

WHAT: This notebook runs effect estimation using the CausalModule from CausalModule.py. It is meant to serve as a reference.

WHY: A straightforward script that compiles all the necessary steps to run effect estimation.

ASSUMES: Nothing; the entire pipeline is compiled for reference

FUTURE IMPROVEMENTS: Allowing for command line arguments to specify the necessary parameters

VARIABLES: - data: Pandas DataFrame containing the dataset.

- discovery_algorithm: Causal discovery algorithm to discover the causal graph.
- treatment_variable: The variable to be treated.
- outcome_variable: The outcome variable to be measured.
- treatment_value: The value of the treatment variable for the treatment group.
- control_value: The value of the treatment variable for the control group.

WHO: S.K.S 2025/08/19

Preliminaries

I would suggest that you first suppress warnings as it alleviates some really annoying and persistent library update messages.

```
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

Data Preparation

Next, for the data preparation – I am using a synthetic dataset directly from DoWhy but you should change as needed.

Please do note the data types of the columns and also the general format.

- It is pretty important that there are no missing values
- Also, just as important, that all data is numeric
- Ensure that the column data types are correct; in the scenario where a variable is discrete ensure that the dtype is [int]

```
import dowhy.datasets
dataset = dowhy.datasets.linear_dataset(beta=10,
    num_common_causes=5,
    num_instruments = 2,
    num_treatments=1,
    num_samples=10000,
    treatment_is_binary=True,
```

```

        outcome_is_binary=True,
        stddev_treatment_noise=10)
data = dataset['df']

print("setting the treatment and outcome variable dtypes to be of type
integer...")
data['v0'] = data['v0'].astype(int)
data['y'] = data['y'].astype(int)

print("=====")

print(f"data dtypes:\n {data.dtypes}")

print("=====")

print("data preview...")
print(data.head())
print()
print(f"treatment variable: {dataset['treatment_name']}")
print(f"outcome variable: {dataset['outcome_name']}")
print("=====")
discovery_algorithm = "pc"
treatment_variable = dataset['treatment_name'][0]
outcome_variable = dataset['outcome_name'][0]
treatment_value = 1
control_value = 0

```

```

/opt/anaconda3/envs/iocp/lib/python3.11/site-packages/tqdm/auto.py:21:
TqdmWarning: IPProgress not found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
    from .autonotebook import tqdm as notebook_tqdm

```

```

setting the treatment and outcome variable dtypes to be of type integer...
=====
data dtypes:
Z0    float64
Z1    float64
W0    float64
W1    float64
W2    float64
W3    float64
W4    float64
v0     int64
y      int64
dtype: object
=====

```

```
data preview...
      Z0      Z1      W0      W1      W2      W3      W4  v0  y
0  0.0  0.744181 -0.978462  0.695354  0.808075  0.345512  2.135094  1  1
1  0.0  0.044442 -0.914150 -0.293767  0.526123  1.501304 -0.021218  0  1
2  0.0  0.234661  0.773234 -0.269556 -0.290135  0.710612 -0.463679  0  0
3  0.0  0.984151 -1.687205  0.829002  0.690670  1.967674 -1.036918  1  1
4  0.0  0.035240  0.120505 -0.435666 -0.430934  0.994293 -1.632256  0  0

treatment variable: ['v0']
outcome variable: y
=====
```

Causal Pipeline for Classification

Remember that the current state of the module [08/19/25] covers two separate causal tasks – effect estimation and classification using interventional samples.

The below is for the former task of effect estimation.

We should begin by first creating an instance of the custom CausalModule class.

```
from CausalModule import CausalModule

causal_module = CausalModule(
    data=data,
    treatment_variable=treatment_variable,
    outcome_variable=outcome_variable,
)
```

```
2025-08-21 14:52:59,662 INFO: CausalModule initialized with provided
parameters.
```

Next, let's discover a causal graph. If you already have a causal graph, you can alternatively use `input_causal_graph()` but for now let's assume that we are yet to discover the causal graph.

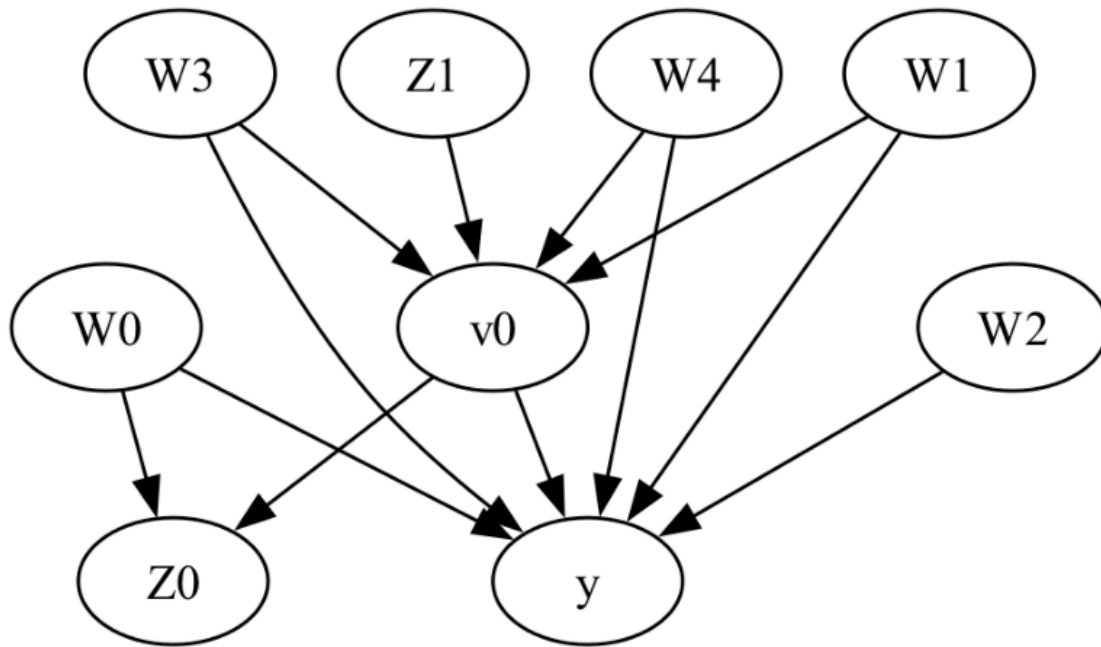
```
causal_module.find_causal_graph(algo=discovery_algorithm)
```

```
2025-08-21 14:52:59,668 INFO: Finding causal graph using pc algorithm
Depth=5, working on node 8: 100%[██████████] 9/9 [00:00<00:00, 2370.41it/s]
```

```
<networkx.classes.digraph.DiGraph at 0x163f9a110>
```

Now that we have discovered a causal graph, it might be a good idea to first see how the graph looks like.

```
causal_module.see_graph()
```



It might also be a good idea to see the graph properties.

```
causal_module.see_graph_properties()
```

```
2025-08-21 14:53:00,914 INFO: =====
2025-08-21 14:53:00,915 INFO: Number of nodes: 9
2025-08-21 14:53:00,916 INFO: =====
2025-08-21 14:53:00,916 INFO: Number of edges: 12
2025-08-21 14:53:00,917 INFO: =====
2025-08-21 14:53:00,917 INFO: Edge: Z1 -> v0, Weight: 1
2025-08-21 14:53:00,917 INFO: Edge: W0 -> Z0, Weight: 1
2025-08-21 14:53:00,918 INFO: Edge: W0 -> y, Weight: 1
2025-08-21 14:53:00,918 INFO: Edge: W1 -> v0, Weight: 1
2025-08-21 14:53:00,918 INFO: Edge: W1 -> y, Weight: 1
2025-08-21 14:53:00,919 INFO: Edge: W2 -> y, Weight: 1
2025-08-21 14:53:00,919 INFO: Edge: W3 -> v0, Weight: 1
2025-08-21 14:53:00,919 INFO: Edge: W3 -> y, Weight: 1
2025-08-21 14:53:00,919 INFO: Edge: W4 -> v0, Weight: 1
2025-08-21 14:53:00,920 INFO: Edge: W4 -> y, Weight: 1
2025-08-21 14:53:00,920 INFO: Edge: v0 -> Z0, Weight: 1
2025-08-21 14:53:00,920 INFO: Edge: v0 -> y, Weight: 1
2025-08-21 14:53:00,920 INFO: =====
2025-08-21 14:53:00,921 INFO: Paths from v0 [treatment] to y [outcome]: 1
```

```

2025-08-21 14:53:00,921 INFO: v0 -> y
2025-08-21 14:53:00,922 INFO: =====
2025-08-21 14:53:00,922 INFO: Markov blanket of v0: ['Z0', 'Z1', 'W2', 'W0',
'W4', 'W3', 'W1', 'y']
2025-08-21 14:53:00,922 INFO: Markov blanket of y: ['W2', 'W0', 'W3', 'W1',
'v0', 'W4']

```

```

{'num_nodes': 9,
 'num_edges': 12,
 'edge_weights': {'Z1->v0': 1,
 'W0->Z0': 1,
 'W0->y': 1,
 'W1->v0': 1,
 'W1->y': 1,
 'W2->y': 1,
 'W3->v0': 1,
 'W3->y': 1,
 'W4->v0': 1,
 'W4->y': 1,
 'v0->Z0': 1,
 'v0->y': 1},
 'all_paths': [['v0', 'y']],
 'treatment_mb': ['Z0', 'Z1', 'W2', 'W0', 'W4', 'W3', 'W1', 'y'],
 'outcome_mb': ['W2', 'W0', 'W3', 'W1', 'v0', 'W4']}

```

It is crucial that we validate the graph and make changes if relations in the graph don't align with the statistical relations in the data.

For now I will just test with 10 permutations to preserve time and resources. Remember that you can utilize `n_jobs` to make this run faster if needed.

```
causal_module.refute_cgm(n_perm=10)
```

```

2025-08-21 14:53:00,928 INFO: Refuting the discovered/given causal graph
Test permutations of given graph: 100%[██████████] 10/10 [00:30<00:00, 3.01s/
it]

```

```
<networkx.classes.digraph.DiGraph at 0x12d60df50>
```

We can take a look at what the graph refutation results look like.

```
causal_module.see_graph_refutation()
```

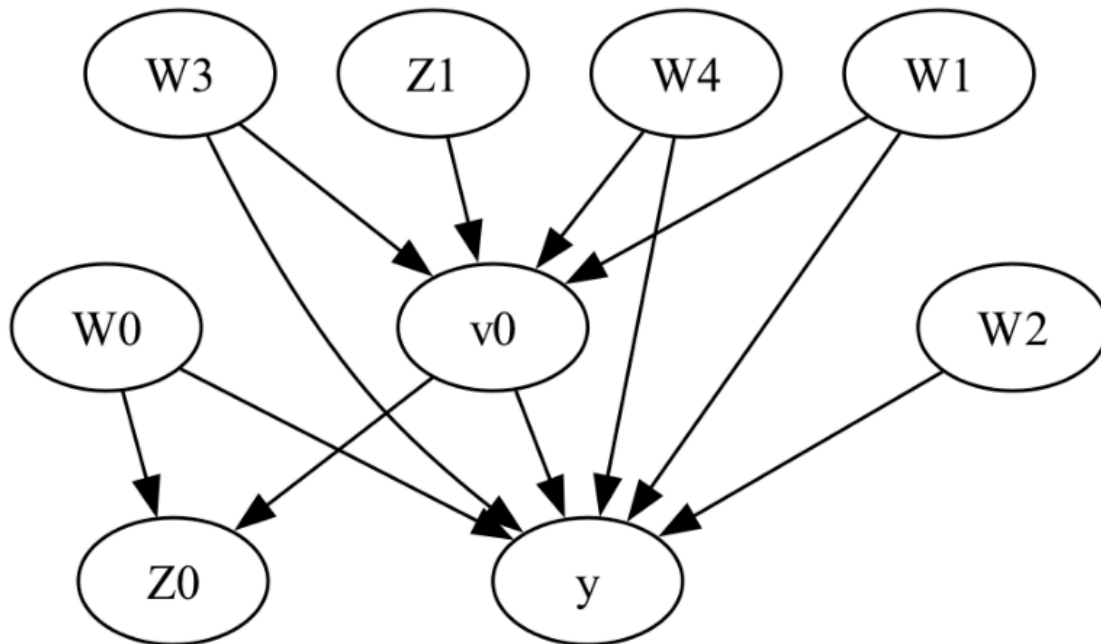
```
2025-08-21 14:53:39,940 INFO: Graph refutation metrics: TPA: 0/10 (p-value: 0.00), LMC: 8/43 (p-value: 0.00)
```

In the above graph refutation result the two fraction/p-values represent the following (respectively):

- Measure whether the LCMs implied by our graph satisfy the data. Compares the number of LCMs violated by our graph with the number of LCMs violated by a randomly permuted set of graphs.
- Check whether the graph is falsifiable. Assuming our graph is correct, how many other permuted graphs share the same number of LCM violations.

We might also want to see what the graph now looks like (since the function could have made modifications to the original graph if some relations hadn't matched with the data).

```
causal_module.see_graph()
```



Next, we should create a causal model that can be understood by DoWhy.

```
causal_module.create_model()
```

```
2025-08-21 14:53:40,176 INFO: Creating a causal model from the discovered/  
given causal graph
```

```
2025-08-21 14:53:40,178 INFO: Model to find the causal effect of treatment
['v0'] on outcome ['y']
```

```
<dowhy.causal_model.CausalModel at 0x10db7aa90>
```

Saving the module instance

Now imagine we want to save the module instance to load it back in later, how can we do this?

We need to first import some utility functions from `utilities/utils.py`

```
from utilities.utils import save_instance_to_pickle, load_instance_from_pickle
```

```
save_instance_to_pickle(instance=causal_module,
file_path='model/081925_5:30.pkl')
```

```
CausalModule instance saved to model/081925_5:30.pkl
```

Loading module instance

Now let's load back in the module instance and continue with the classification task.

```
causal_module_loaded =
load_instance_from_pickle(file_path='model/081925_5:30.pkl')
```

```
CausalModule instance loaded from model/081925_5:30.pkl
```

Estimation

We need to first identify an estimand expression (a statistical expression that encodes the relationship between the treatment and outcome)

```
causal_module_loaded.identify_effect()
```

```
2025-08-21 14:54:20,224 INFO: Identifying the effect estimand of the treatment
on the outcome variable
2025-08-21 14:54:20,228 INFO: Causal effect can be identified.
2025-08-21 14:54:20,229 INFO: Instrumental variables for treatment and
outcome:['Z1']
2025-08-21 14:54:20,231 INFO: Frontdoor variables for treatment and outcome:[]
2025-08-21 14:54:20,231 INFO: Note that you can also use other methods for the
identification process. Below are method descriptions taken directly from
DoWhy's documentation
```

```

2025-08-21 14:54:20,232 INFO: maximal-adjustment: returns the maximal set that
satisfies the backdoor criterion. This is usually the fastest way to find a
valid backdoor set, but the set may contain many superfluous variables.
2025-08-21 14:54:20,232 INFO: minimal-adjustment: returns the set with minimal
number of variables that satisfies the backdoor criterion. This may take
longer to execute, and sometimes may not return any backdoor set within the
maximum number of iterations.
2025-08-21 14:54:20,233 INFO: exhaustive-search: returns all valid backdoor
sets. This can take a while to run for large graphs.
2025-08-21 14:54:20,233 INFO: default: This is a good mix of minimal and
maximal adjustment. It starts with maximal adjustment which is usually fast.
It then runs minimal adjustment and returns the set having the smallest number
of variables.

```

```

<dowhy.causal_identifier.identified_estimand.IdentifiedEstimand at
0x164fbba50>

```

Next, we should actually use the identified estimand to estimate a causal effect between the treatment and outcome. Remember to set the control value and treatment value for the treatment variable in the parameters.

```

causal_module_loaded.estimate_effect(ctrl_val=control_value,
trtm_val=treatment_value)

```

```

2025-08-21 14:54:20,238 INFO: Estimating the effect of the treatment on the
outcome variable
2025-08-21 14:54:20,239 INFO: linear_regression
2025-08-21 14:54:20,240 INFO: INFO: Using Linear Regression Estimator
2025-08-21 14:54:20,242 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,324 INFO: INFO: The sample size: 10000
2025-08-21 14:54:20,324 INFO: INFO: The number of simulations: 399
2025-08-21 14:54:20,328 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,400 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,476 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,551 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,625 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,699 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,770 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,843 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:20,915 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:21,008 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:21,082 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:21,154 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:21,227 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:54:21,298 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 

```


[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]


```
2025-08-21 14:54:49,833 INFO: b: y~v0+W3+W1+W4+v0*W2+v0*W0
2025-08-21 14:54:49,904 INFO: Note that it is ok for your treatment to be a
continuous variable, DoWhy automatically discretizes at the backend.
```

```
<dowhy.causal_estimator.CausalEstimate at 0x164a84690>
```

Similar to graphical refutation, it is always good practice to validate the resulting estimate using robustness tests as well.

```
causal_module_loaded.refute_estimate()
```

```
2025-08-21 14:54:49,910 INFO: Refuting the estimated effect of the treatment
on the outcome variable
2025-08-21 14:54:49,912 INFO: Refutation over 100 simulated datasets of
PlaceboType.PERMUTE treatment
2025-08-21 14:54:49,918 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:49,995 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,069 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,143 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,217 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,290 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,361 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,434 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,507 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,580 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,651 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,724 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,801 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,873 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:50,946 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,018 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,092 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,167 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,241 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,313 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,384 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,459 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,532 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,604 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,699 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,771 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,843 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,916 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:51,988 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:52,059 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:52,131 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
```

[illegible]

```

2025-08-21 14:54:55,631 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:55,701 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:55,771 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:55,843 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:55,914 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:55,984 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,055 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,125 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,196 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,269 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,342 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,414 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,488 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,563 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,635 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,706 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,779 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,849 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,920 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:56,994 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:57,066 INFO: b: y~placebo+W3+W1+W4+placebo*W2+placebo*W0
2025-08-21 14:54:57,136 INFO: Making use of Bootstrap as we have more than 100
examples.

```

Note: The greater the number of examples, the more accurate are the confidence estimates

```

2025-08-21 14:54:57,137 INFO: Refutation over 100 simulated datasets, each
with a random common cause added

```

```

2025-08-21 14:54:57,141 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,214 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,284 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,357 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,442 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,531 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,603 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,676 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,761 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,835 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,909 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:57,983 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,056 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,130 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,206 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,283 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,363 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,440 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,511 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,586 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0
2025-08-21 14:54:58,661 INFO: b: y~v0+W3+W1+W4+w_random+v0*W2+v0*W0

```

[illegible]

```

2025-08-21 14:55:02,255 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,328 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,400 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,473 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,547 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,621 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,694 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,765 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,837 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,909 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:02,983 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,057 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,130 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,202 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,275 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,349 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,421 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,493 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,566 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,638 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,710 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,783 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,855 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:03,928 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,000 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,071 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,143 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,217 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,288 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,361 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,431 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + w_{\text{random}} + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,501 INFO: Making use of Bootstrap as we have more than 100
examples.

```

Note: The greater the number of examples, the more accurate are the confidence estimates

```

2025-08-21 14:55:04,501 INFO: Refutation over 0.9 simulated datasets of size
9000.0 each
2025-08-21 14:55:04,504 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,578 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,652 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,726 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,799 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,872 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:04,946 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:05,022 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:05,098 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:05,172 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 
2025-08-21 14:55:05,245 INFO: b:  $y \sim v_0 + W_3 + W_1 + W_4 + v_0 * W_2 + v_0 * W_0$ 

```

[illegible]

```

2025-08-21 14:55:08,876 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:08,950 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,025 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,099 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,172 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,249 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,323 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,398 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,473 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,546 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,622 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,721 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,796 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,872 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:09,946 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,019 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,094 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,167 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,241 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,314 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,388 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,462 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,536 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,610 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,685 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,760 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,833 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,908 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:10,982 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,058 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,133 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,207 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,280 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,354 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,428 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,505 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,580 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,656 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,730 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,805 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,878 INFO: b:  $y \sim v_0 + w_3 + w_1 + w_4 + v_0 * w_2 + v_0 * w_0$ 
2025-08-21 14:55:11,952 INFO: Making use of Bootstrap as we have more than 100
examples.

```

Note: The greater the number of examples, the more accurate are the confidence estimates

```
[<dowhy.causal_refuter.CausalRefutation at 0x160576950>,  
<dowhy.causal_refuter.CausalRefutation at 0x164af98d0>,  
<dowhy.causal_refuter.CausalRefutation at 0x16507b450>]
```

All **RELEVANT** metrics are first stored in the instance itself and can be retrieved like this.

```
causal_module_loaded.store_results()
```

```
2025-08-21 14:55:11,959 INFO: =====  
2025-08-21 14:55:11,959 INFO: Number of nodes: 9  
2025-08-21 14:55:11,960 INFO: =====  
2025-08-21 14:55:11,960 INFO: Number of edges: 12  
2025-08-21 14:55:11,960 INFO: =====  
2025-08-21 14:55:11,961 INFO: Edge: Z1 -> v0, Weight: 1  
2025-08-21 14:55:11,961 INFO: Edge: W0 -> Z0, Weight: 1  
2025-08-21 14:55:11,962 INFO: Edge: W0 -> y, Weight: 1  
2025-08-21 14:55:11,962 INFO: Edge: W1 -> v0, Weight: 1  
2025-08-21 14:55:11,963 INFO: Edge: W1 -> y, Weight: 1  
2025-08-21 14:55:11,963 INFO: Edge: W2 -> y, Weight: 1  
2025-08-21 14:55:11,964 INFO: Edge: W3 -> v0, Weight: 1  
2025-08-21 14:55:11,964 INFO: Edge: W3 -> y, Weight: 1  
2025-08-21 14:55:11,964 INFO: Edge: W4 -> v0, Weight: 1  
2025-08-21 14:55:11,965 INFO: Edge: W4 -> y, Weight: 1  
2025-08-21 14:55:11,966 INFO: Edge: v0 -> Z0, Weight: 1  
2025-08-21 14:55:11,967 INFO: Edge: v0 -> y, Weight: 1  
2025-08-21 14:55:11,967 INFO: =====  
2025-08-21 14:55:11,967 INFO: Paths from v0 [treatment] to y [outcome]: 1  
2025-08-21 14:55:11,968 INFO: v0 -> y  
2025-08-21 14:55:11,968 INFO: =====  
2025-08-21 14:55:11,968 INFO: Markov blanket of v0: ['Z0', 'Z1', 'W2', 'W0',  
'W4', 'W3', 'W1', 'y']  
2025-08-21 14:55:11,969 INFO: Markov blanket of y: ['W2', 'W0', 'W3', 'W1',  
'v0', 'W4']  
2025-08-21 14:55:11,972 INFO: Graph properties saved to outputs/results/  
graph_properties.csv  
2025-08-21 14:55:11,974 INFO: Graph refutation metrics saved to outputs/  
results/graph_refutation.csv  
2025-08-21 14:55:11,974 INFO: =====  
2025-08-21 14:55:11,974 INFO: Number of nodes: 9  
2025-08-21 14:55:11,975 INFO: =====  
2025-08-21 14:55:11,975 INFO: Number of edges: 12  
2025-08-21 14:55:11,975 INFO: =====  
2025-08-21 14:55:11,976 INFO: Edge: Z1 -> v0, Weight: 1  
2025-08-21 14:55:11,976 INFO: Edge: W0 -> Z0, Weight: 1  
2025-08-21 14:55:11,976 INFO: Edge: W0 -> y, Weight: 1  
2025-08-21 14:55:11,976 INFO: Edge: W1 -> v0, Weight: 1  
2025-08-21 14:55:11,977 INFO: Edge: W1 -> y, Weight: 1
```



```

2025-08-21 14:55:11,977 INFO: Edge: W2 -> y, Weight: 1
2025-08-21 14:55:11,977 INFO: Edge: W3 -> v0, Weight: 1
2025-08-21 14:55:11,978 INFO: Edge: W3 -> y, Weight: 1
2025-08-21 14:55:11,978 INFO: Edge: W4 -> v0, Weight: 1
2025-08-21 14:55:11,978 INFO: Edge: W4 -> y, Weight: 1
2025-08-21 14:55:11,978 INFO: Edge: v0 -> Z0, Weight: 1
2025-08-21 14:55:11,979 INFO: Edge: v0 -> y, Weight: 1
2025-08-21 14:55:11,979 INFO: =====
2025-08-21 14:55:11,979 INFO: Paths from v0 [treatment] to y [outcome]: 1
2025-08-21 14:55:11,979 INFO: v0 -> y
2025-08-21 14:55:11,980 INFO: =====
2025-08-21 14:55:11,980 INFO: Markov blanket of v0: ['Z0', 'Z1', 'W2', 'W0',
'W4', 'W3', 'W1', 'y']
2025-08-21 14:55:11,980 INFO: Markov blanket of y: ['W2', 'W0', 'W3', 'W1',
'v0', 'W4']
2025-08-21 14:55:12,011 INFO: Graph Quality Score: [[14  2]
[ 4 16]]
2025-08-21 14:55:12,011 WARNING: No node quality score to see.
2025-08-21 14:55:12,013 INFO: Graph quality score saved to outputs/results/
graph_quality_score.csv
2025-08-21 14:55:12,015 INFO: Graph quality summary saved to outputs/results/
graph_quality_summary.csv
2025-08-21 14:55:12,016 INFO: Node quality score saved to outputs/results/
node_quality_score.csv
2025-08-21 14:55:12,016 INFO: Effect estimate saved to outputs/results/
effect_estimate.csv
2025-08-21 14:55:12,018 INFO: Estimate refutation metrics saved to outputs/
results/estimate_refutation.csv
2025-08-21 14:55:12,018 WARNING: No predictions made yet. Please call
batch_classify.

```

Note the warnings in the logger in the above output – these should help navigate missing results. In our case we did not perform classification and so those results are not stored.

```
causal_module_loaded.results.keys()
```

```
dict_keys(['graph_properties', 'graph_refutation', 'node_quality_score',
'graph_quality_score', 'graph_quality_summary', 'effect_estimate',
'estimate_refutation'])
```

```
print(causal_module_loaded.results['graph_quality_score'])
```

```
[[14  2]
[ 4 16]]
```