A Breath of Fresh Air: Visualizing How Networks "Breathe"

Stephen Jasina
University of Wisconsin
Madison, WI, USA

Loqman Salamatian
Columbia University
New York, NY, USA

Paul Barford
University of Wisconsin
Madison, WI, USA

Mark Crovella
Boston University
Boston, MA, USA

Walter Willinger
NIKSUN Inc.
Princeton, NJ, USA

Abstract

Even though scientific studies have shown that humans are inherently visual creatures, nearly every published networking research paper presents its results in the form of figures such as line graphs, histograms, bar charts, or scatter plots that can be printed on paper but are often some of the least memorable aspects of a paper. In this work, we call on networking researchers to be more creative in utilizing digital media to communicate the findings of their studies and be more cognizant of the extraordinary capabilities of human readers to process and retain visual information, especially as network telemetry datasets critical for monitoring and diagnosing "network health" continue to grow in size and in the amount of semantic-rich information they contain. To illustrate what we have in mind, we consider the use case where sets of simultaneously collected time series that represent latency measurements over time between different pairs of routers or vantage points within a network (e.g., ESnet) are used to define that network's dynamically changing delay space. By representing successive snapshots of this delay space as 2D manifolds in 3D and animating the resulting manifold views, we transform the information contained in all the simultaneously collected time series into a visualization that effectively shows how a network "breathes" and that can be directly used for diagnosing aspects of a network's health.

CCS Concepts

• Networks → Network measurement; **• Human-centered computing → Visualization systems and tools**.

HotNets '25, College Park, MD, USA

ACM ISBN 979-8-4007-2280-6/25/11
https://doi.org/10.1145/3772356.3772424

ACM Reference Format:
Stephen Jasina, Loqman Salamatian, Paul Barford, Mark Crovella, and Walter Willinger. 2025. A Breath of Fresh Air: Visualizing How Networks "Breathe". In *The 24th ACM Workshop on Hot Topics in Networks (HotNets '25), November 17–18, 2025, College Park, MD, USA.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3772356.3772424

This submission includes essential animations. Please review it using a computer with animation support, not a printed or static PDF version.

1 Introduction

Humans are inherently visual creatures. A commonly cited statistic is that humans remember 10% of what they hear, but simply adding a visual aid increases recall to 65% [10]. While the exact numbers are contested, the *picture superiority effect* is a well-known phenomenon [17]. However, even just a cursory survey of the published scientific literature in general, and in particular the networking research literature, shows that authors of scientific papers seem to dismiss or be largely unaware of the impact or importance of visuals on readers' understanding and memory retention. In fact, it is rare for a networking researcher to remember a published paper primarily because of a visual it contained and that apparently succeeded in leveraging the reader's cognitive ability of correctly recalling the paper's main topic and key findings at a later date.

At the same time, today's network operators are routinely collecting increasingly rich telemetry data, from thousands of vantage points in their networks, at ever finer temporal granularity and for ever more performance-related metrics. As a result, their challenge has changed from data collection to effectively mining the resulting "big data" and extracting intelligence that can be acted upon by network operators to diagnose or mitigate encountered networking problems. Unfortunately, existing analysis and inference tools produce highly fragmented views of the data and easily overwhelm traditional dashboards that scale poorly with the dimensionality of contemporary network telemetry data (e.g., number of different time series, performance metrics, geo-located vantage points) and prevent operators from obtaining a high-level understanding of their dynamically changing networks that enables meaningful troubleshooting.

The purpose of this paper is to call on the networking research community to acknowledge the challenges posed by the emerging "big (network telemetry) data," revamp its largely dated approaches to scientific communication and publication, and more fully exploit the demonstrable impact of visuals on readers' minds by exploring and leveraging innovative and effective visualization and animation techniques. However, for such techniques to be useful in practice, a concerted effort involving their developers (e.g., researchers) and potential users (e.g., operators) will be needed that calls for close collaboration between the networking research and operator communities.

As a concrete instantiation of this broader challenge, we present a use case that can serve as a roadmap for successfully addressing the posed challenge and entails innovations on three fronts:

The concept of "network delay space": We rely on suitable mathematical techniques to represent simultaneously measured network latencies between different pairs of vantage points in a network at a given point in time t as a 2D manifold in 3D (i.e., the network delay space at time t).

The notion of a "breathing" network: We exploit animation to transform sets of entire time series of these latency measurements into a visualization that shows how these network delay spaces breathe (i.e., change over time).

The need to be useful (i.e., more than "eye candy"): We show that rather than trying to make sense of large collections of simultaneously measured latency time series, network operators can use this animation to obtain a network-wide view of their infrastructures' evolving performance, detect anomalies, and reason about observed changes in their networks' dynamics as captured in the totality of available latency measurements.

To be even more concrete, we use ESnet, a DoE-funded high-performance, unclassified network built to support scientific research [15], to illustrate our use case.

We posit that compared to our novel manifold-based animation of network delay spaces, conventional line plot-type representations of time series data, especially when shown in large quantities, fail to appeal to visual creatures (i.e., readers) and stand little to no chance of being remembered for or associated with the notion of Internet latencies. While some may object to using animations as visuals because they cannot be viewed "on printed paper" but require a computer monitor, we argue that it is about time for our community to fully embrace and make use of modern means of communication and publication, irrespective of whether or not they are suitable for "printed paper."

This work does not raise any ethical concerns.

2 On Visualizing Data

Visualization plays a central role in making complex data intelligible. As Tufte argues in his seminal works [21, 22], well-designed visualizations are tools for reasoning about quantitative information. They reveal structure, highlight patterns, and support comparison, enabling users to perceive relationships that would be difficult or impossible to discern from raw numbers alone. Tufte emphasizes clarity, integrity, and the efficient use of visual space as fundamental to effective data graphics.

This paper contributes to this longstanding effort by creating animated maps that depict physical geography and incorporate dynamic aspects of network performance explicitly into the geometry of the evolving maps. In particular, in this work we focus on dynamic network aspects in the form of measured latency time series between pairs of geo-located routers or vantage points in a network. Building on established techniques for manifold learning such as Principal Component Analysis (PCA)[25], t-SNE[23], and UMAP [9] that aim to extract meaningful low-dimensional embeddings of complex high-dimensional datasets, our approach uses curvature to reconcile measured latencies with geographic space, producing visualizations that are both interpretable and analytically rich.

However, these general-purpose dimensionality reduction tools fall short in realizing our objective of creating interpretable maps that preserve both spatial and performance behavior by respecting geography as well as network semantics. For similar reasons, we also have to rule out applying ridge plots [24] or conventional cartograms [2, 20] for drawing augmented maps, leveraging geographic information systems (GISs) like ArcGIS [3] that allow for the animation of (topographical) maps, or using Nam [4], an early network visualization tool that supports packet-level animation.

To achieve our objective, we reinterpret the set of latencies measured at a fixed point in time (i.e., a "snapshot") as defining an implicit metric space and use curvature to mediate between this inferred geometry and real-world spatial layouts. Specifically, we use Ollivier-Ricci curvature [16] to quantify how measured network latencies diverge from expectations based on Euclidean distance, translating these differences into geometric deformations of a 2D surface embedded in 3D space. In contrast to previous research such as Ni et al. [13] that explored the use of curvature for simple graph abstractions of Internet infrastructure, our focus is on latency data and its continuous embedding into a geographically grounded surface, and we leverage Ricci curvature to provide a rigorous framework for understanding how metric properties differ across neighboring regions.

Earlier work [18, 19] introduced a method and an initial tool for using curvature-based techniques to expose and visualize key features of these snapshots derived from measured network latencies in a real-world network. This paper extends those ideas by considering a series of such snapshots taken at successive points in time and then gluing them together to create an animation over time that incorporates physical geography and network dynamics (i.e., latencies) directly into the geometry of the evolving maps itself.

From a data representation perspective, the importance of such an animation is that it provides an effective and compact, though unconventional, alternative perspective of the joint behavior in time of a large number of simultaneously measured latency time series, one time series for each pair of geo-dispersed locations within a given network. On the one hand, the simultaneous depiction of hundreds to thousands (or more) of univariate times series in ways that is informative, effective and prevents "cluttering" is a known difficult problem data visualization [12, 21, 24]. At the same time, some of today's large service providers have the capability to routinely measure and collect increasingly fine-grained and voluminous telemetry data for the pertinent performance metrics that inform the providers' operators about the health of their global-scale network infrastructures [1, 5, 11]. Faced with such large and semantics-rich Internet datasets that typically include thousands or more performance metric-specific time series, the ability to effectively and intelligently visualize a large number of them takes on new urgency.

3 Methodology

To describe how we transform raw data in the form of measured latency time series into a full-fledged animation, we break down our method into three main steps: data collection and preprocessing, manifold creation, and finally, animation. An open source implementation of these tools is available on GitHub [8].

3.1 Data Collection and Preprocessing

The input to our method is a collection of delay measurements in the form of time series, one time series per pair of geo-located routers or vantage points in a network. In our case, we collect data from the perfSONAR [7] endpoints of the U.S. portion of ESnet [15], which is a DoE-funded high-performance, unclassified network built to support scientific research. We obtain a week's worth of round-trip time (RTT) measurements between each pair of endpoints[1] from March 24 to March 31, 2025, and we aggregate the data across 1 hour time intervals. For each endpoint, we also collect its location as a latitude-longitude pair.

With these week-long per-hour time series, we can take snapshots of (aggregated) RTT measurements at each hour. However, for the purpose of our envisioned animation, this data may be too noisy with respect to time. In particular, our method creates a graph where an edge between endpoints u and v exists when its RTT is measured to be below some threshold T_{uv}. This graph and the choice of T_{uv} will be further detailed in Section 3.2. If the RTT between u and v oscillates only slightly, then the edge between u and v will appear and disappear in quick order, resulting in undesirable behavior from an animation point of view. We avoid this behavior by preprocessing the data and annotating each RTT measurement with a boolean for whether we will include or exclude the corresponding edge from the graph. Specifically, we employ a "windowing" strategy to ensure that an edge only changes its inclusion in the graph if its RTT changes by at least w. In practice, choosing $w = 1$ms filters out most undesired noise while still allowing for significant variations in the animation across time.

3.2 Manifold Creation

Our goal for this second step is to turn a given time t snapshot of aggregated RTT measurements within ESnet into a 2D manifold in 3D space. In other words, we create a compact and interpretable representation of the delay space of the network at time t. To this end, we closely follow the steps described by Salamatian *et al.* in [19], where a more detailed explanation can be found.

We first select a *performance threshold*[2] ϵ that typically ranges between 5ms and 25ms. Selecting lower values of ϵ captures local behavior of the network, while the use of higher values of ϵ reveals the global network structure. For a pair of endpoints u and v, we set $T_{uv} = \mathrm{GCL}_{uv} + \epsilon$, where GCL_{uv} is the *great circle latency* between u and v. Then we follow the graph construction described in 3.1.

For a snapshot at time t, we now have a graph G_t with nodes representing endpoints and edges connecting pairs with acceptable latency. To capture the structure of this graph more precisely, we compute the Ricci curvature of each edge. In this context, Ricci curvature quantifies how much an edge contributes to the overall "connectivity" of the network: edges that act as structural bottlenecks or bridges

[1] perfSONAR endpoints in ESnet are time synchronized via NTP and measure RTT across the network on 10min intervals.

[2] [19] refers to ϵ as the *residual latency* and includes a comprehensive strategy for selecting this parameter.

tend to have more negative curvature, as in [19]. For an intuitive understanding and formal treatment of Ricci curvature, we refer the reader to [14], especially [14, Figure 4].

We then embed the network into a 2D surface in 3D space whose Gaussian curvature approximates the Ricci curvature of the graph. Our goal is to recover a surface whose curvature structure reflects that of the graph; this curvature alignment indirectly shapes the geodesics on the surface, so that they reflect the network's underlying delay and routing behavior. To construct such a surface, we define a loss function with two components: (1) a curvature-matching term that penalizes discrepancies between the Ricci curvature of each edge and the Gaussian curvature of the corresponding location on the surface, and (2) a regularization term that encourages smoothness in the resulting surface.

By minimizing this loss function using a standard optimization routine [6], we obtain a manifold that approximates the delay space of the network at time t, meaning that for any two points on the manifold, walking along the shortest path on the surface between the two points connects them by their geodesic whose length encodes the measured latency at time t between the pair of points.

We further post-process this manifold by flattening the surface around the edges of the network (i.e., in regions not covered by the network graph). We also highlight (in red) areas of the manifold that significantly change over a short period of time by comparing the heights at time t to a moving average of the heights before time t. These additional steps help to draw attention to the relevant parts of the surface.

3.3 Animation and Scalability

Finally, we consider all time t snapshots and stitch together the resulting manifolds from Section 3.2 to create a single, cohesive animation. Our strategy is to use the different time t manifolds as key frames. For the frames in between the snapshots, we simply interpolate linearly between the z-coordinates (or "heights"). While other methods of interpolation (splines, etc.) are possible, we find that linear interpolation produces sufficiently smooth animations.

Note that our manifold animations are aggregations of 673 time series of hourly RTT measurements taken over the course of a week, totaling more than 100,000 data points. The thresholding process described in Sections 3.1 and 3.2 allows for an even greater degree of scalability in the case of larger latency data sets.

4 Network Delay Space: A Snapshot in Time

Figure 1 shows a single key frame generated using the technique from Section 3.2. Drawn onto the manifold are the locations of the perfSONAR endpoints colocated with routers in ESnet. The figure also includes a single geodesic (shortest) path on the manifold from Seattle to Boston. Notably, even with this single frame, a viewer can quickly attain an understanding of the delay space by looking for *hill* and *valleys* and *saddle* shapes. Hills/valleys correspond to areas with rich connectivity, whereas saddles go with links that are critical to connectivity. As demonstrated by the depicted geodesic, shortest paths circumvent hills/valleys (Wisconsin) and are attracted to saddles (Colorado).

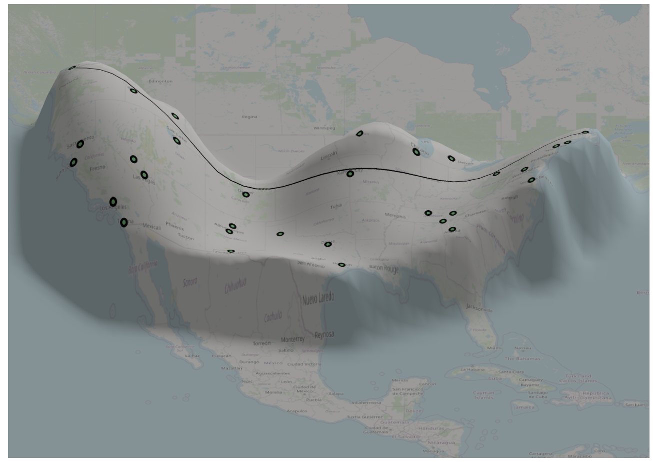
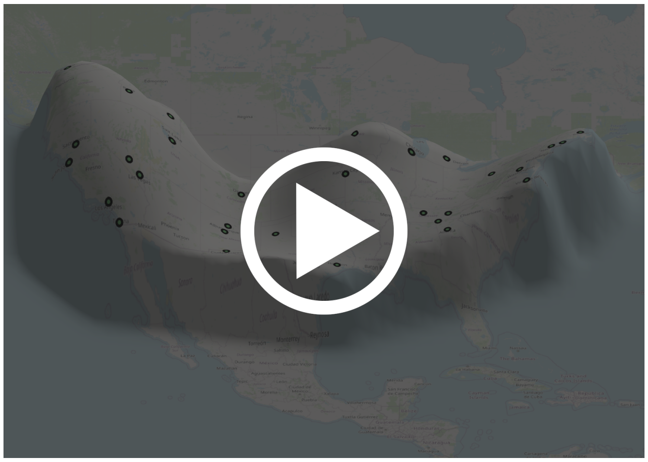


Figure 1: A snapshot in time of the ESnet delay space. Circles on the surface are the locations of perfSONAR endpoints in ESnet. The black line spanning the surface is the geodesic path from Seattle to Boston.

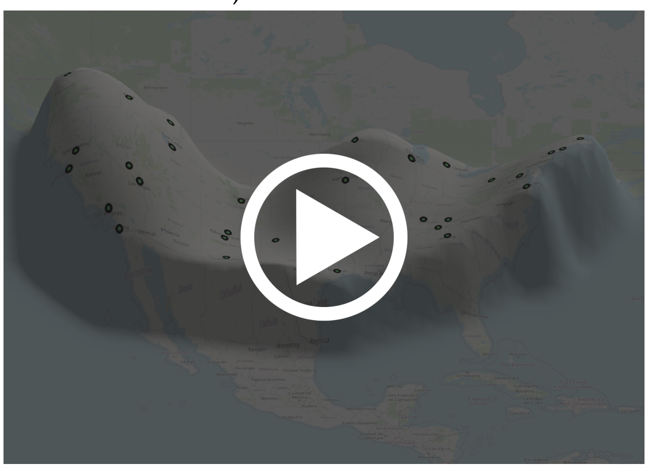
5 Network Delay Space: A "Breathing" Network

Stitching together a series of snapshots yields the moving surface shown in Figure 2a. For additional clarity, as mentioned in Section 3.2, we draw translucent red patches onto the surface in regions where the manifold changes significantly. As seen by the sparsity of these red patches, changes in ESnet's delay space tend to be localized, rarely radiating across larger portions of this network. We view this as an indication of effective network management whereby instances such as link failure are prevented from cascading across the larger network.

Overall, we see the manifold changing in fits and starts, exhibiting stable behavior over disjoint stretches in time that are interspersed with "active" durations during which the manifold undergoes easily visible shifts. The animation depicts the evolution of ESnet's delay space over time and in (geographic) space and exposes just a few "interesting" periods that deserve the network operators' attention. However, as can be expected from an operational network such as



(a) Wall clock–aligned animation (each hour lasts half a second in the animation).



(b) Enhanced animation (time is sped up during uninteresting periods when manifold is stable).

Figure 2: Animations of ESnet's delay space over 1 week, with significant height changes shown in red.
Click anywhere on the images above to watch the videos online.

ESnet, stable periods dominate over "active" periods, creating the association of a relatively "uninteresting" or "boring" animation with a well-performing and smoothly-operating network. Such wall clock–aligned animations can easily be enhanced with a small amount of postprocessing that simply speeds up time during "uninteresting" periods when the manifold remains largely unchanged. To illustrate, the animation in Figure 2b is such an enhanced version of the wall clock-aligned animation in Figure 2a.

The visualization can be further embellished by drawing geodesic paths between endpoints. Figure 3 shows an overhead view of the surface along with the geodesic path

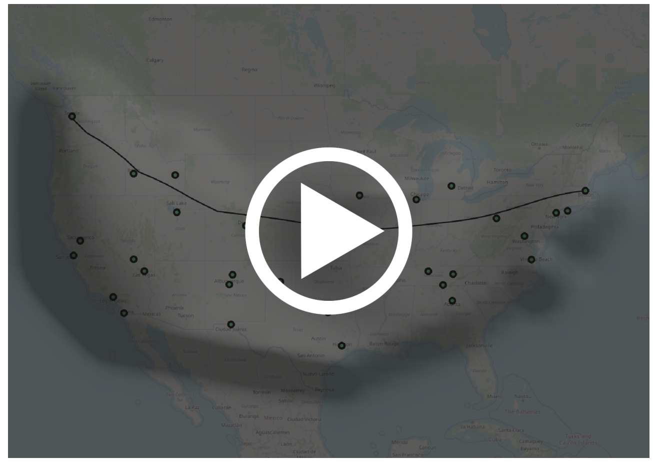


Figure 3: An animation of ESnet's delay space highlighting how the Seattle-Boston geodesic changes with measured RTT. In the animation, a supplementary line plot shows the measured RTT (blue) and geodesic distance on the manifold (orange) between Seattle and Boston.
Click anywhere on the image above to watch the video online.

between Seattle and Boston. As the surface morphs, the geodesic shifts and curves to avoid newly formed peaks and valleys in favor of saddles.

Notably, the shown geodesic on the manifold between Seattle and Boston moves around within the manifold and increases and decreases in length depending on how the measured RTT between the two routers behaves.

6 Network Delay Space: More Than "Eye Candy"

In this section, we demonstrate how an animated manifold offers a powerful new lens for detecting and localizing network disruptions. By embedding time-varying latency measurements into an animated manifold, we create a visual diagnostic tool that is sensitive not only to when performance shifts occur, but also to where they are happening within the network. We illustrate this point through events drawn from our week-long ESnet trace, as illustrated by Figure 4.

The first incident occurs on March 25, 2025 from 02:00 UTC to 07:00 UTC. Examining the time series individually reveals a sudden increase in latency across a range of paths, but offers little clarity about how these changes relate to each other. Without anchoring the paths in space, it is difficult to tell whether these increases reflect a meaningful spatially coordinated disruption or are simply a distributed set of unrelated shifts. In other words, the time series view suggests

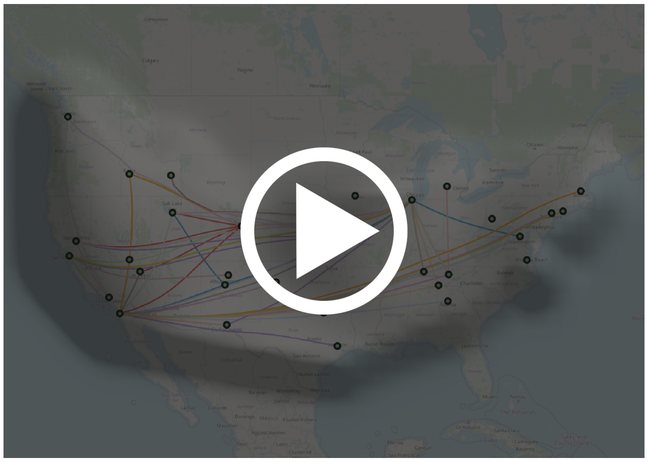


Figure 4: Animation of ESnet delay space over a 1 week period along with the timeseries of delays shown on the manifold. The animation highlights the scope and impact of several "events" that occurred during this period.
Click anywhere on the image above to watch the video online.

something is happening, but it cannot tell us what or where that something is happening.

In contrast, the manifold view reveals meaningful and rich insights: a large peak emerges near Utah, lifting a broad region of the surface. This topographical change radiates outward in multiple directions, effectively splitting the manifold into two regions connected only by a narrow bridge through Arizona. As a result, paths between the East and West coasts are redirected toward that saddle point, causing a significant bundling of all of the geodesics.

Importantly, making this initial diagnosis would be difficult based on looking at the time series alone. In fact, many of the affected end-to-end paths do not obviously traverse Utah, and uncovering that detail would require traceroute data—and even then, the presence of MPLS tunnels could obscure the true path.

The animation highlights several other regional-scale disruptions throughout the week (e.g., March 26 near Louisiana, Arkansas, and Kentucky, or March 27 near Texas). As a representative example, we focus on an event beginning at 14:00 UTC on March 28, 2025. While the time series view reveals an increase in latency across a limited set of paths, it again offers little guidance about scope or cause. The manifold, in contrast, clearly shows that the disturbance is highly localized: two small peak form in the southern portion of the map, one centered around New Mexico, West Texas, and another one around Tulsa, while the remainder of the surface remains stable. Affected geodesics bend gently upward in this region, tracing a coherent visual ripple, while unaffected paths stay identical. This kind of subtle but spatially structured deformation is easy to overlook in raw time series but clearly stands out in the animation. This visual signature of a confined regional event helps operators quickly triage which parts of their network to investigate and narrow down which ones deserve more focus.

7 What's Next?

Extending beyond latency: While this paper focuses on latency measurements, we are actively extending our methodology to incorporate other telemetry signals such as packet loss and link utilization. In ongoing work, we construct overlays on top of the delay manifold that represent link-level metrics. For example, we draw arcs between nodes corresponding to physical links and annotate them with utilization measurements. This construction is feasible in networks like ESnet, which publish link utilization statistics. These metrics are directly attributable to specific links and integrate naturally into our spatial visualization.

In many other networks, however, link-level utilization is not directly observable. Instead, operators or researchers must rely on end-to-end throughput measurements (e.g., from iPerf), which do not easily decompose into per-link contributions. Extending our methodology to incorporate throughput in these settings presents a major challenge: it requires inferring the internal path taken by each flow and attributing observed throughput to load along that path. One possible direction is to overlay inferred routing paths on the delay manifold and annotate them with throughput-based estimates of load or bottlenecks, but this method calls for more complex inference techniques and requires assumptions about routing behavior. Building such overlays remains an open and promising area for future work.

Network respiration. We are developing a diagnostic playbook grounded in manifold representations to help operators connect visual patterns to real network behaviors. While our current animations primarily highlight sudden disruptions, we have initial evidence that they can also capture more subtle, continuous dynamics—what we refer to as a network's "breathing." These dynamics manifest as a slow, spatially coordinated deformations that reflect underlying diurnal cycles, shifting traffic loads, and baseline variability. Although such rhythms are only faintly visible in a lightly loaded research network like ESnet, we expect them to emerge more clearly in production networks that experience sustained, high utilization, and richer traffic dynamics resulting from realistic mixtures of residential and commercial customer traffic.

Beyond ESnet: The public Internet. Generalizing our approach to the public Internet poses substantial challenges.

Within a single network, manifold-based representations often work well because routing decisions tend to follow physical constraints: shortest-path routing over a known, relatively stable topology. When traffic shifts, those shifts typically reflect changes in the underlying cost (in the OSPF sense) or availability of physical links. Because routing decisions still aim to minimize end-to-end path cost over a fixed topology, the resulting changes tend to preserve the overall spatial structure of the network: nearby nodes remain nearby, path lengths change gradually, and traffic continues to follow topologically plausible paths. In this sense, the deformation remains structurally coherent and reflects continuous adaptation within a stable underlying graph, rather than abrupt or arbitrary redirections.

In contrast, when traffic traverses multiple administrative domains, the assumptions that underlie this geometric coherence begin to break down. At interconnection points, traffic is often not routed based on physical proximity or network distance, but rather based on business agreements, BGP policies, and peering strategies. These decisions can introduce abrupt and opaque transitions in path selection, resulting in discontinuities that cannot be easily reconciled with a smooth manifold. Each independently operated network can be viewed as defining its own delay space or manifold, shaped by internal policies, topology, and traffic engineering objectives. The connections between these networks, however, resemble discontinuous "wormholes"—transitions that obey an entirely different logic and do not preserve the geometric assumptions of the underlying spaces. Modeling how these independent manifolds can be stitched together remains an open and difficult problem.

This challenge is especially relevant to large CDNs and cloud providers that collect rich telemetry not only from within their controlled infrastructure but also from user-facing traffic that traverses third-party networks. While internal telemetry is well-instrumented and tied to known infrastructure, external data often lacks the context necessary for interpretation: we may observe path changes or performance degradation, but lack visibility into the routing policies, economic incentives, or topology that caused them. Developing new ways to model these new stitched manifolds across networks could unlock new diagnostic capabilities, enabling CDNs to reason more precisely about performance and resilience in the Internet at large.

8 Conclusion

The broader goal of this work is to reimagine how interactive visualization can support both network research and network operations. Networks are spatiotemporal systems, and we argue for the importance of reclaiming time as a first-class visual dimension. In particular, our work demonstrates one way to build tools that not only summarize large-scale telemetry but also support intuitive exploration and pattern recognition. We hope this work encourages others to embrace more dynamic and expressive visualizations—especially as network telemetry continues to grow in volume and complexity.

Acknowledgements

This material is based upon work supported in part by the National Science Foundation under Grant Nos. CNS-2312709, CNS-2312711, CNS-2319367, and CNS-2319369. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] Amazon. 2025. Amazon CloudWatch. https://docs.aws.amazon.com/AmazonCloudWatch/latest/monitoring/WhatIsCloudWatch.html.

[2] Colette Cauvin and C Schneider. 1989. Cartographic transformations and the piezopleth maps method. *The Cartographic Journal* 26, 2 (1989), 96–104.

[3] Esri. 1982. ArcGIS. https://www.arcgis.com/.

[4] D. Estrin, M. Handley, J. Heidemann, S. McCanne, Ya Xu, and H. Yu. 2000. Network visualization with Nam, the VINT network animator. *Computer* 33, 11 (2000), 63–68. doi:10.1109/2.881696

[5] Google. 2025. Cloud Monitoring. https://cloud.google.com/monitoring/docs.

[6] Aric A. Hagberg, Daniel A. Schult, and Pieter J. Swart. 2008. Exploring Network Structure, Dynamics, and Function using NetworkX. In *Proceedings of the 7th Python in Science Conference*, Gaël Varoquaux, Travis Vaught, and Jarrod Millman (Eds.). Pasadena, CA USA, 11 – 15.

[7] Andreas Hanemann, Jeff W. Boote, Eric L. Boyd, Jérôme Durand, Loukik Kudarimoti, Roman Łapacz, D. Martin Swany, Szymon Trocha, and Jason Zurawski. 2005. PerfSONAR: A Service Oriented Architecture for Multi-domain Network Monitoring. In *Service-Oriented Computing - ICSOC 2005*, Boualem Benatallah, Fabio Casati, and Paolo Traverso (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 241–254.

[8] Stephen Jasina, Loqman Salamatian, and Joshua Mathews. 2025. Matisse. https://github.com/StephenJasina/linear-geodesic-optimization/releases/tag/v2.0.0.

[9] Leland McInnes, John Healy, and James Melville. 2020. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. https://arxiv.org/abs/1802.03426

[10] John Medina. 2008. *Brain Rules: 12 Principles for Surviving and Thriving at Work, Home, and School.* Pear Press, Seattle, Washington.

[11] Microsoft. 2025. Azure Network Watcher. https://learn.microsoft.com/en-us/azure/network-watcher/network-watcher-overview.

[12] Dominik Moritz and Danyel Fisher. 2018. Visualizing a Million Time Series with the Density Line Chart. arXiv:1808.06019 [cs.HC] https://arxiv.org/abs/1808.06019

[13] Chien-Chun Ni, Yu-Yao Lin, Jie Gao, Xianfeng David Gu, and Emil Saucan. 2015. Ricci curvature of the Internet topology. In *2015 IEEE Conference on Computer Communications (INFOCOM)*. IEEE, Hong Kong, 2758–2766. doi:10.1109/INFOCOM.2015.7218668

[14] Chien-Chun Ni, Yu-Yao Lin, Feng Luo, and Jie Gao. 2019. Community detection on networks with Ricci flow. *Scientific reports* 9, 1 (2019), 1–12.

[15] United States Department of Energy. 1986. ESnet. https://www.es.net/.

[16] Yann Ollivier. 2009. Ricci curvature of Markov chains on metric spaces. *Journal of Functional Analysis* 256, 3 (2009), 810–864.

[17] Allan Paivio and Kalman Csapo. 1973. Picture superiority in free recall: Imagery or dual coding? *Cognitive Psychology* 5, 2 (1973), 176–206. doi:10.1016/0010-0285(73)90032-7

[18] Loqman Salamatian, Scott Anderson, Joshua Mathews, Paul Barford, Walter Willinger, and Mark Crovella. 2023. A Manifold View of Connectivity in the Private Backbone Networks of Hyperscalers. *Commun. ACM* 66, 8 (jul 2023), 95–103. doi:10.1145/3604620

[19] Loqman Salamatian, Scott Anderson, Joshua Matthews, Paul Barford, Walter Willinger, and Mark Crovella. 2022. Curvature-based analysis of network connectivity in private backbone infrastructures. *Proceedings of the ACM on Measurement and Analysis of Computing Systems* 6, 1 (2022), 1–32.

[20] Hui Sun and Zhilin Li. 2010. Effectiveness of cartogram for the representation of spatial data. *The Cartographic Journal* 47, 1 (2010), 12–21.

[21] Edward R Tufte. 1983. *The Visual Display of Quantitative Information.* Graphics Press, Cheshire, Connecticut.

[22] Edward R Tufte. 1990. *Envisioning Information.* Graphics Press, Cheshire, Connecticut.

[23] Laurens van der Maaten and Geoffrey Hinton. 2008. Visualizing Data Using t-SNE. *Journal of Machine Learning Research* 9 (2008), 2579–2605.

[24] Claus O. Wilke. 2019. *Fundamentals of Data Visualization.* O'Reilly Media, Sebastopol, California.

[25] Svante Wold, Kim Esbensen, and Paul Geladi. 1987. Principal component analysis. *Chemometrics and intelligent laboratory systems* 2, 1-3 (1987), 37–52.