pysubgroup Documentation

Release 0.0.2

Florian Lemmerich

Apr 24, 2020

CONTENTS:

pysubgroup is a Python package that enables subgroup discovery in Python+pandas (scipy stack) data analysis environment. It provides for a lightweight, easy-to-use, extensible and freely available implementation of state-of-the-art algorithms, interestingness measures and presentation options.

As of 2018, this library is still in a prototype phase. It has, however, been already successfully employed in active application projects.

CHAPTER

ONE

PYSUBGROUP

pysubgroup is a Python package that enables subgroup discovery in Python+pandas (scipy stack) data analysis environment. It provides for a lightweight, easy-to-use, extensible and freely available implementation of state-of-the-art algorithms, interestingness measures and presentation options.

As of 2018, this library is still in a prototype phase. It has, however, been already succeesfully employed in active application projects.

1.1 Subgroup Discovery

Subgroup Discovery is a well established data mining technique that allows you to identify patterns in your data. More precisely, the goal of subgroup discovery is to identify descriptions of data subsets that show an interesting distribution with respect to a pre-specified target concept. For example, given a dataset of patients in a hospital, we could be interested in subgroups of patients, for which a certain treatment X was successful. One example result could then be stated as:

"While in general the operation is successful in only 60% of the cases", for the subgroup of female patients under 50 that also have been treated with drug d, the successrate was 82%."

Here, a variable *operation success* is the target concept, the identified subgroup has the interpretable description *female=True AND age<50 AND drug_D = True*. We call these single conditions (such as *female=True*) selection expressions or short *selectors*. The interesting behavior for this subgroup is that the distribution of the target concept differs significantly from the distribution in the overall general dataset. A discovered subgroup could also be seen as a rule:

```
female=True AND age<50 AND drug_D = True ==> Operation_outcome=SUCCESS
```

Computationally, subgroup discovery is challenging since a large number of such conjunctive subgroup descriptions have to be considered. Of course, finding computable criteria, which subgroups are likely interesting to a user is also an eternal struggle. Therefore, a lot of literature has been devoted to the topic of subgroup discovery (including some of my own work). Recent overviews on the topic are for example:

- Herrera, Franciso, et al. "An overview on subgroup discovery: foundations and applications." Knowledge and information systems 29.3 (2011): 495-525.
- Atzmueller, Martin. "Subgroup discovery." Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 5.1 (2015): 35-49.
- And of course, my point of view on the topic is summarized in my dissertation:

1.2 Prerequisites and Installation

pysubgroup is built to fit in the standard Python data analysis environment from the scipy-stack. Thus, it can be used just having pandas (including its dependencies numpy, scipy, and matplotlib) installed. Visualizations are carried out with the matplotlib library.

pysubgroup consists of pure Python code. Thus, you can simply download the code from the repository and copy it in your `site-packages` directory. pysubgroup is also on PyPI and should be installable using:

```
pip install pysubgroup
```

1.3 How to use:

A simple use case (here using the well known *titanic* data) can be created in just a few lines of code:

[1]:
```
import pysubgroup as ps

# Load the example dataset
from pysubgroup.tests.DataSets import get_titanic_data
data = get_titanic_data()

target = ps.BinaryTarget ('Survived', True)
searchspace = ps.create_selectors(data, ignore=['Survived'])
task = ps.SubgroupDiscoveryTask (
    data,
    target,
    searchspace,
    result_set_size=5,
    depth=2,
    qf=ps.WRAccQF())
result = ps.BeamSearch().execute(task)
```

The first two lines imports *pysubgroup* package. The following lines load an example dataset (the popular titanic dataset).

Therafter, we define a target, i.e., the property we are mainly interested in (_'survived'}. Then, we define the searchspace as a list of basic selectors. Descriptions are built from this searchspace. We can create this list manually, or use an utility function. Next, we create a SubgroupDiscoveryTask object that encapsulates what we want to find in our search. In particular, that comprises the target, the search space, the depth of the search (maximum numbers of selectors combined in a subgroup description), and the interestingness measure for candidate scoring (here, the Weighted Relative Accuracy measure).

The last line executes the defined task by performing a search with an algorithm—in this case beam search. The result of this algorithm execution is stored in a SubgroupDiscoveryResults object.

To just print the result, we could for example do:

[5]:
```
result.to_dataframe()
```

[5]:

	quality	description
0	0.132150	Sex=='female'
1	0.101331	Parch==0 AND Sex=='female'
2	0.079142	Sex=='female' AND SibSp: [0:1[
3	0.077663	Cabin.isnull() AND Sex=='female'
4	0.071746	Embarked=='S' AND Sex=='female'

CHAPTER

TWO

HOW PYSUBGROUP WORKS

just ignore the following code block for non technical people, but have a look at the example dataFrame (table) that we created

[1]:
```
import pysubgroup as ps
import pandas as pd
pd.set_option('display.width', 1000)
pd.set_option('display.max_colwidth', 300)
products = ['toast', 'bread', 'bread', 'toast', 'bread', 'bread','toast', 'bread',
↪'bread', 'pizza']
amount =  [100,1000,100,1000,10000,540,750,860,350,400]
was_fraud =  [1,0,0,0,1,1,1,0,0,0]
day_of_month = [15,20,30,17,12,7,11,14,20,27]
is_gold = [1,0,1,0,0,0,1,1,1,0]
df = pd.DataFrame.from_dict({'product': products, 'was_fraud': was_fraud, 'amount':␣
↪amount, 'day_of_month' : day_of_month, 'is_gold':is_gold})
df
```

[1]:
```
  product  was_fraud  amount  day_of_month  is_gold
0   toast          1     100            15        1
1   bread          0    1000            20        0
2   bread          0     100            30        1
3   toast          0    1000            17        0
4   bread          1   10000            12        0
5   bread          1     540             7        0
6   toast          1     750            11        1
7   bread          0     860            14        1
8   bread          0     350            20        1
9   pizza          0     400            27        0
```

[2]:
```
target = ps.BinaryTarget('was_fraud', 1) # we are looking for fraud=1
search_space = ps.create_selectors(df, ignore='was_fraud') # define what we are␣
↪looking for
search_space
```

[2]:
```
[product=='toast',
 product=='bread',
 product=='pizza',
 amount<350,
 amount: [350:540[,
 amount: [540:860[,
 amount: [860:1000[,
 amount>=1000,
 day_of_month<12,
 day_of_month: [12:15[,
```

(continues on next page)

(continued from previous page)

```
day_of_month: [15:20[,
day_of_month: [20:27[,
day_of_month>=27,
is_gold==0,
is_gold==1]
```

As you can see, pysubgroup created selectors for us, treating nominal columns (product, is_gold) different from numeric columns (where it uses intervals selectors) you can also create your own selectors see below

[3]:
```
my_selector = ps.IntervalSelector('amount', 500, 25000)
print(my_selector)
search_space.append(my_selector) # add my selector to searchspace
```

```
amount: [500:25000[
```

Now that we have defined where we want to search we write all that information into a task object:

[4]:
```
quality_function = ps.StandardQF(0) # Looks for subgroups with highest true positives␣
↪ratio
min_quality = 0.2 # Minimum required quality = min true positive ratio
task = ps.SubgroupDiscoveryTask(df, target, search_space, quality_function, result_
↪set_size=10, depth=3, min_quality=min_quality)
```

now that we have that task object we can run the algorithm (Here Depth first search)

[5]:
```
result = ps.SimpleDFS().execute(task) # Run the algorithm
result.to_dataframe(include_info=True) # Show the output
```

[5]:
```
   quality                                           description  size_sg ␣
↪size_dataset  positives_sg  positives_dataset  size_complement  relative_size_sg ␣
↪relative_size_complement  coverage_sg  coverage_complement  target_share_sg  target_
↪share_complement  target_share_dataset  lift
0      0.6  amount: [500:25000[ AND amount: [540:860[ AND product=='toast'        1  ␣
↪       10            1                   4                 9               0.1  ␣
↪                  0.9          0.25                 0.75             1.0          ␣
↪     0.333333                 0.4   2.5
1      0.6    amount: [500:25000[ AND day_of_month<12 AND product=='toast'        1  ␣
↪       10            1                   4                 9               0.1  ␣
↪                  0.9          0.25                 0.75             1.0          ␣
↪     0.333333                 0.4   2.5
2      0.6      amount: [540:860[ AND day_of_month<12 AND product=='toast'        1  ␣
↪       10            1                   4                 9               0.1  ␣
↪                  0.9          0.25                 0.75             1.0          ␣
↪     0.333333                 0.4   2.5
3      0.6                              amount<350 AND product=='toast'        1  ␣
↪       10            1                   4                 9               0.1  ␣
↪                  0.9          0.25                 0.75             1.0          ␣
↪     0.333333                 0.4   2.5
4      0.6                       amount: [540:860[ AND product=='toast'        1  ␣
↪       10            1                   4                 9               0.1  ␣
↪                  0.9          0.25                 0.75             1.0          ␣
↪     0.333333                 0.4   2.5
5      0.6         amount<350 AND day_of_month: [15:20[ AND product=='toast'        1  ␣
↪       10            1                   4                 9               0.1  ␣
↪                  0.9          0.25                 0.75             1.0          ␣
↪     0.333333                 0.4   2.5
6      0.6           amount: [540:860[ AND is_gold==1 AND product=='toast'        1  ␣
↪       10            1                   4                 9               0.1  ␣
↪                  0.9          0.25                 0.75             1.0          ␣
↪     0.333333                 0.4   2.5
```

(continues on next page)

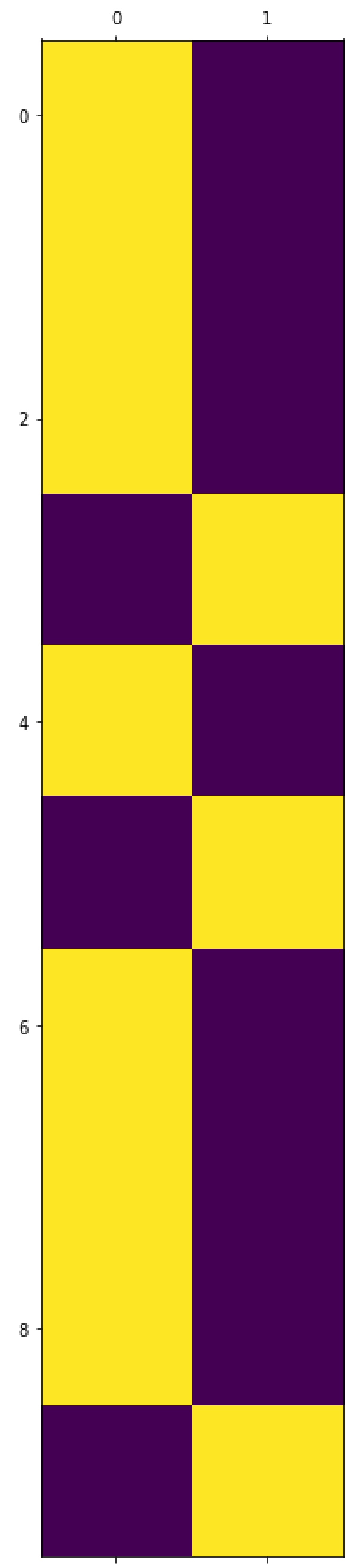
(continued from previous page)

```
7      0.6          day_of_month<12 AND is_gold==1 AND product=='toast'        1 ␣
↪       10           1                   4                 9                0.1 ␣
↪                  0.9         0.25                 0.75              1.0       ␣
↪      0.333333                  0.4    2.5
8      0.6                         day_of_month<12 AND product=='toast'        1 ␣
↪       10           1                   4                 9                0.1 ␣
↪                  0.9         0.25                 0.75              1.0       ␣
↪      0.333333                  0.4    2.5
9      0.6               amount<350 AND is_gold==1 AND product=='toast'        1 ␣
↪       10           1                   4                 9                0.1 ␣
↪                  0.9         0.25                 0.75              1.0       ␣
↪      0.333333                  0.4    2.5
```

[6]:
```
# Visualize resultset, see there is quite some redundancy
import matplotlib.pyplot as plt
plt.matshow(result.supportSetVisualization())
```

```
Discarding 8 entities that are not covered
```

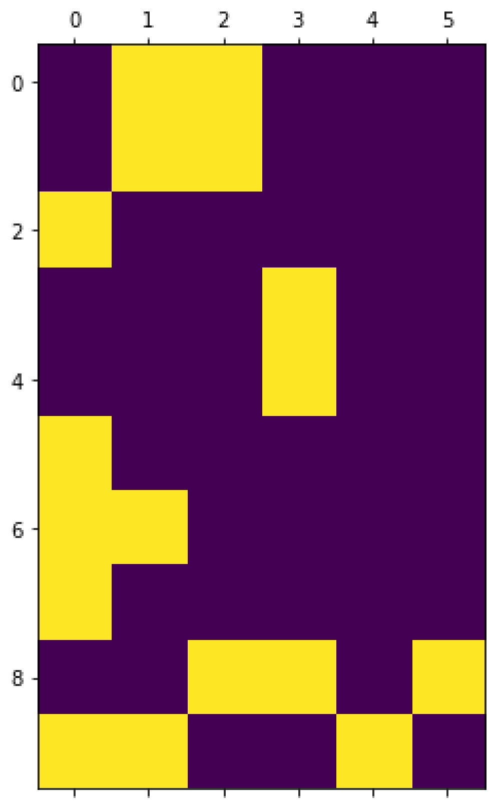
[6]:
```
<matplotlib.image.AxesImage at 0x2c8420d7b48>
```


0
1
0
2
4
6
8

[7]:
```
# we can already avoid redundancy a little but its quite slow!
quality_function = ps.GeneralizationAwareQF(ps.StandardQF(0)) # Looks for subgroups␣
↪with highest true positives ratio, trying to avoid redundancy
task = ps.SubgroupDiscoveryTask(df, target, search_space, quality_function, result_
↪set_size=10, depth=3, min_quality=min_quality)
result = ps.SimpleDFS().execute(task)
plt.matshow(result.supportSetVisualization())
```

```
Discarding 4 entities that are not covered
```

[7]:
```
<matplotlib.image.AxesImage at 0x2c84212da48>
```



[8]:
```
result.to_dataframe(include_info=True) # Show the output, avoiding redundancy
```

[8]:
```
    quality                                   description  size_sg  size_dataset  positives_
↪sg  positives_dataset  size_complement  relative_size_sg  relative_size_complement ␣
↪coverage_sg  coverage_complement  target_share_sg  target_share_complement  target_
↪share_dataset      lift
0  0.600000                          amount: [540:860[        2            10            ␣
↪ 2                  4                 8                0.2                      0.8 ␣
↪       0.50                 0.50         1.000000                 0.250000          ␣
↪          0.4  2.500000
1  0.600000                              day_of_month<12        2            10            ␣
↪ 2                  4                 8                0.2                      0.8 ␣
↪       0.50                 0.50         1.000000                 0.250000          ␣
↪          0.4  2.500000
2  0.500000    amount<350 AND day_of_month: [15:20[        1            10            ␣
↪ 1                  4                 9                0.1                      0.9 ␣
↪       0.25                 0.75         1.000000                 0.333333          ␣
↪          0.4  2.500000
```

(continues on next page)

(continued from previous page)

```
3  0.500000  amount>=1000 AND day_of_month: [12:15[       1           10       ␣
↪ 1                 4                 9               0.1                      0.9 ␣
↪       0.25                 0.75         1.000000                0.333333     ␣
↪         0.4  2.500000
4  0.500000    day_of_month: [12:15[ AND is_gold==0       1           10       ␣
↪ 1                 4                 9               0.1                      0.9 ␣
↪       0.25                 0.75         1.000000                0.333333     ␣
↪         0.4  2.500000
5  0.500000    day_of_month: [15:20[ AND is_gold==1       1           10       ␣
↪ 1                 4                 9               0.1                      0.9 ␣
↪       0.25                 0.75         1.000000                0.333333     ␣
↪         0.4  2.500000
6  0.333333         is_gold==1 AND product=='toast'       2           10       ␣
↪ 2                 4                 8               0.2                      0.8 ␣
↪       0.50                 0.50         1.000000                0.250000     ␣
↪         0.4  2.500000
7  0.333333         amount<350 AND product=='toast'       1           10       ␣
↪ 1                 4                 9               0.1                      0.9 ␣
↪       0.25                 0.75         1.000000                0.333333     ␣
↪         0.4  2.500000
8  0.266667         is_gold==0 AND product=='bread'       3           10       ␣
↪ 2                 4                 7               0.3                      0.7 ␣
↪       0.50                 0.50         0.666667                0.285714     ␣
↪         0.4  1.666667
9  0.266667                        product=='toast'       3           10       ␣
↪ 2                 4                 7               0.3                      0.7 ␣
↪       0.50                 0.50         0.666667                0.285714     ␣
↪         0.4  1.666667
```

[ ]:

```

```

CHAPTER

THREE

SELECTORS

Selectors are objects that if applied to a dataset yield a set of instances. If an instance is retured from a selector we say that the selectors covers that instance. While the term selectors usually only refers to basic selectors, conjunctions and disjunctions as well as negated selectors are also in a general sense selectors. Broadly speaking anything that implements the code:*covers* function is a selector. We will first introduce the frequently used basic selectors and thereafter the more general selectors that are the conjunction and disjunction. We conclude the chapter by showing how to implement a selectors yourself.

3.1 Basic Selectors

The pysubgroup package provides two basic selectors: The EqualitySelector and the IntervalSelector. Lets start by exploring the EqualitySelector:

```
import pysubgroup as ps
import pandas as pd

# create dataset
first_names = ['Alex', 'Anna', 'Alex']
sur_names = ['Smith', 'Johnson', 'Williams']
ages =  [40, 25, 32]
df = pd.DataFrame.from_dict({'First_name':first_names, 'Sur_name': sur_names, 'age':
↪ages})

# create selector
alex_selector = ps.EqualitySelector('First_name', 'Alex')
age_selector = ps.EqualitySelector('age', 22)
# apply selectors to dataframe
print('instances with ', str(alex_selector), alex_selector.covers(df))
print('instances with', str(age_selector), age_selector.covers(df))
```

```
instances with  First_name=='Alex' [ True False  True]
instances with age==22 [False False False]
```

The output indicates that the first and third instance in the dataset have a first name that is equal to `'Alex'`. The second output shows that no instances in our dataset is of age 22. The EqualitySelector selector can be used on many different datatypes, but is most useful on binary, string and categorical data. In addition to the EqualitySelector the pysubgroup package also provides the IntervalSelector. The following codes selects all instances from the database, which are in the age range 18 (included) to 40 (excluded).

```
interval_selector = ps.IntervalSelector('age', 18, 40)
print(interval_selector.covers(df))
```

```
[False  True  True]
```

The outpu shows that the second and third instance in our dataset have an age within the interval $[18, 40)$.

Selectors are the building block of all rules generated with the pysubgroup package. If you want to write your own custom selector that is not a problem see customselector for references.

3.2 Negations

The pysubgroup package also provides the NegatedSelector class that takes any selector (not just basic ones) and inverts it.

```
inverted_selector = ps.NegatedSelector(alex_selector)
print('instances with first name not equal to Alex', inverted_selector.covers(df))
```

```
instances with first name not equal to Alex [False  True False]
```

The output is: `instances with first name not equal to Alex [False, True, False]`.

3.3 Conjunctions

Most of the rules that are generated with the pysubgroup package use conjunctions to form more complex queries. Continuing the running example from above we can find all persons whose name is Alex *and* which have an age in the interval $[18, 40)$ like so:

```
conj = ps.Conjunction([interval_selector, alex_selector])
print('instances with', str(conj), conj.covers(df))
```

```
instances with First_name=='Alex' AND age: [18:40[ [False False  True]
```

The output shows that only the last instance is covered by our conjunction.

3.4 Disjunctions

The pysubgroup package also provides disjunctions with the `Disjunction` class. Continuing the running example we can find all persons whose name is Alex *or* which have an age in the interval $[18, 40)$ like so:

```
disj = ps.Disjunction([interval_selector, alex_selector])
print('instances with', str(disj), disj.covers(df))
```

```
instances with First_name=='Alex' OR age: [18:40[ [ True  True  True]
```

We can see that all instances are covered by our conjunction.

3.5 Implementing your own

As already mentioned in the introduction on selectors, anything that provides a cover function is a selector. In this case we will show how to implement a custom basic selector that checks whether a string contains a given substring:

```
class StrContainsSelector:
    def __init__(self, column, substr):
        self.column = column
        self.substr = substr

    def covers(self, df):
        return df[self.column].str.contains(self.substr).to_numpy()

contains_selector = StrContainsSelector('Sur_name','m')
print(contains_selector.covers(df))
```

```
[ True False  True]
```

The output shows that only the first and last instance contain an m in their name. In addition to the covers function it is certainly advised to also implement the `__str__` and `__repr__` functions. This selector can now be added to the searchspace for any algorithm execution.

CHAPTER

FOUR

TARGETS AND QUALITY FUNCTIONS

To define the goal of our subgroup discovery task, we use targets and quality functions. Targets are used to define which attributes play a significant role and can provide common statistics for a subgroup in question. Quality functions assign a score to each subgroup. These scores are used by all the algorithms to determine the most interesting subgroups.

4.1 Frequent Itemset Targets

The most simple target is the *FITarget* with its associated quality functions *CountQF* and *AreaQf*. The CountQF simple counts the number of instances covered by the subgroup in question. The AreaQF multiplies the depth or length of the subgroup description with the number of instances covered by that description.

4.2 Binary Targets

For Boolean or Binary Targets we provide the *ChiSquaredQF* as well as the *StandardQF* quality functions. The *StandardQF* quality function uses a parameter α to weight the relative size $\frac{N_{SG}}{N}$ of a subgroup and multiplies it with the differences in relations of positive instances p to the number of instances N

$$\left(\frac{N_{SG}}{N}\right)^{\alpha}\left(\frac{p_{SG}}{N_{SG}}-\frac{p}{N}\right)$$

The *StandardQF* also supports an optimistic estimate.

The *ChiSquaredQF* is calculated based on the following contigency table which is then passed to the scipy chi2_contigency function. The small n represents the number of negative instances and should not be confused with the capital N which represents the total number of instances.

p_{SG}	$p - p_{SG}$
n_{SG}	$n - n_{SG}$

4.3 Nominal Targets

Currently pysubgroup only supports nominal targets as binary targets. So you can look for deviations of one nominal value with respect to all othe nominal values.

4.4 Numeric Targets

For numeric targets pysubgroup offers the *StandardQFNumeric* which is defined similar to the StandardQF

$$\left(\frac{N_{SG}}{N}\right)^{\alpha}(\mu_{SG} - \mu)$$

where μ_{SG} and μ are the mean value for the subgroup and entire dataset respectively. For the *StandardQFNumeric* we offer three optimistic estimates: Average, Summation and Ordering. These are in detail described in Florian Lemmerich's dissertation. You can choose between the different optimistic estimates by using the keyword argument `estimator` the different options are `'sum'`, `'average'`, and `'order'`

4.5 Custom Quality Function

To create a custom quality function that works will all algorithms except gp_growth.

```
class MyQualityFunction:
    def calculate_constant_statistics(self, task):
        """ calculate_constant_statistics
            This function is called once for every execution,
            it should do any preparation that is necessary prior to an execution.
        """
        pass

    def calculate_statistics(self, subgroup, data=None):
        """ calculates necessary statistics
            this statistics object is passed on to the evaluate
            and optimistic_estimate functions
        """
        pass

    def evaluate(self, subgroup, statistics_or_data=None):
        """ return the quality calculated from the statistics """
        pass

    def optimistic_estimate(self, subgroup, statistics=None):
        """ returns optimistic estimate
            if one is available return it otherwise infinity"""
        pass
```

CHAPTER

FIVE

GP-GROWTH

This tree based algorithm uses a condensed representation (a so called valuation basis) to find interesting subgroups. The main advantage of this approach is, that the (potentially large) database has to be scanned only twice and thereafter all the necessary information is represented as more compact pattern-tree. Gp-growth is a generalisation of the popular fp-growth algorithm. So refer to instructional material on fp-growth for more in depth knowledge on the workings of this tree based algorithm.

Contents

5.1 Basic usage

The basic usage of the gp-growth algorithm is not very different from the usage of any other algorithm in this package.

```
import pysubgroup as ps

# Load the example dataset
from pysubgroup.tests.DataSets import get_titanic_data
data = get_titanic_data()

target = ps.NominalSelector ('Survived', True)
searchspace = ps.create_selectors(data, ignore=['Survived'])
task = ps.SubgroupDiscoveryTask (data, target, dearchspace, result_set_size=5,␣
↪depth=2, qf=ps.WRAccQF())
GpGrowth.execute(task)
```

But beware that gp-growth is using an exhaustive search strategy! This can greatly increase the runtime for high search depth. You can specify the `mode` argument in the constructor of GpGrowth to run gp-growth either bottom up (`mode='b_u'`) or top down (`mode='b_u'`). As gp growth is a generalisation of fp-growth you can also perform standard fp-growth using gp_growth by using the CountQF (*Frequent Itemset Targets*) quality function.

5.2 Create a custom target

If you consider to use the gp-growth algorithm for your custom target that is totally possible if you find a valuation basis. We will now first introduce the concept of a valuation basis and thereafter outline the gp-growth interface that you have to support to use your quality function with our gp-growth implementation.

5.2.1 Valuation Basis

Think of a valuation basis as a codensed representation of a subgroup that allows to quickly compute the same representation for a union of two disjoint subgroups.

We call the function which takes the valuation basis of two disjoint sets and computes the valuation basis for the unified set `merge`. The function that compute the necessary statistics from a valuation basis `stats_from_basis`.

Now we can formulate: Given two disjoint sets A and B with $A \cap B = \emptyset$ and their valuation bases $v(A)$ and $v(B)$ with their functions `stats_from_basis` and `merge` as defined above, we can compute the properties of $A \cup B$ instead of from the union of the instances from the merged valuation basis. This can be summarized through the following equation:

$$props\_from\_instances(A \cup B) = props\_from\_basis(merge(v(A), v(B)))$$

5.2.2 Required Methods

To make a target and quality function suitable for gp-growth you have to provide several methods (all methods start with `gp_` to indicate that they are used in the gp-growth algorithm). In addition to the standard quality function methods (see *Custom Quality Function*) the following methods should be implemented to make a quality funciton usable with gp_growth.

```
class MyGpQualityFunction
    def gp_get_basis(self, row_index):
    """ returns the valuation basis of the element at this row_index """
        pass

    def gp_get_null_vector(self):
    """ returns the zero element of the valuation basis """
        pass

    @staticmethod
    def gp_merge(v_l, v_r):
    """ merges the v_r valuation basis into the v_l valuation basis inplace! """
        pass

    def gp_get_statistics(self, cover_arr, v):
    """ computes the statistics for this quality function from the valuation basis v "
↪""
        pass

    @property
    def gp_requires_cover_arr(self) -> bool:
    """ returns a boolean value that indicates whether a cover array is required when␣
↪calling the gp_get_statistics function

        usually this value is False
    """
        pass
```

5.2.3 Saving a gp_tree

It is possible to save a gp tree to a txt file for e.g. debugging purpose. You therefor have to implementd the gp_to_str function which takes a valuation basis and returns a string representation. It is an intentional choide to not call the `str` function on the valuation basis directly.

```
def gp_to_str(self, basis) -> str:
""" returns a string representation of the valuation basis """
    pass
```

CHAPTER

SIX

PYSUBGROUP

6.1 pysubgroup package

6.1.1 Submodules

6.1.2 pysubgroup.algorithms module

Created on 29.04.2016

@author: lemmerfn

class Apriori(*representation_type=None*, *combination_name='Conjunction'*, *use_numba=True*)

> **execute**(*task*)
>
> **get_next_level**(*promising_candidates*)
>
> **get_next_level_candidates**(*task*, *result*, *next_level_candidates*)
>
> **get_next_level_candidates_vectorized**(*task*, *result*, *next_level_candidates*)
>
> **get_next_level_numba**(*promising_candidates*)
>
> **reprune_lower_levels**(*promising_candidates*, *depth*)

class BeamSearch(*beam_width=20*, *beam_width_adaptive=False*)

> Implements the BeamSearch algorithm. Its a basic implementation
>
> **execute**(*task*)

class BestFirstSearch

> **execute**(*task*)

class DFS(*apply_representation*)

> Implementation of a depth-first-search with look-ahead using a provided datastructure.
>
> **execute**(*task*)
>
> **search_internal**(*task*, *result*, *sg*)

class DFSNumeric

> **execute**(*task*)
>
> **search_internal**(*task*, *prefix*, *modification_set*, *result*, *bitset*)

tpl
alias of `size_mean_parameters`

class GeneralisingBFS

execute (*task*)

class SimpleDFS

execute (*task*, *use_optimistic_estimates=True*)

search_internal (*task*, *prefix*, *modification_set*, *result*, *use_optimistic_estimates*)

class SimpleSearch (*show_progress=True*)

execute (*task*)

class SubgroupDiscoveryTask (*data*, *target*, *search_space*, *qf*, *result_set_size=10*, *depth=3*, *min_quality=0*, *weighting_attribute=None*)
Capsulates all parameters required to perform standard subgroup discovery

6.1.3 pysubgroup.boolean_expressions module

class BooleanExpressionBase

abstract append_and (*to_append*)

abstract append_or (*to_append*)

class Conjunction (*selectors*)

append_and (*to_append*)

append_or (*to_append*)

covers (*instance*)

property depth

pop_and ()

pop_or ()

class DNF (*selectors=None*)

append_and (*to_append*)

append_or (*to_append*)

pop_and ()

class Disjunction (*selectors*)

append_and (*to_append*)

append_or (*to_append*)

covers (*instance*)

6.1.4 pysubgroup.fi_target module

Created on 29.09.2017

@author: lemmerfn

class AreaQF

evaluate(*subgroup*, *statistics=None*)

is_applicable(*subgroup*)

supports_weights()

class CountQF

evaluate(*subgroup*, *statistics=None*)

is_applicable(*subgroup*)

optimistic_estimate(*subgroup*, *statistics=None*)

supports_weights()

class FITarget

calculate_statistics(*subgroup*, *data*, *weighting_attribute=None*)

get_attributes()

get_base_statistics(*data*, *subgroup*, *weighting_attribute=None*)

class SimpleCountQF

calculate_constant_statistics(*task*)

calculate_statistics(*subgroup*, *data=None*)

gp_get_null_vector()

gp_get_params(*_cover_arr*, *v*)

gp_get_stats(*_*)

gp_merge(*l*, *r*)

property gp_requires_cover_arr

gp_to_str(*stats*)

tpl

alias of `CountQF_parameters`

6.1.5 pysubgroup.gp_growth module

class GpGrowth(*mode='b_u'*)

> **calculate_quality_function_for_patterns**(*patterns, selectors_sorted, arrs*)
>
> **check_constraints**(*node*)
>
> **create_copy_of_path**(*nodes, new_nodes, stats*)
>
> **create_copy_of_tree_top_down**(*root, nodes=None, parent=None*)
>
> **create_new_tree_from_nodes**(*nodes*)
>
> **execute**(*task*)
>
> **get_nodes_upwards**(*node*)
>
> **get_prefixes_top_down**(*alpha, max_length*)
>
> **get_stats_for_class**(*cls_nodes*)
>
> **get_top_down_tree_for_class**(*cls_nodes, cls*)
>
> **insert_into_tree**(*root, nodes, new_stats, classes, max_depth*)
>
> Creates a tree of a maximum depth = depth
>
> **merge_trees_top_down**(*nodes, mutable_root, other_root*)
>
> **nodes_to_cls_nodes**(*nodes*)
>
> **normal_insert**(*root, nodes, new_stats, classes*)
>
> **prepare_selectors**(*search_space*)
>
> **recurse**(*cls_nodes, prefix, is_single_path=False*)
>
> **recurse_top_down**(*cls_nodes, root, depth_in=0*)
>
> **remove_infrequent_class**(*nodes, cls_nodes, stats_dict*)
>
> **remove_infrequent_nodes**(*new_nodes*)
>
> **to_file**(*task, path*)

6.1.6 pysubgroup.measures module

Created on 28.04.2016

@author: lemmerfn

class AbstractInterestingnessMeasure

> **ensure_statistics**(*subgroup, statistics_or_data*)
>
> **abstract is_applicable**(*subgroup*)
>
> **abstract supports_weights**()

class BoundedInterestingnessMeasure

class CombinedInterestingnessMeasure(*measures, weights=None*)

> **evaluate_from_dataset**(*data, subgroup, weighting_attribute=None*)

evaluate_from_statistics(*instances_dataset*, *positives_dataset*, *instances_subgroup*, *positives_subgroup*)

is_applicable(*subgroup*)

optimistic_estimate_from_dataset(*data*, *subgroup*, *weighting_attribute=None*)

optimistic_estimate_from_statistics(*instances_dataset*, *positives_dataset*, *instances_subgroup*, *positives_subgroup*)

supports_weights()

class CountCallsInterestingMeasure(*qf*)

calculate_statistics(*sg*, *data=None*)

is_applicable(*subgroup*)

supports_weights()

class GeneralizationAwareQF(*qf*)

calculate_constant_statistics(*task*)

calculate_statistics(*subgroup*, *data=None*)

evaluate(*subgroup*, *statistics_or_data=None*)

class ga_tuple(*subgroup_quality*, *generalisation_quality*)

Create new instance of ga_tuple(subgroup_quality, generalisation_quality)

property generalisation_quality

Alias for field number 1

property subgroup_quality

Alias for field number 0

get_qual_and_previous_qual(*subgroup*, *data*)

is_applicable(*subgroup*)

supports_weights()

class GeneralizationAwareQF_stats(*qf*)

calculate_constant_statistics(*task*)

calculate_statistics(*subgroup*, *data=None*)

evaluate(*subgroup*, *statistics_or_data=None*)

ga_tuple

alias of `ga_stats_tuple`

get_max(**args*)

get_stats_and_previous_stats(*subgroup*, *data*)

is_applicable(*subgroup*)

supports_weights()

maximum_statistic_filter(*result_set*, *statistic*, *maximum*)

minimum_quality_filter(*result_set*, *minimum*)

minimum_statistic_filter (*result_set*, *statistic*, *minimum*, *data*)

overlap_filter (*result_set*, *data*, *similarity_level=0.9*)

overlaps_list (*sg*, *list_of_sgs*, *data*, *similarity_level=0.9*)

unique_attributes (*result_set*, *data*)

6.1.7 pysubgroup.model_target module

class EMM_Likelihood (*model*)

  calculate_constant_statistics (*task*)

  calculate_statistics (*subgroup*, *data=None*)

  evaluate (*subgroup*, *statistics=None*)

  get_tuple (*sg_size*, *params*, *cover_arr*)

  gp_get_params (*cover_arr*, *v*)

  is_applicable (_)

  supports_weights ()

  tpl
    alias of `EMM_Likelihood`

class PolyRegression_ModelClass (*x_name='x'*, *y_name='y'*, *degree=1*)

  calculate_constant_statistics (*task*)

  fit (*subgroup*, *data=None*)

  gp_get_null_vector ()

  gp_get_params (*v*)

  gp_get_stats (*row_index*)

  static gp_merge (*u*, *v*)

  likelihood (*stats*, *sg*)

  loglikelihood (*stats*, *sg*)

class beta_tuple (*beta*, *size*)
  Create new instance of beta_tuple(beta, size)

  property beta
    Alias for field number 0

  property size
    Alias for field number 1

6.1.8 pysubgroup.nominal_target module

6.1.9 pysubgroup.numeric_target module

Created on 29.09.2017

@author: lemmerfn

class GAStandardQFNumeric(*a*, *invert=False*)

> **evaluate_from_dataset**(*data*, *subgroup*, *weighting_attribute=None*)
>
> **is_applicable**(*subgroup*)
>
> **supports_weights**()

class NumericTarget(*target_variable*)

> **calculate_statistics**(*subgroup*, *data*)
>
> **get_attributes**()
>
> **get_base_statistics**(*data*, *subgroup*, *weighting_attribute=None*)

class StandardQFNumeric(*a*, *invert=False*, *estimator='sum'*)

> **class Average_Estimator**(*qf*)
>
> > **calculate_constant_statistics**(*task*)
> >
> > **get_data**(*task*)
> >
> > **get_estimate**(*subgroup*, *sg_size*, *sg_mean*, *cover_arr*, *_*)
>
> **class Ordering_Estimator**(*qf*)
>
> > **calculate_constant_statistics**(*task*)
> >
> > **get_data**(*task*)
> >
> > **get_estimate**(*subgroup*, *sg_size*, *sg_mean*, *cover_arr*, *target_values_sg*)
> >
> > **get_estimate_numpy**(*values_sg*, *a*, *mean_dataset*)
>
> **class Summation_Estimator**(*qf*)
>
> > **calculate_constant_statistics**(*task*)
> >
> > **get_data**(*task*)
> >
> > **get_estimate**(*subgroup*, *sg_size*, *sg_mean*, *cover_arr*, *_*)
>
> **calculate_constant_statistics**(*task*)
>
> **calculate_statistics**(*subgroup*, *data=None*)
>
> **evaluate**(*subgroup*, *statistics=None*)
>
> **is_applicable**(*subgroup*)
>
> **optimistic_estimate**(*subgroup*, *statistics=None*)

static standard_qf_numeric(*a*, *_*, *mean_dataset*, *instances_subgroup*, *mean_sg*)

supports_weights()

tpl
alias of `StandardQFNumeric_parameters`

get_max_generalization_mean(*data*, *subgroup*, *weighting_attribute=None*)

6.1.10 pysubgroup.refinement_operator module

class RefinementOperator

class StaticGeneralizationOperator(*selectors*)

refinements(*sG*)

class StaticSpecializationOperator(*selectors*)

refinements(*subgroup*)

6.1.11 pysubgroup.representations module

class BitSetRepresentation(*df*, *selectors_to_patch*)

Conjunction
alias of *BitSet_Conjunction*

Disjunction
alias of *BitSet_Disjunction*

patch_classes()

patch_selector(*sel*)

class BitSet_Conjunction(**args*, ***kwargs*)

append_and(*to_append*)

compute_representation()

n_instances = 0

property size

class BitSet_Disjunction(**args*, ***kwargs*)

append_or(*to_append*)

compute_representation()

property size

class NumpySetRepresentation(*df*, *selectors_to_patch*)

Conjunction
alias of *NumpySet_Conjunction*

patch_classes()

patch_selector(*sel*)

class **NumpySet_Conjunction**(**args*, ***kwargs*)

all_set = None

append_and(*to_append*)

compute_representation()

property **size**

class **RepresentationBase**(*new_conjunction*, *selectors_to_patch*)

patch_all_selectors()

patch_classes()

patch_selector(*sel*)

undo_patch_classes()

class **SetRepresentation**(*df*, *selectors_to_patch*)

Conjunction
alias of `Set_Conjunction`

patch_classes()

patch_selector(*sel*)

class **Set_Conjunction**(**args*, ***kwargs*)

all_set = {}

append_and(*to_append*)

compute_representation()

property **size**

6.1.12 pysubgroup.subgroup module

Created on 28.04.2016

@author: lemmerfn

class **EqualitySelector**(*attribute_name*, *attribute_value*, *selector_name=None*)

property **attribute_name**

property **attribute_value**

classmethod **compute_descriptions**(*attribute_name*, *attribute_value*, *selector_name*)

covers(*data*)

set_descriptions(*attribute_name*, *attribute_value*, *selector_name=None*)

class IntervalSelector(*attribute_name*, *lower_bound*, *upper_bound*, *selector_name=None*)

property attribute_name

classmethod compute_descriptions(*attribute_name*, *lower_bound*, *upper_bound*, *selector_name=None*)

classmethod compute_string(*attribute_name*, *lower_bound*, *upper_bound*, *rounding_digits*)

covers(*data_instance*)

property lower_bound

set_descriptions(*attribute_name*, *lower_bound*, *upper_bound*, *selector_name=None*)

property upper_bound

class NegatedSelector(*selector*)

property attribute_name

covers(*data_instance*)

set_descriptions(*selector*)

class SelectorBase

abstract set_descriptions(**args*, ***kwargs*)

class Subgroup(*target*, *subgroup_description*)

calculate_statistics(*data*, *weighting_attribute=None*)

covers(*instance*)

get_base_statistics(*data*, *weighting_attribute=None*)

create_nominal_selectors(*data*, *ignore=None*)

create_nominal_selectors_for_attribute(*data*, *attribute_name*, *dtypes=None*)

create_numeric_selector_for_attribute(*data*, *attr_name*, *nbins=5*, *intervals_only=True*, *weighting_attribute=None*)

create_numeric_selectors(*data*, *nbins=5*, *intervals_only=True*, *weighting_attribute=None*, *ignore=None*)

create_selectors(*data*, *nbins=5*, *intervals_only=True*, *ignore=None*)

remove_target_attributes(*selectors*, *target*)

6.1.13 pysubgroup.utils module

Created on 02.05.2016

@author: lemmerfn

class SubgroupDiscoveryResult(*results*, *task*)

supportSetVisualization(*in_order=True*, *drop_empty=True*)

to_dataframe(*include_info=False*)

to_descriptions()

to_subgroups()

add_if_required(*result*, *sg*, *quality*, *task*, *check_for_duplicates=False*)

as_df(*data*, *result*, *statistics_to_show=('size_sg'*, *'size_dataset'*, *'positives_sg'*, *'positives_dataset'*, *'size_complement'*, *'relative_size_sg'*, *'relative_size_complement'*, *'coverage_sg'*, *'coverage_complement'*, *'target_share_sg'*, *'target_share_complement'*, *'target_share_dataset'*, *'lift')*, *autoround=False*, *weighting_attribute=None*, *include_target=False*)

conditional_invert(*val*, *invert*)

count_bits(*bitset_as_int*)

effective_sample_size(*weights*)

equal_frequency_discretization(*data*, *attribute_name*, *nbins=5*, *weighting_attribute=None*)

find_set_bits(*bitset_as_int*)

float_formatter(*x*, *digits=2*)

intersect_of_ordered_list(*list_1*, *list_2*)

is_categorical_attribute(*data*, *attribute_name*)

is_numerical_attribute(*data*, *attribute_name*)

minimum_required_quality(*result*, *task*)

overlap(*sg*, *another_sg*, *data*)

perc_formatter(*x*)

powerset(*[1,2,3]) --> () (1,) (2,) (3,) (1,2) (1,3) (2,3) (1,2,3*)

print_result_set(*data*, *result*, *statistics_to_show*, *weighting_attribute=None*, *print_header=True*, *include_target=False*)

remove_selectors_with_attributes(*selector_list*, *attribute_list*)

result_as_table(*data*, *result*, *statistics_to_show*, *weighting_attribute=None*, *print_header=True*, *include_target=False*)

results_as_df(*data*, *result*, *statistics_to_show=('size_sg'*, *'size_dataset'*, *'positives_sg'*, *'positives_dataset'*, *'size_complement'*, *'relative_size_sg'*, *'relative_size_complement'*, *'coverage_sg'*, *'coverage_complement'*, *'target_share_sg'*, *'target_share_complement'*, *'target_share_dataset'*, *'lift')*, *autoround=False*, *weighting_attribute=None*, *include_target=False*)

results_df_autoround(*df*)

to_bits(*list_of_ints*)

to_latex(*data*, *result*, *statistics_to_show*)

6.1.14 pysubgroup.visualization module

compare_distributions_numeric(*sgs, data, bins*)

plot_distribution_numeric(*sg, data, bins*)

plot_npspace(*result_df, data, annotate=True, fixed_limits=False*)

plot_roc(*result_df, data, qf=<pysubgroup.binary_target.StandardQF object>, levels=40, annotate=False*)

plot_sgbars(*result_df, _, ylabel='target share', title='Discovered Subgroups', dynamic_widths=False, _suffix=''*)

similarity_dendrogram(*result, data*)

similarity_sgs(*sgd_results, data, color=True*)

6.1.15 Module contents

CHAPTER SEVEN

INDICES AND TABLES

- genindex
- modindex
- search

PYTHON MODULE INDEX

p

INDEX

D

E

F

G

I

L

M

N

O

P

R

S

T

U