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Topological Data Analysis in Tracking Cognitive and Physiological States

Introduction

Topological Data Analysis (TDA) provides tools like **persistent homology** to quantify the *"shape"* of high-dimensional data. In neuroscience, TDA has been harnessed to capture invariant structures in brain signals (EEG, fMRI) and behavior that correlate with cognitive states. Instead of focusing on pairwise correlations or average activity, persistent homology extracts multiscale topological features – e.g. **Betti numbers** (counts of connected components, loops, voids) – that describe how brain network connectivity or state-space geometry evolves as a threshold or scale parameter varies [1] [2] . These features serve as compact *signatures* of cognitive processes and physiological states, revealing patterns (holes, clusters) that traditional analyses might miss [3] [4] . Crucially, TDA's invariants are robust to noise and coordinate transforms, making them attractive for brain data, which are notoriously high-dimensional and noisy [1] . Recent research – spanning human neuroscience and machine learning – has applied persistent homology to track changes in **attention**, **cognitive engagement**, and even transitions into altered states (meditation, mind-wandering, seizure, anesthesia). Below, we survey peer-reviewed studies showing how TDA confirms hypothesized topologies of cognitive dynamics, detects regime shifts in attention via topological "signatures," and enables *"holographic inference"* of internal states from external measurements. We also highlight specialized metrics (beyond raw Betti counts) and tools/datasets emerging in this domain.

Topology of Cognitive Processes: Toroidal Manifolds and Loops in Brain Dynamics

One striking example of TDA confirming a hypothesized cognitive topology is the **toroidal structure** in grid-cell neural activity. Gardner *et al.* (2022) used persistent homology to show that the joint firing patterns of hundreds of entorhinal grid cells lie on a 2D torus [5] . In this study, high-density electrophysiology in freely moving rats produced an n-dimensional state-space of population activity; persistent homology revealed two persistent 1D holes and one 2D void in this space, exactly matching a torus's homology (H_1: two independent loops; H_2: one void) [5] . In other words, as the animal explored a 2D arena, the neural state traced a torus – a topological confirmation of continuous attractor models of spatial mapping. This *"toroidal manifold"* was visualized via dimensionality reduction, showing a donut-like point cloud where movement on the torus corresponded to the animal's position [5] [6] . The persistent loops were maintained across different environments and sleep, providing strong evidence (a kind of **torus confidence**) that the internal cognitive map has toroidal geometry [7] .

Topological analysis has also illuminated **recurrent loops** in other cognitive processes. Persistent H_1 features (1D loops) often indicate cyclic or recurrent dynamics in brain state-space [8] . For example, a persistent loop in an fMRI-derived state-space might signify a brain network cycling through a sequence of states during a working memory task. Savva (2025) notes that stable H_1 loops reflect *recurrent information flow* – the brain revisiting a configuration repeatedly – as in sustained working memory or rhythmic motor

control [8] [9] . In one study, Lee *et al.* (2018) found such "harmonic holes" as key features of functional brain networks, suggesting that cognitive processes often involve **topological cycles** that could encode maintenance of information or periodic attention shifts [10] . Furthermore, higher-dimensional holes (H_2 voids) may correspond to *nested* cognitive structure: e.g. a complex task with multiple sub-loops can form a cavity in state-space, reflecting constraints that organize those loops [11] [12] . Santoro *et al.* (2024) recently demonstrated this in human fMRI: by modeling **higher-order interactions** (3-node and 4-node relations) as simplicial complexes, they detected local 2D voids in functional connectivity patterns that were highly predictive of which task a subject was performing [12] . This aligns with the idea that cognition involves not just pairwise connections but *higher-order* network structure – effectively, **multi-loop topologies** – that can be quantified by persistent homology.

Notably, Santoro and colleagues introduced a **"hyper-coherence"** measure for brain activity based on the presence/absence of topological loops in networks of BOLD co-fluctuations. They treated each timepoint's functional connectivity as a weighted simplicial complex (including triangles for 3-region interactions), then tracked how loops (H_1 cycles) form or break as they sweep a threshold [13] [14] . They defined a *hyper-complexity indicator* as the sliced Wasserstein distance between the persistence diagram of H_1 loops and an empty diagram (no loops) [14] . A large value indicates a complex topology with robust loops, whereas a value near zero means a loop-free (tree-like or fragmented) network [14] . Using this, they showed that different cognitive tasks produce distinct topological "landscapes" of brain activity: e.g. tasks engaging frontoparietal networks yielded higher H_1 persistence (more sustained loops), whereas passive rest showed fewer, shorter loops [15] [16] . Such results support the notion that **coherent cognitive states** (with stable recurrent dynamics) manifest as persistent loops, whereas **fragmented or flexible states** may show transient or no loops. In sum, TDA provides a quantitative handle on the oft-theorized but hard-to-measure "shape" of cognition – from rings and tori in neural manifolds to loops and cavities reflecting recurrent or hierarchical mental processes.

Topological Signatures of Attention and State Transitions

Beyond confirming the existence of particular shapes, TDA has been used to *track changes* in cognitive state – for instance, detecting when a person's attention shifts or when the brain enters a new regime (engaged vs. mind-wandering, etc.). A pioneering study by Saggar *et al.* (2018) applied TDA (specifically the Mapper algorithm coupled with persistent homology) to time-resolved fMRI during task-switching [17] [18] . Without needing to pre-define states, their approach revealed an intrinsic organization of whole-brain activity and could **flag transitions** between cognitive tasks on the order of 4–9 seconds, much faster than conventional methods [19] . In a multitask experiment with known ground-truth switch times, the TDA-based analysis identified both within-task and between-task transitions with high temporal precision, effectively detecting when the brain "moved" from one network configuration to another [19] . These topological transitions were not only timely but behaviorally relevant: individuals whose brain activity showed more distinct topological states between tasks also tended to have better task performance [19] . This suggests persistent homology can serve as a sensitive marker of attention shifts, picking up subtle reconfigurations in functional connectivity that herald a regime change (e.g. from focused task engagement to an "off-task" state).

Though direct studies of **mind-wandering via TDA** are still nascent, the above evidence implies a clear use-case: by monitoring the *appearance or disappearance of topological features* in brain signals, one could potentially detect when a person lapses into mind-wandering (a change in network organization akin to a phase transition). For instance, a focused attention state might maintain a certain number of persistent loops or components in EEG phase-space, whereas a mind-wandering state could either introduce new

loops (if the brain starts cycling through different idle patterns) or collapse them (if connectivity becomes more random). The **regime shifts** would show up as changes in Betti numbers over time. Some recent work in dynamic functional connectivity aligns with this idea: *network metastability* and *integration-segregation balance* have been linked to attention, and TDA provides a way to quantify these. Wang *et al.* (2025) demonstrated that individuals have unique topological fingerprints in resting-state fMRI – essentially, each person's brain hovers around an idiosyncratic set of topological features (H_0 and H_1 patterns) even as it transitions through states [20] [21] . When attention lapses or switches, one might observe a departure from that baseline "fingerprint." In ADHD, for example, TDA has revealed **altered transition patterns**: Gracia-Tabuenca *et al.* (2020) showed that ADHD children's brain networks become connected (collapse to one component) at lower threshold values than controls, indicating **decreased segregation** and potentially more abrupt state transitions [22] [23] . This was consistent across multiple brain atlases and especially pronounced in frontal and default-mode networks [23] . In practical terms, such differences mean that an ADHD brain may traverse connectivity states differently (perhaps less stability in a focused configuration, more rapid merging of networks – a possible correlate of attention fluctuation). Thus, by examining features like the shape of the Betti–0 curve (which tracks the merging of network components), TDA can sensitively detect **attention-regime shifts** and network "collapse" points. In one visualization, the Betti–0 curves of ADHD vs. typically developing children showed distinct slopes and areas under the curve, allowing classification of the groups and pinpointing thresholds where their brain connectivity organization diverged [22] [24] . These topological markers of reduced network modularity (lower $β\_0$ persistence) align with cognitive symptoms of ADHD (difficulty sustaining segregated task-focused networks) [23] [24] .

Beyond fMRI, **EEG-based** TDA has also succeeded in capturing attention and awareness states. *Persistent homology on EEG phase-space reconstructions* (delay embeddings of multichannel EEG) can reveal early-warning signs of transitions like epileptic seizures or loss of consciousness. Lucas *et al.* (2024) found that as a seizure approaches, the variance of Betti–1 (loop count) in EEG phase-space shows a marked rise – often 60–80 seconds before clinical onset [25] . Intuitively, the EEG dynamics become topologically more complex (more 1D cycles) as the brain's activity starts to oscillate into seizure patterns, providing a **topological precursor** that outperforms standard variance metrics. Similarly, Varley *et al.* (2021) distinguished two anesthetic-induced unconscious states (propofol vs. ketamine) by their EEG topologies [26] [27] . Propofol, which produces a deep unconsciousness, led to a brain-state topology with fewer persistent loops (indicating a globally coherent, suppressed dynamical regime), whereas ketamine – which induces a dissociated state with vivid internal experiences – preserved more complex topological features (loops and cavities), reflecting richer dynamics despite the lack of external responsiveness [26] . These findings underscore that **physiological regime shifts** (awake to anesthetized, interictal to seizure, etc.) are detectable via changes in persistent homology. By monitoring the birth and death of topological features in real time, one can perform a form of *cognitive state tracking* – for example, a sudden drop in $β\_0$ (many brain regions becoming connected) might signal a transition into a synchronized, less conscious state, whereas a spike in $β\_1$ variability might warn of an oncoming epileptic event [25] .

Holographic Inference: Inferring Internal States from Peripheral Signals

A powerful aspect of TDA is that it enables *"holographic" inference*, where one can infer hidden mental states from externally measurable patterns by leveraging topological signatures. The idea is that even peripheral signals – EEG on the scalp, wearables capturing physiology, or behavioral time series – carry an imprint of the brain's state in their shape. TDA methods have begun to decode these states without needing direct

access to internal variables. For instance, in an **eye-blink and behavior dataset**, one could construct a point-cloud of timing intervals or eye-movement trajectories and apply persistent homology to detect loops corresponding to rhythmic attention oscillations. While such specific studies are emerging, we do have concrete demonstrations in related domains: **meditative states** versus normal waking have been distinguished using only EEG recordings and TDA features. Gupta *et al.* (2024) extracted persistent homology features (e.g. *Betti curve areas* and *persistent entropy* of EEG signals across multiple frequency bands) to characterize different meditation practices [28] [29] . They reported that these topological features varied systematically with the level of meditative absorption – notably, certain brain regions (frontal lobe) exhibited more sustained topological activity (more persistent H_0 components) when processing disorderly/random images versus ordered patterns [30] . By training classifiers on these features, they achieved high accuracy distinguishing meditative versus non-meditative EEG segments. In other words, the *whole-brain consciousness state* was inferred from the *topology of EEG data* [31] [32] . Such an approach treats the EEG as a "hologram" of the brain's cognitive state, where persistent homology extracts the latent structure (e.g. coherence of rhythms, complexity of neural oscillation patterns) that correlates with internal awareness.

Another example is in **mild cognitive impairment (MCI)**, an early sign of dementia. Rutkowski *et al.* (2023) showed that TDA features from EEG during a memory task can predict which individuals have MCI, even before clinical dementia onset [33] [34] . They built on Varley's method of converting EEG time-series into persistence diagrams (using embedding and cosine distance for brain waves) and derived features like the *number of persistent cycles* and *normalized persistence entropy* [35] [36] . These features were used as input to machine learning models, yielding successful MCI classification and even regression of cognitive scores. Essentially, the brain's internal **cognitive decline** was inferred from scalp measurements by recognizing changes in topological invariants (e.g. MCI patients showed fewer persistent loops and lower persistence entropy in certain EEG bands, indicating a loss of complexity consistent with reduced cognitive flexibility [37] [36]). This approach exemplifies holographic inference: the topology of an external signal (EEG) mirrored the internal neural network integrity. Likewise, in the seizure prediction study noted earlier, an algorithm could infer the *impending loss of cortical stability* (internal state) from the *rising Betti-1 variance* in the EEG (peripheral signal) [25] . In a sense, the peripheral data's topological structure acts as a **proxy** for unobserved brain changes.

It's worth noting that TDA-based holographic inference is not limited to EEG/fMRI. Any high-dimensional behavioral readout that reflects cognitive state could be analyzed topologically. For example, recent work has even applied persistent homology to **kinematic and gait data** to evaluate neurological conditions, treating body movement patterns as a manifold. While those studies are beyond our current scope, they highlight a trend: *topological signatures are emerging as cross-modal biomarkers*. They allow researchers to connect the dots from external measurements (which are easier to get) to internal states (which are complex and hidden) by focusing on abstract shape characteristics that remain consistent across that divide.

Advanced Topological Metrics and Tools

Early applications of TDA in neuroscience often reported simple metrics like Betti numbers (e.g. the count of loops at a particular scale). More recent studies have introduced a richer arsenal of **persistent descriptors**

to better capture cognitive-state nuances. These go beyond raw Betti counts to quantify the *lifespans* and *distributions* of topological features:

- **Persistence Diagrams and Barcodes:** These are the fundamental outputs of persistent homology, plotting the "birth" and "death" of each topological feature. Many studies now compare whole persistence diagrams between conditions (e.g. using bottleneck or Wasserstein distances) [1]. Santoro *et al.* used a sliced Wasserstein distance from the persistence diagram to the empty diagram as a summary of loop complexity (the *hyper-complexity indicator*) [16], giving a single number to represent how far a brain state is from having no loops at all.

- **Betti Curves and Betti Surfaces:** Instead of single Betti numbers at an arbitrary threshold, a Betti *curve* tracks, say, β_0 or β_1 as a function of the filtration value. The *area under this curve*, its slope, or other shape parameters can serve as features. In the ADHD study, features like the **AUC of the β_0 curve, its slope, and kurtosis** were used in logistic regression to distinguish patients from controls [22] [38]. Significant differences in these Betti-curve-derived metrics indicated altered network integration in ADHD [23] [24]. Betti curves thus capture the *global cohesion* of brain networks across scales, rather than at one arbitrary threshold.

- **Persistence Entropy:** This metric treats the persistence diagram like a probability distribution (each feature's lifetime contributing to an entropy measure). It summarizes the **overall topological complexity** in a single value. Persistence entropy has been applied to EEG data – for example, to characterize meditative vs. normal states, researchers found it correlated with cognitive load [31] [32]. In a recent physical review study, persistent entropy combined with total persistence explained more variance in an experimental factor (like seizure vs. baseline condition) than conventional power-spectrum measures [39] [40]. High entropy generally means many topological features with varied lifetimes (more complex dynamics), whereas low entropy implies a simpler, more ordered state.

- **Persistence Landscapes and Silhouettes:** These are vectorized summaries of persistence diagrams, often used to feed into machine learning. A persistence landscape is essentially a functional summary of the barcode, and a silhouette is a weighted average of lifespan distributions. According to a 2025 review, **persistence landscapes, images, and silhouettes** have been increasingly adopted in EEG analysis [41] [2]. They allow use of topological features in standard statistical pipelines. For example, one can average landscapes across subjects or use them as features in a classifier, which is harder to do directly with raw diagrams. The review notes that persistence **images** (heatmap representations of diagrams) and **heat kernel** representations are also gaining traction [42]. Gupta *et al.* and Kang *et al.* converted persistence diagrams into heat kernel signatures (smooth density maps) to use as features for EEG-based mental state classification [43]. Such **topological feature engineering** often boosts performance when combined with conventional features.

- **Novel Persistence Ratios and Amplitudes:** New scalar features have been defined to capture specific aspects of the persistence spectrum. For instance, the *maximum persistence* (longest lifespan of any feature, sometimes called persistence *amplitude*) can indicate the strongest topological signal (e.g. the most dominant loop). Varley's anesthesia study noted whether maximum β_1 persistence changed under ketamine vs. propofol [44] [36]. Additionally, a *latter ratio* (possibly the ratio of late-born to early-born features, or of cumulative lifetimes between conditions) was explored in the context of EEG conscious awareness levels [45] [46]. While definitions vary, these ratios aim to distill

how quickly topology "fills in" as connections are added – effectively a measure of network **coherence vs. fragmentation**. A high ratio might mean a network remains fragmented (many components) until very high thresholds (indicative of strong modularity), whereas a low ratio means components merge early (indicative of a more integrated or coherent network).

Researchers are also developing **significance tests** for topological features, which can be seen as confidence measures for certain shapes. For example, to verify the toroidal structure in grid-cell data, Gardner *et al.* used bootstrapped confidence sets on the persistence diagram to ensure the two H_1 loops were not spurious [47] [5] . In general, statistical methods for persistent homology (e.g. permutation tests on diagram distances, or confidence intervals on Betti curves) allow one to attach a *"p-value"* to claims like *"the data's shape is a torus."* These methods (Chazal *et al.*, 2014; Fasy *et al.*, 2014) give a more rigorous **"torus confidence"** by constructing bands around persistence diagrams that would occur under random noise [48] [49] . If the observed homology points lie outside those bands in the right configuration (two long-lived H_1 and one H_2), one can state with high confidence that a torus is present. Such approaches are increasingly important as TDA moves from exploratory analysis to hypothesis-driven testing in cognitive science.

On the tooling and data side, the growth of TDA in neuroscience has been facilitated by **open-source libraries** and large datasets. Key software libraries include *Ripser* (C++/Python, for fast Vietoris-Rips persistent homology), *GUDHI* (Python/C++, general computational topology), and *giotto-TDA* (a high-level Python library integrating scikit-learn pipelines). Many studies cited here used Ripser for its efficiency on dense data [45] . For example, Varley et al. employed Ripser to compute persistent homology on EEG time-delay embeddings, enabling real-time analysis of 128-channel signals. The **scikit-tda** project also provides convenient tools for persistence landscapes, images, and plotting barcodes. Combined with standard machine learning libraries, these tools make it feasible to include topological features in classification/ regression models for cognitive states [41] [50] .

Large public datasets have spurred TDA applications by providing testbeds for complex cognitive phenomena. The **Human Connectome Project (HCP)** data (as used by Santoro et al. 2024) allowed testing higher-order topology on 100 subjects' fMRI across multiple tasks [51] [52] . Open fMRI and EEG datasets for mind-wandering, meditation, and disease (ADHD-200 for ADHD fMRI; Temple University EEG for seizure; etc.) have similarly enabled topological analyses that generalize. For instance, the CHB-MIT EEG database (24 patients, ~200 seizures) was used in the seizure prediction via Betti-1 variance [53] , illustrating how a challenging clinical inference can be tackled with TDA on openly available data. As the community produces more shared datasets of brain and behavior (including simultaneous multimodal recordings), we expect **holographic inference via TDA** to become even more powerful – allowing researchers to train models on one person's peripheral signals to predict another person's cognitive state, based on the universal language of topology.

Conclusion

Topological data analysis is emerging as a **unifying framework** to understand and monitor cognitive and physiological states. By focusing on the *shape* of brain data – rather than specific location-based activity or pairwise connectivity – TDA can confirm deep theoretical structures (like toroidal cognitive maps and recurrent loops), identify subtle transitions between mental states (attention vs. mind-wandering, wake vs. anesthesia), and enable inference of internal brain states from external measurements (EEG, behavior) with high sensitivity. Crucially, the use of advanced persistent-homology-based metrics (persistence diagrams, entropy, Betti curves, etc.) provides multiple lenses on brain dynamics: from quantifying how *integrated or*

segregated brain networks are, to measuring how *repetitive or exploratory* neural state trajectories become. The studies surveyed here, spanning meditative practice to ADHD, and from task performance to seizures, collectively demonstrate that **persistent homology and Betti numbers can serve as biomarkers of cognition** – capturing phenomena like "coherence versus fragmentation" of mental activity in rigorous mathematical terms. As open-source TDA tools continue to mature and integrate with machine learning, we anticipate wider adoption in neuroscience and beyond. Already, concepts like a "brain's topological fingerprint" [20] [21] or "topological predictors of cognitive resilience" are taking shape, hinting that one day clinicians might assess your attention lapses or risk of Alzheimer's via the holes and voids in your data. In summary, TDA adds a new, powerful dimension to cognitive state tracking – one where **loops, holes, and voids in data become windows into the mind**.

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