Lambda School Data Science — Tree Ensembles

Model Interpretation

Objectives

- Partial Dependence Plots
- Shapley Values

Pre-reads

1. Kaggle / Dan Becker: Machine Learning Explainability
    - https://www.kaggle.com/dansbecker/partial-plots (https://www.kaggle.com/dansbecker/partial-plots)
    - https://www.kaggle.com/dansbecker/shap-values (https://www.kaggle.com/dansbecker/shap-values)
2. Christoph Molnar: Interpretable Machine Learning
    - https://christophm.github.io/interpretable-ml-book/pdp.html (https://christophm.github.io/interpretable-ml-book/pdp.html)
    - https://christophm.github.io/interpretable-ml-book/shapley.html (https://christophm.github.io/interpretable-ml-book/shapley.html)

Libraries

- PDPbox (https://github.com/SauceCat/PDPbox): `pip install pdpbox`
- shap (https://github.com/slundberg/shap): `conda install -c conda-forge shap` / `pip install shap`

Types of explanations

Global explanation: all features in relation to each other

- Feature Importances (mean decrease impurity)
- Permutation Importances

- Drop-Column Importances

Global explanation: individual feature in relation to target

- Partial Dependence plots

Individual prediction explanation

- Shapley Values

Note that the coefficients from a linear model give you all three types of explanations!

Titanic

In [4]:
```
!echo y | conda install -c conda-forge seaborn
```

```
Collecting package metadata (repodata.json): done
Solving environment: done

## Package Plan ##

  environment location: /Library/anaconda3

  added / updated specs:
    - seaborn


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    seaborn-0.9.0              |             py_1         163 KB  conda-forge
    ------------------------------------------------------------
                                           Total:         163 KB

The following NEW packages will be INSTALLED:

  seaborn            conda-forge/noarch::seaborn-0.9.0-py_1


Proceed ([y]/n)?

Downloading and Extracting Packages
seaborn-0.9.0        | 163 KB    | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

In [5]:
```
%matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score

def load_titanic():
    df = sns.load_dataset('titanic')
    df['age'] = df['age'].fillna(df['age'].mean())
    df['class'] = df['class'].map({'First': 1, 'Second': 2, 'Third': 3})
    df['female'] = df['sex'] == 'female'
    X = df[['age', 'class', 'fare', 'female']]
    y = df['survived']
    return X, y

X, y = load_titanic()
```

Naive majority class baseline

In [6]:
```
y.value_counts(normalize=True)
```

Out[6]:
```
0    0.616162
1    0.383838
Name: survived, dtype: float64
```

Logistic Regression

In [7]:
```
lr = LogisticRegression(solver='lbfgs')
cross_val_score(lr, X, y, scoring='accuracy', cv=5, n_jobs=-1)
```

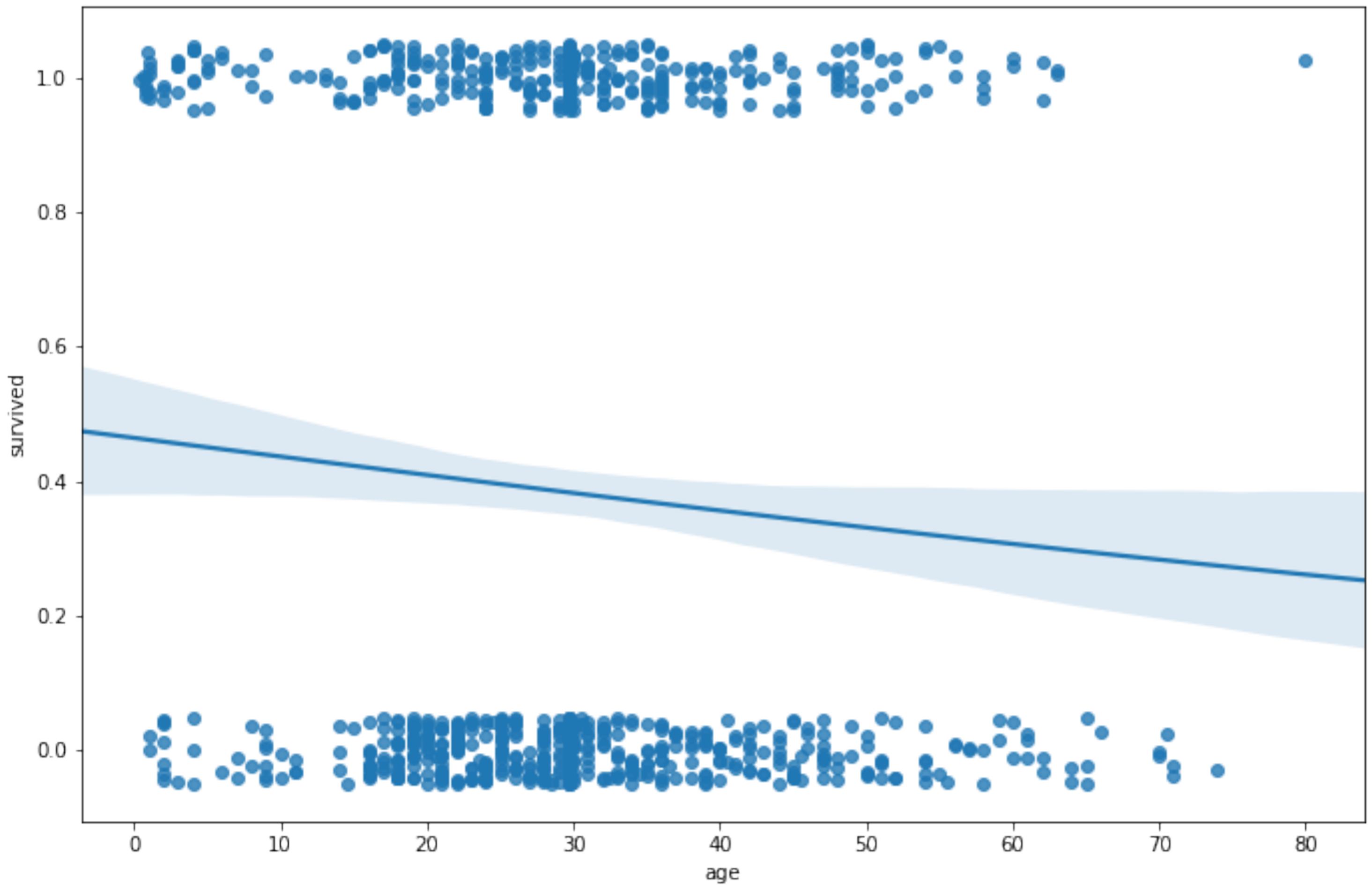
Out[7]:
```
array([0.7877095 , 0.78212291, 0.78651685, 0.7752809 , 0.80225989])
```

In [8]:
```
lr.fit(X, y)
pd.Series(lr.coef_[0], X.columns)
```

Out[8]:
```
age      -0.032595
class    -1.112937
fare      0.000805
female    2.512794
dtype: float64
```

In [9]:
```
g = sns.regplot(x=X['age'], y=y, logistic=True, y_jitter=.05)
g.figure.set_size_inches(11.5, 7.5)
```

```
/Library/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tuple sequence for multidime
nsional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array i
ndex, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Gradient Boosting

In [10]:
```
gb = GradientBoostingClassifier()
cross_val_score(gb, X, y, scoring='accuracy', cv=5, n_jobs=-1)
```

Out[10]:
```
array([0.80446927, 0.82681564, 0.85393258, 0.83146067, 0.84745763])
```

In [11]:
```
gb.fit(X, y)
pd.Series(gb.feature_importances_, X.columns)
```

Out[11]:
```
age       0.131213
class     0.173489
fare      0.199991
female    0.495308
dtype: float64
```

In [20]:
```
!echo y | conda update -n base -c defaults conda
```

```
Collecting package metadata (repodata.json): done
Solving environment: done

## Package Plan ##

  environment location: /Library/anaconda3

  added / updated specs:
    - conda


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    _py-xgboost-mutex-2.0      |            cpu_0           8 KB
```

```
    astor-0.8.0                |         py37_0          45 KB
    c-ares-1.15.0              |    h1de35cc_1001        83 KB
    clang_osx-64-4.0.1         |     h1ce6c1d_16        140 KB
    clangxx_osx-64-4.0.1       |     h22b1bf0_16        140 KB
    conda-4.7.10               |         py37_0         3.0 MB
    conda-package-handling-1.3.11|         py37_0         260 KB
    dill-0.3.0                 |         py37_0         116 KB
    glue-core-0.14.2           |         py37_0         1.4 MB
    libprotobuf-3.8.0          |      hd9629dc_0         4.4 MB
    markdown-3.1.1             |         py37_0         113 KB
    mock-3.0.5                 |         py37_0          47 KB
    mpl-scatter-density-0.6    |           py_0         647 KB
    plotly-4.0.0               |           py_0         3.8 MB
    protobuf-3.8.0             |   py37h0a44026_0         678 KB
    python-graphviz-0.10.1     |           py_0          22 KB
    tabulate-0.8.3             |         py37_0          38 KB
    ------------------------------------------------------------
                                           Total:        14.9 MB

The following packages will be REMOVED:

  pbr-5.1.3-py_0

The following packages will be UPDATED:

  astor                                     0.7.1-py37_0 --> 0.8.0-py37_0
  c-ares                               1.15.0-h1de35cc_1 --> 1.15.0-h1de35cc_1001
  clang_osx-64                         4.0.1-h1ce6c1d_11 --> 4.0.1-h1ce6c1d_16
  clangxx_osx-64                       4.0.1-h22b1bf0_11 --> 4.0.1-h22b1bf0_16
  dill                                      0.2.9-py37_0 --> 0.3.0-py37_0
  glue-core                                0.14.1-py37_0 --> 0.14.2-py37_0
  libprotobuf                           3.7.1-hd9629dc_0 --> 3.8.0-hd9629dc_0
  markdown                                    3.1-py37_0 --> 3.1.1-py37_0
  mock                                      2.0.0-py37_0 --> 3.0.5-py37_0
  mpl-scatter-densi~                          0.5-py_0 --> 0.6-py_0
  plotly                                      3.7.0-py_0 --> 4.0.0-py_0
  protobuf                           3.7.1-py37h0a44026_0 --> 3.8.0-py37h0a44026_0
```

```
The following packages will be SUPERSEDED by a higher-priority channel:

  _py-xgboost-mutex                          conda-forge --> pkgs/main
  conda                                      conda-forge --> pkgs/main
  conda-package-han~ conda-forge::conda-package-handling-1~ --> pkgs/main::conda-package-handling-1.3.11-py37_0
  python-graphviz                            conda-forge --> pkgs/main
  tabulate           conda-forge/noarch::tabulate-0.8.3-py~ --> pkgs/main/osx-64::tabulate-0.8.3-py37_0


Proceed ([y]/n)?

Downloading and Extracting Packages
dill-0.3.0           | 116 KB    | ##################################### | 100%
protobuf-3.8.0       | 678 KB    | ##################################### | 100%
python-graphviz-0.10 | 22 KB     | ##################################### | 100%
conda-4.7.10         | 3.0 MB    | ##################################### | 100%
astor-0.8.0          | 45 KB     | ##################################### | 100%
markdown-3.1.1       | 113 KB    | ##################################### | 100%
libprotobuf-3.8.0    | 4.4 MB    | ##################################### | 100%
tabulate-0.8.3       | 38 KB     | ##################################### | 100%
clang_osx-64-4.0.1   | 140 KB    | ##################################### | 100%
conda-package-handli | 260 KB    | ##################################### | 100%
plotly-4.0.0         | 3.8 MB    | ##################################### | 100%
clangxx_osx-64-4.0.1 | 140 KB    | ##################################### | 100%
mpl-scatter-density- | 647 KB    | ##################################### | 100%
c-ares-1.15.0        | 83 KB     | ##################################### | 100%
glue-core-0.14.2     | 1.4 MB    | ##################################### | 100%
mock-3.0.5           | 47 KB     | ##################################### | 100%
_py-xgboost-mutex-2. | 8 KB      | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

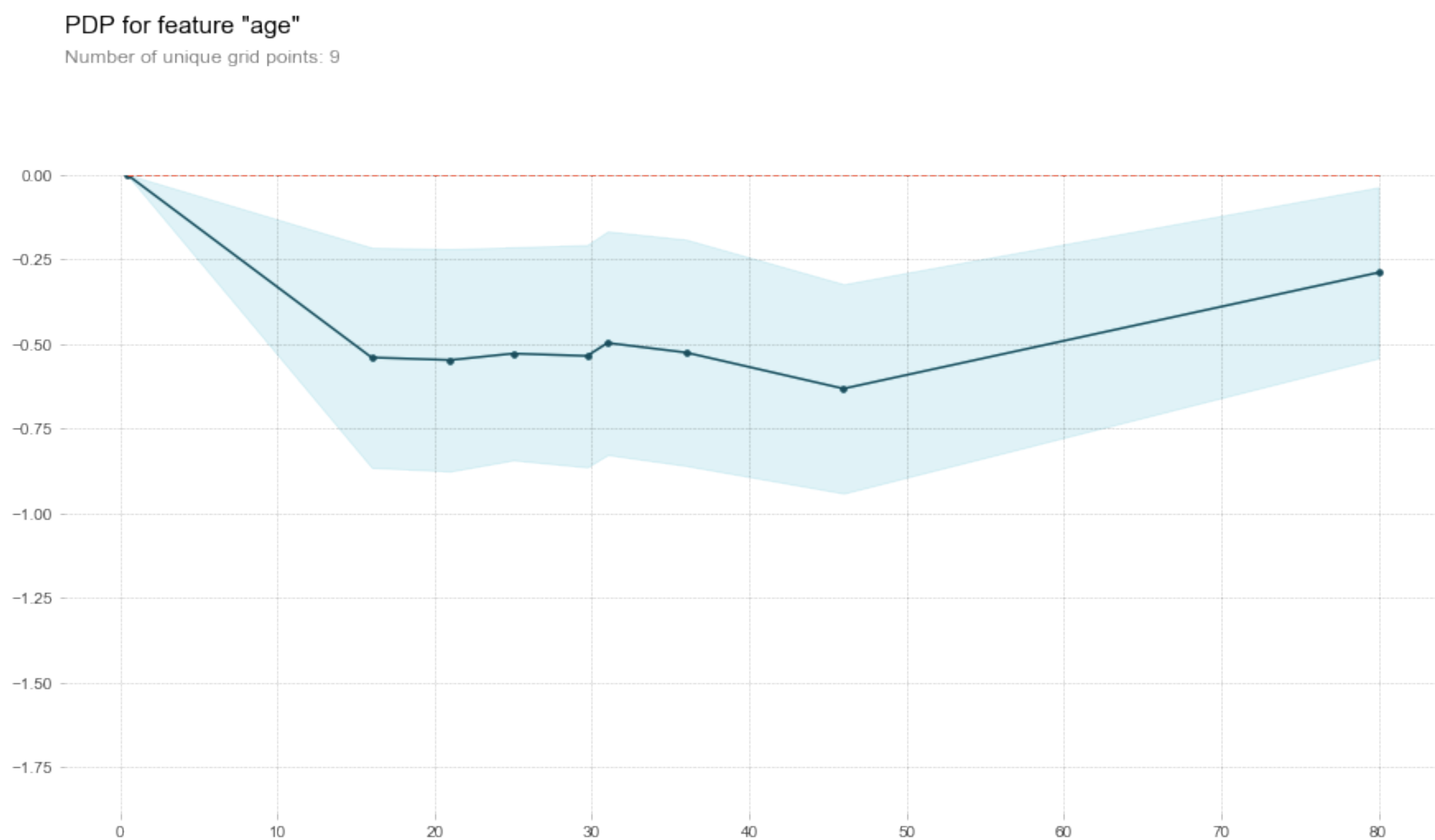
In [21]:

```
from pdpbox.pdp import pdp_isolate, pdp_plot

feature='age'
```

```
feature = 'age'
pdp_isolated = pdp_isolate(model=gb, dataset=X, model_features=X.columns,
                           feature=feature)

pdp_plot(pdp_isolated, feature);
```



age

From [PDPbox documentation (https://pdpbox.readthedocs.io/en/latest/)](https://pdpbox.readthedocs.io/en/latest/):

> **The common headache**: When using black box machine learning algorithms like random forest and boosting, it is hard to understand the relations between predictors and model outcome. For example, in terms of random forest, all we get is the feature importance. Although we can know which feature is significantly influencing the outcome based on the importance calculation, it really sucks that we don't know in which direction it is influencing. And in most of the real cases, the effect is non-monotonic. We need some powerful tools to help understanding the complex relations between predictors and model prediction.

In [18]:
```
!echo y | conda install -c conda-forge pdpbox
```

```
Collecting package metadata: done
Solving environment: done


==> WARNING: A newer version of conda exists. <==
  current version: 4.6.14
  latest version: 4.7.10

Please update conda by running

    $ conda update -n base -c defaults conda



## Package Plan ##

  environment location: /Library/anaconda3

  added / updated specs:
    - pdpbox
```

```
The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    _r-mutex-1.0.1             |      anacondar_1           3 KB  conda-forge
    conda-4.7.10               |           py37_0         3.0 MB  conda-forge
    conda-package-handling-1.4.1|           py37_0         261 KB  conda-forge
    matplotlib-base-3.1.1      |   py37h3a684a6_1         6.6 MB  conda-forge
    pdpbox-0.2.0               |             py_0        55.1 MB  conda-forge
    ------------------------------------------------------------
                                           Total:        65.0 MB

The following NEW packages will be INSTALLED:

  conda-package-han~ conda-forge/osx-64::conda-package-handling-1.4.1-py37_0
  matplotlib-base    conda-forge/osx-64::matplotlib-base-3.1.1-py37h3a684a6_1
  pdpbox             conda-forge/noarch::pdpbox-0.2.0-py_0

The following packages will be UPDATED:

  _r-mutex           pkgs/r/osx-64::_r-mutex-1.0.0-anacond~ --> conda-forge/noarch::_r-mutex-1.0.1-anacondar_1
  conda                      pkgs/main::conda-4.6.14-py37_0 --> conda-forge::conda-4.7.10-py37_0


Proceed ([y]/n)?

Downloading and Extracting Packages
conda-package-handli | 261 KB    | ##################################### | 100%
matplotlib-base-3.1. | 6.6 MB    | ##################################### | 100%
conda-4.7.10         | 3.0 MB    | ##################################### | 100%
pdpbox-0.2.0         | 55.1 MB   | ##################################### | 100%
_r-mutex-1.0.1       | 3 KB      | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

[Animation by Christoph Molnar (https://twitter.com/ChristophMolnar/status/1066398522608635904)](https://twitter.com/ChristophMolnar/status/1066398522608635904), author of [*Interpretable Machine Learning* (https://christophm.github.io/interpretable-ml-book/)](https://christophm.github.io/interpretable-ml-book/)

> Partial dependence plots show how a feature affects predictions of a Machine Learning model on average.
>
> 1. Define grid along feature
> 2. Model predictions at grid points
> 3. Line per data instance -> ICE (Individual Conditional Expectation) curve
> 4. Average curves to get a PDP (Partial Dependence Plot)

Compare Predictions

In [16]:
```
from sklearn.model_selection import cross_val_predict

y_pred_lr = cross_val_predict(lr, X, y, cv=5, n_jobs=-1)
y_pred_gb = cross_val_predict(gb, X, y, cv=5, n_jobs=-1)

preds = pd.DataFrame({'true': y, 'lr': y_pred_lr, 'gb': y_pred_gb})

gb_right = preds['gb'] == preds['true']
lr_wrong = preds['lr'] != preds['true']

len(preds[gb_right & lr_wrong]) / len(preds)
```

Out[16]:
```
0.08417508417508418
```

In [17]:
```
preds[gb_right & lr_wrong].head()
```

Out[17]:

	true	lr	gb
27	0	1	0
64	0	1	0
71	0	1	0
74	1	0	1
78	1	0	1

In [18]:
```
data_for_prediction = X.loc[27]

data_for_prediction
```

Out[18]:
```
age          19
class         1
fare        263
female    False
Name: 27, dtype: object
```

Explain individual prediction

[https://www.kaggle.com/dansbecker/shap-values (https://www.kaggle.com/dansbecker/shap-values)](https://www.kaggle.com/dansbecker/shap-values)

In [30]:
```
#pip install shap
!echo y | conda install -c conda-forge shap
```

```
Collecting package metadata (repodata.json): done
Solving environment: done

## Package Plan ##

  environment location: /Library/anaconda3

  added / updated specs:
    - shap


The following NEW packages will be INSTALLED:

  shap               conda-forge/osx-64::shap-0.29.3-py37h86efe34_0


Proceed ([y]/n)?
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

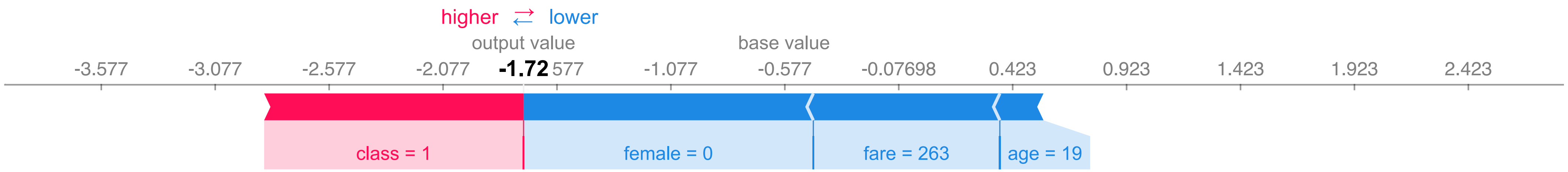
In [19]:
```
import shap

# Create object that can calculate shap values
explainer = shap.TreeExplainer(gb)

# Calculate Shap values
shap_values = explainer.shap_values(data_for_prediction)

shap.initjs()
shap.force_plot(explainer.expected_value, shap_values, data_for_prediction)
```

Out[19]:



Lending Club

In [20]:
```
import category_encoders as ce
import pandas as pd
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import make_pipeline

# Load data from https://www.kaggle.com/c/ds1-tree-ensembles/data
X_train = pd.read_csv('/Users/wel51x/Downloads/ds2-tree-ensembles/train_features.csv')
X_test = pd.read_csv('/Users/wel51x/Downloads/ds2-tree-ensembles/test_features.csv')
y_train = pd.read_csv('/Users/wel51x/Downloads/ds2-tree-ensembles/train_labels.csv')['charged_off']
```

```
y_train = pd.read_csv('/Users/wel51x/Downloads/ds2-tree-ensembles/train_labels.csv')['charged_off']
sample_submission = pd.read_csv('/Users/wel51x/Downloads/ds2-tree-ensembles/sample_submission.csv')


def wrangle(X):
    X = X.copy()

    # Drop some columns
    X = X.drop(columns='id')  # id is random
    X = X.drop(columns=['member_id', 'url', 'desc'])  # All null
    X = X.drop(columns='title')  # Duplicative of purpose
    X = X.drop(columns='grade')  # Duplicative of sub_grade

    # Transform sub_grade from "A1" - "G5" to 1.1 - 7.5
    def wrangle_sub_grade(x):
        first_digit = ord(x[0]) - 64
        second_digit = int(x[1])
        return first_digit + second_digit/10

    X['sub_grade'] = X['sub_grade'].apply(wrangle_sub_grade)

    # Convert percentages from strings to floats
    X['int_rate'] = X['int_rate'].str.strip('%').astype(float)
    X['revol_util'] = X['revol_util'].str.strip('%').astype(float)

    # Transform earliest_cr_line to an integer: how many days it's been open
    X['earliest_cr_line'] = pd.to_datetime(X['earliest_cr_line'], infer_datetime_format=True)
    X['earliest_cr_line'] = pd.Timestamp.today() - X['earliest_cr_line']
    X['earliest_cr_line'] = X['earliest_cr_line'].dt.days

    # Create features for three employee titles: teacher, manager, owner
    X['emp_title'] = X['emp_title'].str.lower()
    X['emp_title_teacher'] = X['emp_title'].str.contains('teacher', na=False)
    X['emp_title_manager'] = X['emp_title'].str.contains('manager', na=False)
    X['emp_title_owner']   = X['emp_title'].str.contains('owner', na=False)

    # Drop categoricals with high cardinality
    X = X.drop(columns=['emp_title', 'zip_code'])
```

```
    # Transform features with many nulls to binary flags
    many_nulls = ['sec_app_mths_since_last_major_derog',
                  'sec_app_revol_util',
                  'sec_app_earliest_cr_line',
                  'sec_app_mort_acc',
                  'dti_joint',
                  'sec_app_collections_12_mths_ex_med',
                  'sec_app_chargeoff_within_12_mths',
                  'sec_app_num_rev_accts',
                  'sec_app_open_act_il',
                  'sec_app_open_acc',
                  'revol_bal_joint',
                  'annual_inc_joint',
                  'sec_app_inq_last_6mths',
                  'mths_since_last_record',
                  'mths_since_recent_bc_dlq',
                  'mths_since_last_major_derog',
                  'mths_since_recent_revol_delinq',
                  'mths_since_last_delinq',
                  'il_util',
                  'emp_length',
                  'mths_since_recent_inq',
                  'mo_sin_old_il_acct',
                  'mths_since_rcnt_il',
                  'num_tl_120dpd_2m',
                  'bc_util',
                  'percent_bc_gt_75',
                  'bc_open_to_buy',
                  'mths_since_recent_bc']

    for col in many_nulls:
        X[col] = X[col].isnull()

    # For features with few nulls, do mean imputation
    for col in X:
        if X[col].isnull().sum() > 0:
```

```
            X[col] = X[col].fillna(X[col].mean())

    # Return the wrangled dataframe
    return X


# Wrangle train and test in the same way
X_train = wrangle(X_train)
X_test  = wrangle(X_test)
```

In [25]:

```
%%time
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(
    X_train, y_train, test_size=0.2, stratify=y_train, random_state=42)

encoder = ce.OrdinalEncoder()
X_train = encoder.fit_transform(X_train)
X_val = encoder.transform(X_val)
gb = GradientBoostingClassifier()
gb.fit(X_train, y_train)
y_pred_proba = gb.predict_proba(X_val)[:,1]
print('Validation ROC AUC:', roc_auc_score(y_val, y_pred_proba))
```

```
Validation ROC AUC: 0.7226505704278647
CPU times: user 14min 17s, sys: 14.4 s, total: 14min 31s
Wall time: 15min 2s
```

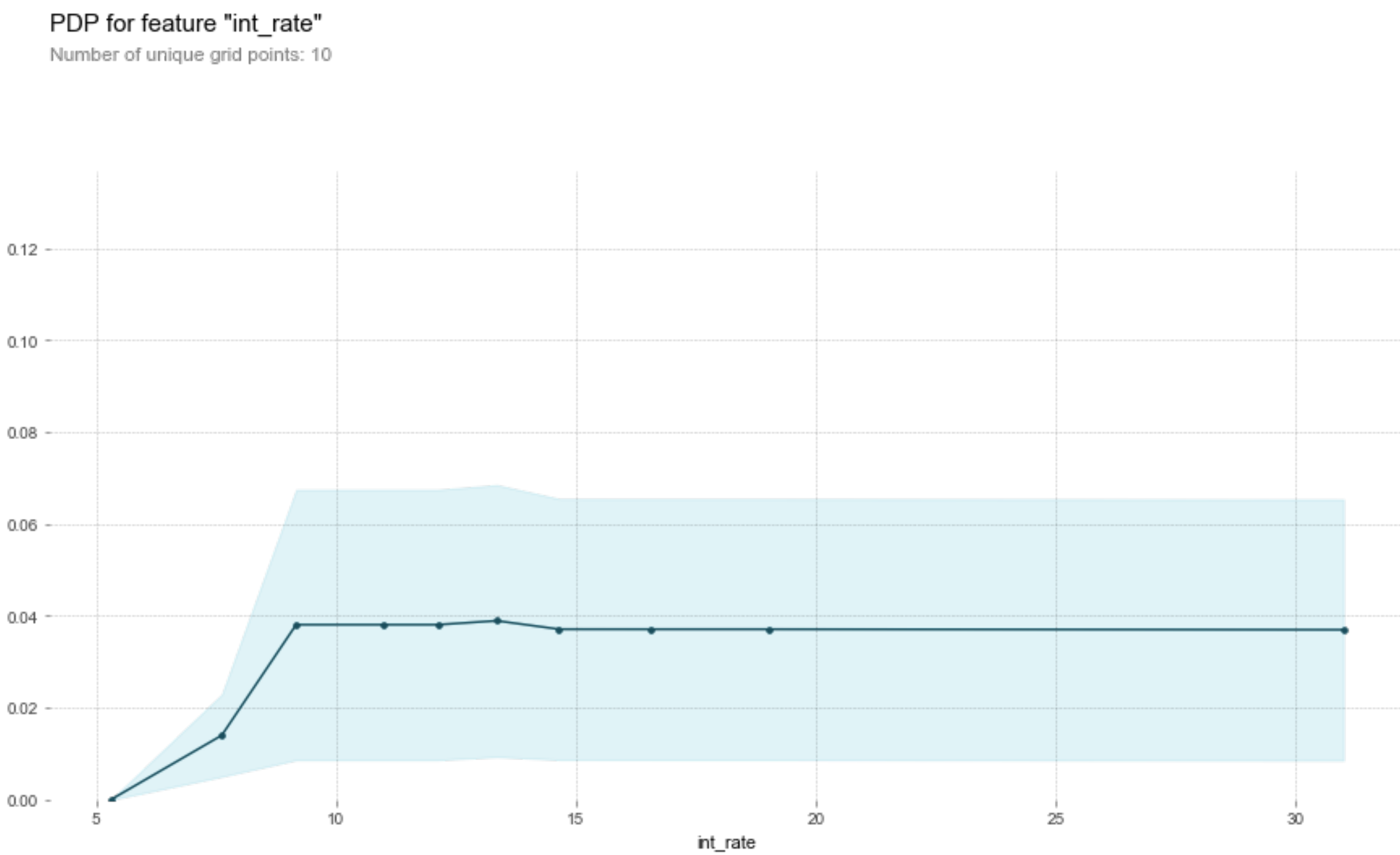
Partial Dependence Plot

In [26]:

```
from pdpbox.pdp import pdp_isolate, pdp_plot

feature='int_rate'
pdp_isolated = pdp_isolate(model=gb, dataset=X_val,
```

```
                                   model_features=X_val.columns, feature=feature)
pdp_plot(pdp_isolated, feature);
```



Individual predictions

In [27]:
```
import numpy as np
y_pred = (y_pred_proba >= 0.5).astype(int)
confidence = np.abs(y_pred_proba - 0.5)
preds = pd.DataFrame({'y_val': y_val, 'y_pred': y_pred,
                      'y_pred_proba': y_pred_proba,
                      'confidence': confidence})

preds.head()
```

Out[27]:

	y_val	y_pred	y_pred_proba	confidence
734948	0	0	0.120889	0.379111
662775	1	0	0.444685	0.055315
1293995	0	0	0.184529	0.315471
121846	0	0	0.055538	0.444462
1040519	0	0	0.105202	0.394798

In [28]:
```
# True positives, with high confidence
preds[(y_val==1) & (y_pred==1)].sort_values(by='confidence', ascending=False).head()
```

Out[28]:

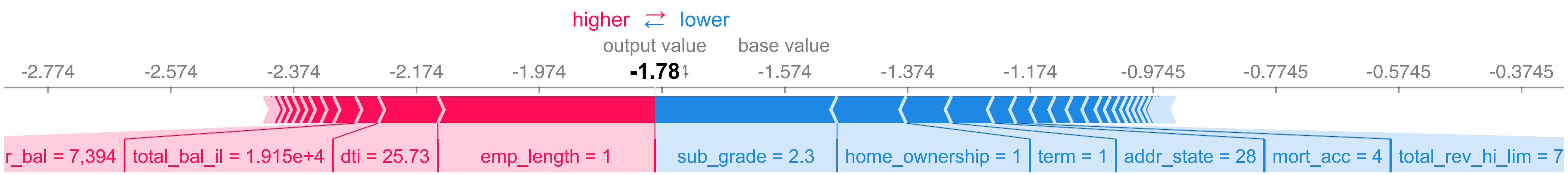
	y_val	y_pred	y_pred_proba	confidence
509674	1	1	0.778066	0.278066
1075507	1	1	0.746171	0.246171
1237423	1	1	0.729384	0.229384
525726	1	1	0.725751	0.225751
411364	1	1	0.725219	0.225219

In [30]:
```
X_val.shape
```

Out[30]: (209513, 98)

In [32]:
```
data_for_prediction = X_val.iloc[17575]
explainer = shap.TreeExplainer(gb)
shap_values = explainer.shap_values(data_for_prediction)
shap.force_plot(explainer.expected_value, shap_values, data_for_prediction)
```

Out[32]:



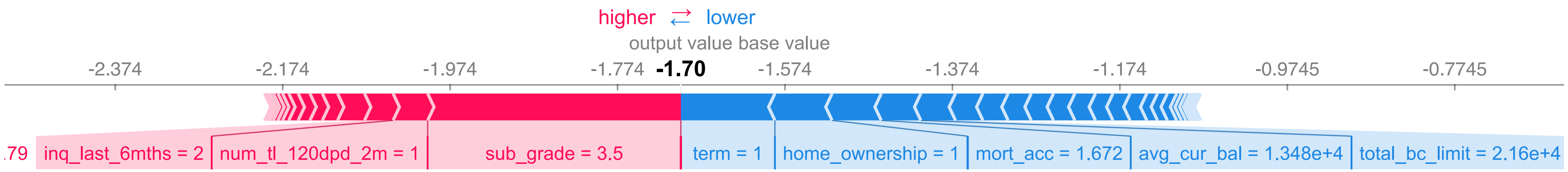
In [33]:
```
# True negatives, with high confidence
preds[(y_val==0) & (y_pred==0)].sort_values(by='confidence', ascending=False).head()
```

Out[33]:

	y_val	y_pred	y_pred_proba	confidence
716929	0	0	0.025035	0.474965
1024450	0	0	0.025919	0.474081
440926	0	0	0.025988	0.474012
626127	0	0	0.026001	0.473999
1129419	0	0	0.026023	0.473977

In [34]:
```
data_for_prediction = X_val.loc[1778]
shap_values = explainer.shap_values(data_for_prediction)
shap.force_plot(explainer.expected_value, shap_values, data_for_prediction)
```

Out[34]:



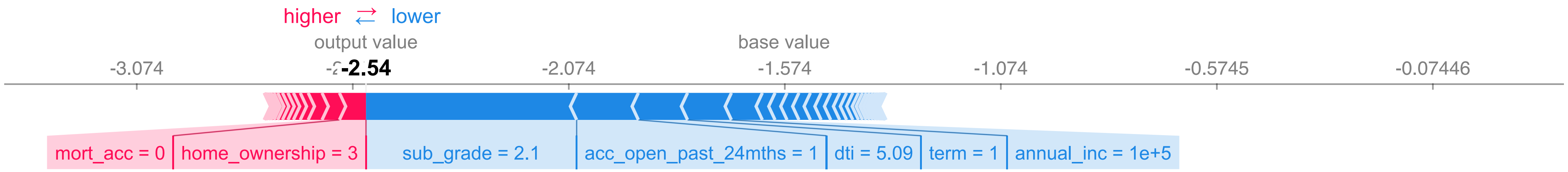
In [35]:
```
# False positives, with high (mistaken) confidence
preds[(y_val==0) & (y_pred==1)].sort_values(by='confidence', ascending=False).head()
```

Out[35]:

	y_val	y_pred	y_pred_proba	confidence
929700	0	1	0.733019	0.233019
1124876	0	1	0.724849	0.224849
1218998	0	1	0.713815	0.213815
14044	0	1	0.708883	0.208883
314029	0	1	0.708107	0.208107

In [36]:
```
data_for_prediction = X_val.loc[33542]
shap_values = explainer.shap_values(data_for_prediction)
shap.force_plot(explainer.expected_value, shap_values, data_for_prediction)
```

Out[36]:



In [37]:
```
data_for_prediction
```

Out[37]:
```
loan_amnt                          12000
funded_amnt                        12000
term                                   1
```

```
int_rate                              8.18
installment                         377.04
sub_grade                              2.1
emp_length                           False
home_ownership                           3
annual_inc                          100000
purpose                                  2
addr_state                               9
dti                                   5.09
delinq_2yrs                              0
earliest_cr_line                      7035
inq_last_6mths                           0
mths_since_last_delinq               False
mths_since_last_record               False
open_acc                                 7
pub_rec                                  1
revol_bal                            15692
revol_util                            61.3
total_acc                               18
initial_list_status                      2
collections_12_mths_ex_med               0
mths_since_last_major_derog           True
application_type                         1
annual_inc_joint                      True
dti_joint                             True
acc_now_delinq                           0
tot_coll_amt                             0
                                     ...
num_rev_accts                           11
num_rev_tl_bal_gt_0                      5
num_sats                                 7
num_tl_120dpd_2m                     False
num_tl_30dpd                             0
num_tl_90g_dpd_24m                       0
num_tl_op_past_12m                       0
pct_tl_nvr_dlq                        94.4
percent_bc_gt_75                     False
```

```
pub_rec_bankruptcies                         0
tax_liens                                    1
tot_hi_cred_lim                          25600
total_bal_ex_mort                        15692
total_bc_limit                           21900
total_il_high_credit_limit                   0
revol_bal_joint                           True
sec_app_earliest_cr_line                  True
sec_app_inq_last_6mths                    True
sec_app_mort_acc                          True
sec_app_open_acc                          True
sec_app_revol_util                        True
sec_app_open_act_il                       True
sec_app_num_rev_accts                     True
sec_app_chargeoff_within_12_mths          True
sec_app_collections_12_mths_ex_med        True
sec_app_mths_since_last_major_derog       True
disbursement_method                          1
emp_title_teacher                        False
emp_title_manager                         True
emp_title_owner                          False
Name: 33542, Length: 98, dtype: object
```

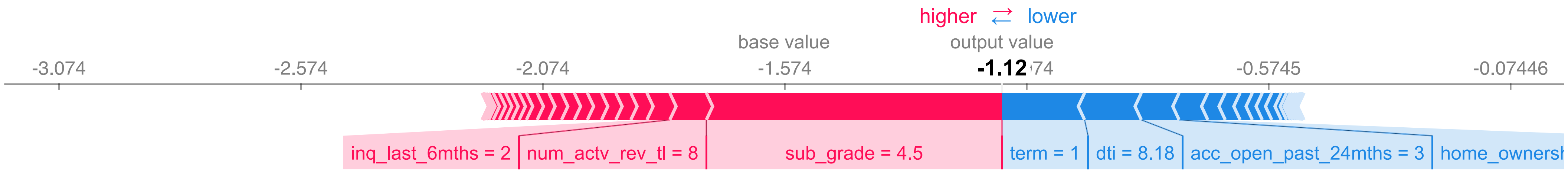
In [38]:
```
# False negatives, with high (mistaken) confidence
preds[(y_val==1) & (y_pred==0)].sort_values(by='confidence', ascending=False).head()
```

Out[38]:

	y_val	y_pred	y_pred_proba	confidence
923003	1	0	0.028394	0.471606
374806	1	0	0.029279	0.470721
415599	1	0	0.031176	0.468824
1117287	1	0	0.031621	0.468379
1049990	1	0	0.031804	0.468196

In [40]:
```
data_for_prediction = X_val.iloc[30492]
shap_values = explainer.shap_values(data_for_prediction)
shap.force_plot(explainer.expected_value, shap_values, data_for_prediction)
```

Out[40]:



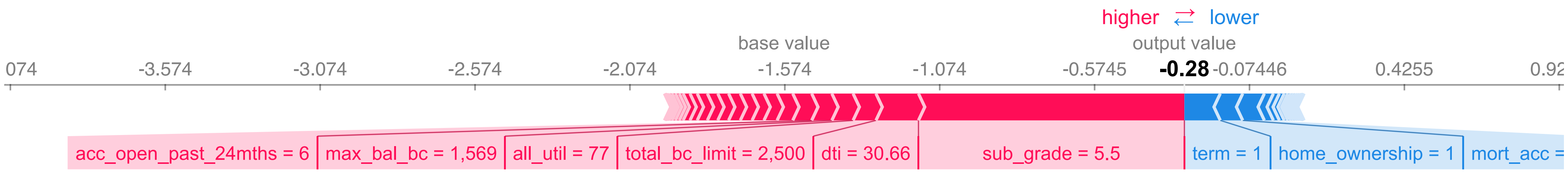
In [41]:
```
# Most uncertain predictions (least confidence)
preds.sort_values(by='confidence', ascending=True).head()
```

Out[41]:

	y_val	y_pred	y_pred_proba	confidence
1224267	0	0	0.499996	0.000004
1041474	0	0	0.499991	0.000009
1115932	0	0	0.499979	0.000021
926988	1	0	0.499973	0.000027
1032678	0	0	0.499969	0.000031

In [43]:
```
data_for_prediction = X_val.iloc[33095]
shap_values = explainer.shap_values(data_for_prediction)
shap.force_plot(explainer.expected_value, shap_values,
                data_for_prediction)
```

Out[43]:



In [44]:
```
data_for_prediction
```

Out[44]:
```
loan_amnt                         15600
funded_amnt                       15600
term                                  1
int_rate                           26.3
```

```
installment                              631.03
sub_grade                                   5.5
emp_length                                False
home_ownership                                1
annual_inc                                42000
purpose                                       2
addr_state                                   32
dti                                       30.66
delinq_2yrs                                   1
earliest_cr_line                           6152
inq_last_6mths                                0
mths_since_last_delinq                    False
mths_since_last_record                     True
open_acc                                     11
pub_rec                                       0
revol_bal                                  5187
revol_util                                 66.5
total_acc                                    21
initial_list_status                           2
collections_12_mths_ex_med                    0
mths_since_last_major_derog               False
application_type                              1
annual_inc_joint                           True
dti_joint                                  True
acc_now_delinq                                0
tot_coll_amt                                  0
                                         ...
num_rev_accts                                10
num_rev_tl_bal_gt_0                           5
num_sats                                     11
num_tl_120dpd_2m                          False
num_tl_30dpd                                  0
num_tl_90g_dpd_24m                            0
num_tl_op_past_12m                            3
pct_tl_nvr_dlq                             76.2
percent_bc_gt_75                          False
pub_rec_bankruptcies                          0
```

```
tax_liens                                   0
tot_hi_cred_lim                        164158
total_bal_ex_mort                       39247
total_bc_limit                           2500
total_il_high_credit_limit              43257
revol_bal_joint                          True
sec_app_earliest_cr_line                 True
sec_app_inq_last_6mths                   True
sec_app_mort_acc                         True
sec_app_open_acc                         True
sec_app_revol_util                       True
sec_app_open_act_il                      True
sec_app_num_rev_accts                    True
sec_app_chargeoff_within_12_mths         True
sec_app_collections_12_mths_ex_med       True
sec_app_mths_since_last_major_derog      True
disbursement_method                         1
emp_title_teacher                       False
emp_title_manager                       False
emp_title_owner                         False
Name: 329957, Length: 98, dtype: object
```

In [0]:

```

```