where the size of one variable increases as the other variable also decreases.

In [53]:
```
#Applying monotonicity constrain
params = {
    'monotone_constraints':'(0,0,1,-1,0,0,-1)'
}
model_constrained = xgb.XGBRegressor(**params, n_estimators=500, max_depth=20, learning_rate=0.1, subsample=0.8, random_st
model_constrained.fit(df_c_features, df_c['two_year_recid'])
```

```
pandas.Int64Index is deprecated and will be removed from pandas in a future version. Use pandas.Index with the appropriate
dtype instead.
```

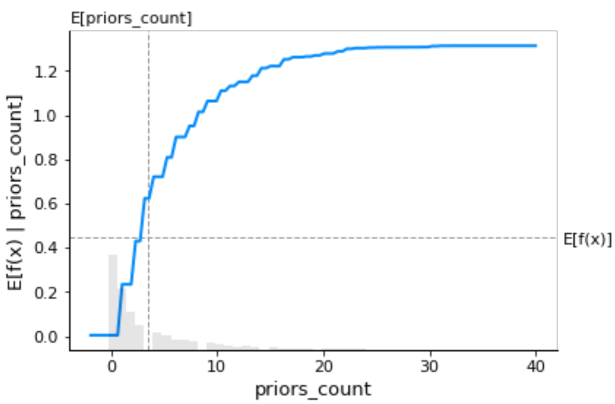
Out[53]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_delta_step=0,
             max_depth=20, min_child_weight=1, missing=nan,
             monotone_constraints='(0,0,1,-1,0,0,-1)', n_estimators=500,
             n_jobs=8, num_parallel_tree=1, predictor='auto', random_state=33,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=0.8,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

In [54]:
```
#Display the shap partial dependency plot
import shap
shap.plots.partial_dependence(
    'decile_score', model_constrained.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



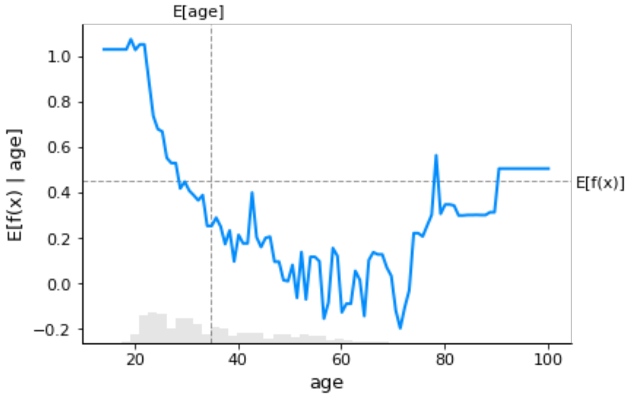
Now, the plot is looking more balanced and clearly showing the proportional impact of decile_score value to the target variable.

In [55]:
```
shap.plots.partial_dependence(
    'priors_count', model_constrained.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



Now, the plot is looking more balanced and clearly showing the proportional impact of priors_count value to the target variable.

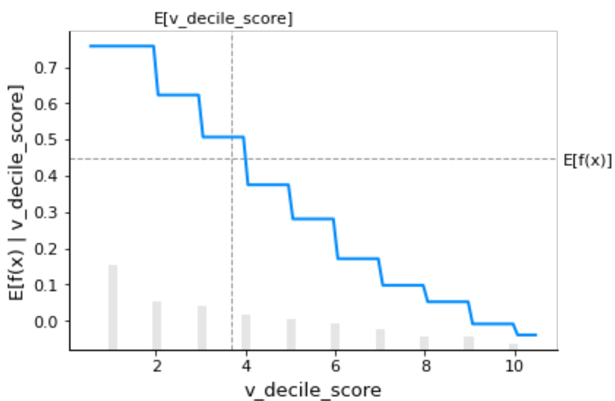
In [56]:
```
shap.plots.partial_dependence(
    'age', model_constrained.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```



Now, in the plot, upper and lower influence data point of 'age' variable is more clear. Below age 25 has higher influence of the precdicted result.

In [57]:

```
shap.plots.partial_dependence(
    'v_decile_score', model_constrained.predict, df_c_features,
    ice=False, model_expected_value=True, feature_expected_value=True
)
```

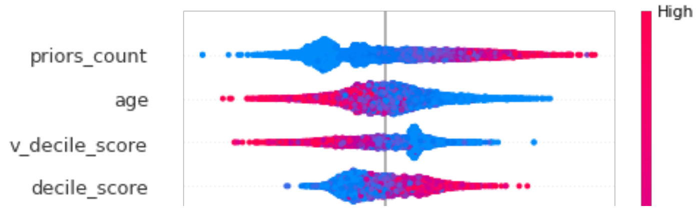


The influence of v_decile_score to the target variable was quite fuzzy, here is clear enough; less v_decile_score indicates high chance of target variable.

In [58]:

```
#The updated TreeExplainer plot
explainer = shap.TreeExplainer(model_constrained)
shap_values = explainer(df_c_features)
shap.summary_plot(shap_values, df_c_features)
```

```
ntree_limit is deprecated, use `iteration_range` or model slicing instead.
```



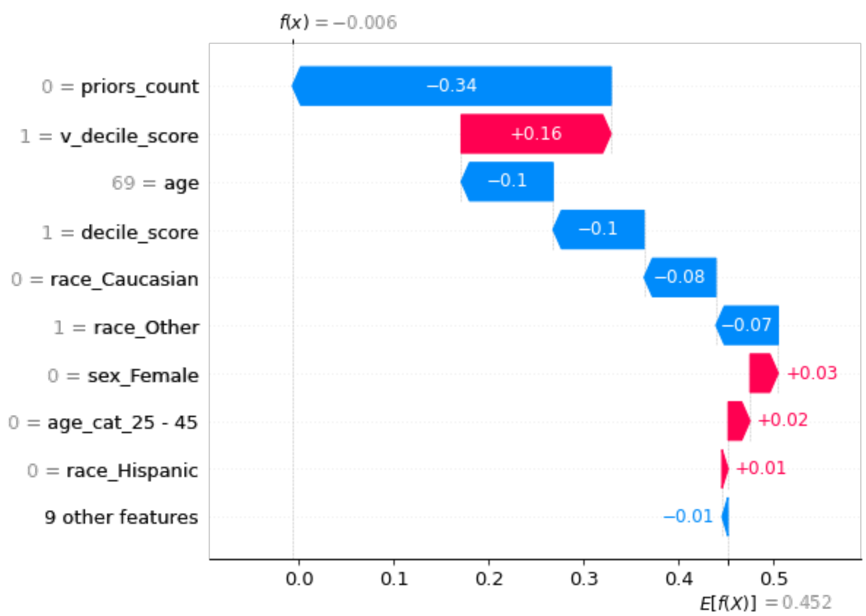
Observation About TreeExplainer Plot:

-We can see that 'priors_count' is the first most important feature for our new model. The higher values of priors_count (red dots) tend to contribute positively to the prediction. In comparison, the lower values (blue dots) have negative contributions. This makes sense, since the more priors_count a person have, the more likely that person will be in been jail for a new crime in next two years. The same observation is true form the variable 'decile_score'.

-The oposite scenerio is shown in the variable 'age' and 'v_decile_score'. The higher the value of age and v_decile_score (red dots), these tend to contribute negetively to the prediction and vice versa.

In [59]:

```
#Creating waterfall plot
shap.plots.waterfall(shap_values[0])
```

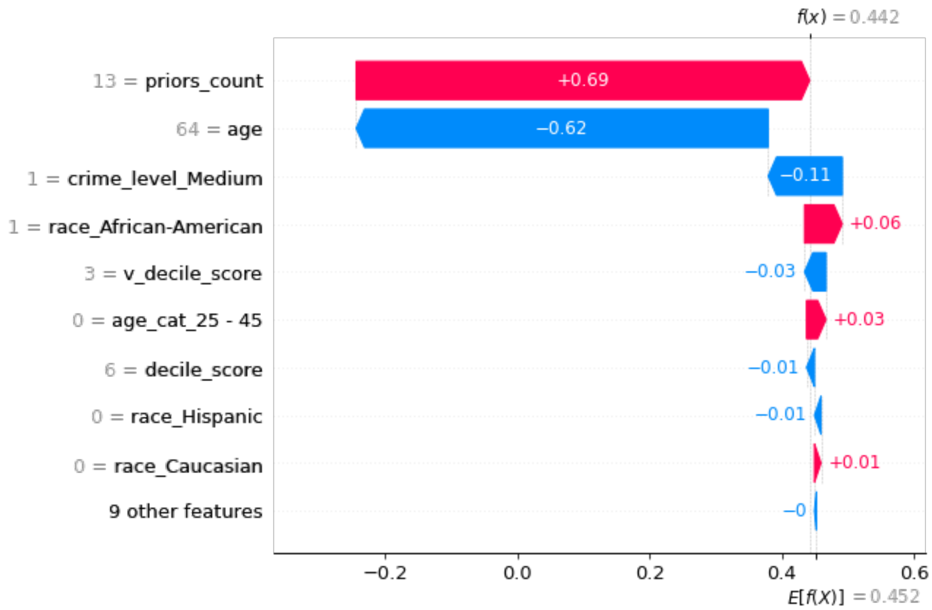


Comment about Waterfall Plot:

On this plot, we are seeing two values. At the bottom of the plot, E(f(x)), the average predicted score of the dataset is 0.452. At the top of the plot, f(x), the predicted score for the sample is, is -006. Between these two values, the waterfall plots how each feature contributes to the changes of prediction from E(f(x)) to f(x). Here, the 'priors_count' has the most impact. It pulled the prediction down, while the 'v_decile_score' value has increased the prediction.

In [60]:

```
#Updated Waterfall plot
shap.plots.waterfall(shap_values[20])
```



Comment about Waterfall Plot:

On this plot, we are seeing two values. At the bottom of the plot, E(f(x)), the average predicted score of the dataset is 0.452. At the top of the plot, f(x), the predicted score for the sample is, is 0.442, which is very near to the average one. Between these two values, the waterfall plots how each feature contributes to the changes of prediction from E(f(x)) to f(x). Here, the 'priors_count' has the most impact. It has increased the prediction to happen, while the age value has pulled the prediction.

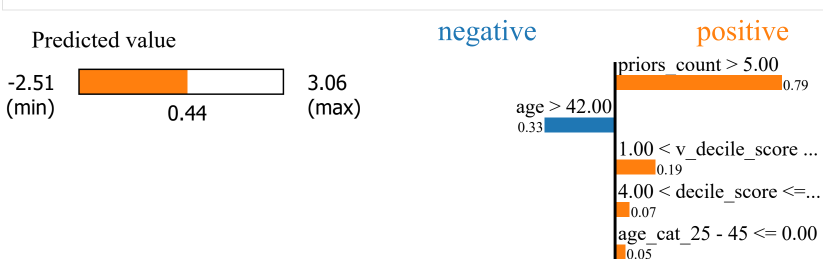
Using Lime to the re-shaffle the Dataset

In [61]:
```
explainer = lime.lime_tabular.LimeTabularExplainer(
    df_c_features.to_numpy(), feature_names=df_c_features.columns, class_names=['two_year_recid'],
    verbose=True, mode='regression', random_state=33)
```

In [62]:
```
exp = explainer.explain_instance(df_c_features.iloc[20], model_constrained.predict, num_features=5)
```

```
Intercept 0.24731035190611944
Prediction_local [1.00690098]
Right: 0.44194847
```

In [63]:
```
exp.show_in_notebook(show_table=True)
```



Feature	Value
priors_count	13.00
age	64.00
v_decile_score	3.00
decile_score	6.00
age_cat_25 - 45	0.00

Observation about LIME Output:

-We can see that the predicted score for this sample is 0.44194847. The local prediction result is increased here and become 1. Which indicates improvement of the model output.

-The features and their contributions (blue being negative, orange being positive) to this prediction are shown, as well as their feature values for this sample. Here, the feature 'priors_count' with a value of 13, 'decile_score' with a value of 6, v_decile score with a value of 3 have the strongest positive effects on the prediction. The percentage of each features chance to prediction is increased compared to previous one; the negative is shown in the age variable at age 64.