py-ciu_README_notebook

October 12, 2023

1 Usage of py-ciu

This notebook is included for the purpose of illustrating the use of the CIU method and hos to use the py-ciu package. The notebook is also used for generating the file "docs/py-ciu_README_notebook.html" and ensuring that all examplesexecute correctly (similarly to the "R" version of CIU, where the entire README is generated by R Studio).

[1]:
```
# Execute this for running the package as cloned source code from Github.
# Then your working directory should be the downloaded package directory␣
↪(py-ciu). For installing the
# package as "editable", do '!pip install -e .' instead:
#!pip install .
# For checking the version (and get other information), do
!pip show py-ciu
```

```
Name: py-ciu
Version: 0.1.0
Summary: Python implementation of the Contextual Importance and Utility (CIU)
explainable AI method
Home-page: https://github.com/KaryFramling/py-ciu
Author: Vlad Apopei, Kary Främling, others
Author-email: kary.framling@umu.se
License: MIT
Location: /Users/framling/Documents/Software/Python/py-ciu/lib/python3.8/site-
packages
Requires: matplotlib, numpy, pandas, scikit-learn, xgboost
Required-by:
```

Import the library:

[2]:
```
# If everything is set up correctly, then this should execute fine.
import ciu as ciu
from ciu import determine_ciu
```

Now, we can call the `determine_ciu` function which takes the following parameters:

- `case`: A dictionary that contains the data of the case.
- `predictor`: The prediction function of the black-box model *py-ciu* should call.

- `dataset`: Dataset to deduct min_maxs from (dictionary). Defaults to `None`.
- `min_maxs` (optional): dictionary (`'feature_name': [min, max, is_int]` for each feature), or infered from dataset. Defaults to `None`
-
- `samples` (optional): The number of samples *py-ciu* will generate. Defaults to `1000`.
- `prediction_index` (optional): In case the model returns several predictions, it is possible to provide the index of the relevant prediction. Defaults to `None`.
- `category_mapping` (optional): A mapping of one-hot encoded categorical variables to lists of categories and category names. Defaults to `None`.
- `feature_interactions` (optional): A list of `{key: list}` tuples of features whose interactions should be evaluated. Defaults to `[]`.

Here we can use a simple example with the well known Iris flower dataset

[3]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

iris=datasets.load_iris()

df = pd.DataFrame(data = np.c_[iris['data'], iris['target']],
              columns = iris['feature_names'] + ['target'])
df['species'] = pd.Categorical.from_codes(iris.target, iris.target_names)
df.columns = ['s_length', 's_width', 'p_length', 'p_width', 'target', 'species']

X = df[['s_length', 's_width', 'p_length', 'p_width']]
y = df['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=123)
```

Then create and train a model, in this case an `LDA` model

[4]:
```
model = LinearDiscriminantAnalysis()
model.fit(X_train, y_train)
```

[4]:
```
LinearDiscriminantAnalysis()
```

Now simply use our Iris flower data and the model, following the parameter descriptions above

[5]:
```
iris_df = df.apply(pd.to_numeric, errors='ignore')

iris_ciu = determine_ciu(
    X_test.iloc[[42]],
    model.predict_proba,
```

```
    iris_df.to_dict('list'),
    samples = 1000,
    prediction_index = 2
)
iris_ciu.explain_tabular()
```

[5]:

Features	CI	CU	cmin	cmax	outval
s_length	0.000142	0.975772	9.998581e-01	1.0	0.999997
s_width	0.000229	0.985208	9.997709e-01	1.0	0.999997
p_length	1.000000	0.999997	6.676649e-19	1.0	0.999997
p_width	1.000000	0.999997	4.436498e-08	1.0	0.999997

1.1 Boston Housing example

Let's import a test from the ciu_tests file

[6]:

```
from ciu_tests.boston_gbm import get_boston_gbm_test
```

The `get_boston_gbm_test` function returns a CIU Object that we can store and use as such

[7]:

```
boston_ciu = get_boston_gbm_test()
boston_ciu.explain_tabular()
```

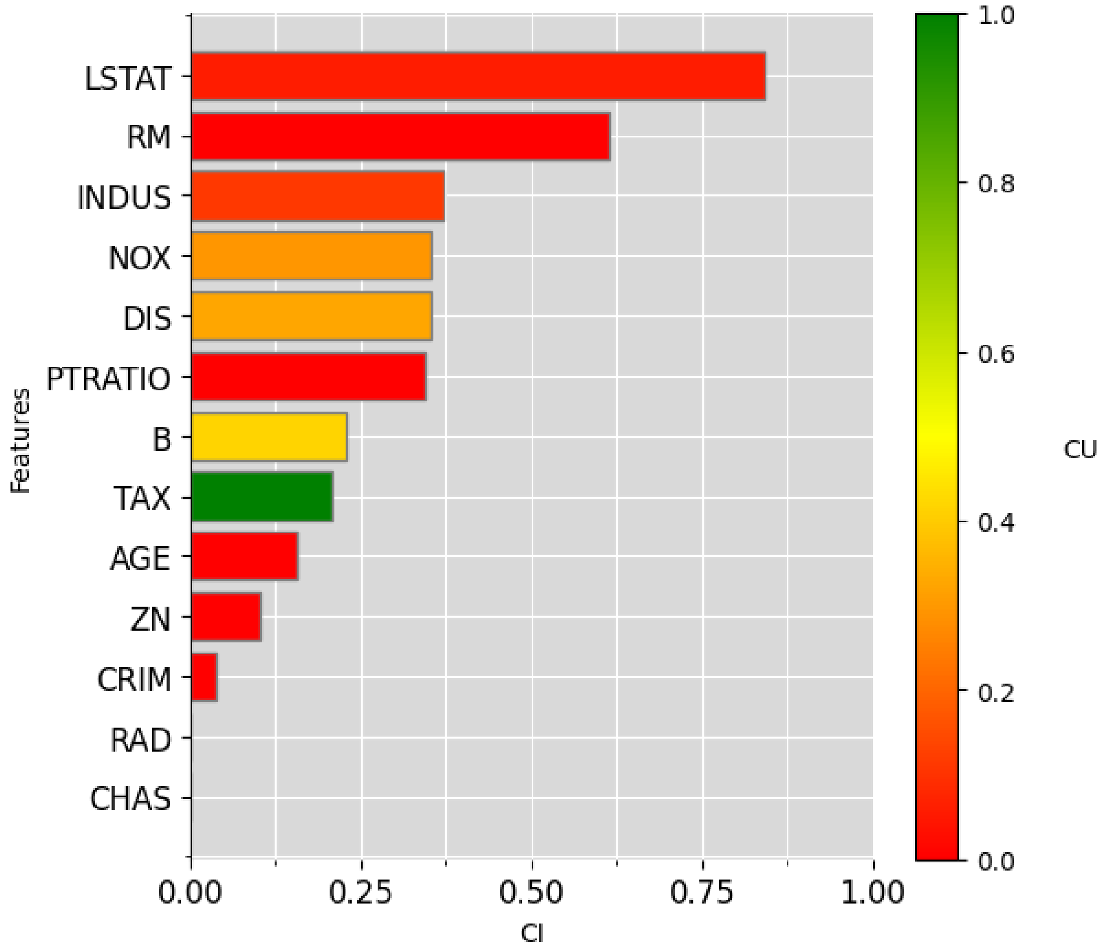
[7]:

Features	CI	CU	cmin	cmax	outval
CRIM	0.038656	0.001000	19.622561	19.862825	19.622561
ZN	0.103355	0.001000	19.622561	20.264963	19.622561
INDUS	0.372466	0.109379	19.369341	21.684408	19.622561
CHAS	0.000000	0.001000	19.622561	19.622561	19.622561
NOX	0.353558	0.295538	18.973103	21.170647	19.622561
RM	0.612313	0.001000	19.622561	23.428408	19.622561
AGE	0.157492	0.001000	19.622561	20.601456	19.622561
DIS	0.352549	0.326209	18.907747	21.099024	19.622561
RAD	0.000000	0.001000	19.622561	19.622561	19.622561
TAX	0.207469	1.000000	18.333031	19.622561	19.622561
PTRATIO	0.343926	0.001000	19.622561	21.760239	19.622561
B	0.229873	0.416789	19.027060	20.455841	19.622561
LSTAT	0.841821	0.058552	19.316196	24.548552	19.622561

Now we can also plot the CI/CU values using the CIU Object's `plot_ciu` function

[8]:

```
boston_ciu.plot_ciu() # Default plot, using colour codes
```

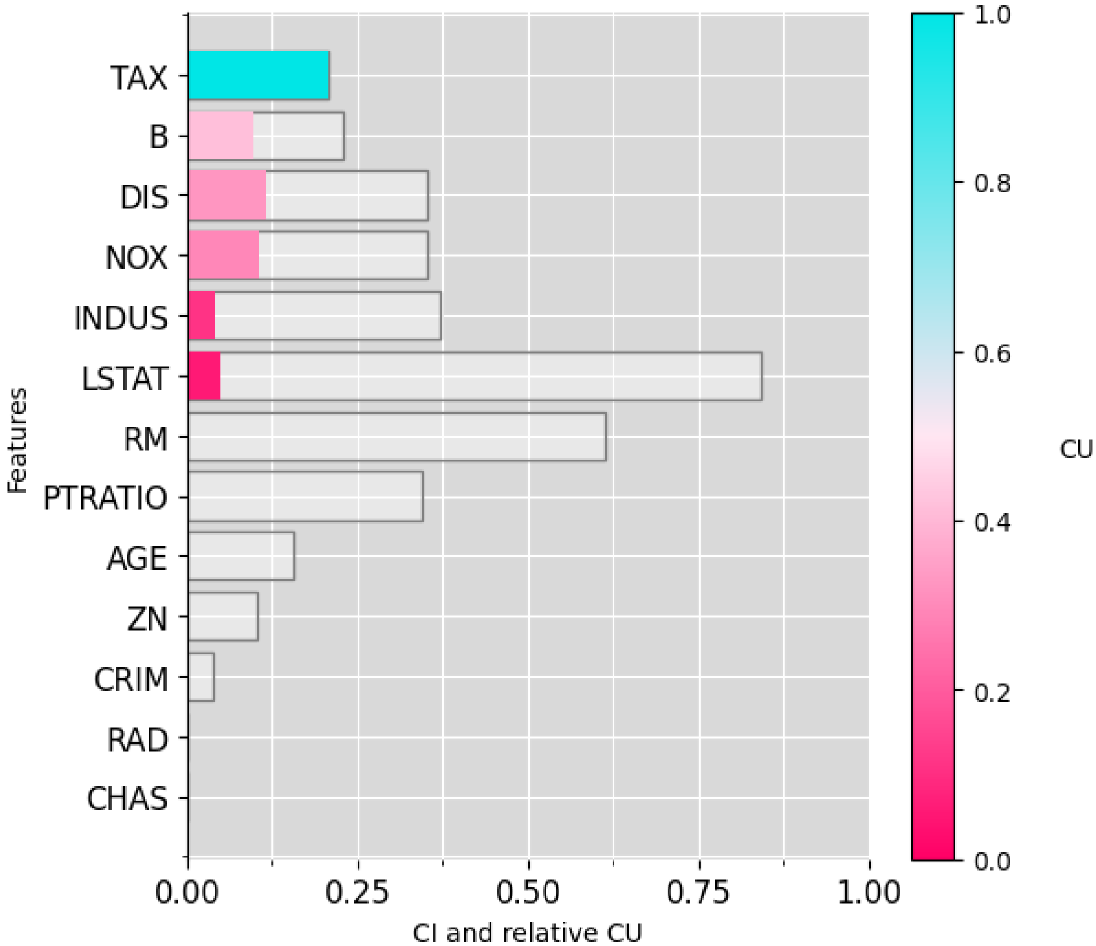


Likewise there are also several options available using the following parameters:

- `plot_mode`: defines the type plot to use between 'default', 'overlap' and 'combined'.
- `include`: defines whether to include interactions or not.
- `sort`: defines the order of the plot bars by the 'ci' (default), 'cu' values or unsorted if None.
- `color_blind`: defines accessible color maps to use for the plots, such as 'protanopia', 'deuteranopia' and 'tritanopia'.
- `color_edge_cu`: defines the hex or named color for the CU edge in the overlap plot mode.
- `color_fill_cu`: defines the hex or named color for the CU fill in the overlap plot mode.
- `color_edge_ci`: defines the hex or named color for the CI edge in the overlap plot mode.
- `color_fill_ci`: defines the hex or named color for the CI fill in the overlap plot mode.

Here's an example using some of these parameters to create a modified version of the above plot

[9]:
```
boston_ciu.plot_ciu(plot_mode="combined", color_blind='tritanopia', sort='cu')
```



1.2 Contextual influence

Contextual influence is calculated from CI and CU as follows:

$$\phi_{j,\{i\},\{I\}}(x) = \omega_{j,\{i\},\{I\}}(x)(CU_{j,\{i\}}(x) - \phi_0),$$

where ϕ_0 is the *baseline/reference* value ($y(u(0))$ in the plot). For instance, $\phi_0 = 0.5$ signifies using the average utility value 0.5 as the baseline, which is the case in the *age* plot above. An explanation using Contextual influence on the titanic dataset can be obtained as follows:

Note: the dataset and model used are not identical to the R version, therefore the results will see a slight variance.

[10]:
```python
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from ciu.ciu_core import determine_ciu

data = pd.read_csv("https://raw.githubusercontent.com/KaryFramling/py-ciu/
↪master/ciu_tests/data/titanic.csv")
data = data.drop(data.columns[0], axis=1)
unused = ['PassengerId','Cabin','Name','Ticket']

for col in unused:
    data = data.drop(col, axis=1)

from sklearn.preprocessing import LabelEncoder
data = data.dropna().apply(LabelEncoder().fit_transform)
train = data.drop('Survived', axis=1)

model = RandomForestClassifier(n_estimators=100)
model.fit(train, data.Survived)
```

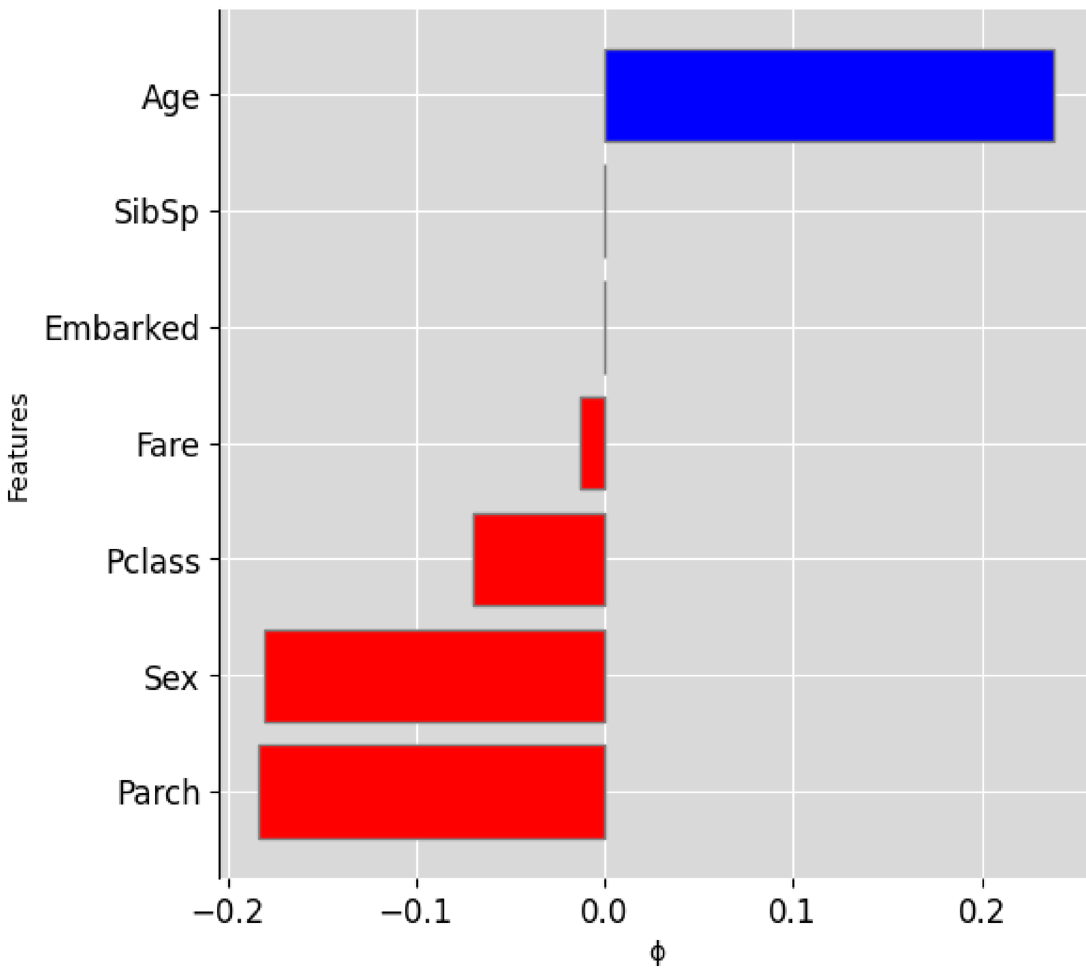
[10]:
```
RandomForestClassifier()
```

Create a new instance to explain:

[11]:
```python
# Create test instance (8-year old boy)
new_passenger = pd.DataFrame.from_dict({"Pclass" : [1], "Sex": [1], "Age": [8],␣
↪"SibSp": [0], "Parch": [0], "Fare": [72], "Embarked": [2]})

ciu_titanic = determine_ciu(
    new_passenger,
    model.predict_proba,
    train.to_dict('list'),
    samples = 1000,
    prediction_index = 1
)
```

Output a bar chart using Contextual Influence:

[12]:
```python
ciu_titanic.plot_ciu(use_influence=True)
```



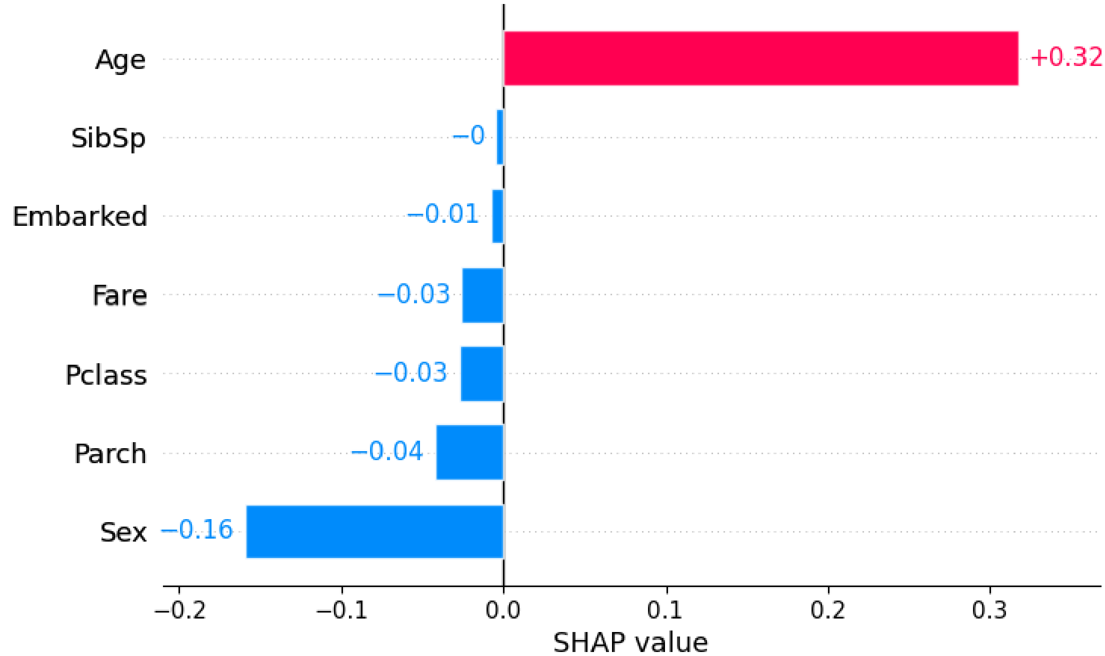
Remark: The Equation for Contextual influence is similar to the definition of Shapley values for linear models, except that the input value x_i is replaced by its utility value(s) $CU_{j,\{i\}}(x)$. In practice, **all *Additive Feature Attribution (AFA)* methods estimate influence values, not feature importance. Most state-of-the-art methods such as *Shapley values*, *LIME*,** are AFA methods.

Influence values give no counter-factual information and are easily misinterpreted. Below, we create a Shapley value explanation using the IML package. In that explanation, for instance the close-to-zero Shapley value for *Parch* gives the impression that it's a non-important feature, which is clearly wrong based on the CIU explanation.

[13]:
```
import shap
explainer = shap.Explainer(model, train)
shap_values = explainer(new_passenger)
shap.plots.bar(shap_values[0,:,1], order=np.argsort(shap_values[0,:,1].values)[:
↪:-1])
```

```
IProgress not found. Please update jupyter and ipywidgets. See
```

https://ipywidgets.readthedocs.io/en/stable/user_install.html

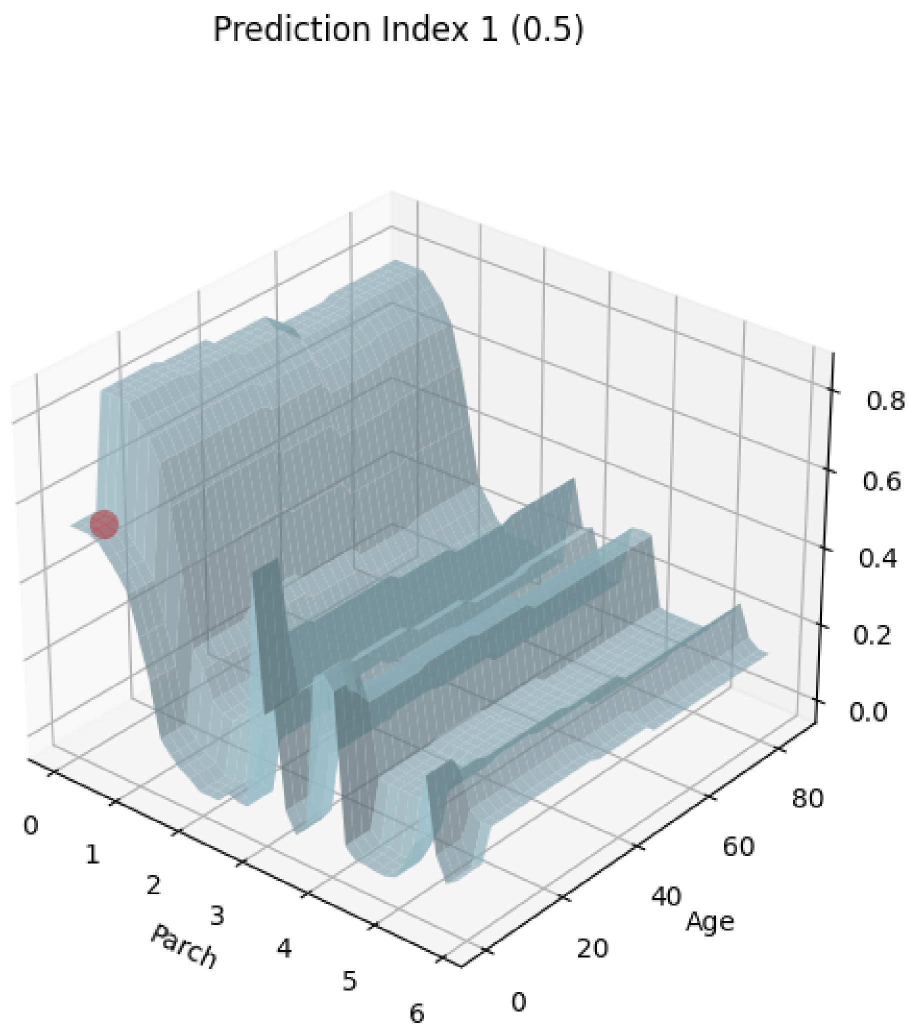


1.3 Intermediate Concepts

CIU can use named feature coalitions and structured vocabularies. Such vocabularies allow explanations at any abstraction level and can make explanations interactive.

The following code snippet plots the joint effect of features *age* and *parch* for the studied Titanic case (applicable for numeric features). It therefore shows how the coalition of those two features affects the output value and how CI and CU can be deduced in the same way as for a single feature.

[14]:
```
ciu_titanic.plot_3D(ind_inputs=[4,2])
```



1.3.1 Titanic Example

We define a small vocabulary for Titanic as follows:

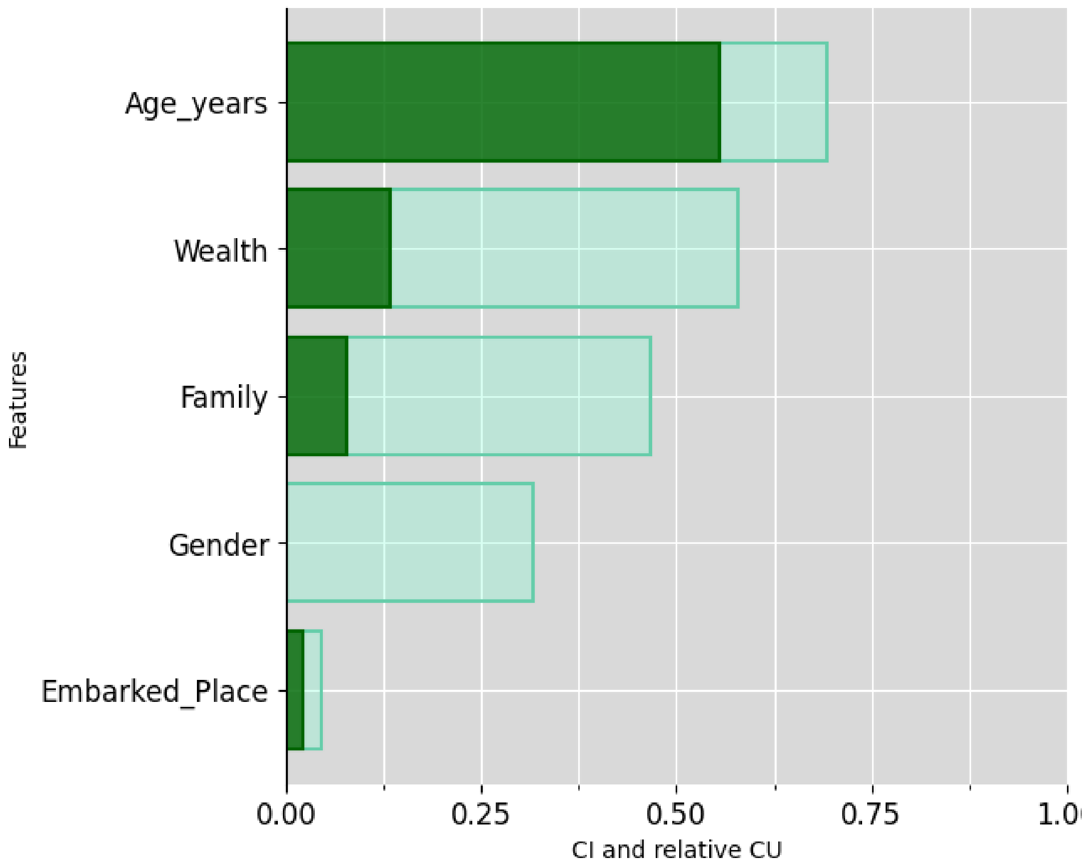
[15]:
```
intermediate_tit = [
        {"Wealth":['Pclass', 'Fare']},
        {"Family":['SibSp', 'Parch']},
        {"Gender":['Sex']},
        {"Age_years":['Age']},
        {"Embarked_Place":['Embarked']}
    ]
```

Then we create a new CIU object that uses that vocabulary and get top-level explanation.

[16]:
```
ciu_titanic = determine_ciu(
    new_passenger,
    model.predict_proba,
    train.to_dict('list'),
    samples = 1000,
    prediction_index = 1,
    intermediate_concepts=intermediate_tit
)
```

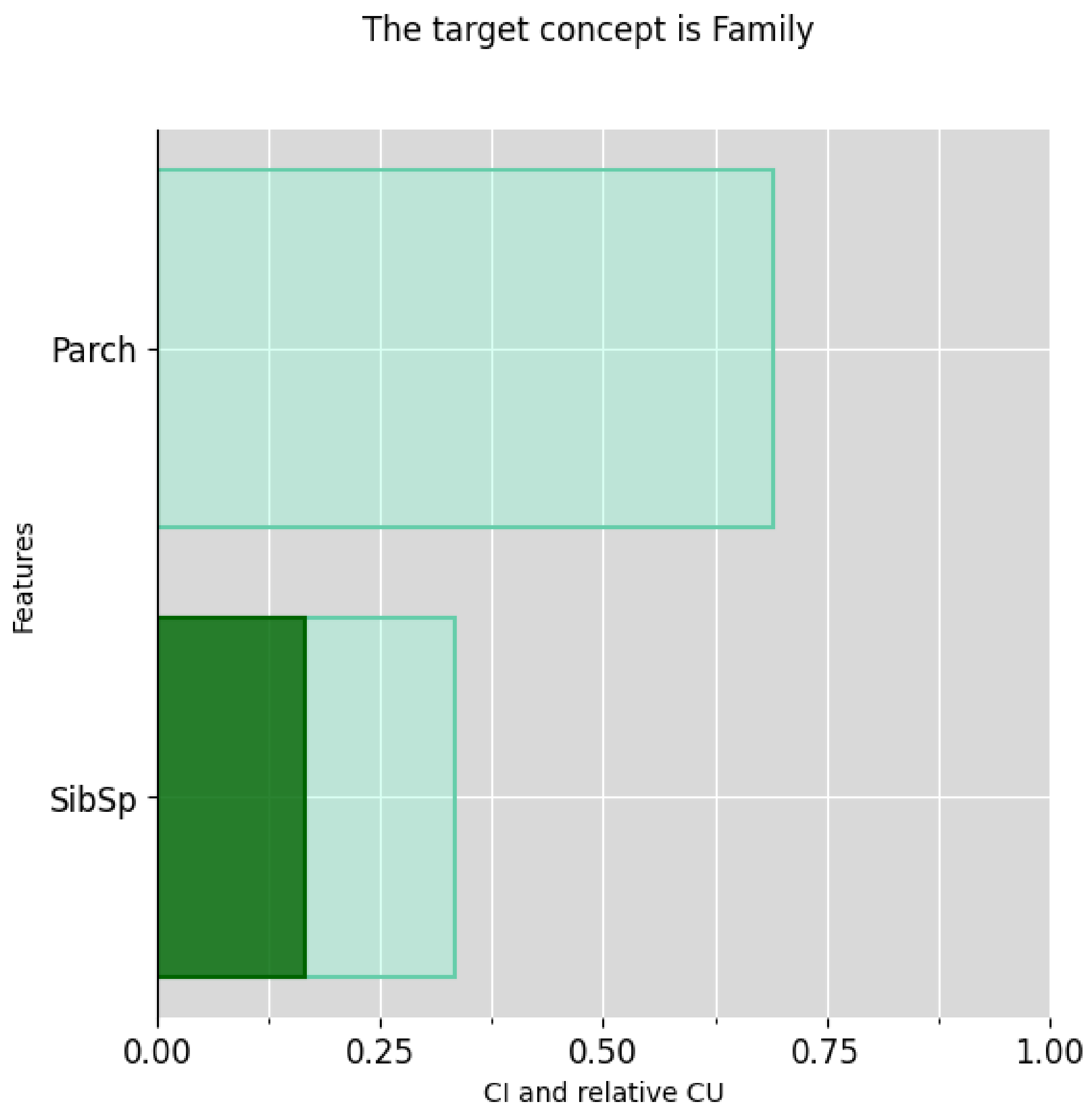
First barplot explanation:

[17]:
```
ciu_titanic.plot_ciu(include_intermediate_concepts='only', plot_mode='overlap')
```

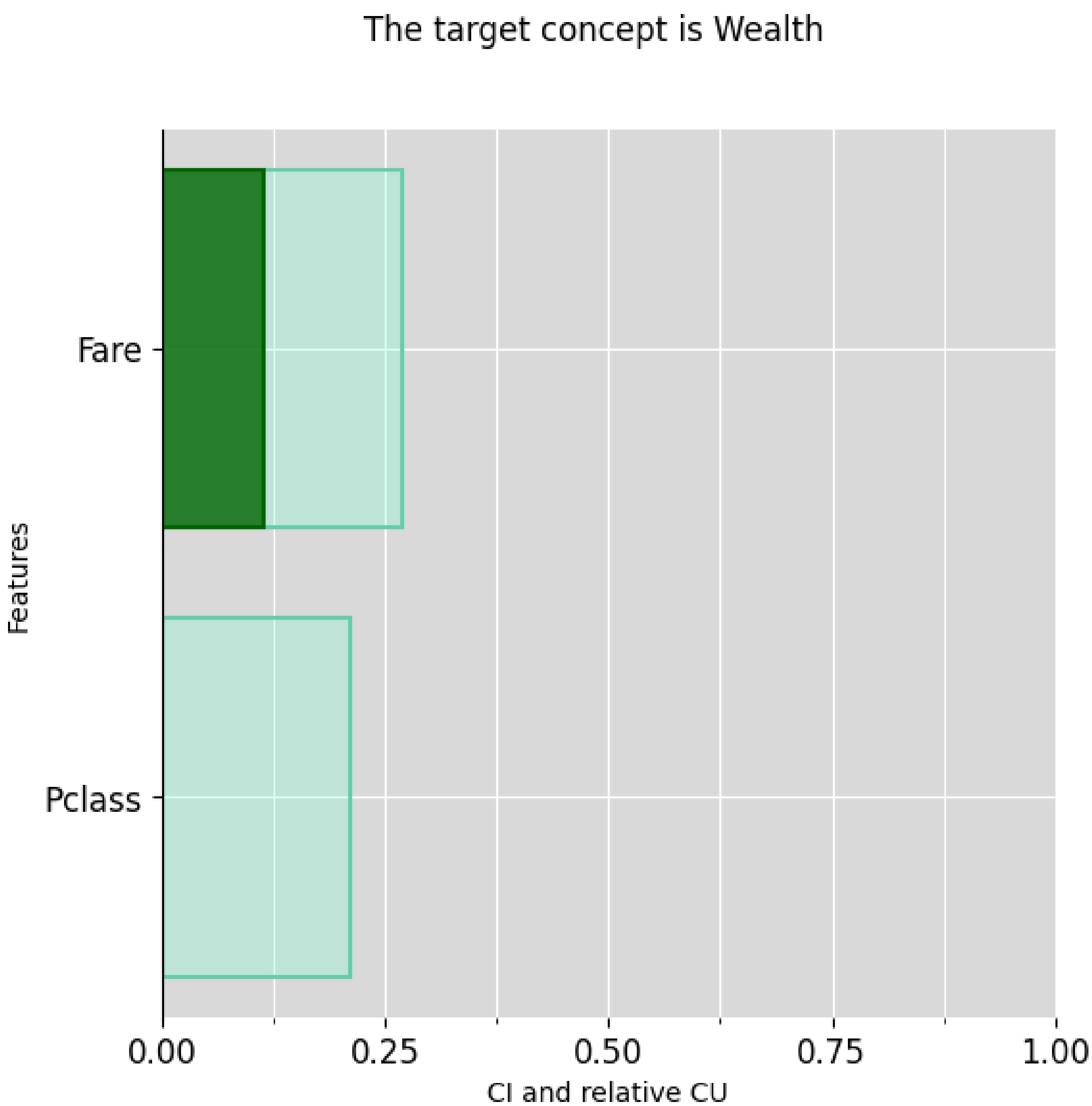


Then explain WEALTH and FAMILY

[18]:
```
ciu_titanic.plot_ciu(target_concept="Family", plot_mode="overlap")
```



[19]:
```
ciu_titanic.plot_ciu(target_concept="Wealth", plot_mode="overlap")
```



Same thing using textual explanations:

```
[20]: ciu_titanic.explain_text(include_intermediate_concepts="only")
```

```
[20]: ['The feature "Wealth", which is of normal importance (CI=57.78%), is not
typical for its prediction (CU=23.08%).',
 'The feature "Family", which is of normal importance (CI=46.67%), is not
typical for its prediction (CU=16.67%).',
 'The feature "Gender", which is of low importance (CI=31.7%), is not typical
for its prediction (CU=0.1%).',
 'The feature "Age_years", which is of high importance (CI=69.26%), is very
typical for its prediction (CU=80.21%).',
 'The feature "Embarked_Place", which is of very low importance (CI=4.44%), is
```

```
somewhat typical for its prediction (CU=50.0%).']
```

[21]:
```python
ciu_titanic.explain_text(target_concept="Family")
```

[21]:
```
['The intermediate concept "Family", is not typical for its prediction
(CU=16.67%).',
 'The feature "SibSp", which is of low importance (CI=33.33%), is typical for
its prediction (CU=50.0%).',
 'The feature "Parch", which is of high importance (CI=69.05%), is not typical
for its prediction (CU=0.1%).']
```

[22]:
```python
ciu_titanic.explain_text(target_concept="Wealth")
```

[22]:
```
['The intermediate concept "Wealth", is not typical for its prediction
(CU=23.08%).',
 'The feature "Pclass", which is of low importance (CI=21.15%), is not typical
for its prediction (CU=0.1%).',
 'The feature "Fare", which is of low importance (CI=26.92%), is somewhat
typical for its prediction (CU=42.86%).']
```

1.4 Ames Housing Example

Ames housing is a data set about properties in the town Ames in the US. It contains over 80 features that can be used for learning to estimate the sales price. The following code imports the data set (make sure that you have the path to the CSV file set correctly!), does some pre-processing and trains a Gradient Boosting model:

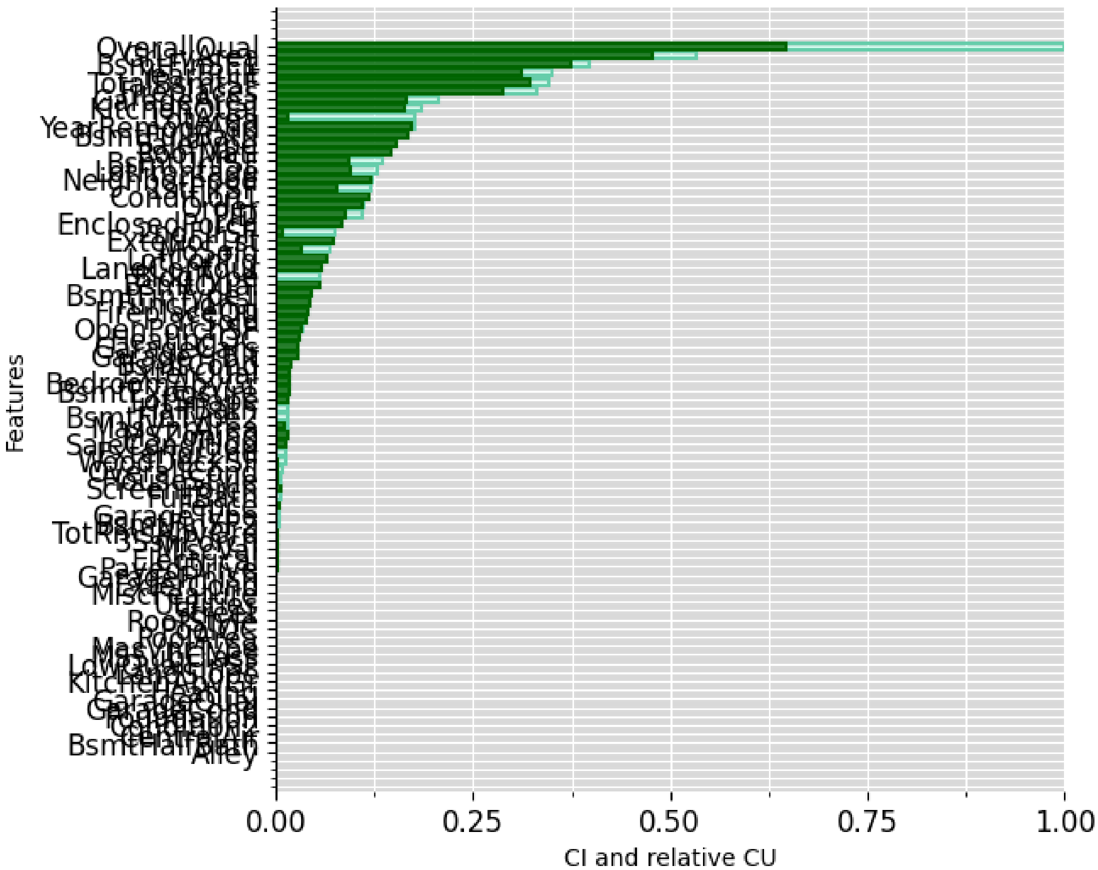
[23]:
```python
from ciu.ciu_core import determine_ciu
import pandas as pd
import xgboost as xgb
from sklearn.model_selection import train_test_split

df = pd.read_csv('ciu_tests/data/AmesHousing.csv')

#Checking for missing data
missing_data_count = df.isnull().sum()
missing_data_percent = df.isnull().sum() / len(df) * 100

missing_data = pd.DataFrame({
    'Count': missing_data_count,
    'Percent': missing_data_percent
})

missing_data = missing_data[missing_data.Count > 0]
missing_data.sort_values(by='Count', ascending=False, inplace=True)

#This one has spaces for some reason
```

```
df.columns = df.columns.str.replace(' ', '')


#Taking care of missing values
from sklearn.impute import SimpleImputer
# Group 1:
group_1 = [
    'PoolQC', 'MiscFeature', 'Alley', 'Fence', 'FireplaceQu', 'GarageType',
    'GarageFinish', 'GarageQual', 'GarageCond', 'BsmtQual', 'BsmtCond',
    'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'MasVnrType'
]
df[group_1] = df[group_1].fillna("None")

# Group 2:
group_2 = [
    'GarageArea', 'GarageCars', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
    'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath', 'MasVnrArea'
]

df[group_2] = df[group_2].fillna(0)

# Group 3:
group_3a = [
    'Functional', 'MSZoning', 'Electrical', 'KitchenQual', 'Exterior1st',
    'Exterior2nd', 'SaleType', 'Utilities'
]

imputer = SimpleImputer(strategy='most_frequent')
df[group_3a] = pd.DataFrame(imputer.fit_transform(df[group_3a]), index=df.index)

df.LotFrontage = df.LotFrontage.fillna(df.LotFrontage.mean())
df.GarageYrBlt = df.GarageYrBlt.fillna(df.YearBuilt)

#Label encoding
from sklearn.preprocessing import LabelEncoder
df = df.apply(LabelEncoder().fit_transform)

data = df.drop(columns=['SalePrice'])
target = df.SalePrice

#Splitting and training
X_train, X_test, y_train, y_test = train_test_split(data, target, test_size=0.
 ↪3, random_state=123)
xg_reg = xgb.XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.
 ↪5, learning_rate = 0.1, max_depth = 15, alpha = 10)

xg_reg.fit(X_train,y_train)
```

```
[23]: XGBRegressor(alpha=10, base_score=None, booster=None, callbacks=None,
                   colsample_bylevel=None, colsample_bynode=None,
                   colsample_bytree=0.5, device=None, early_stopping_rounds=None,
                   enable_categorical=False, eval_metric=None, feature_types=None,
                   gamma=None, grow_policy=None, importance_type=None,
                   interaction_constraints=None, learning_rate=0.1, max_bin=None,
                   max_cat_threshold=None, max_cat_to_onehot=None,
                   max_delta_step=None, max_depth=15, max_leaves=None,
                   min_child_weight=None, missing=nan, monotone_constraints=None,
                   multi_strategy=None, n_estimators=None, n_jobs=None,
                   num_parallel_tree=None, …)
```

We start with an "explanation" using all 80 basic features, which is not very readable and overly detailed for "ordinary" humans to understand:

```
[24]: test_data_ames = X_test.iloc[[345]]

ciu_ames = determine_ciu(
    test_data_ames,
    xg_reg.predict,
    df.to_dict('list'),
    samples = 1000,
    prediction_index = None
)
ciu_ames.plot_ciu(plot_mode='overlap')
```



Then we create our vocabulary of intermediate concepts, in this case a list containing dictionaries of a `concept->[columns]` structure as follows:

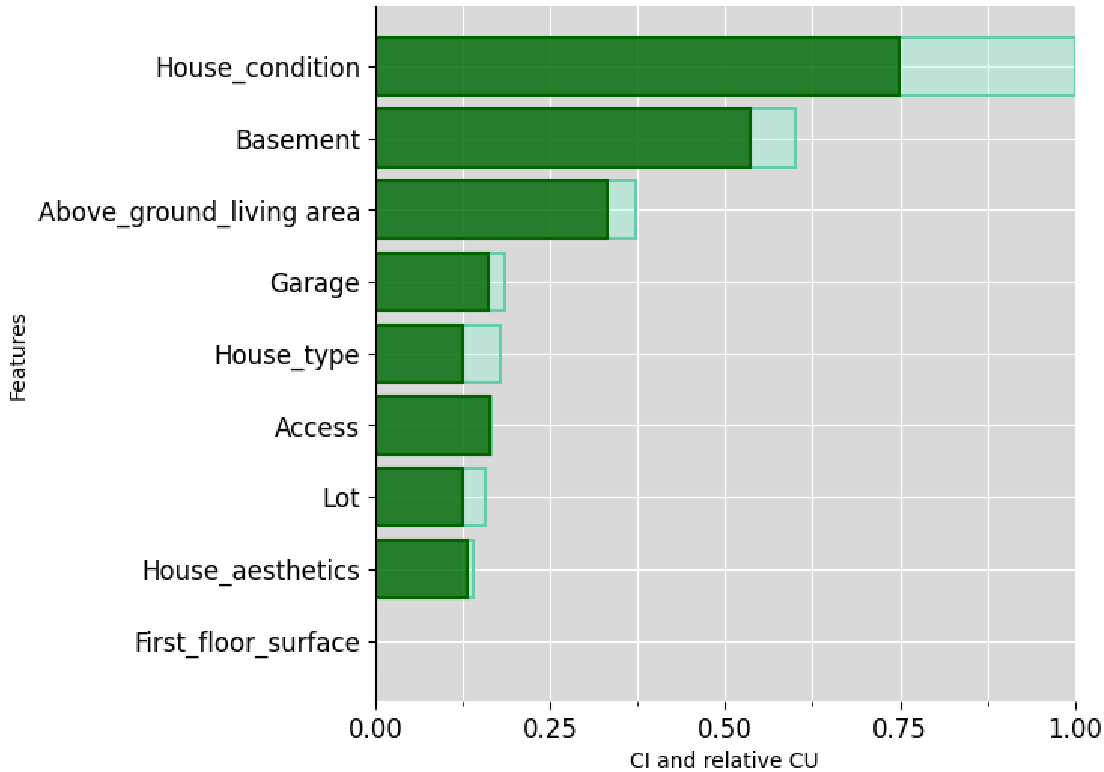
[25]:
```
intermediate = [
    {"Garage":list(df.columns[[58,59,60,61,62,63]])},
    {"Basement":list(df.columns[[30,31,33,34,35,36,37,38,47,48]])},
    {"Lot":list(df.columns[[3,4,7,8,9,10,11]])},
    {"Access":list(df.columns[[13,14]])},
    {"House_type":list(df.columns[[1,15,16,21]])},
    {"House_aesthetics":list(df.columns[[22,23,24,25,26]])},
    {"House_condition":list(df.columns[[17,18,19,20,27,28]])},
    {"First_floor_surface":list(df.columns[[43]])},
    {"Above_ground_living area":[c for c in df.columns if 'GrLivArea' in c]}
]
```

Now we can initialise the CIU object with a relatively expensive (which here corresponds to a "high utility") test case and our newly defined intermediate concepts:

```
[26]: ciu_ames = determine_ciu(
    test_data_ames,
    xg_reg.predict,
    df.to_dict('list'),
    samples = 1000,
    prediction_index = None,
    intermediate_concepts = intermediate
)
```

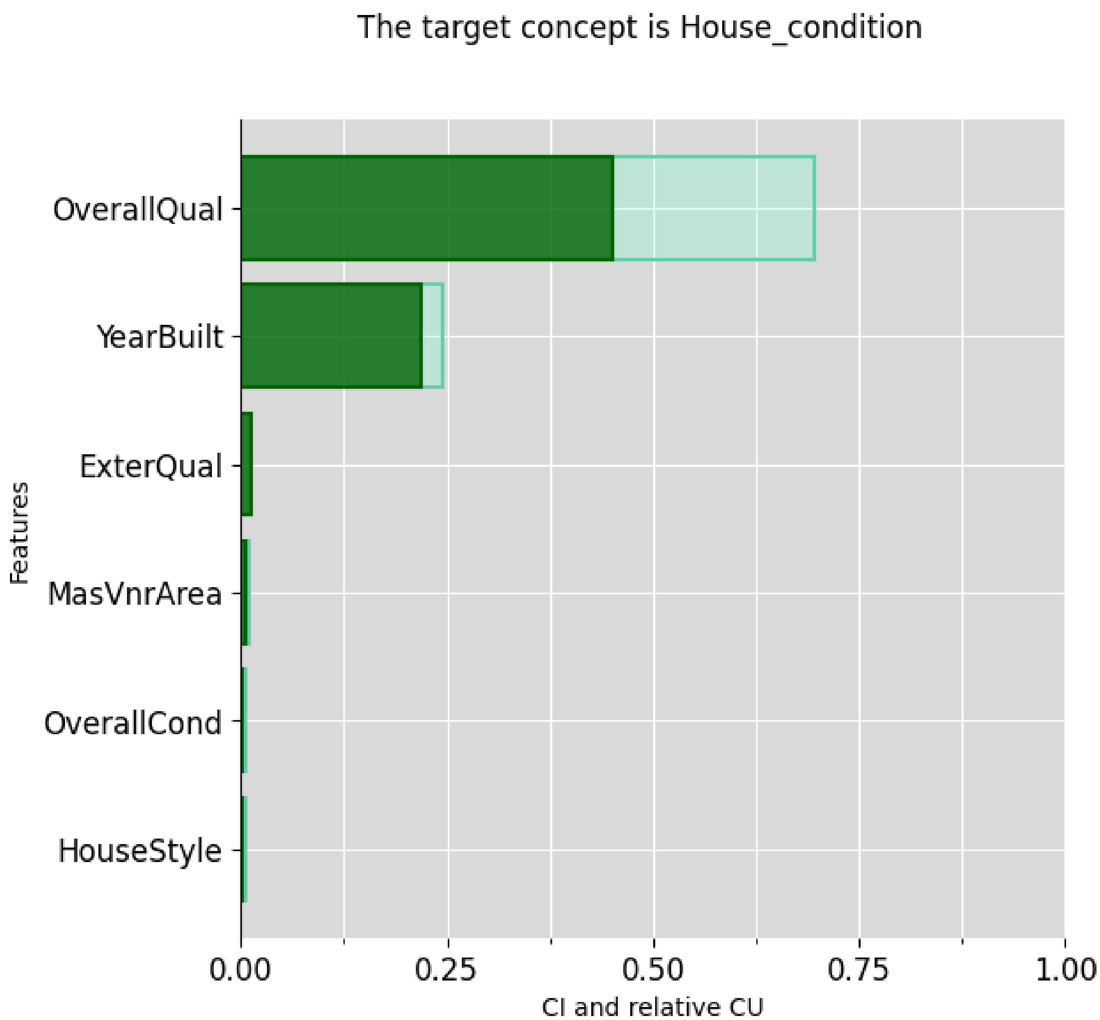
Then the same, using highest-level concepts:

```
[27]: ciu_ames.plot_ciu(include_intermediate_concepts='only', plot_mode='overlap')
```

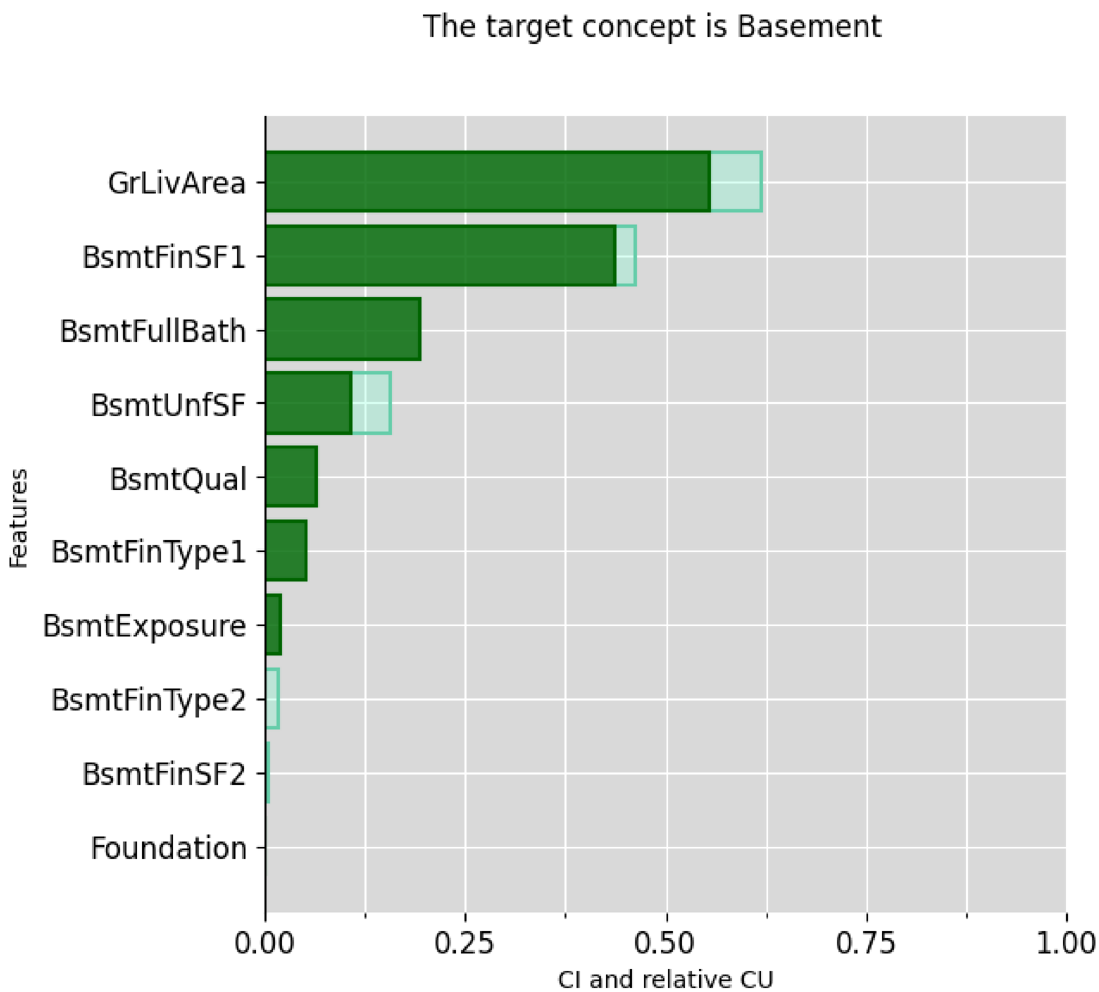


Then explain further some intermediate concepts:

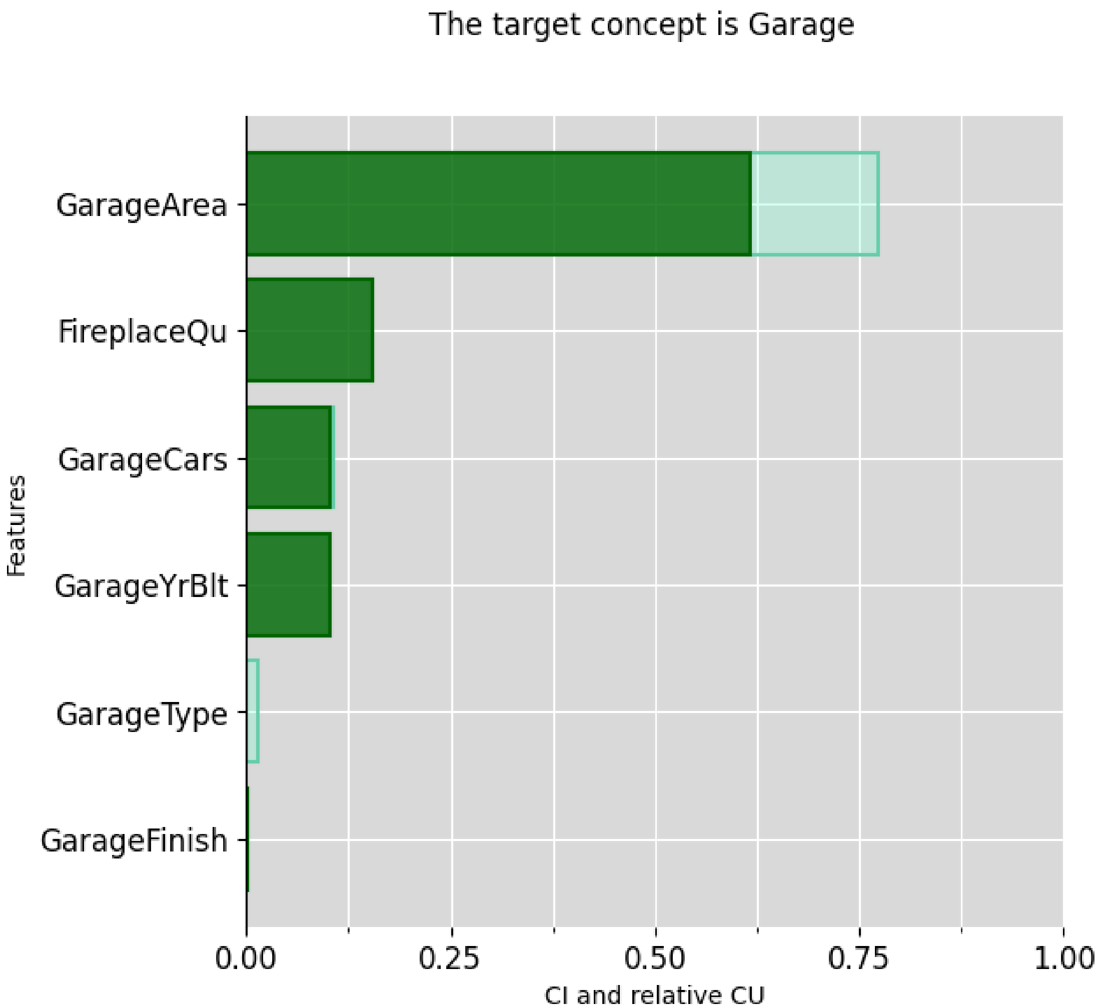
```
[28]: ciu_ames.plot_ciu(target_concept="House_condition", plot_mode="overlap")
```



[29]:
```
ciu_ames.plot_ciu(target_concept="Basement", plot_mode="overlap")
```



[30]:
```
ciu_ames.plot_ciu(target_concept="Garage", plot_mode="overlap")
```



This vocabulary is just an example of what kind of concepts a human typically deals with. Vocabularies can be built freely (or learned, if possible) and used freely, even so that different vocabularies can be used with different users.