CADENCE: Community-Aware Detection of Dynamic Network States

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Abstract

Dynamic interaction data is often aggregated in a sequence of network snapshots before being employed in downstream analysis. The two common ways of defining network snapshots are i) a fixed time interval or ii) fixed number of interactions per snapshot. The choice of aggregation has a significant impact on subsequent analysis, and it is not trivial to select one approach over another for a given dataset. More importantly, assuming snapshot regularity is data-agnostic and may be at odds with the underlying interaction dynamics.

To address these challenges, we propose a method for community-aware detection of network states (CADENCE) based on the premise of stable interaction time-frames within network communities.

We simultaneously detect network communities and partition the global interaction activity into scale-adaptive snapshots where the level of interaction within communities remains stable. We model a temporal network as a node-node-time tensor and use a structured canonical polyadic decomposition with a piece-wise constant temporal factor to iteratively identify communities and their activity levels. We demonstrate that transitions between network snapshots learned by CADENCE constitute network change points of better quality than those predicted by state-of-the-art network change point detectors. Furthermore, the network structure within individual snapshots reflects ground truth communities better than baselines for adaptive tensor granularity. Through a case study on a real-world Reddit dataset, we showcase the interpretability of CADENCE motivated snapshots as periods separated by significant events.

1 Introduction

Temporal interaction data from various domains are often collected at high temporal resolution. Examples include comment exchanges among Reddit users [19], physical contact detected by wearable RFID tags [4] and source-to-destination trips in ride sharing or taxi services [1]. While individual pair-wise events may be recorded at milliseconds granularity, many algorithms for downstream analysis including deep learning on dynamic graphs [14, 20, 28], tensor decomposition [9, 17], and evolutionary clustering [5] typically expect that interactions are aggregated into network snapshots.

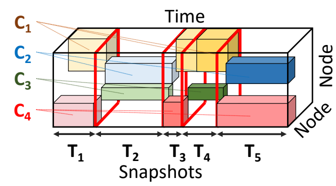

Figure 1: CADENCE models node-node interaction in time as a high resolution 3-way tensor with underlying (potentially overlapping) communities C_i. The timeline is partitioned in (lower resolution) snapshots T_i (network states) during which the level of interactions within each community is stable. The goal is to jointly identify communities and network states.

Defining appropriate snapshots without supervision is not trivial. Existing works that use temporal interaction data define snapshots based on regular temporal intervals (e.g., hourly, daily, weekly) or based on a fixed number of interactions within a snapshot [14]. However, this assumes regularity that may not align well with the natural evolution of within-community interaction activity which could speed up, slow down or abruptly change due to global events affecting the network.

In this work we propose a data-driven approach to partition dynamic interaction data into network snapshots based on periods of stable activity within natural network communities. Fig. 1 presents an illustrative example of the key assumptions behind our methodology. We model temporal interactions as a 3-way node-node-time tensor. We assume that the majority of observed interactions are generated within communities of nodes, C_i, which may overlap. This assumption is in line with affiliation generative models [29] and proposed extensions to temporal communities [9].

We also assume that the network transitions between *temporal states* (or time-frames) during which interaction patterns remain stable [18]. Thus, network snapshots are defined over periods with stable levels of interaction within communities. The points in time where interaction patterns shift are *change points*, which can be triggered by regular day/night or week/weekend boundaries, but also global events such as storms in

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transportation networks or sports events in social communities of sport fans. The example interaction tensor from Fig. 1 has 5 network states T_1 to T_5 with the majority of interactions residing in the colored sub-tensors corresponding to communities during a network state. *Given a high-resolution interaction tensor, our goal is to identify network snapshots corresponding to stable activity states of underlying network communities.*

We propose a method for community-aware detection of network states (CADENCE) based on the premise of stable interaction regimes within stationary network communities. CADENCE detects the underlying communities and partitions the global interaction activity into scale-adaptive snapshots in which community interactions levels remain stable. We derive a scalable solution based on structured non-negative tensor decomposition in which the temporal factor is sparse-coded via a multi-resolution over-complete dictionary. CADENCE's snapshot transitions correspond to change points of better quality than those predicted by state-of-the-art network change point detectors and the network structure within individual snapshots reflects ground truth communities better than baselines for adaptive tensor granularity. Through a case study on a Reddit dataset, we also showcase the interpretability of snapshots as periods separated by significant sports events.

Our contributions in this paper are as follows:

- **Novelty:** We propose CADENCE: a community-aware dynamic network state detector, which to the best of our knowledge, is the first method for unsupervised adaptive aggregation of interactions into snapshots based on periods of stable community activity.
- **Accuracy and Scalability:** CADENCE identifies ground truth network states up to 40% more accurately than state-of-the-art methods. It scales to hundreds of thousands of nodes and millions of time steps when interactions are considered at high temporal resolution.
- **Applicability:** The network states discovered by CADENCE correspond to network snapshots in which ground truth communities have small conductance and improve the downstream task of node classification.

2 Related work

Tensor decomposition extends matrix decomposition to multi-way data. The Canonical Polyadic Decomposition (CPD) (or PARAFAC) represents a tensor as a sum of three way outer products of factors [3], while Tucker decomposition involves a core tensor in addition to factor matrices [25]. Extensions of the basic CPD model regularize the temporal factor to enforce bursty [10], periodic behavior [17] and smooth [9] temporal behavior. The assumptions of smoothness in [9] is similar to our idea of network states, but smoothing is applied to each temporal factor independently, and thus, the resulting fit cannot be interpreted as global network snapshots.

Change point detection in dynamic graphs focuses on anomalous time points in which interaction trends change significantly. Some approaches employ Bayesian frameworks to model interactions and declare change points when model parameters change significantly [23]. Others assume a Hidden Markov Model (HMM) generating interactions and detect change points based on changes in the HMM states [23]. A third group tracks the eigenspectrum of the snapshots' graph Laplacians [12, 13]. The method in [15] employs a standard CPD decomposition but applies post processing of the fitted temporal factor to detect change points. We compare our method to those from [12] and [15] and demonstrate its superior performance in detecting ground truth change points.

Snapshot formation for dynamic network data seeks to define an optimal resolution for aggregation. The method in [24] aggregates sequences of streamed edges into graphs optimizing various network properties. Other approaches detect optimal resolution based on assumptions for underlying information cascade and network growth models [7, 6]. The authors of [27] utilize nonuniform time slices of dynamic graphs to improve visualization. The method in [14] demonstrated that using a constant number of edges per network snapshot can improve link prediction accuracy. The work closest to ours seeks to aggregate a high resolution temporal tensor into frames based on temporally-local goodness heuristics [21]. We compare to the methods from [14] and [21] in our experimental evaluation.

3 Problem formulation

The input to our problem is a set of time ordered (potentially weighted) interaction triplets (v_i, v_j, t_s, w_{ijs}), where $v_i, v_j \in V$ are nodes from a finite node set V of size $|V| = n$, $t_s \in [0, t]$ is a timestamp of the interaction measured at some high resolution (e.g., milliseconds) and w_{ijs} is the weight (or strength) of the interaction. Note that the weight can also correspond to a count of interactions if the data is pre-aggregated at some level. We model such data as a 3-way tensor $\mathcal{X} \in \mathcal{R}^{n \times n \times t}$.

Instead of assuming fixed and regular network snapshots [14], our key assumption is that snapshots correspond to states of the underlying network communities during which the level of within-community interactions is stable. A sketch of this intuition is presented in Fig. 1. The colored sub-tensors correspond to within-community interactions of a stable level. Multiple communities can be active at different levels during each state. The transitions between states can be viewed as change points (red partitions of the temporal mode)

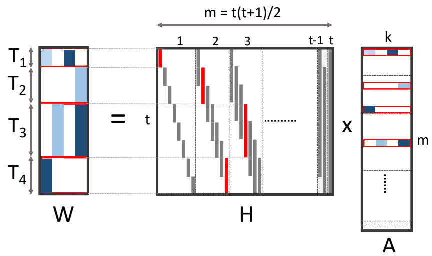


Figure 2: A piece-wise constant temporal factor matrix W as a product of an all-interval aggregation matrix H and a sparse community interaction level matrix A. H can be viewed as an over-complete dictionary and A as sparse coding matrix for W. In order for the resulting W to be piece-wise constant, the selected atoms of H (marked in red) should be mutually orthogonal.

caused by a global event that affects levels of activity in communities.

Given raw interaction data, our goal is to identify:
i) overlapping interaction communities of nodes,
ii) network states of stable activity, and
iii) the levels of community interaction during states.

To operationalize the above intuition we adopt a structured low-rank and non-negative tensor decomposition model [3] with a basic form as follows:

$$\begin{aligned} \mathcal{X} &= [[U, V, W]] \\ &s.t.\ U, V \geq 0, \end{aligned} \tag{3.1}$$

where the $U \in \mathcal{R}^{n\times k}$ and $V \in \mathcal{R}^{n\times k}$ factor matrices represent k overlapping node communities with column loadings that can be interpreted as association strength of each node to the corresponding community. The factor matrix $W \in \mathcal{R}^{t\times k}$ represents the temporal activity trend for each community. The notation $[[U, V, W]]$ stands for a tensor product of factor matrices that produces a rank-k tensor [3].

The basic CPD model from Eq. 3.1 allows for arbitrary interaction levels over time in W and does not readily model temporal states delineated by change points, with piece-wise constant levels within a state (Fig. 1). To this end, we model the temporal factor W as a product of i) an over-complete aggregation dictionary matrix $H \in \mathcal{R}^{t\times m}$ which expresses all possible states (contiguous intervals of time) and ii) an encoding matrix $A \in \mathcal{R}^{m\times k}$ which encodes the levels of community interactions in a given state.

A sketch of the structured temporal factor W is presented in Fig. 2. The non-zero positions of column atoms in the aggregation dictionary H represent all contiguous intervals that may correspond to networks states (colored time segments in H). In this example, the timeline is partitioned into 4 states (or snapshots) with durations $\mathrm{T}_1 = 1$, $\mathrm{T}_2 = 2$ $\mathrm{T}_3 = 3$ and $\mathrm{T}_4 = 2$. Their corresponding atoms in H are colored red and the community interaction levels are encoded in corresponding non-zero rows of matrix A.

For W to encode network states that do not overlap in time, H atoms selected for encoding should be mutually orthogonal and span the timeline. Let $H_{A_i\neq 0}$ denote the principle sub-matrix of H comprised of columns with non-zero corresponding rows in a learned encoding A. Then a valid encoding should satisfy $H^T_{A_i\neq 0} H_{A_i\neq 0} = I$, assuming that all atoms in H have a norm of 1.

Based on the above definition we can formalize our problem as a constrained non-negative tensor factorization as follows:

$$\begin{aligned} &\min_{U,V,A} 1/2 ||\mathcal{X} - [[U, V, HA]]||_F^2 \\ &s.t.\quad U, V \geq 0, \quad ||A||_0 < \theta, \\ &\qquad H^T_{A_i\neq 0} H_{A_i\neq 0} = I, \end{aligned} \tag{3.2}$$

where the minimization term seeks a low-rank representation of the input interaction tensor $\mathcal{X}$ and the constraints ensure that i) the community factors U, V are non-negative, ii) the encoding A via the over-complete dictionary H is sparse employing a bounded L_0 sparsity norm and iii) the atoms of H used to encode interaction levels in A form an orthonormal basis.

4 Optimization framework

The overall optimization problem in Eq. 3.2 in structure closely resembles non-negative CPD tensor factorization prompting potential solutions based on well-established alternating least-squares methods [3]. However, the constraint on selected atoms from H in the encoding of the temporal factor is in essence combinatorial. Relaxations of this constraint will render our main goal of detecting temporal network states unachievable as it is unclear how to reconcile a partitioning of the timeline from overlapping atoms selected for encoding. Another challenge is the exhaustive nature of the atoms in H whose number grows quadratically with the length of the original timeline t (see Fig. 2). To address the above challenges, we combine ideas from non-negative tensor factorization for the community factors and sparse dictionary coding via Orthogonal Matching Pursuit (OMP) [22] for the temporal factor. Specifically, to optimize equation 3.2 we adopt an alternating optimization scheme that updates each of the variables U, V and A while keeping the other two fixed.

Solutions for community factors U and V. Both community factors can be updated in the same manner employing a least squares procedure as they have the same role in the optimization function and share the same constraint. Furthermore, when the input interactions are undirected (i.e., $w_{i,j,s} = w_{j,i,s}$) the two factors should converge to be the same. For the sake of com-

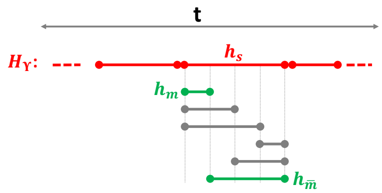


Figure 3: Intuition behind the O^{2}MP greedy selection of H atoms to encode the temporal factor W.

pleteness, we explain the updates for U given fixed V and A, although this step is identical to general CPD solutions [3]. The sub-problem with respect to U is:

$$\min_{U} \frac{1}{2}||X_U^T - U[(HA) \odot V]^T||_F^2, \text{ s.t. } U > 0, \tag{4.3}$$

where X_U^T is the tensor unfolding on the updated mode U and $\odot$ is the Khatri-Rao product [11]. Setting the gradient of Eq. 4.3 with respect to U to 0 and letting $B = [(HA) \odot V]$ we obtain:

$$\begin{aligned} -X_U^T B + UB^T B = 0 \\ U = X_U^T B(B^T B)^{-1} \end{aligned} \tag{4.4}$$

To ensure non-negative entries in U, we replace negative values with zero in line with ALS solutions for non-negative CPD [3]. The solution for V is analogous to that for U.

Solution for A. When the community factors U, V are fixed, the problem with respect to A with only the sparsity constraint is similar to sparse coding by an over-complete dictionary H:

$$\min_{A} \frac{1}{2}||X_W^T - HA[V \odot U]^T||_F^2, \text{ s.t. } ||A||_0 < \theta, \tag{4.5}$$

where X_W^T is the unfolding of the input tensor on its temporal mode. The Orthogonal Matching Pursuit (OMP) [22] has been widely adopted in signal processing for sparse coding problems. Within OMP, atoms from H are iteratively selected based on their alignment with the residual of the signal not represented by previously selected atoms. In order to formulate Eq. 4.7 such that an OMP-like algorithm can be employed, we introduce an intermediate variable $W = HA$:

$$\min_{W} \frac{1}{2}||X_W^T - W[V \odot U]^T||_F^2, \text{ s.t. } W \approx HA, \tag{4.6}$$

where the 0-gradient solution with respect to W just like in ALS is:

$$W = X_W^T (V \odot U)^T (U^T U \circ V^T V)^{-1} \approx HA. \tag{4.7}$$

In other words, we can approximate an unconstrained temporal factor W by a sparse coding solution HA.

Algorithm 1 O^{2}MP: sparse orthogonal atom coding

Input: Temporal factor W, Budget of snapshots b_s
Output: Selected atom and sparse codes H_Υ, A_Υ

```
H_Υ = {1_{1×t}}
C = {atom indices of prefixes and suffixes of 1_{1×t}}
S = ∅
for i=2 to b_s do
    // OMP encoding and residual update
    A_Υ = (H_Υ^T H_Υ)^{-1} H_Υ^T W
    R = W − H_Υ A_Υ
    // OMP-like atom scoring and selection
    Add (c, S_c = Σ_{i=1}^k |h_c^T R_i|) to S, ∀c ∈ C
    Let m be the atom index of maximum S_m
    Let h_m be the atom at index m
    Let h_s ∈ H_Υ be the atom enclosing h_m
    Let h_m̄ be the atom in C satisfying h_m̄ = h_s − h_m
    // Dictionary Updates
    H_Υ = H_Υ \ h_s
    H_Υ = H_Υ ∪ h_m ∪ h_m̄
    C = {atom indices of prefixes and suffixes of h_m and h_m̄}
    Remove (m, S_m) and (m̄, S_m̄) from S
end for
```

The only remaining challenge is the additional constraint $H_{A_i \neq 0}^T H_{A_i \neq 0} = I$ from Eq. 3.2 on using orthogonal atoms from H. Since our dictionary H contains orthogonal atoms corresponding to non-intersecting intervals of time, we restrict the greedy selection of new atoms in the OMP steps to ensure orthogonality of the candidate set.

We call the resulting algorithm O^{2}MP (Alg. 1) as it ensures both orthogonality of the representation and orthogonality of selected atoms. Intuitively O^{2}MP partitions the timeline in a top-down manner by iteratively selecting atoms that ensure best representation of the residual of the signal based on its current representation. This process is demonstrated pictorially in Fig. 3. At any point we maintain a set of non-overlapping atoms in H_Υ starting with the atom spanning the whole time line. Atoms are represented by horizontal time segments which correspond to their non-zero elements Fig. 3. The atoms in the current solution H_Υ are represented with red segments that span the whole timeline and are orthogonal to each other as they do not overlap, i.e., H_Υ satisfies the orthogonality constraint $H_\Upsilon^T H_\Upsilon = I$. Candidate atoms considered in the next iteration are prefixes and suffixes of intervals corresponding to atoms in H_Υ. For example, the candidates considered due to $h_s \in H_\Upsilon$ are depicted below h_s (grey and green atoms). Assuming that candidate atom h_m is selected as the one that best improves the current representation, we substitute its enclosing solution interval h_s with h_m and its complement $h_{\bar{m}} = h_s - h_m$ in the solution set H_Υ.

We list all steps of O^{2}MP in Alg. 1. The algorithm takes as an input the temporal tensor factor W to

Dataset statistics							Maximum Covering Metric				
Dataset	n	t	#e	#CP	#C	Resolution	CADENCE	LAD	TSP-Dif	TSP-LOF	AGT
Syn	500-600	50-2500	3M	49	30	NA	**1.00**	0.70	0.49	0.34	0.20
Taxi	266	8763	25M	106	/	24h-1min	**0.72**	0.60	0.47	0.53	0.14
Reddit F1	100852	365	2M	42	/	Daily	**0.81**	0.71	0.71	0.42	0.29
Hospital	75	17383	64848	/	5	20 Secs	/	/	/	/	

Table 1: Summary statistics of datasets (see Section 5.1) and performance on the change point detection task in terms of covering metric (Section 5.4). #e denotes number of edges, #CP denotes the number of changepoints, and #C is the number of communities.

approximate via the dictionary encoding and a budget of b_s snapshots to create which corresponds to the number of atoms to select for encoding. The output is the selected atoms H_Υ and a corresponding encoding A_Υ. We initialize the selected atom set H_Υ with the last atom in H, namely a vector of all ones spanning the whole timeline (Step 1). Note, that atoms in H in our problem formulation are norm one. However, in our implementation we simply focus on orthogonality, i.e. considered atoms correspond to time intervals of value 1. We use atoms and intervals interchangeably.

In Step 2 we initialize the set of candidate atom indices with those of all prefix and suffix intervals of the all-one vector $\mathbf{1}_{1\times t}$. An example of all prefixes and suffixes of an interval h_s is shown in Fig. 3. Intuitively, these are all pairs of intervals that split an enclosing interval in two. We also initialize an empty priority queue S of ordered pairs (i, S_i), where i is an atom index and S_i is an alignment score of the interval used as a priority value. Each iteration of the main loop of the algorithm (Steps 5-18) replaces an atom $h_s \in H_\Upsilon$ from the current solution with two atoms h_m and $h_{\bar{m}}$ that split h_s in two parts, i.e. $h_s = h_m + h_{\bar{m}}$. An example of such triplet of intervals is presented in Fig. 3. We first obtain the best encoding A_Υ via the set of currently atoms H_Υ (Step 6) and quantify the unrepresented residual R of W (Step 7). The inversion in Step 6 involves a matrix stacking only the selected atoms so far (at most $b_s \times b_s$ matrix) and not the complete dictionary H. Moreover, $H_\Upsilon^T H_\Upsilon$ is diagonal and thus its inverse involves finding the reciprocal of b_s scalars.

Next we compute alignment scores S_c for all atoms whose indices $c \in C$ are in the candidate set and add them to the priority queue S (Step 9). The alignment score $S_c = \sum_{i=1}^{k} |h_c^T R_i|)$ accumulates absolute values of inner products of the atom with columns of the residual. Intuitively, atoms aligned with the residual of each factor are preferred for encoding. This is also an essential step of OMP for sparse coding.

Next we select the atom h_m with the largest alignment score S_m among candidates (top of the the priority queue S). We also identify h_m's unique enclosing atom $h_s \in H_\Upsilon$ from the current solution and its complement $h_{\bar{m}} = h_s - h_m$ (Steps 10-13). We substitute h_s with h_m and $h_{\bar{m}}$ in the current solution H_Υ (Steps 15-16) and create a new set of candidates C to be scored comprising all prefixes and suffixes of both h_m and $h_{\bar{m}}$ (Step 17). Finally, we remove the entries for h_m and $h_{\bar{m}}$ from the priority queue S.

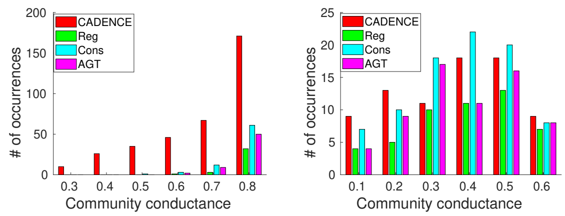
The complexity of the algorithm is $O(b_s(tk + b_s))$. The maintenance of the priority queue S is logarithmic in t assuming binary heaps as its implementation. The tk factor in each iteration is due to the scoring of $O(t)$ new candidates from C in Step 9. When the budget number of partitions is constant with respect to t, the algorithm is linear in the matrix W it approximates. As we demonstrate experimentally, the overall CADENCE algorithm runs in minutes on sparse tensors with up to $100k$ nodes and $35k$ timestamps.

5 Experimental evaluation

We compare CADENCE to sate-of-the-art baselines in terms of quality of snapshots, change point detection and node classification on dynamic graphs.

5.1 Datasets. We employ synthetic and three real-world datasets for evaluation with summary statistics listed in Tbl. 1 and detailed descriptions included in the extended version[1]. The synthetic *Syn* dataset includes 30 stochastic block communities (sizes 15-25) whose network activity level changes over 50 temporal states of varying length. The *Reddit F1* dataset contains interactions between active users in a Formula 1 racing subreddit (`r/formula1`) [19]. We align it to the 2019 Formula 1 Grand Prix calendar to define ground truth change points, at the start and end dates of races. The *Taxi* [1] dataset represents rides between neighborhoods in New York City in 2017. Nodes are neighborhoods and edges correspond to rides. We use working versus non-working days (including holidays) as the ground truth change points (e.g., most Saturdays are change points). Both Reddit F1 and Taxi do not feature ground truth community membership. We also employ the *Hospital* [8] dataset for experiments in Sec. 5.3 ,5.5. Edges represent co-location of people (nodes) at 20-second resolution. The ground truth node classes in this dataset are the labels of doctors, nurses, patients

[1] An extended version of the paper is available at `https://www.cs.albany.edu/~petko/lab/papers/mmtb2023sdm.pdf`



(a) Synthetic (b) Hospital

Figure 4: Comparison of the number of occurrences of communities meeting various conductance thresholds on Synthetic (a) and Hospital (b) datasets (see Sec. 5.3).

and administrators.

5.2 Experimental setup We next discuss briefly evaluation metrics and baselines and provide further details including definition for metrics and parameter tuning for baselines in the extended version.

Metrics. We employ *conductance* to measure the quality of snapshots identified by CADENCE and competitors with respect to ground truth communities [16]. To evaluate the quality of our state identifications we utilize the covering metric defined in [26]. Perfectly aligned predictions result in a value of 1. For the task of node classification, we employ commonly used metrics, namely the F1 measure and accuracy.

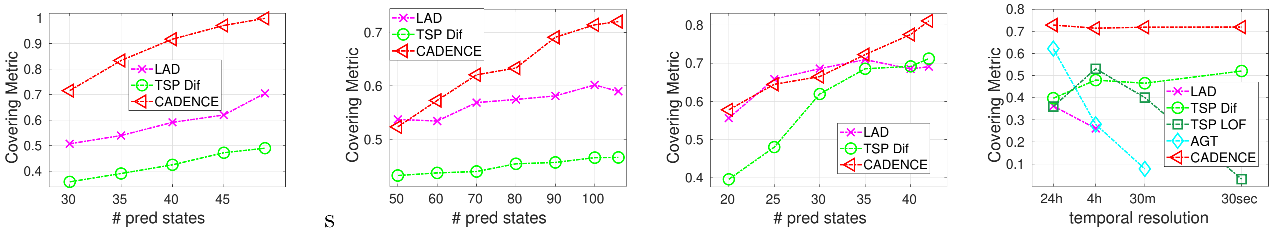
Baselines: For *quality of snapshots* and *node classification* we compare to the following approaches: regular aggregation in time (*Reg*) (e.g., every hour is a snapshot), constant number of edges per snapshot (*Cons*) and Adaptive Granularity in Time Evolving Graphs as Tensors (AGT) [21] which aggregates temporal slices greedily into a single snapshot. For *change point detection and scalability* we compare to AGT [21], LAD [12] which is a state-of-the-art change point detector for dynamic graphs based on the eigenspectra of consecutive snapshots; and Tensorsplat [15] which performs a CPD decomposition on the tensor to obtain a temporal representation of community activity. To identify change points in this temporal representation TSP-LOF follows the approach used in [12] and utilizes local outlier factor [2] where TSP-Dif, measures the absolute difference between consecutive time steps.

5.3 Snapshot quality. We measure the conductance of ground truth communities in Synthetic and Hospital within each snapshot obtained by competing temporal aggregations. Fig. 4 shows how many communities satisfy a given conductance threshold across all snapshots. Although the total number of snapshots are similar for all methods, CADENCE produces more snapshots at low conductance thresholds. Its snapshots exhibit stronger community structure than competing methods because our aggregation is based on finding stable regions of community activity. Naturally, since states correspond to periods of community activity (and thus has more internal edges), our aggregation produces snapshots following the same principle.

5.4 Change Point Detection. We next quantify the level of alignment of predicted state transitions with ground-truth change points in real-world networks. We compare the covering metric of solutions obtained by all competitors on Syn, Taxi, and Reddit F1 with respect to ground truth change points. First, in Tbl. 1 we list the maximum covering metric obtained by all methods. CADENCE exceeds the performance of all baselines. Because the right number of change points is not often known, we are also interested in the trend of covering metric for competitors as a function of the number of predicted change points. TSP-LOF and AGT are not appropriate for such a task as they do not provide ranking of predicted change points. For CADENCE we take the first k state predictions, and for TSP-DIF and LAD we take the top k ranked change points. The prediction quality of CADENCE consistently increases as the number of predicted states approaches the ground truth (Fig. 5). In contrast, other approaches stagnate or even decrease in performance as the number of predicted states increases.

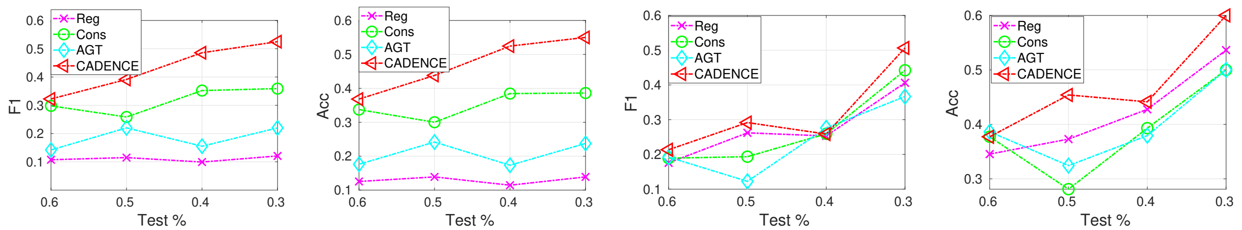
Finally, we examine how CADENCE and competitors predict change points when the data is given at varying temporal resolutions. To this end, we represent the Taxi dataset at different granularities ranging from daily (24h) down to 30 second intervals (30sec). Results are presented in Fig. 5(d). CADENCE's performance is remarkably consistent, indicating that it finds relatively similar change points regardless of the temporal resolution of the input tensor. Even at 30 second resolution which constitutes over a million timesteps CADENCE is able to find the ground truth change points with high accuracy. In contrast competitors' performance vary widely between different resolutions without clear trends. Note that LAD and AGT were not able to complete for resolutions higher than 30 min and 30 sec resolutions due to scalability limitations (see Sec. 5.6).

5.5 Node Classification. Node classification is a central task in (deep) learning on graphs, and is also a relevant downstream task for gauging the quality of temporal aggregation methods for learning on dynamic graphs. In this experiment we demonstrate that a dynamic network represented by CADENCE's snapshots allows for better performance as compared to those by competing approaches. Specifically, we employ AdaNN [28] (with default parameters) as the down-



(a) Synthetic (b) Taxi (c) Reddit F1 (d) CM vs # timepoints

Figure 5: Quality of change point prediction (Sec. 5.4), comparing CADENCE and baselines on synthetic (a), Taxi (b) and Reddit F1 (c) datasets, for increasing number of states. Rightmost figure demonstrates robustness w.r.t. temporal resolution (d).



(a) Synthetic (F1) (b) Synthetic (accuracy) (c) Hospital (F1) (d) Hospital (accuracy)

Figure 6: Comparison of F1 and Accuracy scores obtained by CADENCE and baselines for the task of node classification (see Sec. 5.5) on synthetic (a) (b), and Hospital (c) (d) datasets.

stream framework for node classification. This method uses attention in a neural network to model temporal and spatial information, simultaneously. The focus of this comparison is on the synthetic and Hospital datasets, as they have ground truth class labels.

We compare the quality of node classification for competing methods by remove varying percentages of class labels to use as testing. In each case, 10% of the labels are reserved for validation the remaining labels are used for training. The results are shown in Fig. 6, presented in terms of both the F1 score and accuracy. CADENCE in both datasets either matches or exceeds baselines in all measures across all parameter settings. We expect that this is because AdaNN can utilize community structure in snapshots to better represent the relationship between edges and node labels. As demonstrated in Sec. 5.3, snapshots based on the states identified by CADENCE create a dynamic network representation with strong community structure.

5.6 Scalability. We evaluate the scalability of CADENCE and competing approaches on real world datasets in terms of number of nodes, and number of timesteps using the parameters from Sec. 5.4. Results can seen in Fig. 8. We use the largest dataset across the changed dimension (i.e., Reddit F1 for number of nodes and Taxi for number of timesteps) for this comparison.

To evaluate the impact of the number of nodes on running time we randomly subset the Reddit F1 dataset to 1000, 10000, and 100000 nodes (Fig. 8(a)). CADENCE scales similarly to TSP, taking only seconds to process the dataset even at its largest size. In contrast, for AGT and LAD the running time increases substantially as the size of the data increases. We preform a similar experiment in Fig. 8(b), now considering the Taxi dataset at varying temporal resolutions. In this instance, TSP's running time actually exceeds that of CADENCE although both methods are based on CPD. We suspect that CADENCE has faster convergence because its temporal representation is simpler, having only as much temporal variation as the number of states, and thus converges to the fit criteria in fewer iterations.

5.7 Case Study: Reddit F1. To demonstrates the interpretive power of CADENCE we perform a case study on the Reddit F1 Dataset. We utilize the same parameters as those used from Sec. 5.4.Figure 7 illustrates the Reddit F1 daily interaction volume and the stable community activity states detected using CADENCE. Our method consistently identifies distinct Grand Prix states, with few exceptions.

Highlighted above the time series are three network snapshots identified by CADENCE that correspond to the stable activity states prior to, during, and following a typical Grand Prix. These states cover five, two, and thirteen days of activity on `r/formula1`, respectively. In the network visualizations, nodes are laid out using a force-directed algorithm that draws interacting users together and sends non-interacting users apart. Many nodes appear in more than one snapshot,

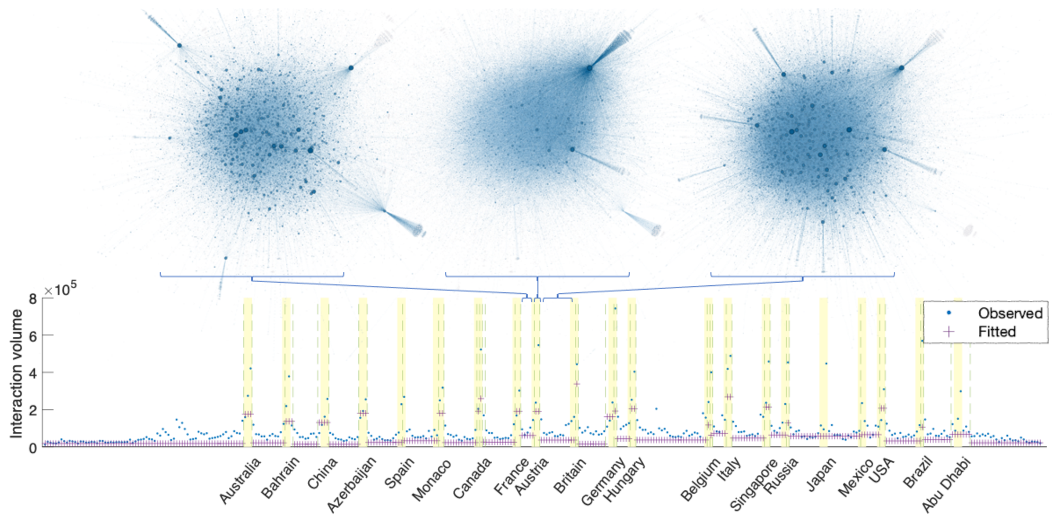
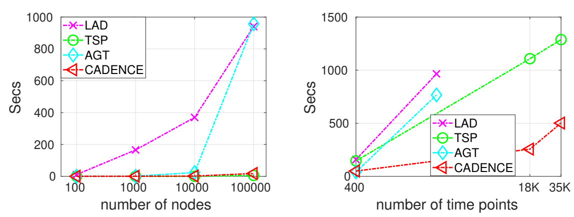


Figure 7: Timeseries of the Reddit F1 daily interaction volume in 2019, with the Formula 1 race schedule highlighted. Predicted values are those fitted by CADENCE in detecting states, with change points noted in green. Network snapshots correspond to the detected states that fall prior to, during, and following the Grand Prix held in Austria over June 28-30, 2019. Node placement is consistent across network snapshots. Larger, darker nodes denote users with greater interaction within a network snapshot.



(a) F1, nodes

(b) Taxi, time points

Figure 8: Comparison of running times between CADENCE and baselines with respect to number of nodes (a), and number of timesteps (b).

so nodes are placed in the same network position across snapshots. Within snapshots, the larger, darker regions correspond to users with a greater number of interactions during that state. The state aligning with the Grand Prix is quite distinct, while the adjacent states have similar activity levels and interaction patterns to each other. Specifically, the Grand Prix state has a higher overall activity level and user interactions are highly concentrated; the interaction network is dominated by only a handful of nodes. Moreover, interaction shifts towards a different community during this state because the Grand Prix draws in a different set of users to `r/formula1` compared to adjacent states. Over half of the nodes in the second network snapshot do not appear in any other snapshot, including a large number who only interacted only with a dominant user pictured in the upper right.

6 Conclusion

In this paper we introduced a framework for identifying states of stable network activity in dynamic networks called CADENCE. It frames a dynamic network as an interaction tensor and utilizes canonical polyadic decomposition with a piece-wise constant temporal factor to decompose an input interaction tensor of potentially high temporal resolution. The decomposition simultaneously detects network communities and partitions the global interaction activity into scale-adaptive snapshots in which community interactions levels remain stable.

We demonstrated that across multiple data sets the snapshots detected by CADENCE reflect the community structure and known change points, and facilitate increased performance in the task of node classification. Furthermore, these benefits do not come at the cost of scalability. CADENCE was able to process dataset with hundreds of thousands of nodes and up to a million time steps in less than 10 minutes. It scales similarly or better than the fastest available baselines and produces snapshots of the best quality compared to those of all baselines. We also demonstrated that discovered states are highly interpretable, capturing windows of diverse network activity associated with real world events in a case study from Reddit. The code for our method is available at `http://www.cs.albany.edu/~petko/lab/code.html`.

7 Acknowledgements

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8 Supplemental material

In the supplemental content we add details additional details. First, an in depth explanations of the datasets, then formally define used metrics. Finally, we provide detailed explanations of competitors and discuss how their hyperparameters were set.

8.1 Dataset Details: Synthetic data generation details The synthetic data, abbreviated Syn, consists of a series of disaggergated stochastic block model graphs stacked into a interaction tensor. In total there are 30 block communities ranging from in size from 15 to 25 nodes. Each community has a 30% chance of becoming "active" during a particular timestep. When a community is "active" 20% of possible internal community edges randomly are assigned and the community has no external edges. When a community is inactive every node has a 20% chance of linking with any node not in a active community. This process is repeated 49 times to create 49 base graph snapshots. Each graph snapshots is then randomly split into 1 to 50 desegregated snapshots. This disaggregation process uniformly in quantity but randomly in edge index distributes the original edges into the selected number of new snapshots. The change points in Syn reflect the time points where the graph snapshot which was disaggregated into said timepoints changes.

Real world details: The **Reddit F1** dataset contains interactions between users active on an online forum about Formula 1 racing (`r/formula1`), extracted from [19]. Forums on Reddit follow a particular format, where users can post content as well as interact with other user via posted comments and endorsements. We consider the interaction network among users, the nodes, where the edges correspond to comments by one user in response to another. The weight of an edge is the net number of endorsements (up-votes minus down-votes) that the comment received. Constructed for each day in 2019, Reddit F1 interaction networks capture the daily activity patterns on `r/formula1`. We use the 2019 Formula 1 Grand Prix calendar to generate ground truth change points, at the start and end dates of races. This dataset does not include ground-truth community membership.

The **Taxi** [1] dataset represents rides taken between neighborhoods in New York City in 2017. Nodes are neighborhoods, and edges correspond to rides from one to another. Edge weights denote the total toll amount of the ride. Unless otherwise stated time steps represent one hour of trips. We use working versus non working days (including holidays) as the ground truth change points (e.g., most Saturdays are change points). This dataset also does not include ground truth community membership.

Finally, we use **Hospital** [8] for experiments for change point detection and node classification. Edges in this dataset consist of co-locations of people (nodes) at 20-second resolution in a hospital. The ground truth node classes in this data set are the labels of doctors, nurses, patients and administrators. This dataset does not include ground truth change points.

8.2 Metric Definitions Conductance is used to evaluate how well the states identified by CADENCE and competitors reflect community structure[16]. Specifically, we quantify the conductance of the cuts needed to separate a community from the rest of the graph, for all communities in all the resulting network snapshots. The conductance of a cut is defined as:

$$Con(S) = \frac{\sum_{i\in S, j\in \tilde{S}} a_{i,j}}{min(a(S), a(\tilde{S}))}$$

Where a is the adjacency matrix of a network snapshot and a(S), is the sum of degrees of nodes in S. At a high level, conductance approaches 0 when a community is well separated from the rest of the graph and approaches 1 when it is well connected to the rest of a graph.

To evaluate the quality of our state identifications in we utilize the covering metric defined in [26]:

$$C(\Theta, \tilde{\Theta}) = \frac{1}{T} \sum_{A\in\Theta} |A| \max_{\tilde{A}\in\tilde{\Theta}} J(A, \tilde{A})$$

Where Θ and $\tilde{\Theta}$ are the ground truth and predicted change points, A and $\tilde{A}$ represent the sets of time points which constitute states, and $J(A, \tilde{A})$ is the Jarccard index of these sets. Perfectly aligned predictions will result in a value of 1.

8.3 Details on Baselines and Parameter Settings. Baselines: We compare CADENCE to approaches designed for two different tasks. The first is tensor aggregation. These approaches are designed to aggregate temporal slices into a smaller number of representative snapshots. We compare to these approaches on the task of producing network snapshots with interpretable community structure as well as node classification, a common downstream task.

Reg: regular aggregation of time points (e.g., every hour is a snapshot). Cons: constant number of edges. In this approach every snapshot has the same number of edges. This aggregation strategy was used in [14] to achieve state-of-the-art performance for the task of link prediction task. Adaptive Granularity in Time Evolving Graphs as Tensors (AGT) [21], seeks to learn temporal aggregations of a tensor that are smaller along the temporal dimension. This approach greedily aggregates

	CADENCE	**TSP-Dif**	**TSP-LOF**			**LAD**		
Dataset	K	K	K	#N	Con	SW	LW	#EV
Syn	30	30	30	2	.001	5	50	500
Taxi	5	500	1000	2	.001	5	75	250
Reddit F1	500	5	20	5	.001	5	50	250

Table 2: Parameters used by methods in change point detection

temporal slices into a single snapshot until a heuristic is met, at which point a new slice is formed and the process is repeated until the last time step is reached. We choose to compare against the so-called infinity-Norm heuristic, empirically shown to perform best[21]. In our network statistic experiments we set the AGT threshold to produce a similar number of snapshots to competitors, and use default parameters otherwise.

The second perspective we compare to is that of change point detection. These methods are not concerned with producing informative snapshots, focusing instead on finding changes in the structure of the dynamic network occurring at particular points in time.

LAD [12] is a state-of-the-art method for change point detection in dynamic graphs which compares the eigenvalues of the graph Laplacian, over time, to quantify how much a graph has changed from its "normal state". The position of the top k values from this quantification are determined to be change points. We compare to [12] in our state detection experiments, employing a grid search across its parameters. Tensorsplat [15] performs a CPD decomposition on the representative tensors to obtain a temporal representation of community activity similar to our approach. However, the authors [15] do not offer an explicit way of identifying change points, thus we explore two different ways of identifying change points based on extracted featurs of Tensorplat (TSP).

TSP-LOF follows the approach used in [12] and utilize local outlier factor [2] to identify anomalies on the learned temporal representation. TSP-Dif, measures the absolute difference between consecutive time steps in its learned temporal representation. The k timepoints that represent the greatest absolute difference are identified as change points. We compare to both TSP-LOF and TSP-Dif in state detection experiments and grid search parameters for both variations.

The AGT approach to tensor aggragation is also included in state-detection comparison, since its heuristics may also be able to accurately capture ground truth changes. However, we do not compare to Reg and Cons on this task. These approaches rely on simple statistics (number of timestamps, number of edges) to define states and produce snapshots, meaning they are agnostic to the structural information held in the tensor.

The optimal parameters found and used in change point detection experiments are included in Table.2.