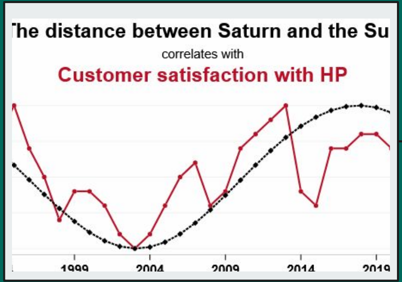
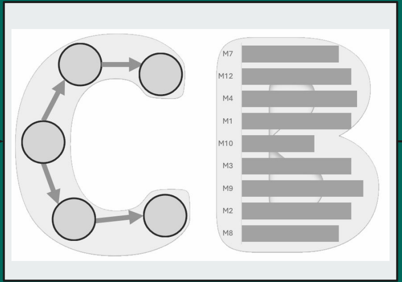
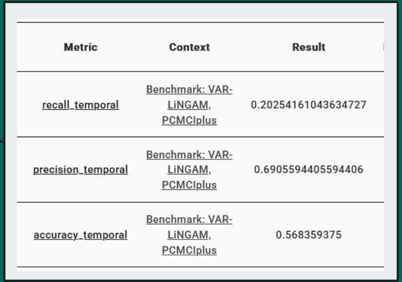
CausalBench: Causal Learning Research Streamlined Understanding Causality



Causality



CausalBench



Metric	Context	Result
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precision_temporal	Benchmark: VAR-LiNGAM, PCMCIplus	0.6905594405594406
accuracy_temporal	Benchmark: VAR-LiNGAM, PCMCIplus	0.568359375

Benchmarking

Ahmet Kapkiç
Pratanu Mandal
Abhinav Gorantla
Dr. Kasim S. Candan

tutorial.causalbench.org

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What is Causality?

Causality is the relationship between an action, event, or state (the cause) and a resulting event or state (the effect).

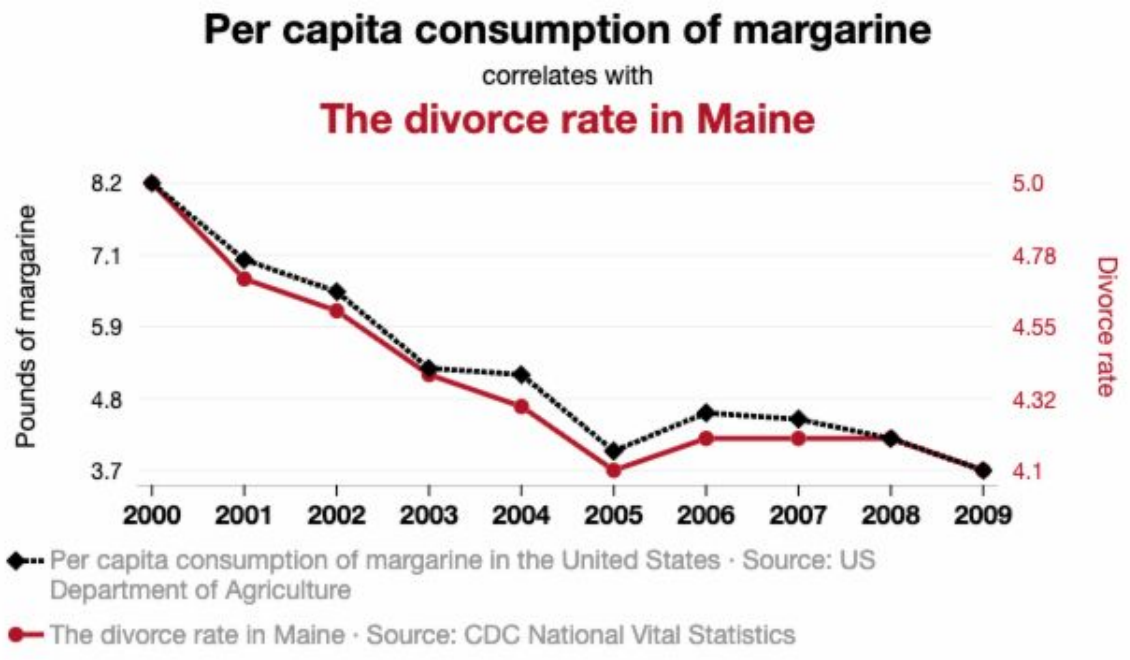
It seeks to answer the question: “Why?”

For example:

- Is rainfall the cause of river flooding?
- What’s the effect of a drug on a patient’s health
- How temperature affects crop yields?

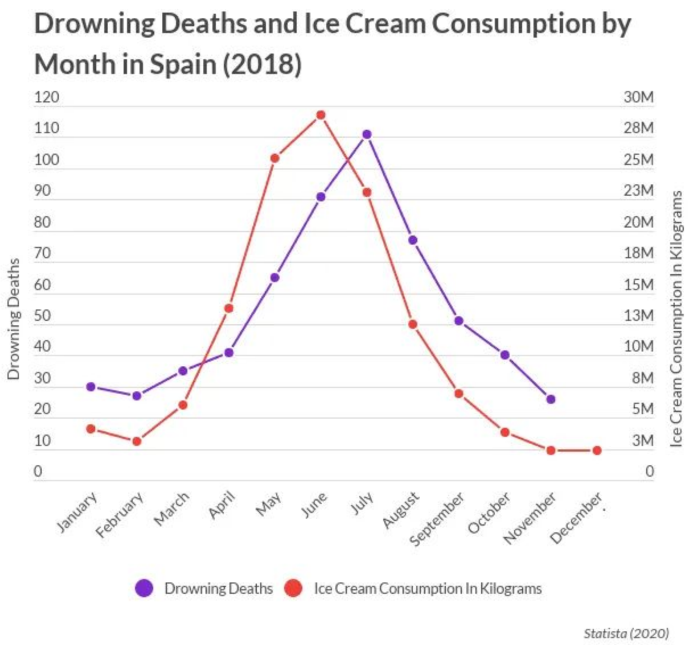
Hook: What does causality produce?

Causality: Correlation is not Causation



https://tylervigen.com/spurious/correlation/5920_per-capita-consumption-of-margarine_correlates-with_the-divorce-rate-in-maine

Ice cream causes drowning?



Ice cream causes drowning?

- A common cause: summer
- Summer is a confounding factor.
- Observational data can lead to wrong conclusions.

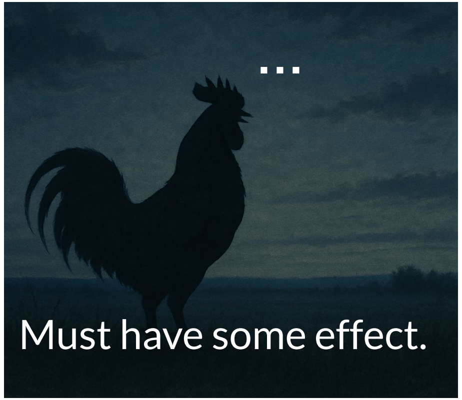
- But how can we learn causality from data?

Causality: How can we learn causality

*Post hoc ergo propter hoc

Intervention on potential cause

Observing without potential cause



Causality: the Simpson Paradox

**Same data, different understanding*

Scenario 1: "Strong"/"Weak" as Precondition

- If *Strong* and *Weak* reflect **baseline susceptibility**.
- **Use grouped data** to examine heterogeneous effects across susceptibility levels.

Scenario 2: "Strong"/"Weak" as Post-Treatment Outcomes

- If *Strong* and *Weak* reflect **response to the vaccine**, they occur after treatment.
- Use **aggregated data** to estimate the overall causal effect.

	Full Population N = 52		
	Success	***Failure***	***Success Rate***
Treatment	20	20	50%
Control	6	6	50%
	Weak, N = 20		
Treatment	8	5	38%
Control	4	3	43%
	Strong, N = 32		
Treatment	12	15	56%
Control	2	3	60%

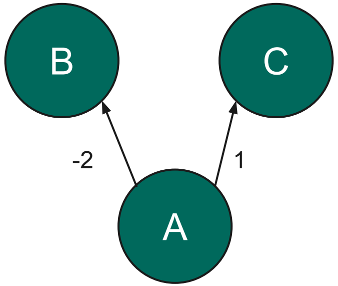
Table: Treatment is the vaccine, Success means not getting the disease. "Strong" and "Weak" refer to patient health conditions.

Causality: Causal Models

1. DAG
2. Potential Outcome
3. SCM or functional causal models (FCM)

Hook: How to explain a cause-effect knowledge to a computer?

Representation: Causal Knowledge - Models



How do we represent causal knowledge?

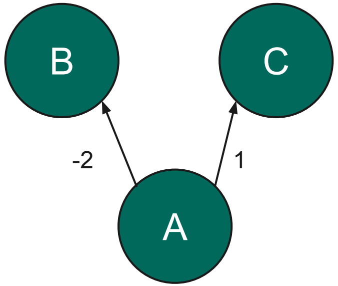
- Directional Acyclic Graphs (DAGs)
  - Variates in the Causal Model are represented as nodes in the DAG.
  - Causal Effects are represented by a directed edge from the node that *causes* the effect to the node that is affected by the cause.
- Structural Causal Matrices (SCM)[1]
  - Causal Model is represented as a set of equations.
  - A variate in a causal model is represented as a function of its parents and external, unobserved noise.
  - The causal model represented as a DAG on this slide can be represented as an SCM in the following manner:
    - B = 2*A + Ub
    - C = 1*A + Uc
    - Where, Ub and Uc are external unobserved noise on variates B and C.

[1] Pearl, J. (2009). *Causality*. Cambridge university press.

Representation: Causal Knowledge - Models

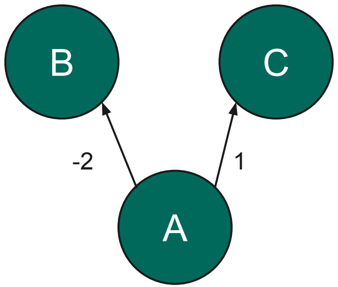
How do we represent a DAG or an SCM in a way a computer can understand?

- Adjacency matrices is one of the common ways a DAG and (linear) SCMs can be encoded.
- The DAG used as an example here can be represented as an adjacency matrix in the following manner:



$$\begin{bmatrix} 0 & -2 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Representation: Causal Knowledge - Models



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What Is Temporal Causal Discovery?

- Extracting cause–effect links from time-ordered data
- Causes must precede their effects

Core Idea:

Learn a directed graph of lagged edges where past values of X help predicting current Y

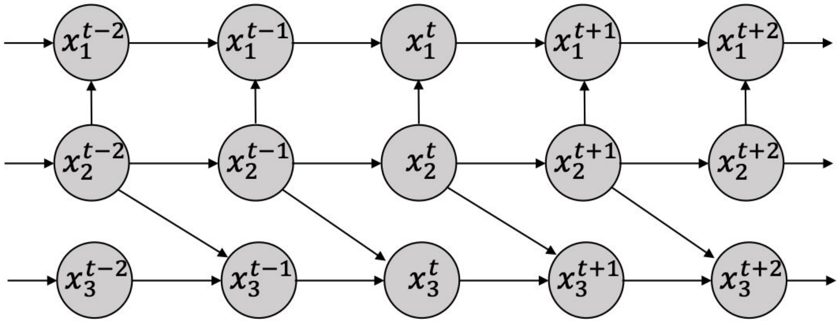
$$X_{t-T} \longrightarrow Y_t$$

Key Difference from Static Causality:

Captures time delays and feedback loops

Not just instantaneous associations

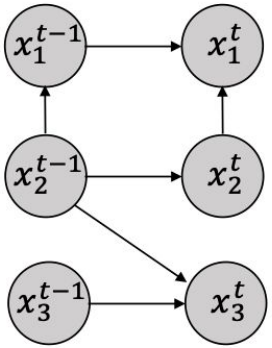
Three Types of Temporal Causal Graphs



(a) Full time causal graph

- Complete graph of dynamic system
- Usually difficult to discover due to the single observation for each series at each time point

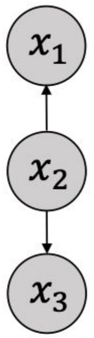
Three Types of Temporal Causal Graphs



(b) Window causal graph

- Assumes time-homogenous causal structure
- The size of window causal graph represents the maximum lag in the full-time causal graph

Three Types of Temporal Causal Graphs



(c) Summary causal graph

- Each individual time-series variable is merged into a single node to create the summary causal graph.
- Represents the causal relations among the time series without displaying any time lags.

Models: Granger Causality (VAR)

- Assumption of linear time-series dynamics
- A time series X Granger-causes Y if past values of X provide unique, significant information about future values of Y
- Learns predictive causality, not necessarily true mechanistic causation.

Hyperparameters

- Maximum lag order: Defines how many past steps will be considered
- Significance level: Threshold to decide causal vs. non-causal

Models: PCMCI[+]

- Constraint-Based method
- Combines linear or nonlinear conditional independence tests to discover the window causal graph
- Initializes by constructing a partially connected graph, where all pair of nodes (x_i^{t-k}, x_j^t) are directed as $x_i^{t-k} \rightarrow x_j^t$ if $k > 0$
- Removes all unnecessary edges based on conditional independence

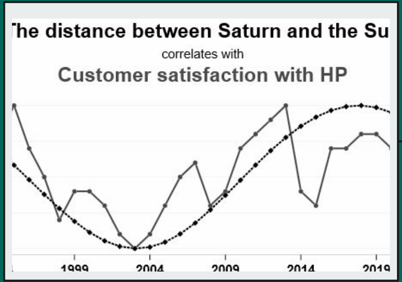
Hyperparameters

Models: Dynamic Bayesian Networks

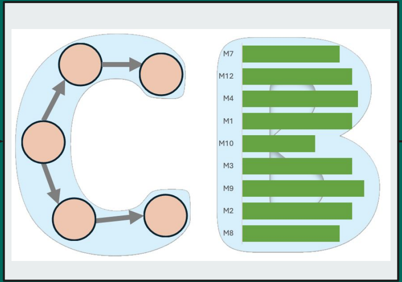
- Score-Based method
- Probabilistically scores multiple models and output the most probable one

Questions?

CausalBench: Causal Learning Research Streamlined
Understanding CausalBench



Causality



CausalBench

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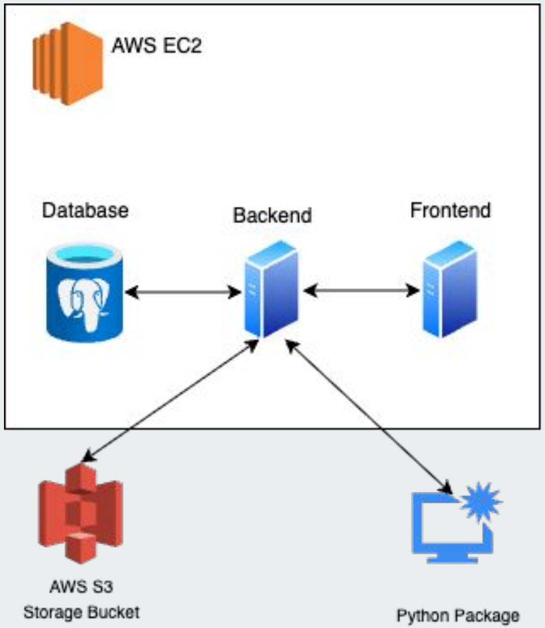
Introduction: CausalBench



- CausalBench is a benchmarking platform for Causal Learning research.
- The goals of CausalBench are:
  - Facilitating collaboration between researchers in sharing their datasets, models and metrics.
  - Enabling reproducibility of experiments.
- CausalBench allows researchers to share and publish their experimental setups and results.

Introduction: CausalBench

- Transparent experiment results. All public experiment results are published to Zenodo.
- Causal Analysis in **CausalBench** - Analyzes experiment results to determine the causal relationship between experiment parameters and results.
- Causal Recommendation in **CausalBench** - Causal Analysis results are used to recommend new experiment settings.

Components of CausalBench

docs.causalbench.org

- CausalBench contains three components:
  - Python Package
  - The Web Server: Backend + Frontend
- The python package handles the process of benchmarking.
- The web backend receives the results from the python package and publishes it to zenodo.
- The web frontend provides users with a GUI to browse benchmark runs, datasets, models, metrics and contexts already published to causalbench.org.

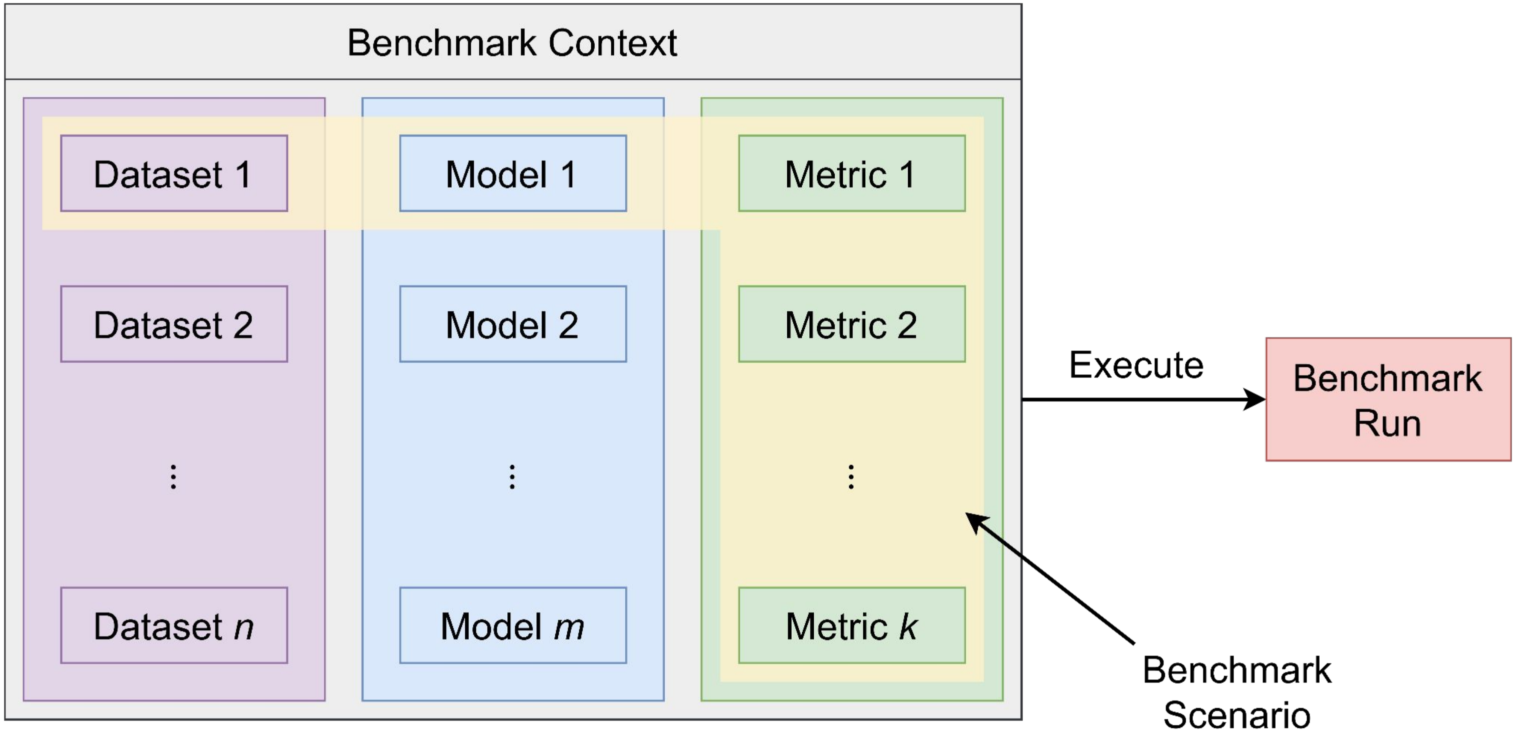
Importance of Proper Benchmarking

- It is important to properly document the experiment and hardware setup when presenting results in a technical/research document.
- Documenting the software and hardware setup makes it easier for the readers of the technical/research document to interpret the results.
- Proper documentation of experimental setup also ensures reproducibility of experiments.

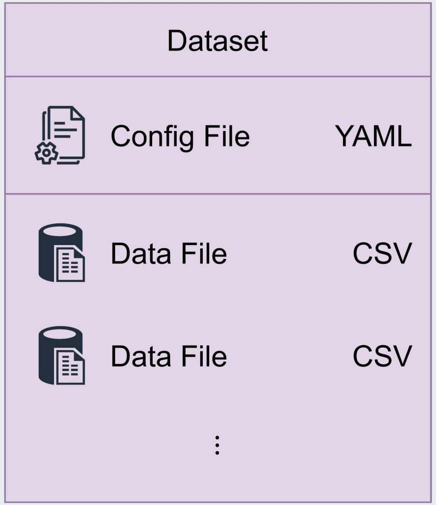
Importance of Profiling

- CausalBench automates this process of documenting the hardware and software configuration.
- Such precise benchmarking is crucial also because it is difficult to compare results from different researchers without knowing the complete context in which the experiment was performed.
- Profiling experiments gives additional insights to the researcher on how their algorithm impacts hardware usage (like memory and disk).

CausalBench: Modules



CausalBench: Modules (Dataset)



Config file:

- Metadata - name, description, and URL
- Names and metadata of data files
- Specifies structure
  - Number of rows
  - columns – number, name, data type, description
  - Index – time, space, etc.

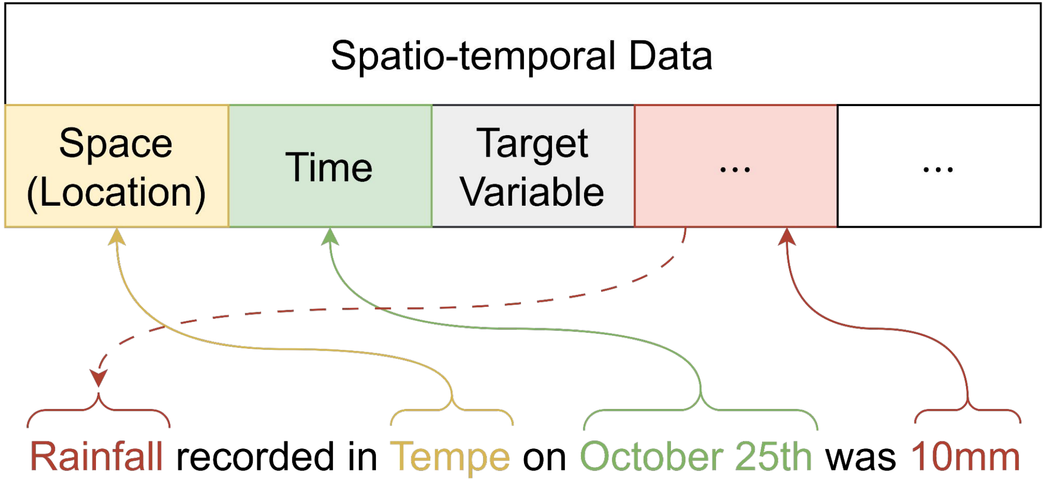
Data file:

- Tabular data
- Data formats
  - Spatio-temporal Data
  - Spatio-temporal Graph

CausalBench: Modules (Dataset) – Data Formats

Spatio-temporal Data:

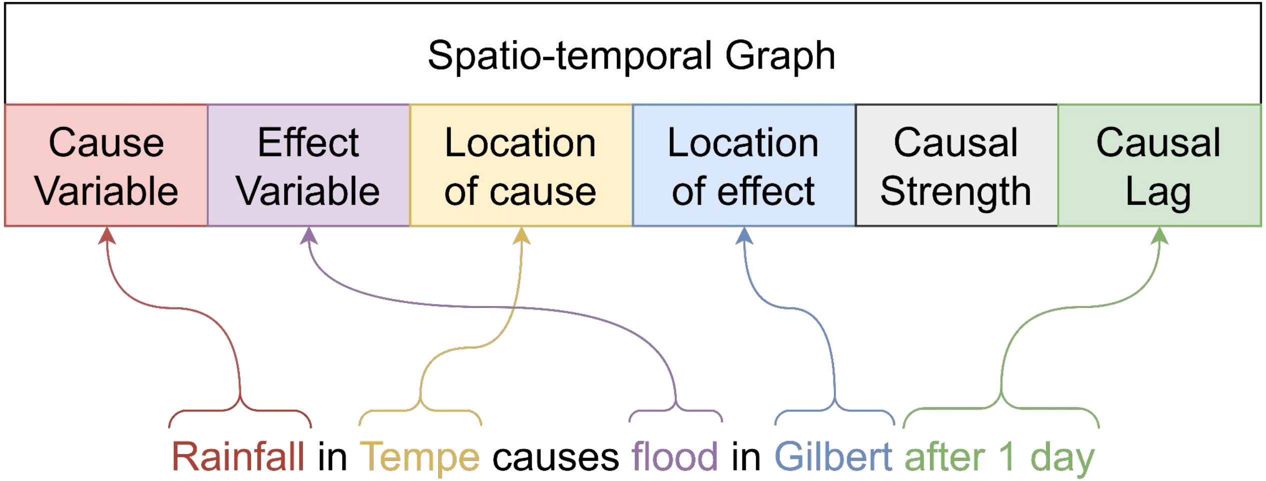
- Tabular format



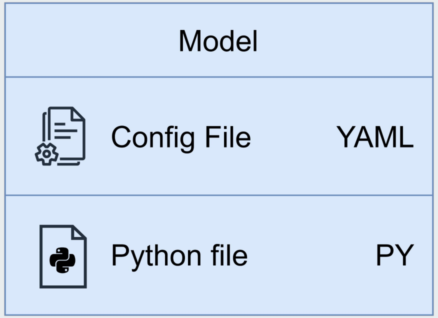
CausalBench: Modules (Dataset) – Data Formats

Spatio-temporal Graph:

- Tabular format



CausalBench: Modules (Model)



Config file:

- Metadata – name, description, and URL
- Name and metadata of python file
- Task – Causal Discovery, Causal Inference, etc.
- Hyperparameters – data type, description, and default value

Python file:

- Function to take accept inputs and provide outputs
    - Comply with function signature specified by task

CausalBench: Modules (Metric)

Metric	
Config File	YAML
Python file	PY

Config file:

- Metadata – name, description, and URL
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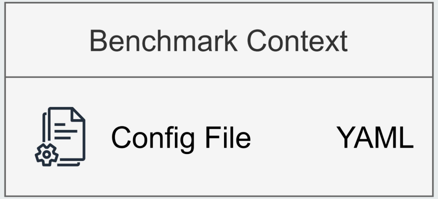
Python file:

- Function to take accept inputs and provide outputs
    - Comply with function signature specified by task

Same structure as model

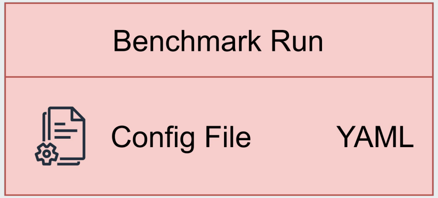
CausalBench: Modules (Benchmark Context)



Config file:

- Metadata – name, description, and URL
- Task – Causal Discovery, Causal Inference, etc.
- Datasets
  - Dataset IDs and versions
  - Data files to task mapping
- Models
  - Model IDs and versions
  - Model hyperparameters (if not using default values)
- Metrics
  - Model IDs and versions
  - Metric hyperparameters (if not using default values)

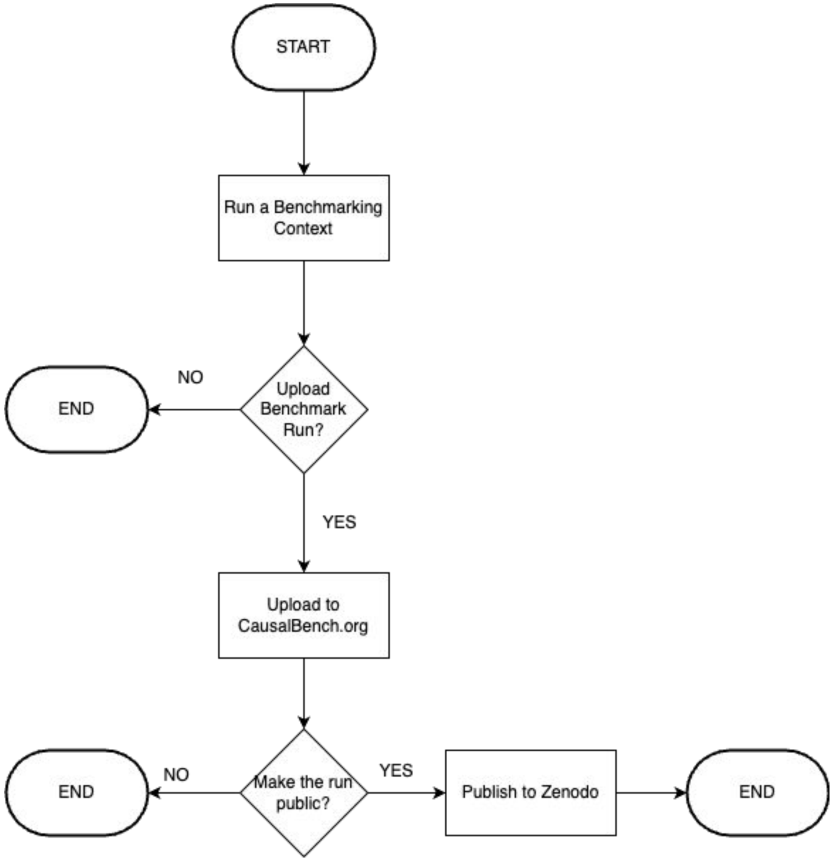
CausalBench: Modules (Benchmark Run)



Config file:

- Reference to Benchmark Context
  - Benchmark Context ID and version
- Hardware Information – Operating System, CPU, GPU, Memory, Disk
- Scenarios
  - Consists of 1 dataset, 1 model, and multiple metrics
  - Dataset
    - ID and version
  - Model and Metrics
    - IDs and versions
    - Output
    - Profiling information – Execution time, CPU used, GPU used, etc.

CausalBench Benchmarking Flow

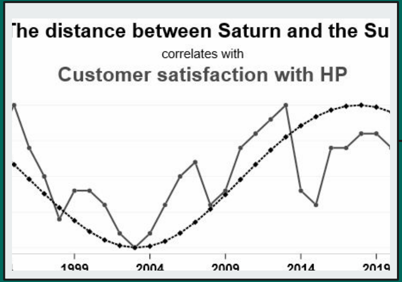


CausalBench Package Setup

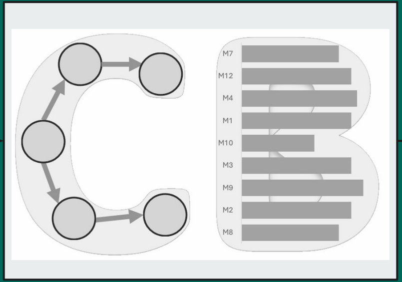
- Pre Requisites: Python (>= 3.10) and pip.
- Install CausalBench python package using "`pip install causalbench-asu`".
- To use the **CausalBench** package, you need a **CausalBench** account.
- On first use, **CausalBench** package will prompt user to input their credentials.

```
WARNING:root:Failed to initialize 'pynvml' library: NVML Shared Library Not Found
WARNING:root:Failed to import 'pyadl' library: name 'struct_AdapterInfo' is not defined
Credentials required
Email: user@gmail.com
Password:
```

CausalBench: Causal Learning Research Streamlined Hands-On Benchmarking



Causality



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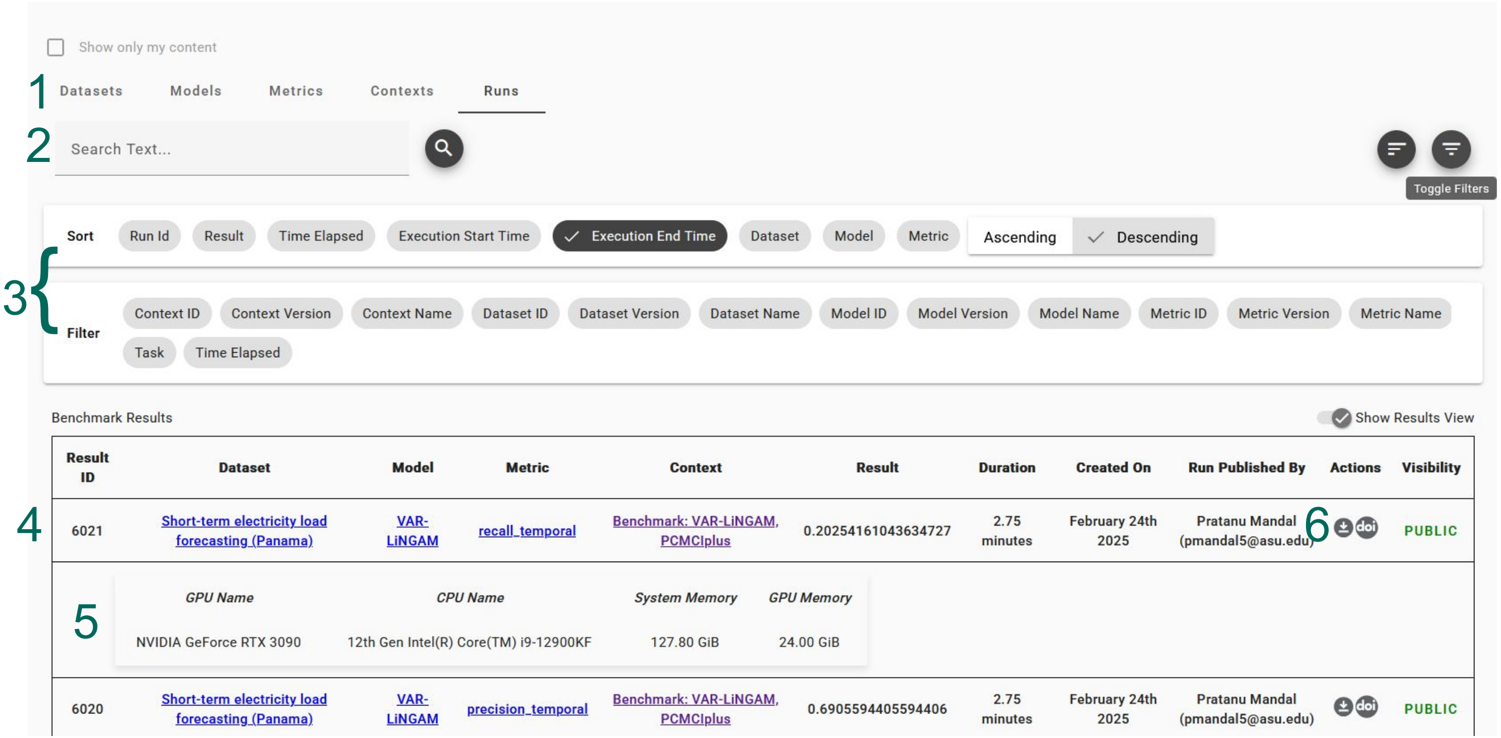
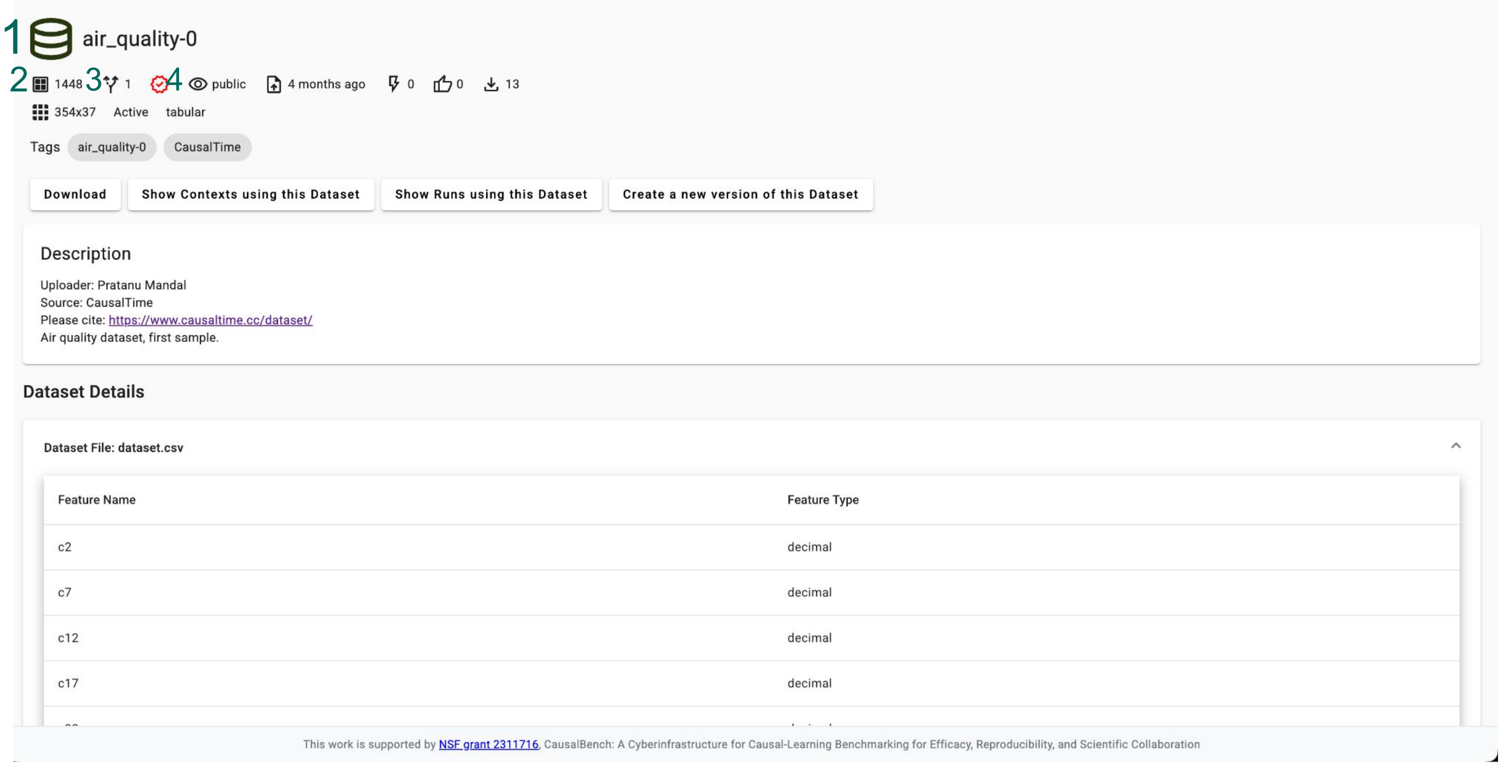
CausalBench Hands-On: Browsing Repositories



1. Repository selector
2. Search Function
3. Filter/Sort
4. Detail overview
5. On-demand details
6. Download/Cite

CausalBench Hands-On: Dataset Detail Page



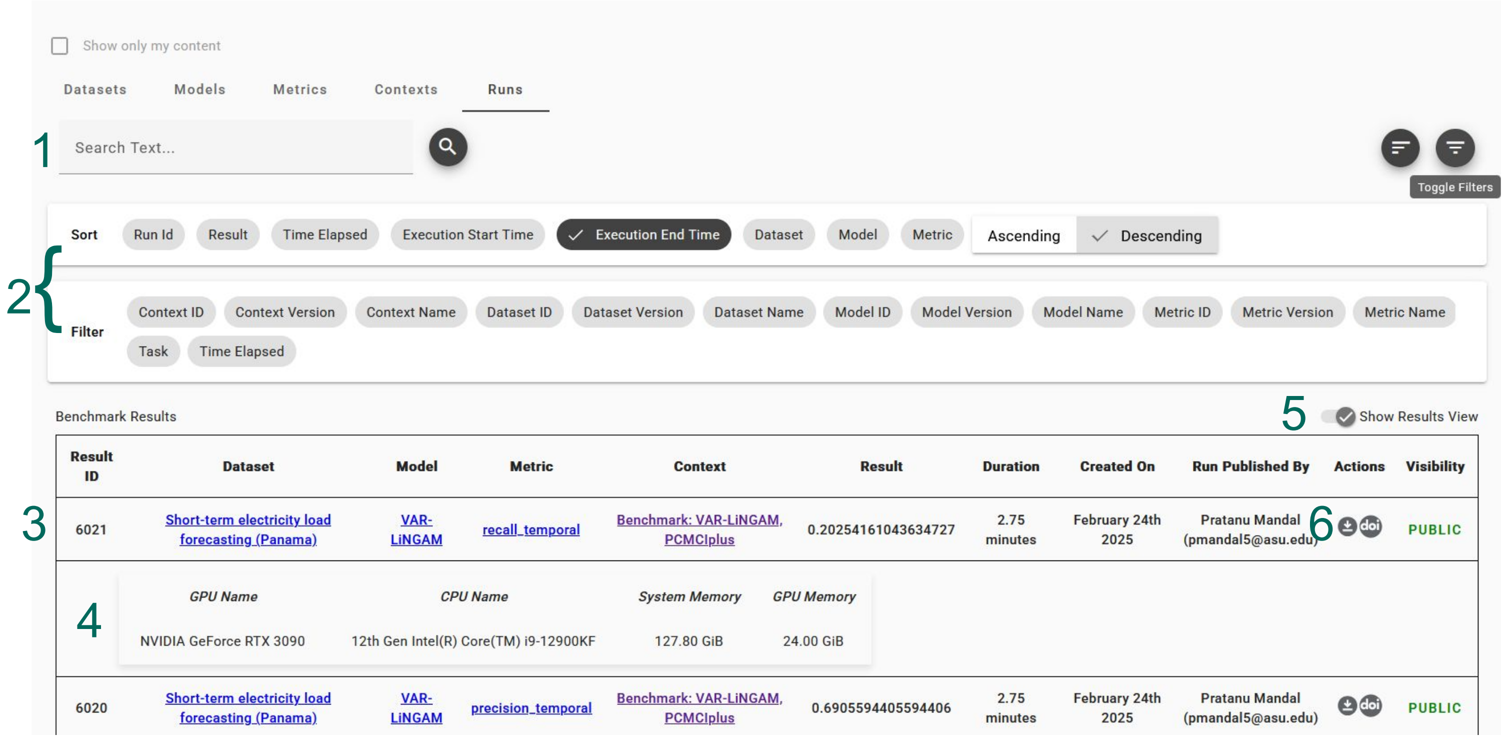
1. Dataset Name
2. Dataset ID
3. Dataset Version
4. Dataset Visibility

CausalBench Hands-On: Building a Context

```
dataset1: Dataset = Dataset(module_id=1, version=1)
```

```
context1: Context = Context.create(module_id=10,
                                  name='Context1',
                                  description='Test static context',
                                  task='discovery.static',
                                  datasets=[(dataset1, {'data': 'file1', 'ground_truth': 'file2'})],
                                  models=[model1, model2],
                                  metrics=[metric1, metric2])
```

CausalBench Hands-On: Browsing Benchmarks



1. Search function
2. Filter/Sort
3. Result overview
4. On-demand details
5. Changing result view
6. Download/Cite

Thank you!

Any questions?

CausalBench

(Product)

KDD Tutorial

(Usage)

Docs/Github

(Contribution)

Further questions? Feedbacks? Want to use CausalBench? support@causalbench.org / akapkic@asu.edu