PhysioNexus

Mapping Cause and Effect In Time-Series Physiological Data

Uncovering Causal Relationships In Time Series Data

PhysioNexus is a open source tool that transforms complex time series data into intuitive network visualizations showing cause-and-effect relationships between physiological data, environmental variables, and external load measurements.

PhysioNexus employs Granger causality and multivariate testing approaches to identify which variables are driving changes in others, revealing the directional flow of influence across physiological systems under stress.

```
# Install the package directly from GitHub
!pip install git+https://github.com/evanpeikon/PhysioNexus.git

# Import and use
from physionexus import PhysioNexus
```

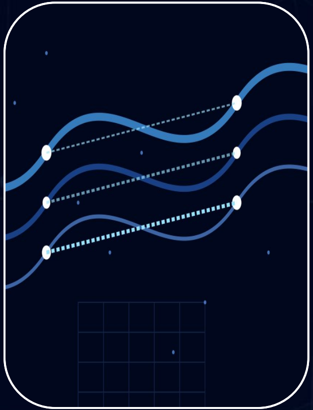
```
# Example Usage
data = pd.read_csv('Path to your CSV file', header=0)

# Run PhysioNexus directly with custom parameters
G, causal_df = PhysioNexus(
    data=data,
    exclude_cols=['Time[s]', 'Time[hh:mm:ss]'],   # Replace with your non-feature columns
    corr_threshold=0.6,                             # Correlation threshold for considering re
    f_stat_threshold=10,                            # F-statistic threshold for Granger causal
    p_value_threshold=0.05,                         # P-value threshold for statistical signif
    max_lag=3,                                      # Maximum lag to consider for Granger caus
    output_dir=None                                 # Optional output directory to store resul
)

# Display the causal relationships (if any were found)
if causal_df is not None:
    print("Found causal relationships:")
    print(causal_df)
else:
    print("No causal relationships were found meeting the specified criteria.")
```

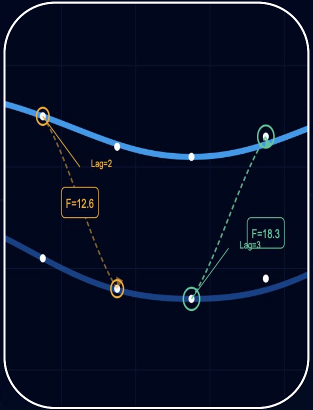
How Does PhysioNexus Work?

PhysioNexus analyzes time series data to reveal cause-and-effect relationships between biometrics like cerebral oxygenation and tissue oxygen consumption, environmental factors like altitude, and external workload. The analysis follows a systematic approach:



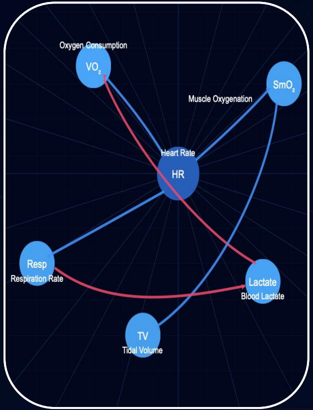
Step 1: Correlation Analysis

Calculate correlations between pairs of time series metrics.



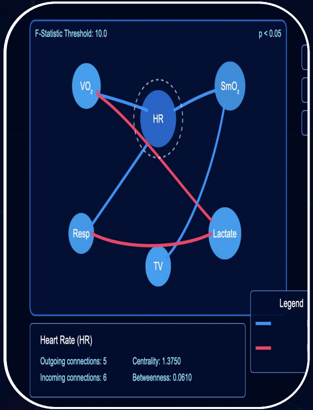
Step 2: Causality Testing

For highly correlated pairs, perform Granger causality and/or multivariate tests to determine potential causal relationships.



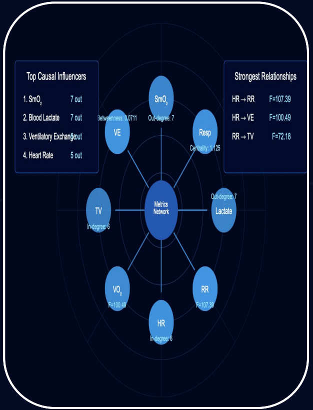
Step 3: Network Construction

Build a directed graph where nodes represent physiologic variables and edges represent causal relationships.



Step 4: Visualization

Creates an intuitive network diagram, causal matrix, and sankey plot with informative attributes.



Step 5: Metric Calculation

Calculates various network statistics to identify key influencers (hubs) and relationship structures.

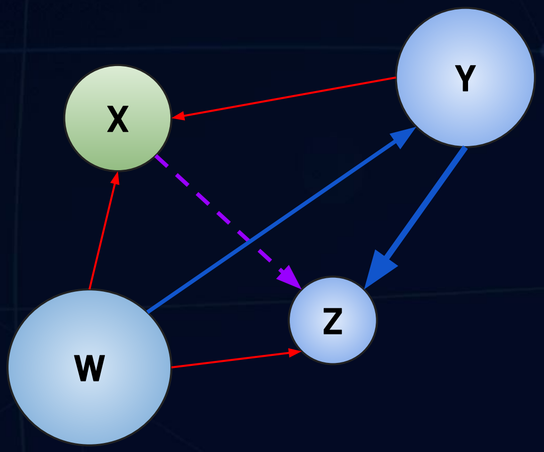
Interpreting The Network Visualization

Visual Elements and Their Meaning:

- Arrows: Direction of influence — which variables is causing changes in another
- Connection Color: Blue for positive relationship, red for negative, purple for multivariate relationships where groups of variables joint cause changes in a target variable.
- Connection Thickness: Strength of correlation.
- Node Size: Larger nodes indicate variables that influence many others

Statistical Significance:

- F-statistic <4: Weak causality, minimal predictive power
- F-statistic 4-10: Moderate evidence, meaningful relationships
- F-statistic 10-30: Strong causal evidence
- F-statistic >30: Extremely strong relationship (p << 0.001)



Understanding Network Metrics

Key Network Metrics:

- Out-Degree: How many variables a node effects
  - High out-degree variables act as system 'drivers' or control points.
- In-Degree: How many variables affect a node
  - High in-degree variables represent integration points
- Degree Centrality: Combined measure identifying the most connected variables overall
  - Highlights central parameters or 'hubs' regardless of relationship directions.
- Betweenness Centrality: Identified 'broker' variables on paths between other nodes.
  - Represent critical intermediate steps in physiological cascades.

```
Top 5 nodes by out-degree (causal influence):
SmO2: 7 outgoing connections
Blood_Lactate: 7 outgoing connections
Ventilatory_Exchange: 6 outgoing connections
HR[bpm]: 5 outgoing connections
Cerebral_O2: 5 outgoing connections

Top 5 nodes by in-degree (influenced by others):
HR[bpm]: 6 incoming connections
Tidal_Volume: 6 incoming connections
Respiration_Rate: 5 incoming connections
RR[ms]: 5 incoming connections
SmO2: 5 incoming connections

Top 5 nodes by degree centrality (overall connection importance):
SmO2: 1.5000
Blood_Lactate: 1.5000
HR[bpm]: 1.3750
Ventilatory_Exchange: 1.2500
Respiration_Rate: 1.1250

Top 5 nodes by betweenness centrality (information flow brokers):
SmO2: 0.1384
Blood_Lactate: 0.1384
Respiration_Rate: 0.0711
HR[bpm]: 0.0610
Tidal_Volume: 0.0295

Top 5 strongest causal relationships by F-statistic:
HR[bpm] → RR[ms]: F=107.39, p=0.00000, correlation=-0.922
HR[bpm] → Ventilatory_Exchange: F=100.49, p=0.00000, correlation=0.926
RR[ms] → Tidal_Volume: F=72.18, p=0.00000, correlation=-0.767
HR[bpm] → Tidal_Volume: F=69.79, p=0.00000, correlation=0.788
Ventilatory_Exchange → Respiration_Rate: F=65.86, p=0.00000, correlation=0.846
```

Potential Use Cases

Exercise Physiology Modeling

- PhysioNexus is currently being used by professional sports teams and human performance groups within the DoD to map cause-effect relationships in time series data from assessments and identify physiological drivers and response networks specific to individuals.
    - Using this tool, coaches and human performance specialists can develop truly personalized training approaches based on these unique causal profiles, targeting the most influential variables for maximum impact.

Training Effect Quantification

- The causal network approach allows practitioners to quantify that X amount of training causes Y% change in target variables by determining edge weights in the network. By comparing causal networks before and after interventions (training programs, nutritional strategies, etc.), users can evaluate whether these interventions fundamentally alter physiological regulation.
    - The causal network approach also enables the detection of early warning signs of fatigue or overtraining through subtle changes in network structure.

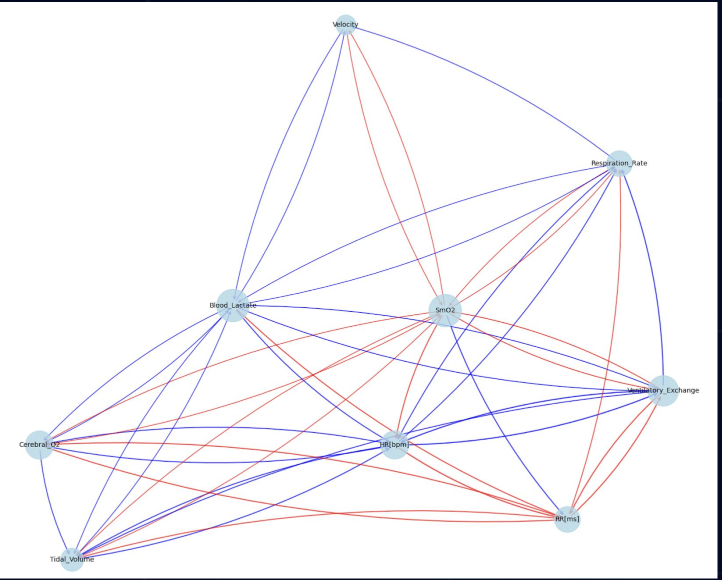
Environmental Adaptation Analysis

- PhysioNexus enables powerful condition-specific comparisons between different environments or states. Researchers can examine how causal relationships transform when comparing high versus low altitude, earth versus space environments, or healthy versus pathological conditions. The enhanced visualizations, as of version 1.0.0, particularly the causal flow diagram, clearly illustrate which physiological systems function as central hubs in different scenarios and how regulatory mechanisms adapt to environmental challenges. This approach can reveal critical insights into physiological adaptation mechanisms that might be missed by conventional analysis methods.

Ramp Incremental Exercise Test Case Study

Key Findings:

- SmO2 and Blood Lactate emerged as regulatory hubs
  - Local muscle response drives cardiorespiratory adjustments during exercise.
- Heart rate functions as both driver and integration point
- Cardiorespiratory Coupling; HR ⟶ VE (F= 105, $p < 0.001$, r=0.92)
  - Cardiac output drives ventilatory responses rather than the reverse during incremental exercise.
- ANS Dynamics: HR ⟶ HRV (F= 107, $p<0.001$, r=-0.02).
  - Progressive withdrawal of PNS tone and increase in SNS drive as exercise intensity increases.
- Respiratory control hierarchy: VE ⟶ RR (F=65, $p<0.001$, r=0.846
  - Breathing frequency training may be less effective than targeting upstream variables.



Overall, this network analysis provides evidence for a hierarchical yet interconnected physiological control system during exercise, where local muscle conditions drive systemic cardiovascular and respiratory responses through complex feedback and feed-forward mechanisms.

Limitations & Future Extensions

Current Limitations

- Granger causality assumes linearity and stationarity, which may not capture complex physiological relationships
- Analysis is sensitive to sampling rate; different causal relationships may emerge at different time scales
- Unmeasured variables could drive apparent causal relationships between measured variables
- The underlying statistical methods assume that the relationships between variables remain constant over time, which may not hold during dynamic physiological processes like exercise where regulation strategies can shift.

Extensions and Future Work

- Nonlinear Analysis: Implement non-linear causality measures using transfer entropy to better capture complex interactions
- Multi-Scale Analysis: Analyze causality at different temporal resolutions to identify relationships across timescales
- Differential Equation Modeling: Transform networks into systems of ODEs for simulation and prediction
- Dynamic Network Analysis: Examine how causal networks evolve during different exercise phases
- Standardized Protocols: Develop protocols for comparing causal networks across different conditions