Python

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CONTENTS

Cegpy (/segpaɪ/) is a Python package for working with Chain Event Graphs (CEG). It supports learning the graphical structure of a Chain Event Graph from data, encoding of parametric and structural priors, estimating its parameters, and performing inference.

It is built on top of the Python network modelling package NetworkX.

Why use cegpy?

CEGs are a flexible family of graphical models that are suitable for exploratory analysis of processes with asymmetries.

This is the first python package for modelling with CEGs. It can handle processes exhibiting context-specific conditional independence relationships and/or structural asymmetries.

It is built with extensibility in mind and is open-source, so new models built on top of CEGs can be built on top of it, and be included into the package. Our aim is to enable researchers to work with CEGs without having to start from scratch. As such, contributions are welcome!

Installation

To use cegpy, first install it using pip:

```
$ pip install cegpy
```

The package is hosted on PyPi!

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Part I

Quick Start

CHAPTER

ONE

CREATION OF A STAGED TREE

1.1 EventTree Class

The first starting point in constructing a Chain Event Graph (CEG) is to create an event tree describing the process being studied. An event tree is a directed tree graph with a single root node. The nodes with no emanating edges are called *leaves*, and the non-leaf nodes are called *situations*.

In this example we work with a data set which contains 4 categorical variables; *Classification*, *Group*, *Difficulty*, and *Response*.

Each individual is given a binary classification; *Blast* or *Non-blast*. Each group is rated on their experience level: *Experienced*, *Inexperienced*, or *Novice*. The classification task they are given has a difficulty rating of *Easy* or *Hard*. Finally, their response is shown: *Blast* or *Non-blast*.

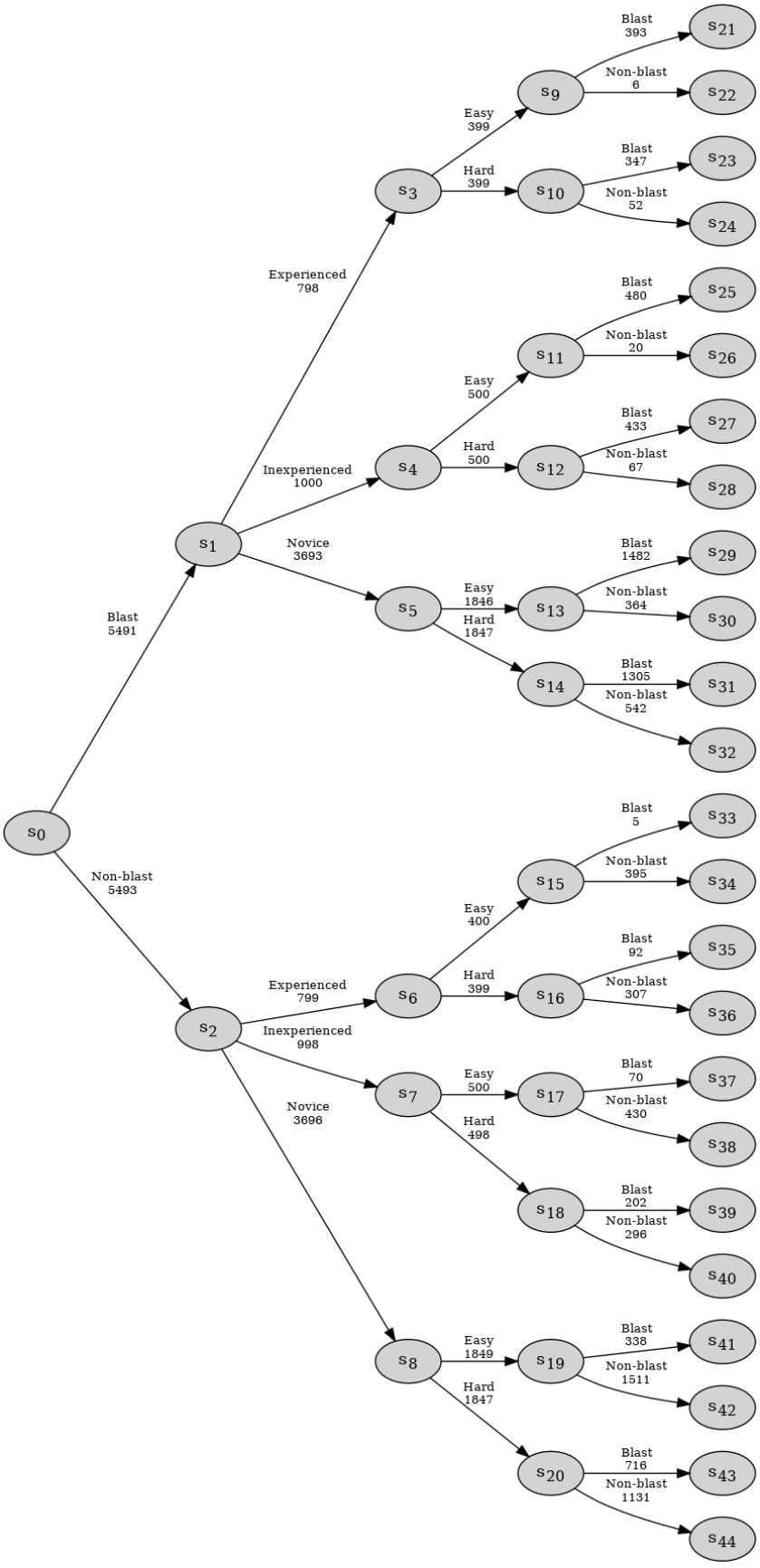
We begin by importing the data set and initializing the `EventTree` object, as shown below:

```
from cegpy import EventTree
import pandas as pd

df = pd.read_excel('../../data/medical_dm_modified.xlsx')
print(df.head())

#initialize the event tree
et = EventTree(df)
```

```
  Classification        Group Difficulty   Response
0          Blast  Experienced       Easy      Blast
1      Non-blast  Experienced       Easy  Non-blast
2      Non-blast  Experienced       Hard      Blast
3      Non-blast  Experienced       Hard  Non-blast
4          Blast  Experienced       Easy      Blast
```

In order to display the EventTree, we can use the method `create_figure()`. The numbers above the edges of the event tree represent the number of individuals who passed through the given edge.

```
et.create_figure()
```


s0
Blast
5491
Non-blast
5493
s1
Experienced
798
Inexperienced
1000
Novice
3693
s2
Experienced
799
Inexperienced
998
Novice
3696
s3
Easy
399
Hard
399
s4
Easy
500
Hard
500
s5
Easy
1846
Hard
1847
s6
Easy
400
Hard
399
s7
Easy
500
Hard
498
s8
Easy
1849
Hard
1847
s9
Blast
393
Non-blast
6
s10
Blast
347
Non-blast
52
s11
Blast
480
Non-blast
20
s12
Blast
433
Non-blast
67
s13
Blast
1482
Non-blast
364
s14
Blast
1305
Non-blast
542
s15
Blast
5
Non-blast
395
s16
Blast
92
Non-blast
307
s17
Blast
70
Non-blast
430
s18
Blast
202
Non-blast
296
s19
Blast
338
Non-blast
1511
s20
Blast
716
Non-blast
1131
s21
s22
s23
s24
s25
s26
s27
s28
s29
s30
s31
s32
s33
s34
s35
s36
s37
s38
s39
s40
s41
s42
s43
s44

1.2 StagedTree Class

In an event tree, each situation is associated with a transition parameter vector which indicates the conditional probability of an individual, who has arrived at the situation, going along one of its edges. In order to create a CEG, we first need to elicit a *staged tree*. This is done by first partitioning situations into *stages*, which are collections of situations in the event tree whose immediate evolutions, i.e. their associated conditional transition parameter vectors, are equivalent. To indicate this symmetry, all situations in the same stage are assigned a single colour.

Identification of the stages in the event tree can be done using any suitable model selection algorithm. Currently, the only available selection algorithm in `cegpy` is the *Agglomerative Hierarchical Clustering (AHC)* algorithm (Freeman and Smith, 2011).

In order to create a staged tree in `cegpy` we first initialize a `StagedTree` object from the dataset and then run the AHC algorithm using the `create_AHC_transitions` method, as displayed below. The output of the AHC algorithm is a dictionary containing the following information:

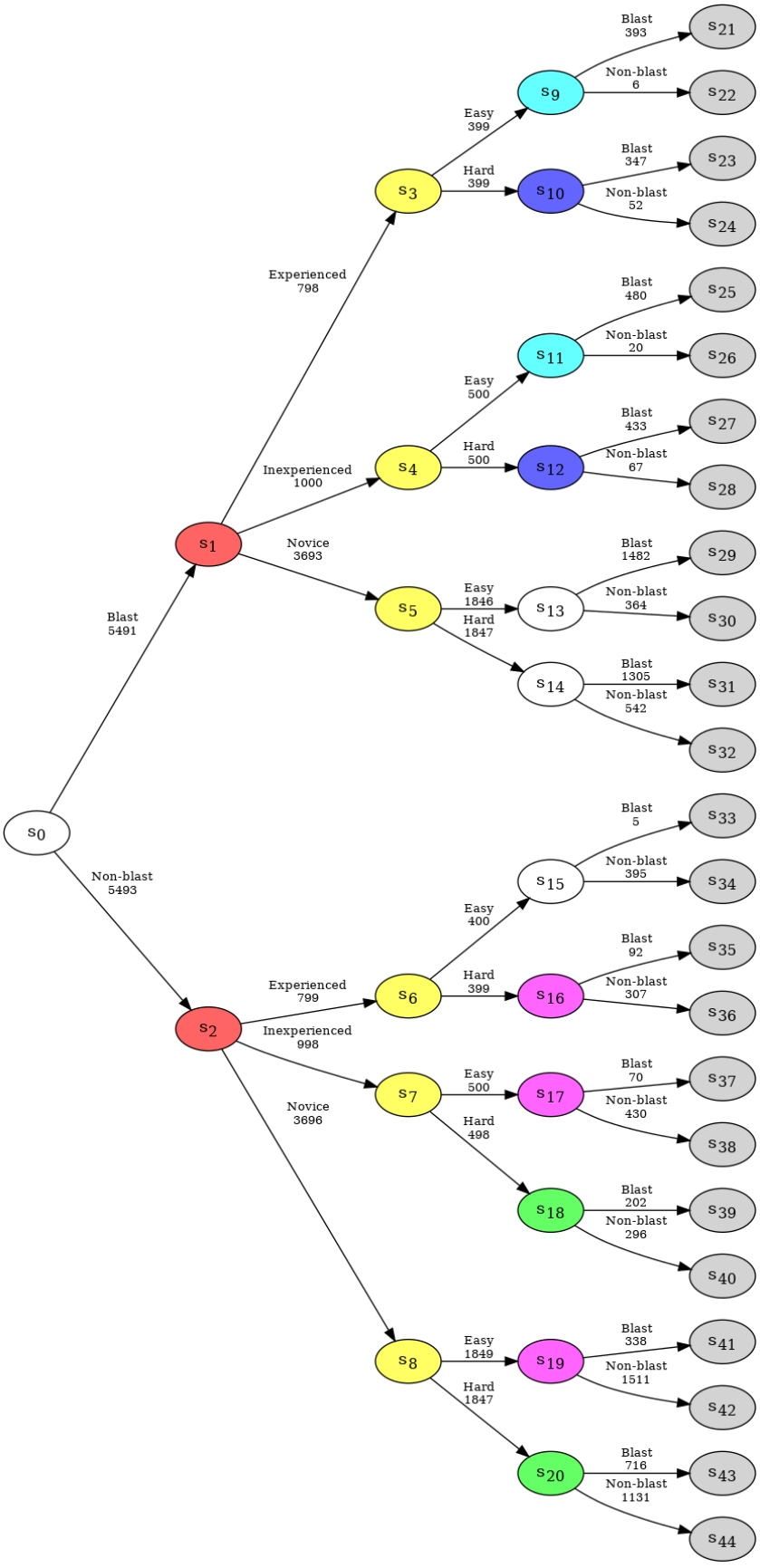
- `Merged Situations` - a list of tuples representing the partition of the nodes into stages
- `Log Likelihood` - the log likelihood of the data under the model selected by AHC

```
from cegpy import StagedTree

st = StagedTree(df)
st.calculate_AHC_transitions()
```

```
{'Merged Situations': [('s2', 's1'),
  ('s20', 's18'),
  ('s12', 's10'),
  ('s8', 's4', 's7', 's6', 's3', 's5'),
  ('s11', 's9'),
  ('s16', 's17', 's19'),
  ('s0',),
  ('s13',),
  ('s14',),
  ('s15',)],
 'Log Likelihood': -30091.353114865367}
```

Within `cegpy`, singleton stages, i.e. stages containing a single situation, are coloured white, leaves and their corresponding sink node are coloured in light-grey. Running AHC on our data set results in the following staged tree.

```
st.create_figure()
```


s0
Blast
5491
Non-blast
5493
s1
Experienced
798
Inexperienced
1000
Novice
3693
s2
Experienced
799
Inexperienced
998
Novice
3696
s3
Easy
399
Hard
399
s4
Easy
500
Hard
500
s5
Easy
1846
Hard
1847
s6
Easy
400
Hard
399
s7
Easy
500
Hard
498
s8
Easy
1849
Hard
1847
s9
Blast
393
Non-blast
6
s10
Blast
347
Non-blast
52
s11
Blast
480
Non-blast
20
s12
Blast
433
Non-blast
67
s13
Blast
1482
Non-blast
364
s14
Blast
1305
Non-blast
542
s15
Blast
5
Non-blast
395
s16
Blast
92
Non-blast
307
s17
Blast
70
Non-blast
430
s18
Blast
202
Non-blast
296
s19
Blast
338
Non-blast
1511
s20
Blast
716
Non-blast
1131
s21
s22
s23
s24
s25
s26
s27
s28
s29
s30
s31
s32
s33
s34
s35
s36
s37
s38
s39
s40
s41
s42
s43
s44

1.2.1 Custom Hyperstages

`cegpy` allows the user to specify which situations are allowed to be merged by the AHC algorithm. This is done by specifying a *hyperstage* (Collazo et al., 2017) which is a collection of sets such that two situations cannot be in the same stage unless they belong to the same set in the hyperstage. Under a default setting in `cegpy`, all situations which have the same number of outgoing edges and equivalent set of edge labels are in the same set within the hyperstage. The default hyperstages of a given tree can be displayed by accessing the `hyperstage` property, which returns a list of lists, where each sublist contains situations belonging to the same hyperstage.

```
st.hyperstage
```

```
[['s0',
  's9',
  's10',
  's11',
  's12',
  's13',
  's14',
  's15',
  's16',
  's17',
  's18',
  's19',
  's20'],
 ['s1', 's2'],
 ['s3', 's4', 's5', 's6', 's7', 's8']]
```

In this example, situations s_1 and s_2 belong to the same hyperstage. Each of them has three emanating edges with labels *Experienced*, *Inexperienced*, and *Novice*. However, stages s_6 and s_15 belong to different hyperstages. They both have two emanating edges, yet different labels: *Easy*, *Hard* and *Blast*, *Non-blast*.

We can specify a different hyperstage at the point of running the AHC algorithm by passing a list defining the hyperstage partition as a parameter to the `calculate_AHC_transitions` method, for example:

```
new_hyperstage = [
    ['s0'],
    ['s3', 's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12',
    's13', 's14', 's15', 's16', 's17', 's18', 's19','s20'],
    ['s1', 's2'],
]
st.calculate_AHC_transitions(hyperstage=new_hyperstage)
```

```
{'Merged Situations': [('s2', 's1'),
  ('s20', 's18'),
  ('s12', 's10'),
  ('s8', 's4', 's7', 's6', 's3', 's5'),
  ('s11', 's9'),
  ('s16', 's17', 's19'),
  ('s0',),
  ('s13',),
  ('s14',),
  ('s15',)],
 'Log Likelihood': -30091.353114865367}
```

1.2.2 Structural and sampling zeros / missing values

The package, by default, treats all blank and `NaN` cells as *structural* missing values, i.e. data that is missing for a logical reason. However, sometimes these might occur due to sampling limitations; *sampling* missing values. We may also not observe a certain value for a variable in our data set (given its ancestral variables) not because that value is a structural zero but because of sampling limitations, in which case we are dealing with *sampling zeros*.

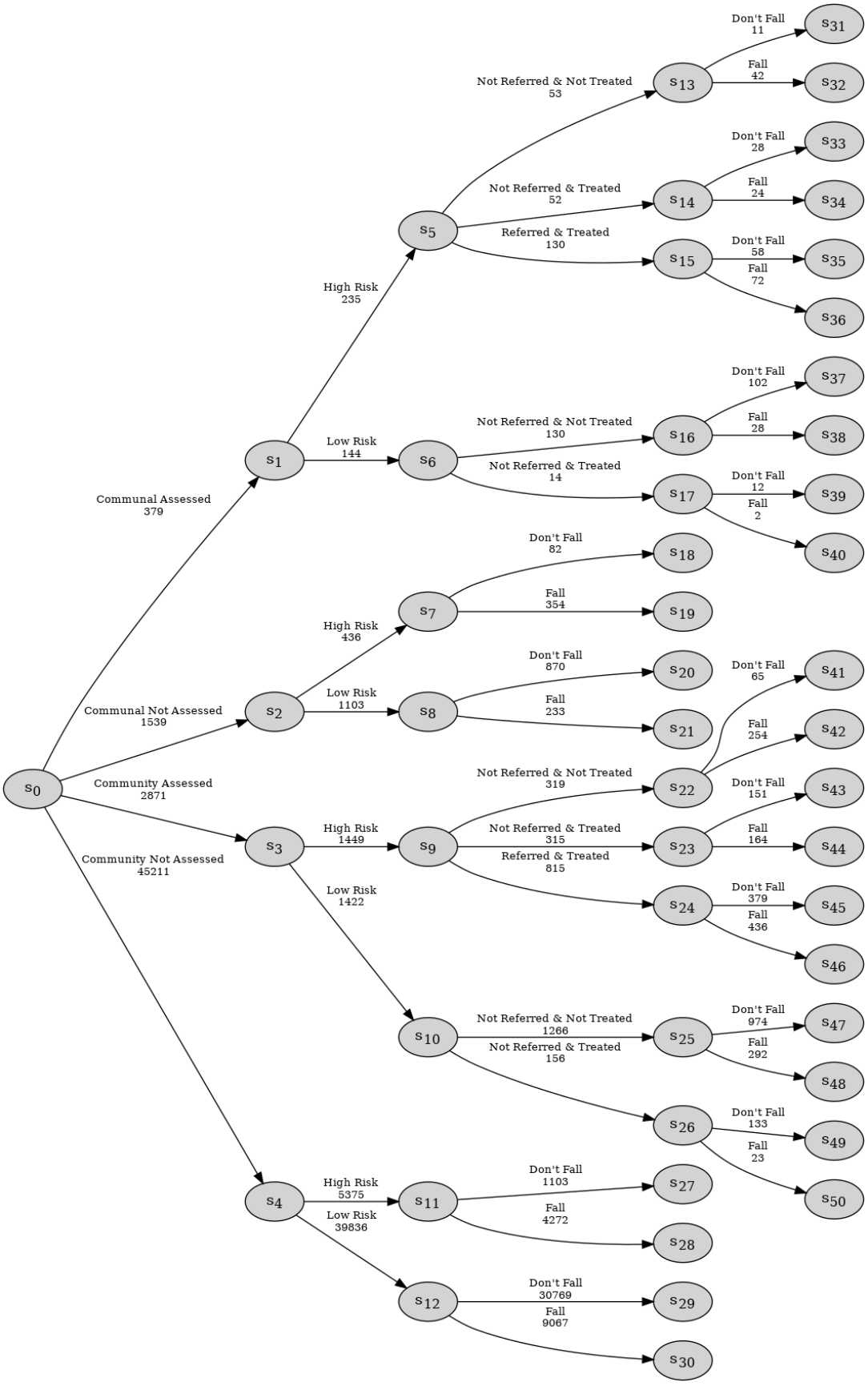
Consider the following example of the `falls.xlsx` data set which provides information concerning adults over the age of 65, and includes four categorical variables as given below with their state spaces:

- **Housing Assessment**: Living situation and whether they have been assessed, state space: `{"Communal Assessed", "Communal Not Assessed", "Community Assessed", "Community Not Assessed"}`;
- **Risk**: Risk of a future fall, state space: `{"High Risk", "Low Risk"}`;
- **Treatment**: Referral and treatment status, state space: `{"Not Referred & Not Treated", "Not Referred & Treated", "Referred & Treated"}`;
- **Fall**: the outcome, state space: `{"Fall", "Don't Fall"}`.

```
df = pd.read_excel('../../data/Falls_Data.xlsx')
df.head()
```

```
        HousingAssessment       Risk Treatment        Fall
0  Community Not Assessed   Low Risk       NaN        Fall
1  Community Not Assessed  High Risk       NaN        Fall
2  Community Not Assessed   Low Risk       NaN  Don't Fall
3  Community Not Assessed   Low Risk       NaN  Don't Fall
4  Community Not Assessed   Low Risk       NaN        Fall
```

```
et = EventTree(df)
et.create_figure()
```


s0
Communal Assessed
379
Communal Not Assessed
1539
Community Assessed
2871
Community Not Assessed
45211
s1
High Risk
235
Low Risk
144
s2
High Risk
436
Low Risk
1103
s3
High Risk
1449
Low Risk
1422
s4
High Risk
5375
Low Risk
39836
s5
Not Referred & Not Treated
53
Not Referred & Treated
52
Referred & Treated
130
s6
Not Referred & Not Treated
130
Not Referred & Treated
14
s7
Don't Fall
82
Fall
354
s8
Don't Fall
870
Fall
233
s9
Not Referred & Not Treated
319
Not Referred & Treated
315
Referred & Treated
815
s10
Not Referred & Not Treated
1266
Not Referred & Treated
156
s11
Don't Fall
1103
Fall
4272
s12
Don't Fall
30769
Fall
9067
s13
Don't Fall
11
Fall
42
s14
Don't Fall
28
Fall
24
s15
Don't Fall
58
Fall
72
s16
Don't Fall
102
Fall
28
s17
Don't Fall
12
Fall
2
s18
s19
s20
s21
s22
Don't Fall
65
Fall
254
s23
Don't Fall
151
Fall
164
s24
Don't Fall
379
Fall
436
s25
Don't Fall
974
Fall
292
s26
Don't Fall
133
Fall
23
s27
s28
s29
s30
s31
s32
s33
s34
s35
s36
s37
s38
s39
s40
s41
s42
s43
s44
s45
s46
s47
s48
s49
s50

Observe that this process has structural asymmetries. None of the individuals assessed to be low risk are referred to the falls clinic and thus, for this group, the count associated with the _Referred & Treated'}$ category is a structural zero:

```
df[df.Risk == "Low Risk"]['Treatment'].value_counts()
```

```
Not Referred & Not Treated    1396
Not Referred & Treated         170
Name: Treatment, dtype: int64
```

Moreover, for individuals who are not assessed, their responses are structurally missing for the `Treatment` variable:

```
# Missing values in each column
print(df.isna().sum())

# Missing values for Treatment are structural,
# they are missing due to the lack of assessment:
df[df.HousingAssessment.isin([
    'Community Not Assessed', 'Communal Not Assessed'
])]['Treatment'].isna().sum()
```

```
HousingAssessment        0
Risk                     0
Treatment            46750
Fall                     0
dtype: int64
```

```
46750
```

In `cegpy` any paths that should logically be in the event tree description of the process but are absent from the dataset due to sampling limitations would need to be manually added by the user using the sampling zero paths argument when initialising the `EventTree` object. Further, not all missing values in the dataset will be structurally missing.

How to distinguish between structural and sampling missing values?

e.g. Falls example: Suppose that some individuals in communal establishments who are not formally assessed but are known to be high risk were actually either `"Not Referred & Treated"` or `"Not Referred & Not Treated"` but that these observations were missing in the `falls.xlsx` dataset due to sampling limitations. All the other blank/`NaN` cells are structurally missing.

```
idx = (df.HousingAssessment == 'Communal Not Assessed') & (df.Risk == 'High Risk')
df[idx]
```

```
           HousingAssessment       Risk Treatment        Fall
67     Communal Not Assessed  High Risk       NaN        Fall
72     Communal Not Assessed  High Risk       NaN        Fall
95     Communal Not Assessed  High Risk       NaN        Fall
102    Communal Not Assessed  High Risk       NaN        Fall
132    Communal Not Assessed  High Risk       NaN        Fall
...                      ...        ...       ...         ...
49065  Communal Not Assessed  High Risk       NaN        Fall
49087  Communal Not Assessed  High Risk       NaN        Fall
49135  Communal Not Assessed  High Risk       NaN  Don't Fall
```

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```
49461  Communal Not Assessed  High Risk       NaN        Fall
49905  Communal Not Assessed  High Risk       NaN        Fall

[436 rows x 4 columns]
```

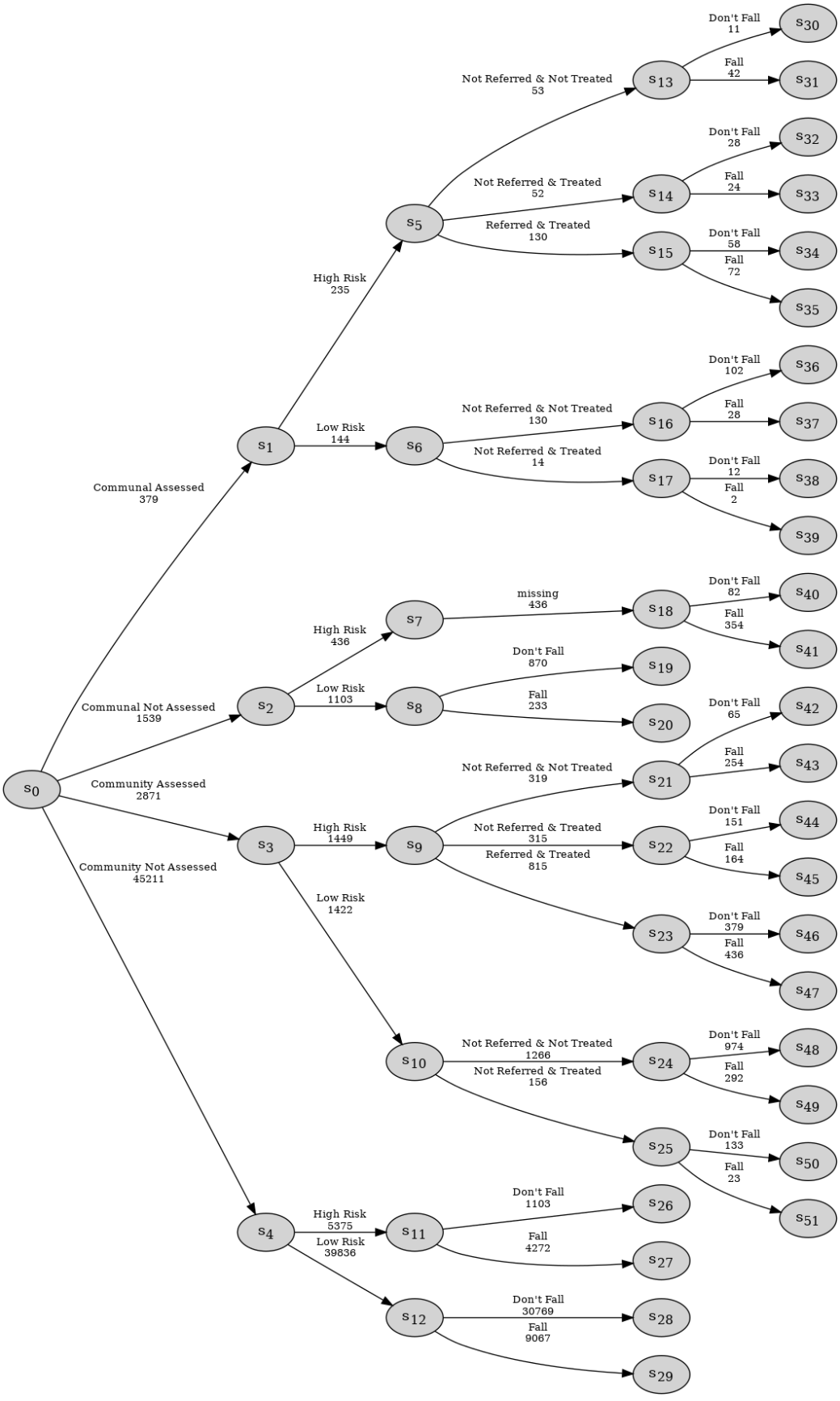
To demarcate the difference between structural and sampling missing values, a user can give different labels to the structural and sampling missing values in the dataset and provide these labels to the `struct_missing_label` and `missing_label` arguments respectively when initialising the `EventTree` or `StagedTree` object.

In our example, we can replace the `NaN` values for the `Treatment` variable among the considered subset of data with a new label, e.g. `samp_miss`:

```
df.loc[idx, 'Treatment'] = 'samp_miss'
```

Next step is to tell the `EventTree` or `StagedTree` object about these missing value arguments as shown below. This will generate a new path along `Communal Not Assessed', High Risk', `missing')}$`:

```
et2 = EventTree(df,
    missing_label='samp_miss',
)
et2.create_figure()
```


s0
Communal Assessed
379
Communal Not Assessed
1539
Community Assessed
2871
Community Not Assessed
45211
s1
High Risk
235
Low Risk
144
s2
High Risk
436
Low Risk
1103
s3
High Risk
1449
Low Risk
1422
s4
High Risk
5375
Low Risk
39836
s5
Not Referred & Not Treated
53
Not Referred & Treated
52
Referred & Treated
130
s6
Not Referred & Not Treated
130
Not Referred & Treated
14
s7
missing
436
s8
Don't Fall
870
Fall
233
s9
Not Referred & Not Treated
319
Not Referred & Treated
315
Referred & Treated
815
s10
Not Referred & Not Treated
1266
Not Referred & Treated
156
s11
Don't Fall
1103
Fall
4272
s12
Don't Fall
30769
Fall
9067
s13
Don't Fall
11
Fall
42
s14
Don't Fall
28
Fall
24
s15
Don't Fall
58
Fall
72
s16
Don't Fall
102
Fall
28
s17
Don't Fall
12
Fall
2
s18
Don't Fall
82
Fall
354
s19
s20
s21
Don't Fall
65
Fall
254
s22
Don't Fall
151
Fall
164
s23
Don't Fall
379
Fall
436
s24
Don't Fall
974
Fall
292
s25
Don't Fall
133
Fall
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s30
s31
s32
s33
s34
s35
s36
s37
s38
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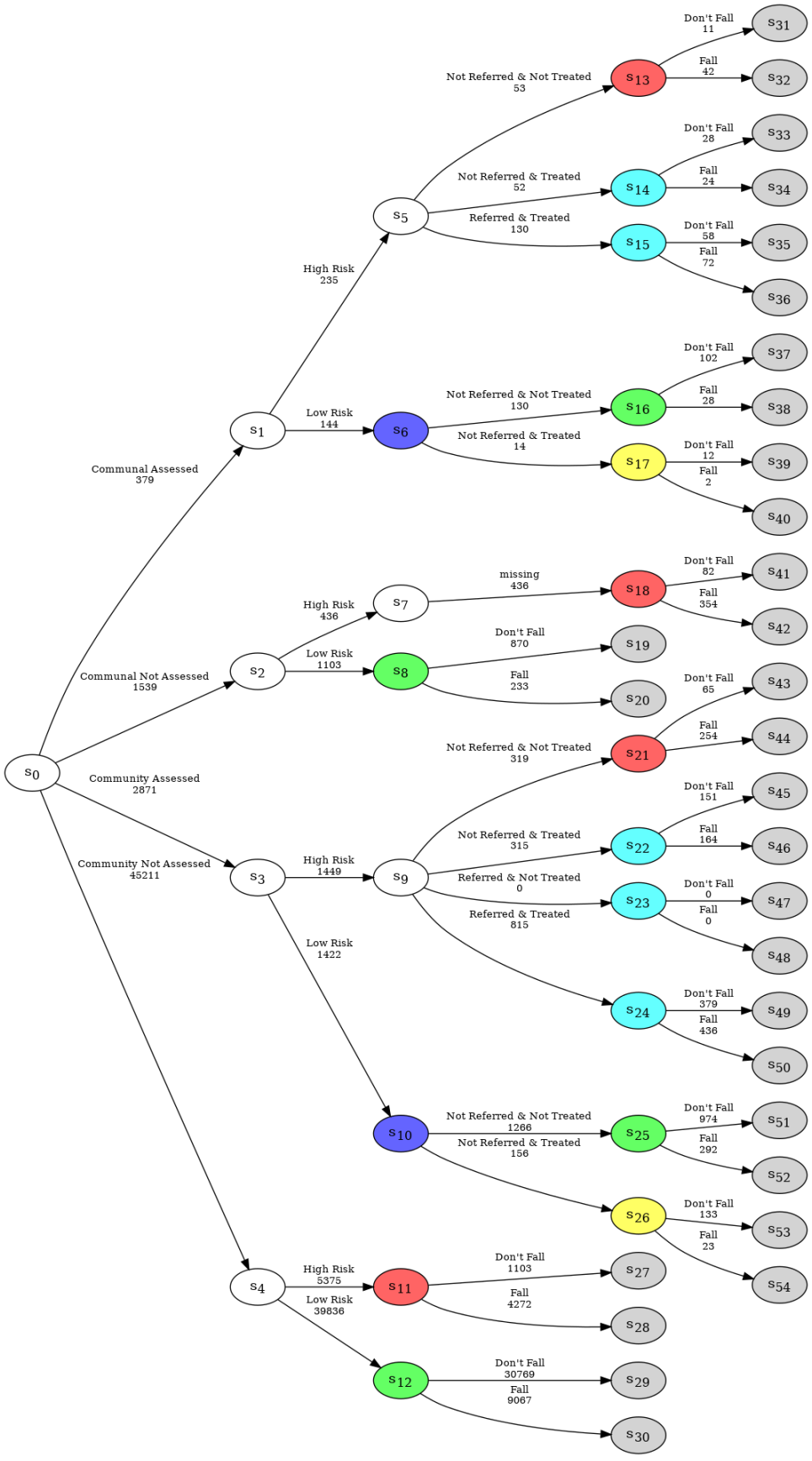
s48
s49
s50
s51

How to add sampling zeros?

e.g. Falls example: Suppose that some individuals in the community who were assessed and high risk were referred and not treated. Suppose that our observations are still the same as in the `falls.xlsx` dataset. Here, by design, this was allowed, but was not observed in the dataset. So we need to add this value in manually as a path `("Community Assessed", "High Risk", "Referred & Not Treated")`. We also need to add in the values that follow it: i.e. `("Community Assessed", "High Risk", "Referred & Not Treated", "Fall")` and `("Community Assessed", "High Risk", "Referred & Not Treated", "Don't Fall")`.

In `cegpy` any paths that should logically be in the event tree description of the process but are absent from the dataset due to sampling limitations would need to be manually added by the user using the sampling zero paths argument when initialising the `EventTree` or `StagedTree` object. No changes need to be made to the dataset, as shown below:

```
st2 = StagedTree(df,
    sampling_zero_paths=[
        ('Community Assessed', 'High Risk', 'Referred & Not Treated'),
        ('Community Assessed', 'High Risk', 'Referred & Not Treated', 'Fall'),
        ('Community Assessed', 'High Risk', 'Referred & Not Treated', "Don't Fall")
])
st2.calculate_AHC_transitions()
st2.create_figure()
```


s0
Communal Assessed
379
Communal Not Assessed
1539
Community Assessed
2871
Community Not Assessed
45211
s1
High Risk
235
Low Risk
144
s2
High Risk
436
Low Risk
1103
s3
High Risk
1449
Low Risk
1422
s4
High Risk
5375
Low Risk
39836
s5
Not Referred & Not Treated
53
Not Referred & Treated
52
Referred & Treated
130
s6
Not Referred & Not Treated
130
Not Referred & Treated
14
s7
missing
436
s8
Don't Fall
870
Fall
233
s9
Not Referred & Not Treated
319
Not Referred & Treated
315
Referred & Not Treated
0
Referred & Treated
815
s10
Not Referred & Not Treated
1266
Not Referred & Treated
156
s11
Don't Fall
1103
Fall
4272
s12
Don't Fall
30769
Fall
9067
s13
Don't Fall
11
Fall
42
s14
Don't Fall
28
Fall
24
s15
Don't Fall
58
Fall
72
s16
Don't Fall
102
Fall
28
s17
Don't Fall
12
Fall
2
s18
Don't Fall
82
Fall
354
s21
Don't Fall
65
Fall
254
s22
Don't Fall
151
Fall
164
s23
Don't Fall
0
Fall
0
s24
Don't Fall
379
Fall
436
s25
Don't Fall
974
Fall
292
s26
Don't Fall
133
Fall
23
s31
s32
s33
s34
s35
s36
s37
s38
s39
s40
s41
s42
s19
s20
s43
s44
s45
s46
s47
s48
s49
s50
s51
s52
s53
s54
s27
s28
s29
s30

CHAPTER

TWO

CREATING A CHAIN EVENT GRAPH

2.1 Example 1: Using a Stratified Dataset

This example builds a **C**hain **E**vent **G**raph (**CEG**) from a discrete dataset showing results from a medical experiment. The dataset used is symmetrical, built from a rectangular dataset. These **CEG**s are known as *stratified* in the literature.

The **A**gglomerative **H**ierarchical **C**lustering (**AHC**) algorithm is used to maximise the log marginal likelihood score of the staged tree/CEG model to determine its stages. The package functions under a Bayesian framework and priors can be supplied to the **AHC** algorithm to override the default settings,

The example `medical.xlsx` dataset contains 4 categorical variables; `Classification`, `Group`, `Difficulty`, `Response`.

Each individual is given a binary classification; `Blast` or `Non-blast`. Each group is rated on their experience level; `Experienced`, `Inexperienced`, or `Novice`. The classification task they are given has a difficulty rating of `Easy` or `Hard`. Finally, their response is shown; `Blast` or `Non-blast`.

Firstly, a staged tree object is created from a data source, and calculate the AHC transitions.

```
from cegpy import StagedTree, ChainEventGraph
import pandas as pd

dataframe = pd.read_excel("medical.xlsx")
dataframe
```

```
      Classification        Group Difficulty   Response
0              Blast  Experienced       Easy      Blast
1          Non-blast  Experienced       Easy  Non-blast
2          Non-blast  Experienced       Hard      Blast
3          Non-blast  Experienced       Hard  Non-blast
4              Blast  Experienced       Easy      Blast
...              ...          ...        ...        ...
10979          Blast       Novice       Easy  Non-blast
10980          Blast       Novice       Easy      Blast
10981      Non-blast       Novice       Easy      Blast
10982          Blast       Novice       Easy  Non-blast
10983      Non-blast       Novice       Hard  Non-blast

[10984 rows x 4 columns]
```

```
# Descriptive statistics for the dataset
dataframe.describe()
```

```
       Classification   Group Difficulty Response
count           10984   10984      10984    10984
unique              2       3          2        2
top         Non-blast  Novice       Easy    Blast
freq             5493    7389       5494     5863
```

The AHC algorithm is executed on the event tree, and the nodes are assigned a colour if they are found to be in the same `stage` as each other. Note that the `calculate_AHC_transitions` method is only available from the StagedTree class and not the EventTree class.

Effectively, nodes in the same stage share the same parameter set; in other words, the immediate future of these nodes is identical. Note that singleton stages are not coloured in the staged tree and its corresponding CEG to prevent visual cluttering.

When the CEG is created, equivalent nodes (precisely, those whose complete future is identical) in a stage will be combined to compress the graph.

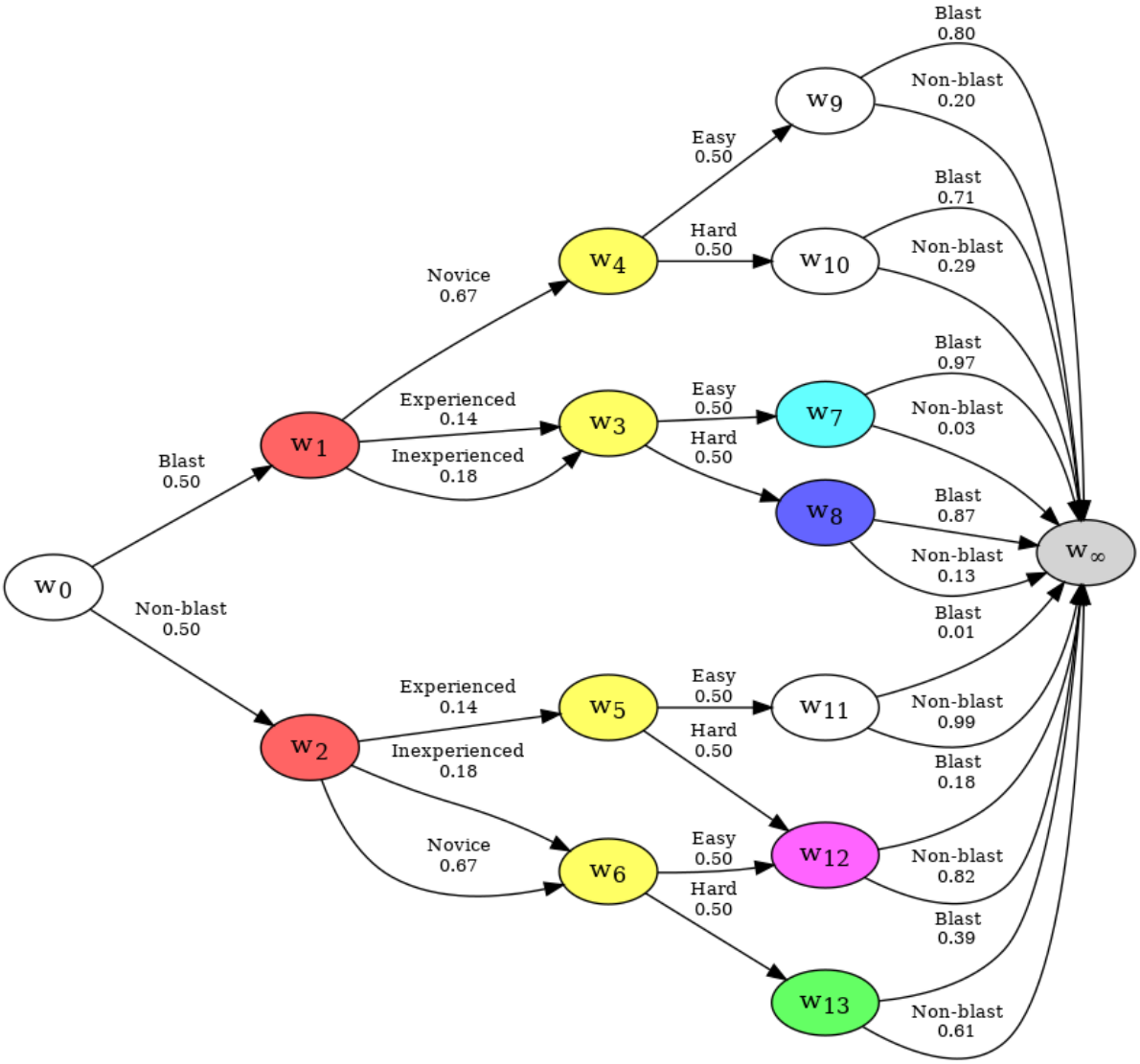
```
staged_tree = StagedTree(dataframe)
staged_tree.calculate_AHC_transitions();
```

Once the AHC algorithm has been run to identify the stages, a CEG can be created by passing the `StagedTree` object into the ChainEventGraph class. When the `ChainEventGraph` is created, it automatically generates the CEG from the `StagedTree` object. The process of generation compares nodes that are in the same stage to determine if they are logically compatible with one another. Once the graph has been constructed, and nodes combined, the probabilities of passing down any given edge are displayed.

Like the `StagedTree`, the graph can be displayed using the `create_figure` method as shown below.

```
from IPython.display import Image

chain_event_graph = ChainEventGraph(staged_tree)
chain_event_graph.create_figure()
```



The tree has now been compressed into a Chain Event Graph. The graph represents the system encoded in the data. All paths start at the root node w0, (which represents an individual entering the system), and terminate at the sink node w∞ (which represents the point at which an individual exits the system).

2.2 Example 2: Chain Event Graph from Non-Stratified Dataset

This example builds a **C**hain **E**vent **G**raph (**CEG**) from a asymmetric dataset. In simple words, a dataset is asymmetric when the event tree describing the dataset is not symmetric around its root. The class of CEGs built from asymmetric event trees is said to be non-stratified. Note that, technically, a CEG is also said to be non-stratified when the order of events along its different paths is not the same, even though its event tree might be symmetric. Whilst such processes can also be easily modelled with the cegpy package, for this example we focus on non-stratified CEGs that are built from asymmetric event trees/datasets.

Asymmetry in a dataset arises when it has structural zeros or structural missing values in certain rows; in other words, the sample space of a variable is different or empty respectively, depending on its ancestral variables. So logically, certain values of the variable will never be observed for certain configurations of its ancestral variables, irrespective of the sample size.

In this example, we consider the falls.xlsx dataset. Here, by interventional design, individuals who are not assessed are not offered referral or treatment. In this case, we would observe individuals in our dataset who are not assessed, going down the 'Not Referred & Not Treated' path with probability 1. This is not helpful, and so we choose to condense the tree and remove this edge. The zero observations for non-assessed individuals for the categories of 'Referred & Treated' and 'Not Referred & Treated' are both structural zeros.

```
from cegpy import EventTree
import pandas as pd

dataframe = pd.read_excel("falls.xlsx")
dataframe
```

```
            HousingAssessment       Risk Treatment        Fall
0      Community Not Assessed   Low Risk       NaN        Fall
1      Community Not Assessed  High Risk       NaN        Fall
2      Community Not Assessed   Low Risk       NaN  Don't Fall
3      Community Not Assessed   Low Risk       NaN  Don't Fall
4      Community Not Assessed   Low Risk       NaN        Fall
...                       ...        ...       ...         ...
49995  Community Not Assessed   Low Risk       NaN  Don't Fall
49996  Community Not Assessed   Low Risk       NaN  Don't Fall
49997  Community Not Assessed   Low Risk       NaN  Don't Fall
49998  Community Not Assessed   Low Risk       NaN        Fall
49999  Community Not Assessed   Low Risk       NaN        Fall

[50000 rows x 4 columns]
```

Note: *When looking at the description of the dataset, the total count in the* `Treatment` *column is not equal to the counts for the other columns. This is the giveaway that the dataset is non-stratified. Extreme care must be taken to ensure that the dataset really is non-stratified, and doesn't simply have sampling-zeros or sampling missing values. The package has no way of distinguishing these on its own unless the user specifies them.*

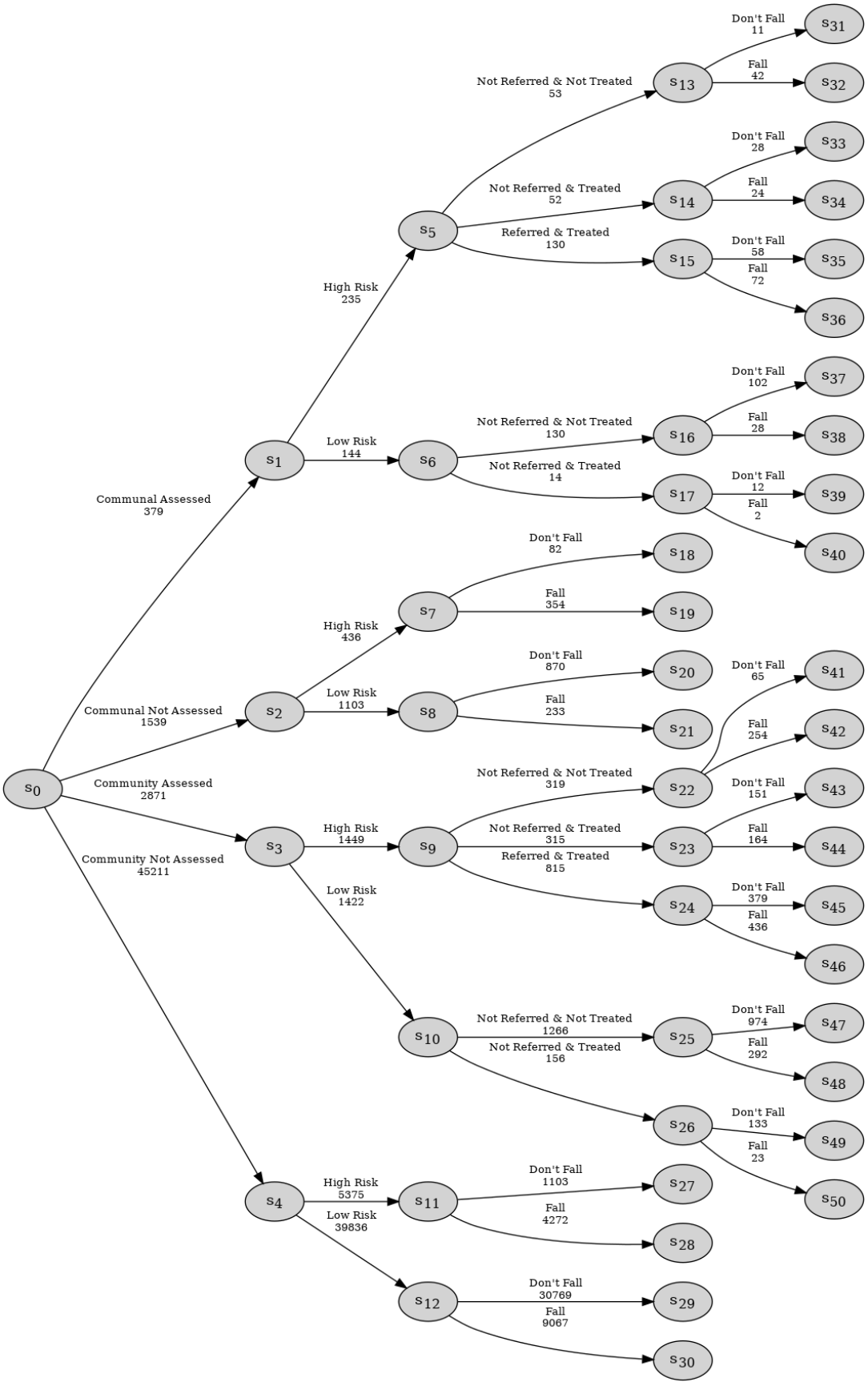
```
dataframe.describe()
```

```
             HousingAssessment      Risk                    Treatment  \
count                    50000     50000                         3250
unique                       4         2                            3
top     Community Not Assessed  Low Risk  Not Referred & Not Treated
freq                     45211     42505                         1768

              Fall
count        50000
unique           2
top     Don't Fall
freq         34737
```

The end result of this is that in the EventTree shown below, paths such as *S0 -> S2 -> S7 -> S18* skip the `Treatment` variable.

```
event_tree = EventTree(dataframe)
event_tree.create_figure()
```


s0
Communal Assessed
379
Communal Not Assessed
1539
Community Assessed
2871
Community Not Assessed
45211
s1
s2
s3
s4
High Risk
235
Low Risk
144
High Risk
436
Low Risk
1103
High Risk
1449
Low Risk
1422
High Risk
5375
Low Risk
39836
s5
s6
s7
s8
s9
s10
s11
s12
Not Referred & Not Treated
53
Not Referred & Treated
52
Referred & Treated
130
Not Referred & Not Treated
130
Not Referred & Treated
14
Don't Fall
82
Fall
354
Don't Fall
870
Fall
233
Not Referred & Not Treated
319
Not Referred & Treated
315
Referred & Treated
815
Not Referred & Not Treated
1266
Not Referred & Treated
156
Don't Fall
1103
Fall
4272
Don't Fall
30769
Fall
9067
s13
s14
s15
s16
s17
s18
s19
s20
s21
s22
s23
s24
s25
s26
s27
s28
s29
s30
Don't Fall
11
Fall
42
Don't Fall
28
Fall
24
Don't Fall
58
Fall
72
Don't Fall
102
Fall
28
Don't Fall
12
Fall
2
Don't Fall
65
Fall
254
Don't Fall
151
Fall
164
Don't Fall
379
Fall
436
Don't Fall
974
Fall
292
Don't Fall
133
Fall
23
s31
s32
s33
s34
s35
s36
s37
s38
s39
s40
s41
s42
s43
s44
s45
s46
s47
s48
s49
s50

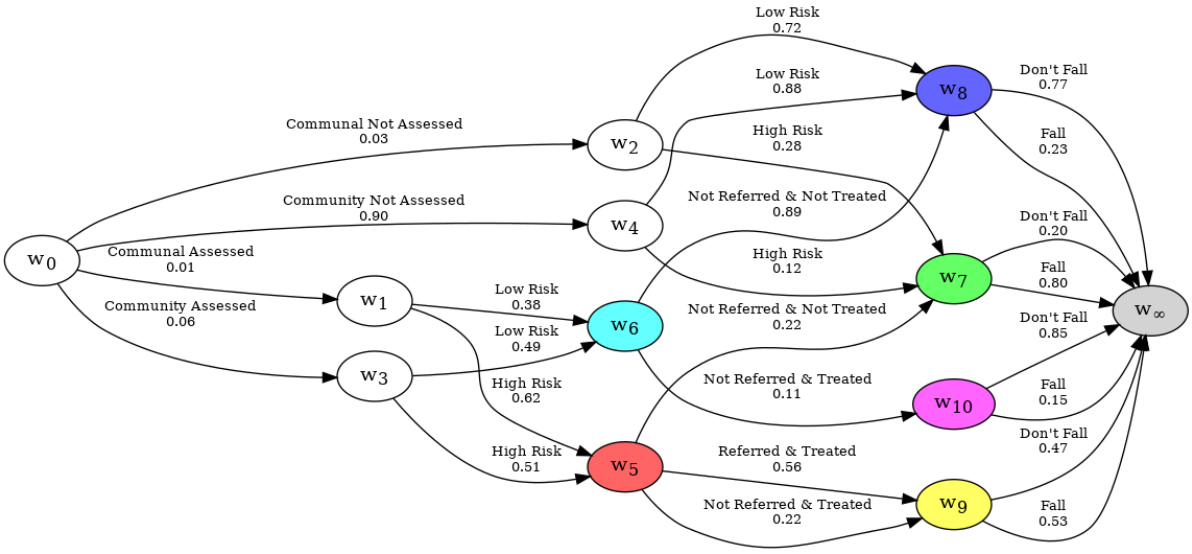
As in the stratified medical example, after initial checks on the dataset, and confirmation that the EventTree looks as expected, the next step is to identify the stages. For this, we use the StagedTree class, which first creates the EventTree internally, ready for the user to run a clustering algorithm on it. In this example we use the .calculate_AHC_transitions() method, which executes the agglomerative hierarchical clustering (AHC) algorithm on the EventTree. The package functions under a Bayesian framework and priors can be supplied to the AHC algorithm to override the default settings.

The resultant CEG has been reduced from the tree representation to a more compact graph.

```
from cegpy import ChainEventGraph, StagedTree

st = StagedTree(dataframe)
st.calculate_AHC_transitions()

ceg = ChainEventGraph(st)
ceg.create_figure()
```



As a CEG is a probabilistic model of a series of events, it may be desirable to view a CEG sub-graph when some or all of the variables are known. This can be especially true for graphs with lots of variables, which can balloon in size. In `cegpy`, this is done by using the `ChainEventGraphReducer` which is covered on the next page.

CHAPTER

THREE

REDUCING A CHAIN EVENT GRAPH

A complete CEG shows all possible trajectories that an individual undergoing the process might experience. However, on observing any evidence, certain or uncertain, some edges and nodes become unvisited with probability 1. The CEG model can be reduced such that these edges and nodes are excluded, without any loss of information. Once reduced, the probabilities displayed can be also be revised.

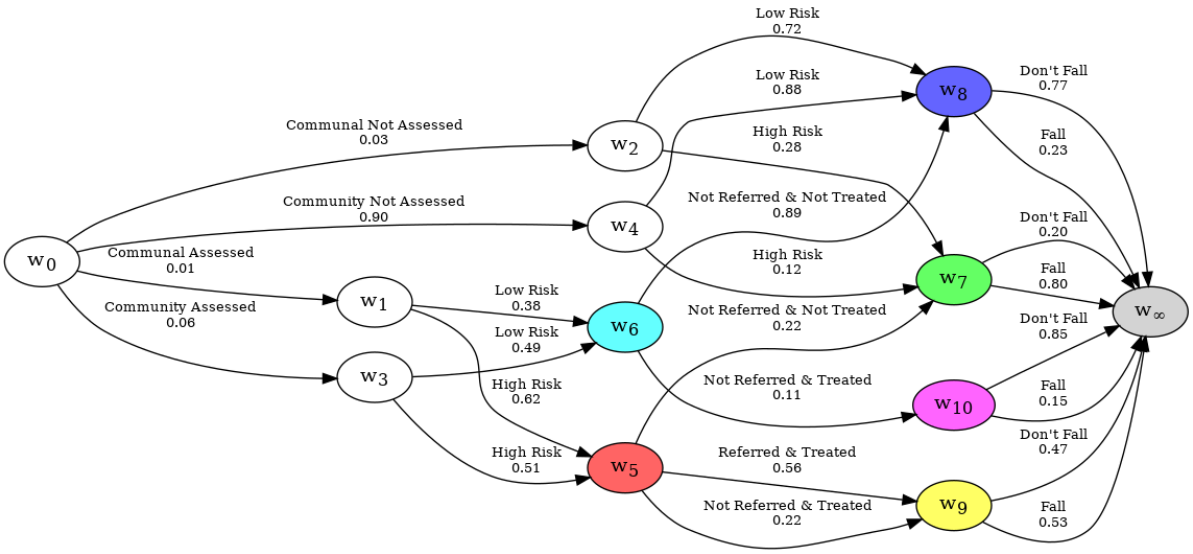
For this example, we will use the `falls.xlsx` dataset.

```
from cegpy import StagedTree, ChainEventGraph, ChainEventGraphReducer
import pandas as pd

dataframe = pd.read_excel("falls.xlsx")

staged_tree = StagedTree(dataframe)
staged_tree.calculate_AHC_transitions()

falls_ceg = ChainEventGraph(staged_tree)
falls_ceg.create_figure()
```



When examining a dataset with a CEG, you may wish to see a subset of the graph, where some events are excluded with probability zero. Consider the CEG representation of the falls dataset; It may be interesting to split the graph into two graphs, one for individuals on the `Communal` paths, and another for people on the `Community` paths. This is achieved by using uncertain evidence. In our case, we know that anyone who is community assessed will have either passed along the `Community Not Assessed` edge or the `Community Assessed` edge, which can be done like so:

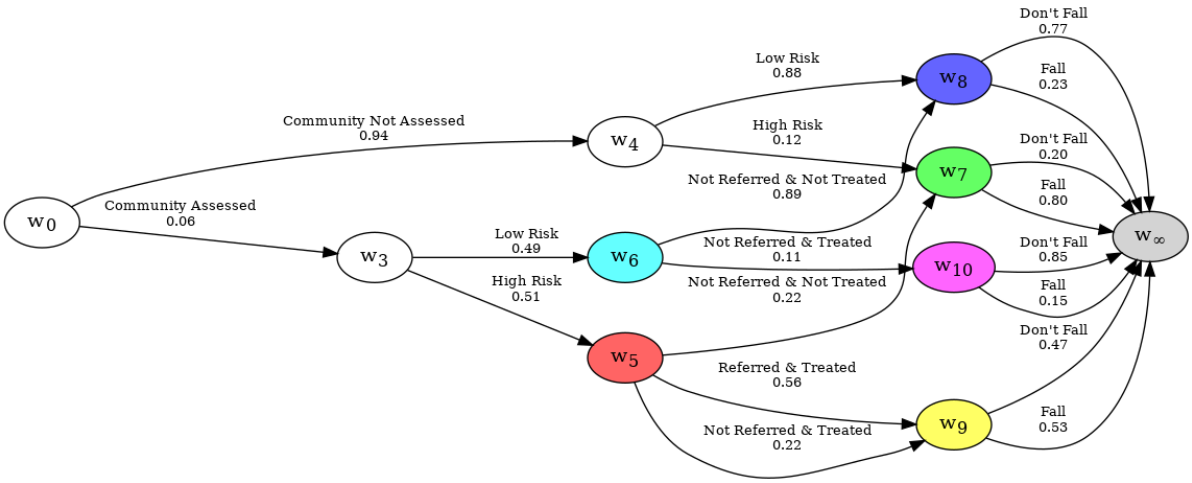
```
from cegpy import ChainEventGraphReducer

reducer = ChainEventGraphReducer(falls_ceg)
reducer.add_uncertain_edge_set(
    edge_set={
        ("w0", "w4", "Community Not Assessed"),
        ("w0", "w3", "Community Assessed"),
    }
)
print(reducer)
```

```
The evidence you have given is as follows:
 Evidence you are certain of:
   Edges = []
   Nodes = {}
 Evidence you are uncertain of:
   Edges = [
     {('w0', 'w4', 'Community Not Assessed'), ('w0', 'w3', 'Community Assessed')},
   ]
   Nodes = {
   }
```

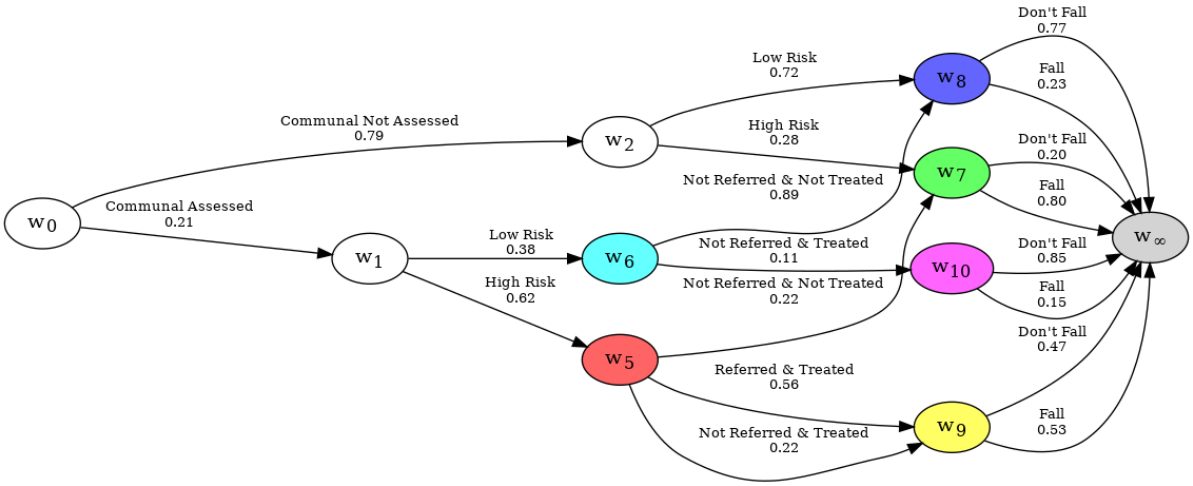
The reduced graph is stored in the `graph` attribute, and is a `ChainEventGraph` object.

```
reducer.graph.create_figure()
```



Likewise, we can do the same for the `Communal` graph. In this case, it could be simpler to just specify the sub-graph which contains all paths that pass through nodes w1 and w2.

```
reducer = ChainEventGraphReducer(falls_ceg)
reducer.add_uncertain_node_set({"w1", "w2"})
reducer.graph.create_figure()
```



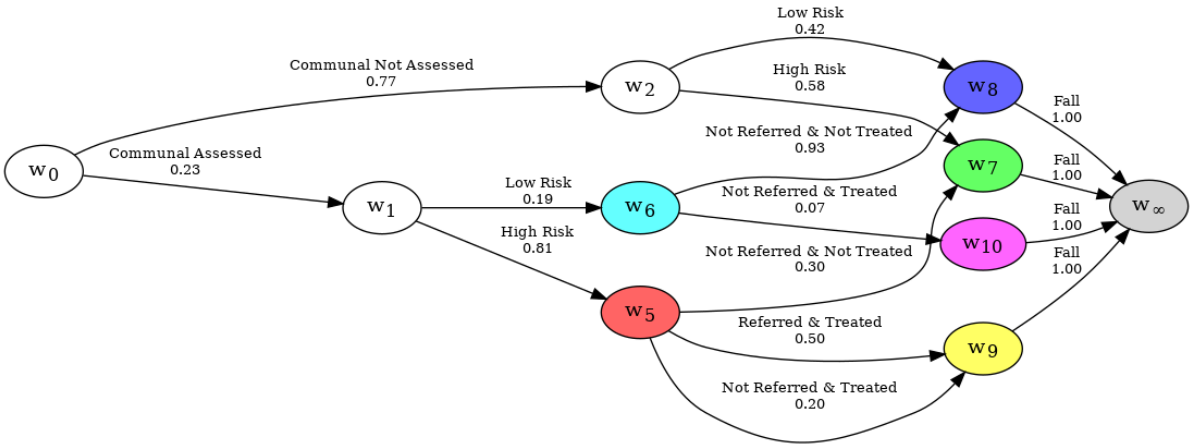
It may also be interesting to see the sub-graph of those `Communal` individuals who had a `Fall`.

```
reducer.add_uncertain_edge_set(
    {
        (u, v, l)
        for (u, v, l) in reducer.graph.edges
        if l == "Fall"
    }
)
print(reducer)
```

```
The evidence you have given is as follows:
 Evidence you are certain of:
   Edges = []
   Nodes = {}
 Evidence you are uncertain of:
   Edges = [
     {('w7', 'w_infinity', 'Fall'), ('w8', 'w_infinity', 'Fall'), ('w9', 'w_
↪infinity', 'Fall'), ('w10', 'w_infinity', 'Fall')},
   ]
   Nodes = {
     {'w2', 'w1'},
   }
```

The probabilities are adjusted across all the edges, and back propagated through the graph automatically.

```
reducer.graph.create_figure()
```

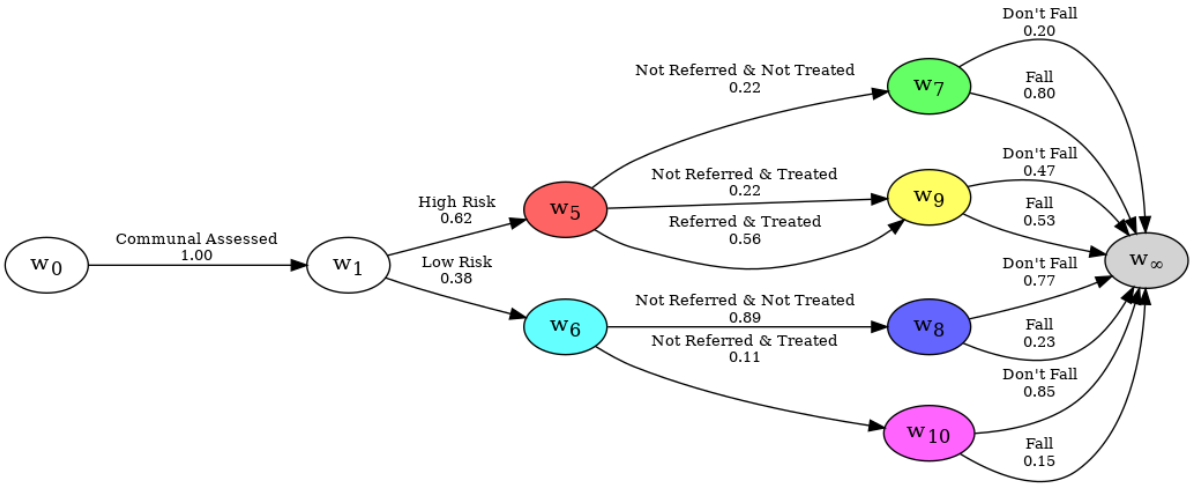


When you would like to adjust the graph to only show paths which pass through a specific edge or node, `certain` evidence is used.

Take the following example. You'd like to see what might have happened to an individual who was `Communal Assessed`. This can be done by using the `add_certain_edge` method.

```
reducer.clear_all_evidence()

reducer.add_certain_edge("w0", "w1", "Communal Assessed")
# or reducer.add_certain_node("w1")
reducer.graph.create_figure()
```



CHAPTER

FOUR

HOW TO MAKE VISUAL CHANGES TO THE GRAPHS?

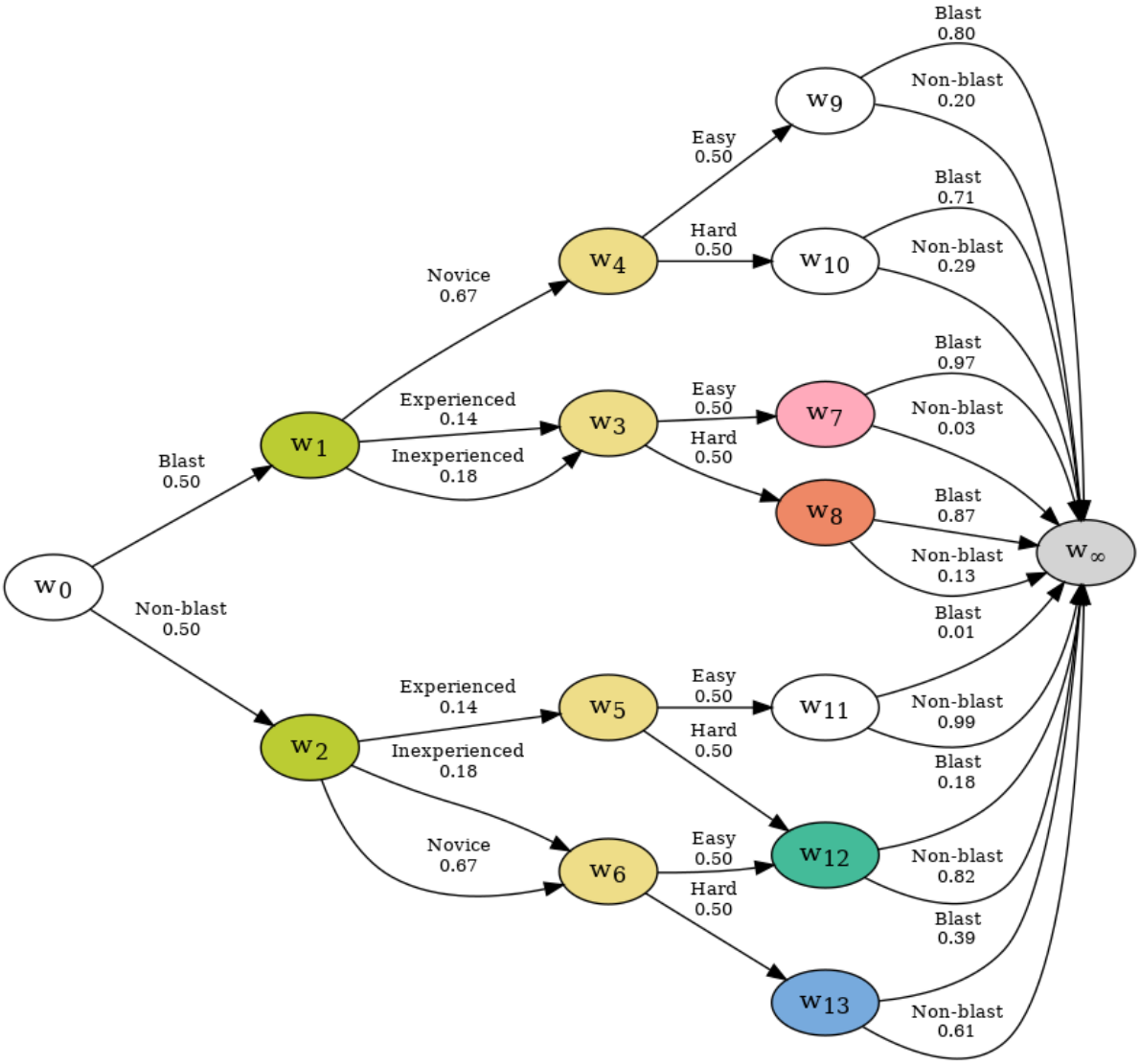
4.1 Changing the colour palette

By default, the colours of the nodes in `cegpy` are selected uniformly at random from the entire spectrum of colours. If we want to use a specific colour palette, a list of colours to be used by the AHC algorithm can be specified as a parameter when calling the `create_AHC_transitions` method, for example:

```
from cegpy import StagedTree, ChainEventGraph
import pandas as pd

df = pd.read_excel('../../data/medical_dm_modified.xlsx')

st = StagedTree(df)
colours = ['#BBCC33','#77AADD','#EE8866','#EEDD88','#FFAABB','#44BB99']
st.calculate_AHC_transitions(colour_list=colours)
ceg = ChainEventGraph(st)
ceg.create_figure()
```



4.2 Modifying graph, node, and edge attributes

The graphs in `cegpy` are built with `GraphViz` and `PyDotPlus`. We can access the underlying `pydotplus.graphviz.Dot` object by accessing the `dot_graph property`. This enables visual modifications of our event tree, staged tree, or CEG. For example, the following code modifies the distance between the nodes, changes the style of each edge labelled `"Hard"` from solid to dashed, and changes the shape of the root node from oval to square.

```
from IPython.display import Image

g = ceg.dot_graph()
g.set('ranksep', 0.1)
g.set('nodesep', 0.2)

for edge in g.get_edge_list():
    if "Hard" in edge.get("label"):
        edge.set_style('dashed')
```

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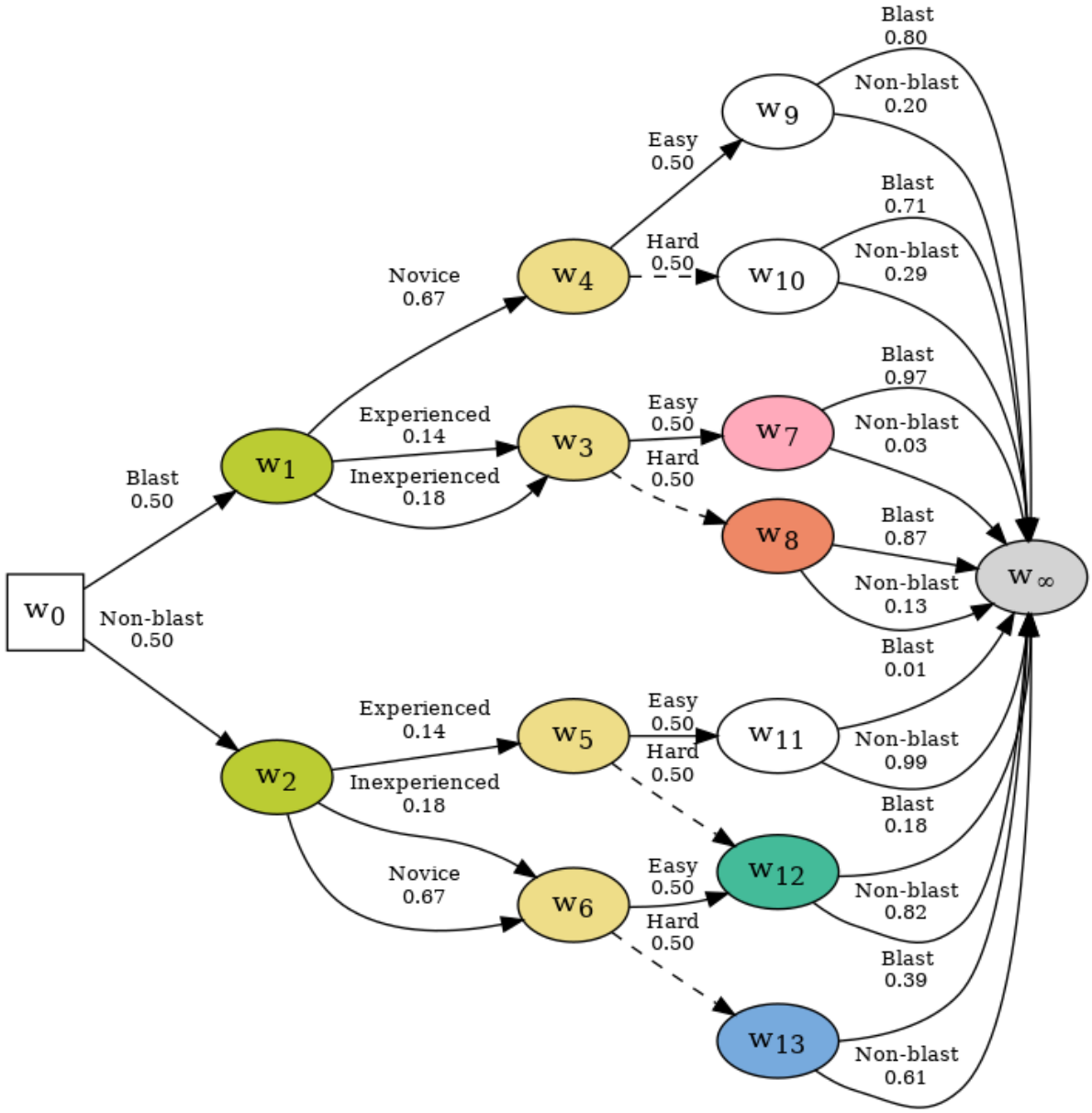
```
g.get_node('w0')[-1].set_shape('square')

Image(g.create_png())
```



For more information about the available graph, node, and edge attributes refer to the GraphViz and PyDotPlus documentation.

Part II

API

CHAPTER

FIVE

EVENTTREE

class cegpy.**EventTree**(*dataframe: DataFrame*, *sampling_zero_paths=None*, *var_order=None*, *struct_missing_label=None*, *missing_label=None*, *complete_case=False*)

Bases: `MultiDiGraph`

This class extends the NetworkX MultiDiGraph class to allow the creation of event tree representations of data.

Parameters

- **dataframe** (*pandas.DataFrame*) – Required - DataFrame containing variables as column headers, with event name strings in each cell. These event names will be used to create the edges of the event tree. Counts of each event will be extracted and attached to each edge.
- **sampling_zero_paths** (*List[Tuple[str]] or None*) – Optional - Paths to sampling zeros.

  Format is as follows: [('edge_1',), ('edge_1', 'edge_2'), …]

  If no paths are specified, default setting is that no sampling zero paths are created.
- **var_order** (*List[str] or None*) – Optional - Specifies the ordering of variables to be adopted in the event tree. Default var_order is obtained from the order of columns in dataframe. String labels in the list should match the column names in dataframe.
- **struct_missing_label** (*str or None*) – Optional - Label in the dataframe for observations which are structurally missing; e.g: Post operative health status is irrelevant for a dead patient. Label example: "struct".
- **missing_label** (*str or None*) – Optional - Label in the dataframe for observations which are missing values that are not structurally missing. e.g: Missing height for some individuals in the sample. Label example: "miss" Whatever label is provided will be renamed in the event tree to "missing".
- **complete_case** (*bool*) – Optional - If True, all entries (rows) with non-structural missing values are removed. Default setting: False.

property root: str

Returns
The name of the root node of the event tree, currently hard coded to 's0'.

Return type
str

property variables: List

Returns
The column headers of the dataset.

Return type
List[str]

property sampling_zeros: Optional[List[Tuple[str]]]

Setting this property will apply sampling zero paths to the tree. If different to previous value, the event tree will be regenerated.

Returns
Sampling zero paths provided by the user.

Return type
List[Tuple[str]] or None

property situations: List[str]

Returns
The situations of the tree (non-leaf nodes).

Return type
List[str]

property leaves: List[str]

Returns
The leaves of the tree.

Return type
List[str]

property edge_counts: Dict

The counts along edges all edges in the tree, where edges are a Tuple like so: ("source_node", "destination_node", "edge_label").

Returns
A mapping of edges to their counts.

Return type
Dict[Tuple[str], Int]

property categories_per_variable: Dict

The number of unique categories/levels for each variable (column headings in dataframe).

Returns
A mapping of variables to the number of unique categories/levels.

Return type
Dict[str, Int]

dot_graph(*edge_info: str = 'count'*) → Dot

Returns Dot graph representation of the event tree. :param edge_info: Optional - Chooses which summary measure to be displayed on edges. In event trees, only "count" can be displayed, so this can be omitted.

Returns
A graphviz Dot representation of the graph.

Return type
pydotplus.Dot

create_figure(*filename=None*, *edge_info: str = 'count'*) → Optional[Image]

Creates event tree from the dataframe.

Parameters

- **filename** (*str*) – Optional - When provided, file is saved to the filename, local to the current working directory. e.g. if filename = "output/event_tree.svg", the file will be saved to: cwd/output/event_tree.svg Otherwise, if function is called inside an interactive notebook, image will be displayed in the notebook, even if filename is omitted. Supports any filetype that graphviz supports. e.g: "event_tree.png" or "event_tree.svg" etc.
- **edge_info** (*str*) – Optional - Chooses which summary measure to be displayed on edges. In event trees, only "count" can be displayed, so this can be omitted.

Returns
The event tree Image object.

Return type
IPython.display.Image or None

CHAPTER

SIX

STAGEDTREE

class cegpy.**StagedTree**(*dataframe*, *sampling_zero_paths=None*, *var_order=None*, *struct_missing_label=None*, *missing_label=None*, *complete_case=False*)

Bases: *EventTree*

Representation of a Staged Tree.

A staged tree is a tree where each node is a situation, and each edge is a transition from one situation to another. Each situation is given a 'stage' which groups it with other situations which have the same outgoing edges, with equivalent probabilities of occurring.

The class is an extension of EventTree.

Parameters

- **dataframe** (*pandas.DataFrame*) – Required - DataFrame containing variables as column headers, with event name strings in each cell. These event names will be used to create the edges of the event tree. Counts of each event will be extracted and attached to each edge.
- **sampling_zero_paths** (*List[Tuple[str]] or None*) – Optional - Paths to sampling zeros.

  Format is as follows: [('edge_1',), ('edge_1', 'edge_2'), …]

  If no paths are specified, default setting is that no sampling zero paths are created.
- **var_order** (*List[str] or None*) – Optional - Specifies the ordering of variables to be adopted in the event tree. Default var_order is obtained from the order of columns in dataframe. String labels in the list should match the column names in dataframe.
- **struct_missing_label** (*str or None*) – Optional - Label in the dataframe for observations which are structurally missing; e.g: Post operative health status is irrelevant for a dead patient. Label example: "struct".
- **missing_label** (*str or None*) – Optional - Label in the dataframe for observations which are missing values that are not structurally missing. e.g: Missing height for some individuals in the sample. Label example: "miss" Whatever label is provided will be renamed in the event tree to "missing".
- **complete_case** (*bool*) – Optional - If True, all entries (rows) with non-structural missing values are removed. Default setting: False.

property prior: Dict[Tuple[str], List[Fraction]]

A mapping of priors keyed by edge. Keys are 3-tuples of the form: (src, dst, edge_label).

Returns

A mapping edge -> priors.

Return type
Dict[Tuple[str], List[Fraction]]

property prior_list: List[List[Fraction]]

Returns
Priors in the form of a list of lists.

Return type
List[List[Fraction]]

property posterior: Dict[Tuple[str], List[Fraction]]

Posteriors along each edge, calculated by adding edge count to the prior for each edge. Keys are 3-tuples of the form: (src, dst, edge_label).

Returns
Mapping of edge -> edge_count + prior

Return type
Dict[Tuple[str], List[Fraction]]

property posterior_list: List[List[Fraction]]

Returns
Posteriors in the form of a list of lists.

Return type
List[List[Fraction]]

property alpha: float

The equivalent sample size set for the root node which is then uniformly propagated through the tree.

Returns
The value of Alpha.

Return type
float

property hyperstage: List[List[str]]

Indication of which nodes are allowed to be in the same stage. Each list is a list of node names e.g. "s0".

Returns
The List of all hyperstages.

Return type
List[List[str]]

property edge_countset: List[List]

Indexed the same as situations. :return: Edge counts emination from each node of the tree. :rtype: List[List]

property ahc_output: Dict

Contains a List of Lists containing all the situations that were merged, and the log likelihood.

Returns
The output from the AHC algorithm.

Return type
Dict

calculate_AHC_transitions(*prior=None*, *alpha=None*, *hyperstage=None*, *colour_list=None*) → Dict

Bayesian Agglommerative Hierarchical Clustering algorithm implementation. It returns a list of lists of the situations which have been merged together, the likelihood of the final model.

Parameters

- **prior** (*Dict[Tuple[str], List[Fraction]]*) – Optional - A mapping of priors keyed by edge. Keys are 3-tuples of the form: (src, dst, edge_label).
- **alpha** (*float*) – Optional - The equivalent sample size set for the root node which is then uniformly propagated through the tree.
- **hyperstage** (*List[List[str]]*) – Optional - Indication of which nodes are allowed to be in the same stage. Each list is a list of node names e.g. "s0".
- **colour_list** (*List[str]*) – Optional - a list of hex colours to be used for stages. Otherwise, colours evenly spaced around the colour spectrum are used.

Returns
The output from the AHC algorithm, specified above.

Return type
Dict

dot_graph (*edge_info: str = 'count'*, *staged: bool = True*)

Returns Dot graph representation of the staged tree.

Parameters

- **edge_info** (*str*) – Optional - Chooses which summary measure to be displayed on edges. Defaults to "count". Options: ["count", "prior", "posterior", "probability"]
- **staged** (*bool*) – if True, returns the coloured staged tree, if False, returns the underlying event tree.

Returns
A graphviz Dot representation of the graph.

Return type
pydotplus.Dot

create_figure (*filename: Optional[str] = None*, *edge_info: str = 'count'*, *staged: bool = True*) → Optional[Image]

Draws the coloured staged tree or the underlying event tree for the process described by the dataset.

Parameters

- **filename** (*str*) – Optional - When provided, file is saved to the filename, local to the current working directory. e.g. if filename = "output/event_tree.svg", the file will be saved to: cwd/output/staged_tree.svg Otherwise, if function is called inside an interactive notebook, image will be displayed in the notebook, even if filename is omitted.

  Supports any filetype that graphviz supports. e.g: "staged_tree.png" or "staged_tree.svg" etc.
- **edge_info** (*str*) – Optional - Chooses which summary measure to be displayed on edges. In event trees, only "count" can be displayed, so this can be omitted.
- **staged** (*bool*) – if True, returns the coloured staged tree, if False, returns the underlying event tree.

Returns
The event tree Image object.

Return type
IPython.display.Image or None

CHAPTER

SEVEN

CHAINEVENTGRAPH

class cegpy.**ChainEventGraph**(*staged_tree: Optional[StagedTree] = None*, *node_prefix: str = 'w'*, *generate: bool = True*)

Bases: `MultiDiGraph`

Representation of a Chain Event Graph.

A Chain Event Graph reduces a staged tree.

The class is an extension of NetworkX MultiDiGraph.

Parameters

- **staged_tree** (`StagedTree`) – A staged tree object where the stages have been calculated.
- **node_prefix** (*str*) – The prefix that is used for the nodes in the Chain Event Graph. Default = "w"
- **generate** (*bool*) – Automatically generate the Chain Event Graph upon creation of the object. Default = True.

property sink: str

Returns
Sink node name

Return type
str

property root: str

Returns
Root node name

Return type
str

property stages: Mapping[str, Set[str]]

Returns
Mapping of stages to constituent nodes.

Return type
Mapping[str, Set[str]]

property path_list: List[List[Tuple[str]]]

Returns
All the paths through the CEG, as a list of lists of edge tuples.

Return type
List[List[Tuple[str]]]

generate() → None

Identifies the positions i.e. the nodes of the CEG and the edges of the CEG along with their edge labels and edge counts. Here we use the algorithm from our paper with the optimal stopping time.

dot_graph(*edge_info: str = 'probability'*) → Dot

Returns Dot graph representation of the CEG. :param edge_info: Optional - Chooses which summary measure to be displayed on edges. Defaults to "count". Options: ["count", "prior", "posterior", "probability"]

Returns
A graphviz Dot representation of the graph.

Return type
pydotplus.Dot

create_figure(*filename=None*, *edge_info: str = 'probability'*) → Optional[Image]

Draws the coloured chain event graph for the staged_tree.

Parameters

- **filename** (*str*) – Optional - When provided, file is saved to the filename, local to the current working directory. e.g. if filename = "output/ceg.svg", the file will be saved to: cwd/output/ceg.svg Otherwise, if function is called inside an interactive notebook, image will be displayed in the notebook, even if filename is omitted.

  Supports any filetype that graphviz supports. e.g: "ceg.png" or "ceg.svg" etc.

- **edge_info** (*str*) – Optional - Chooses which summary measure to be displayed on edges. Value can take: "count", "prior", "posterior", "probability"

Returns
The event tree Image object.

Return type
IPython.display.Image or None

CHAPTER

EIGHT

CHAINEVENTGRAPHREDUCER

class cegpy.**ChainEventGraphReducer**(*ceg:* ChainEventGraph)

Bases: object

Reduces Chain Event Graphs given certain and/or uncertain evidence.

Parameters
ceg (ChainEventGraph) – Chain event graph object to reduce.

property certain_edges: List[Tuple[str]]

Returns
A list of all edges of the ChainEventGraph that have been observed.

certain_edges is a list of edge tuples of the form: *[edge_1, edge_2, … edge_n]*

Each edge tuple takes the form: *("source_node_name", "destination_node_name", "edge_label")*

property uncertain_edges: List[Tuple[str]]

Returns
A list of sets of edges of the ChainEventGraph which might have occurred.

uncertain_edges is a list of sets of edge tuples of the form: *[{(a, b, label), (a, c, label)}, {(x, y, label), (x, z, label)}]*

Each edge tuple takes the form: *("source_node_name", "destination_node_name", "edge_label")*

property certain_nodes: Set[str]

Returns
A set of all nodes of the ChainEventGraph that have been observed.

certain_nodes is a set of nodes of the form: *{"node_1", "node_2", "node_3", … "node_n"}*

property uncertain_nodes: List[Set[str]]

Returns
A list of sets of nodes of the ChainEventGraph where there is uncertainty which of the nodes in each set happened.

uncertain_nodes is a list of sets of nodes of the form: *[{"node_1", "node_2"}, {"node_3", "node_4"}, …]*

property paths: List[List[Tuple[str]]]

Returns
A list of all paths through the reduced ChainEventGraph.

property graph: *ChainEventGraph*

Returns
The reduced graph once all evidence has been taken into account.

Return type
ChainEventGraph

clear_all_evidence() → None
Resets the evidence provided.

add_certain_edge(*src: str*, *dst: str*, *label: str*) → None
Specify an edge that has been observed.

Parameters

- **src** (*str*) – Edge source node label
- **dst** (*str*) – Edge destination node label
- **label** (*str*) – Label of certain edge

remove_certain_edge(*src: str*, *dst: str*, *label: str*) → None
Specify an edge to remove from the certain edges.

Parameters

- **src** (*str*) – Edge source node label
- **dst** (*str*) – Edge destination node label
- **label** (*str*) – Label of certain edge

add_certain_edge_list(*edges: List[Tuple[str]]*) → None
Specify a list of edges that have all been observed.

Parameters
edges (*List[Tuple[str]]*) – List of edge tuples of the form (“src”, “dst”, “label”)

remove_certain_edge_list(*edges: List[Tuple[str]]*) → None
Specify a list of edges that in the certain edge list to remove.

Parameters
edges (*List[Tuple[str]]*) – List of edge tuples of the form (“src”, “dst”, “label”)

add_uncertain_edge_set(*edge_set: Set[Tuple[str]]*) → None
Specify a set of edges where one of the edges has occurred, but you are uncertain of which one it is.

Parameters
edge_set (*Set[Tuple[str]]*) – Set of edge tuples of the form (“src”, “dst”, “label”)

remove_uncertain_edge_set(*edge_set: Set[Tuple[str]]*) → None
Specify a set of edges to remove from the uncertain edges.

Parameters
edge_set (*Set[Tuple[str]]*) – Set of edge tuples of the form (“src”, “dst”, “label”)

add_uncertain_edge_set_list(*edge_sets: List[Set[Tuple[str]]]*) → None
Specify a list of sets of edges where one of the edges has occurred, but you are uncertain of which one it is.

Parameters
edge_set (*List[Set[Tuple[str]]]*) – List of sets of edge tuples of the form (“src”, “dst”, “label”)

remove_uncertain_edge_set_list (*edge_sets: List[Set[Tuple[str]]]*) → None

Specify a list of sets of edges to remove from the evidence list.

Parameters
edge_set (*List[Set[Tuple[str]]]*) – List of sets of edge tuples of the form ("src", "dst", "label")

add_certain_node (*node: str*) → None

Specify a node in the graph that has been observed.

Parameters
node (*str*) – A node label e.g. "w4"

remove_certain_node (*node: str*) → None

Specify a node to be removed from the certain nodes list.

Parameters
node (*str*) – A node label e.g. "w4"

add_certain_node_set (*nodes: Set[str]*) → None

Specify a set of nodes that have been observed.

Parameters
nodes (*Set[str]*) – A set of node labels e.g. {"w4", "w8"}

remove_certain_node_set (*nodes: Set[str]*) → None

Specify a list of nodes to remove from the list of nodes that have been observed.

Parameters
nodes (*Set[str]*) – A set of node labels e.g. {"w4", "w8"}

add_uncertain_node_set (*node_set: Set[str]*) → None

Specify a set of nodes where one of the nodes has occurred, but you are uncertain of which one it is.

Parameters
nodes (*Set[str]*) – A set of node labels e.g. {"w4", "w8"}

remove_uncertain_node_set (*node_set: Set[str]*) → None

Specify a set of nodes to be removed from the uncertain nodes set list.

Parameters
nodes (*Set[str]*) – A set of node labels e.g. {"w4", "w8"}

add_uncertain_node_set_list (*node_sets: List[Set[str]]*) → None

Specify a list of sets of nodes where in each set, one of the nodes has occurred, but you are uncertain of which one it is.

Parameters
nodes (*List[Set[str]]*) – A collection of sets of uncertain nodes.

remove_uncertain_node_set_list (*node_sets: List[Set[str]]*) → None

Specify a list of sets nodes to remove from the list of uncertain sets of nodes.

Parameters
nodes (*List[Set[str]]*) – A collection of sets of uncertain nodes.

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