

# ECO : Comparative Visualization of Time-Evolving Network Summaries



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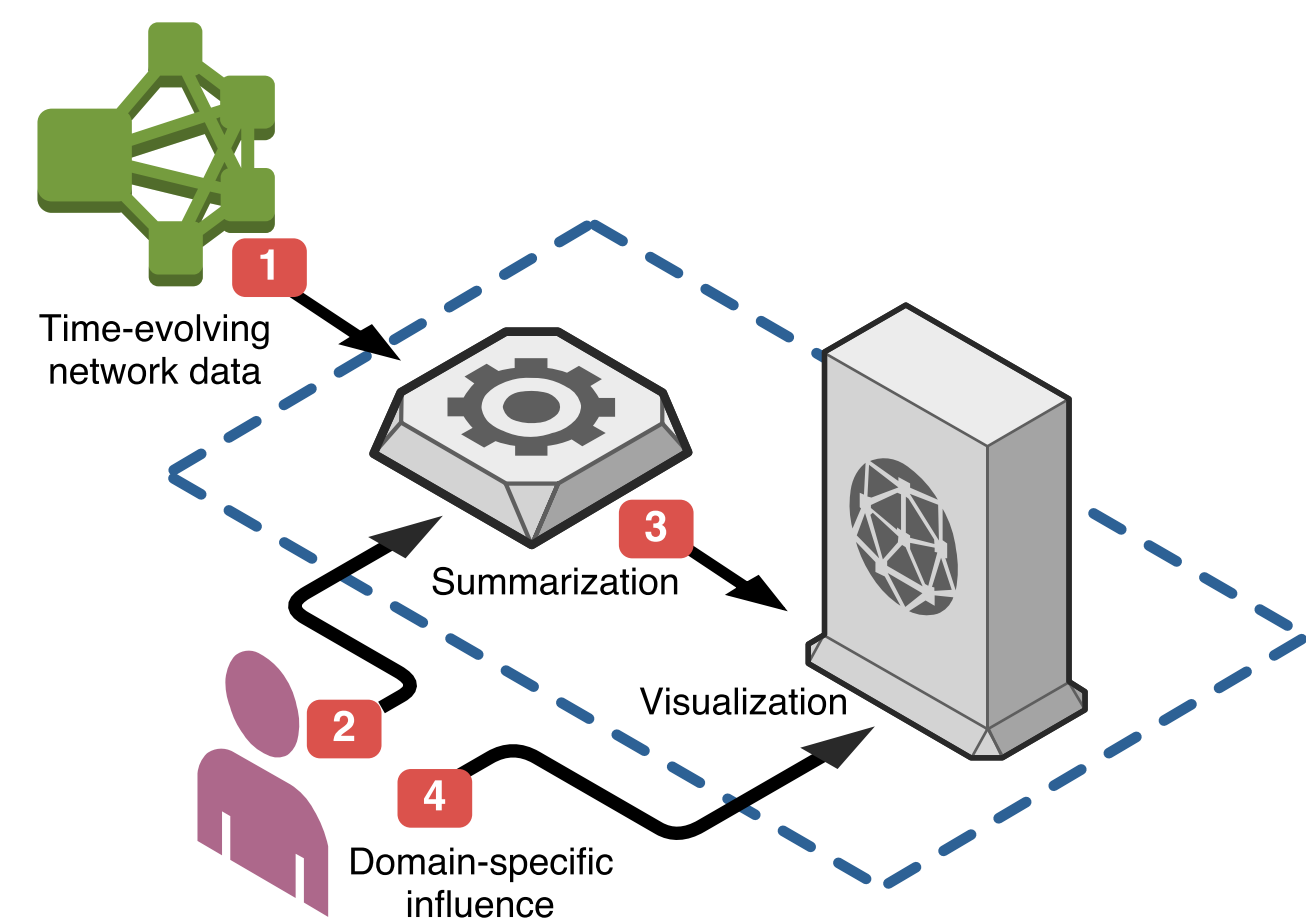


## Introduction

Tracking the evolution of communities in dynamic networks is common in many domains (e.g., neuroscience, sociology, transportation engineering). However, existing graph summary and visualization methods may use criteria that do not optimize for users' specific goals.

How can we assimilate domain expertise when analyzing time-evolving networks? Our end-to-end system, ECO :

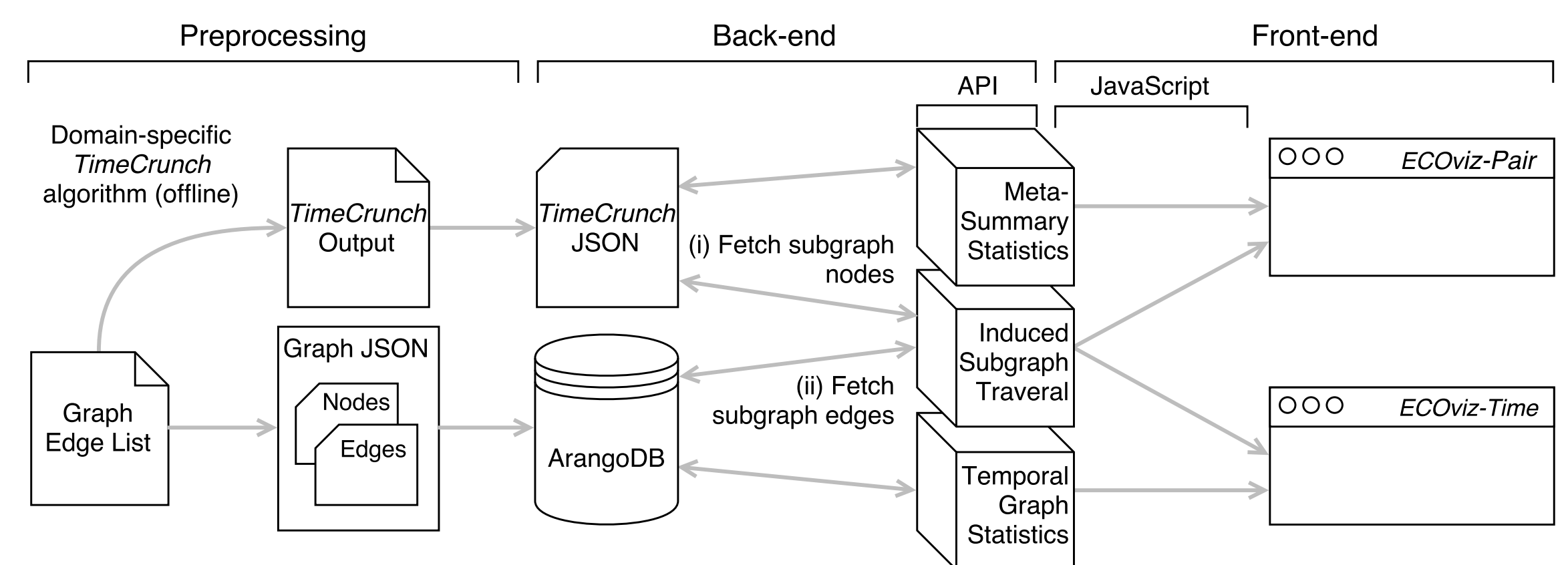
- Extracts *domain-specific* temporal summary structures using a variant of TimeCrunch [1].
- Visualizes *pairwise comparison* and *temporal evolution* of communities.



Given a node set of interest, how can we improve discovery and visualization of salient structures in a time-evolving network?

## End-to-end Visualization Pipeline

Following offline execution of domain-specific TimeCrunch, the web application receives a summary list of structures per temporal graph. It pairs the structural and temporal signature of each structure with edge data from the original network.



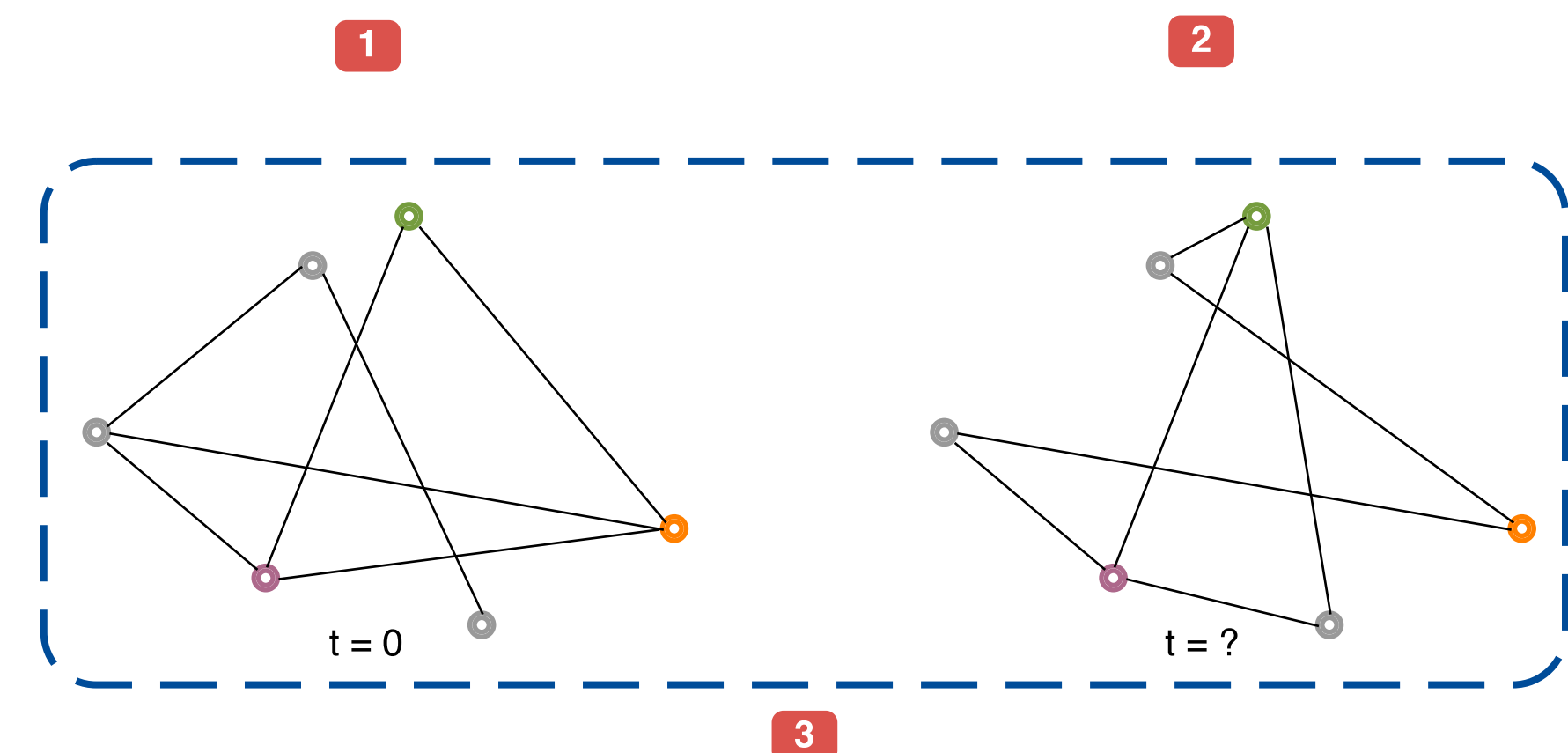
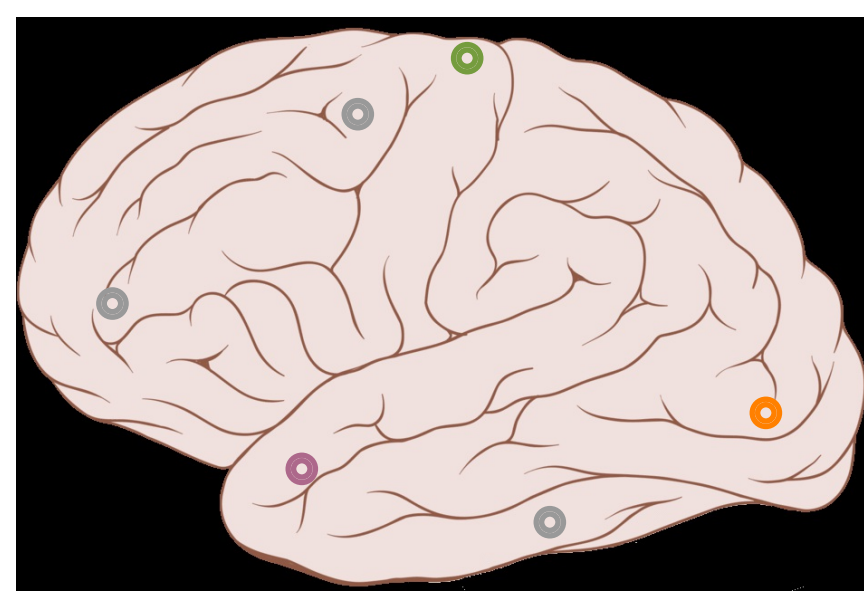
### ECO web application steps

For each temporal snapshot in each summary structure:

1. Fetch participating node IDs from TimeCrunch JSON.
2. Query ArangoDB database for induced subgraph (i.e., participating edges).
3. Make asynchronous JavaScript request to visualize subgraph.

## Graph Construction from fMRI Data

Connectomics, a subfield of neuroscience that explores functional and structural connectivity of the brain, offers unique data to improve understanding of the brain. Instead of being directly observed, functional brain networks are inferred from fMRI blood oxygen level-dependent data.



Typical temporal graph inference: (1) Record fMRI signals from regions of interest, (2) Compute pairwise association between voxel time series, (3) Threshold association values to form unweighted temporal graphs.

## ECO -P : Contrasting Analysis

ECO -P allows domain scientists to explore how tuning preprocessing parameters affects summary generation. Users may compare the summaries of any two parameter sets to infer graph generation quality. Meta-summary charts are also displayed to reveal summary diversity.

Oneshot bipartite core (obc) and periodic full clique (pfc). For the selected subject, left structure corresponds to resting state and right structure to mindful rest.

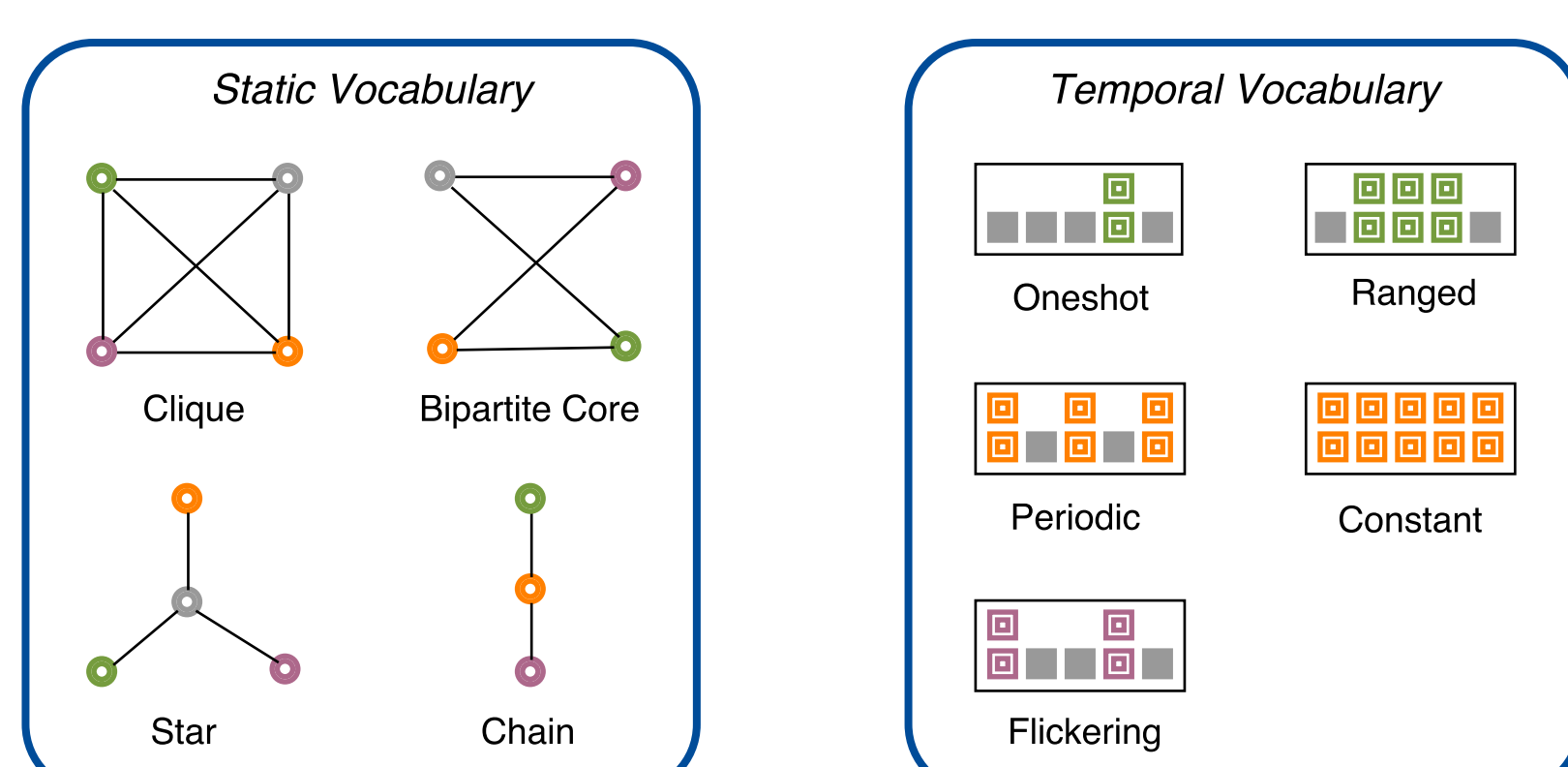
## Domain-specific Graph Summarization

To combine supervised and unsupervised approaches of fMRI data analysis, ECO leverages resting-state network labels to inform TimeCrunch, a dynamic graph summarization algorithm.

### Domain-specific TimeCrunch algorithm

1. Create a set of subgraphs per static snapshot in the temporal graph.
  - Extract *egonets*, one-hop neighborhood subgraphs, of labeled nodes as subgraphs.
2. Label the subgraphs as structures from a static vocabulary.
3. Stitch the static structures into temporal ones.
4. Compile a summary of top structures to best summarize the graph.

The use of egonets as subgraphs helps simulate a supervised approach to analysis, and adapt to the small-worldness of brain networks (instead of targeting high-degree nodes).



Cartesian product of static and temporal vocabulary sets in TimeCrunch.

## ECO -T : Temporal Analysis

In ECO -T, temporal snapshots of a summary are shown in small multiples of node-link or adjacency matrix format. Node label colors aid detection of inter- and intra-community patterns.

Matrix sequence of periodic full clique (pfc), where rows and columns are pre-sorted by node label.

## References

- [1] Neil Shah et al. "TimeCrunch: Interpretable dynamic graph summarization". In: *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 2015, pp. 1055–1064.