Supporting Information for: How is experience transformed into memory?

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Overview

This document provides additional details about the methods we used in the main text. We also include some additional analyses referenced in the main text.

Additional details about topic modeling methods and results

Optimizing topic model parameters

In order to create accurate video and recall models, we used an optimization method that was driven by our ability to explain hand-annotated memory performance metrics collected by **?**. Specifically, we used a grid search to compute the ω (video sliding window duration, in scenes), ρ (recall sliding window duration, in sentences), and K (number of topics) that satisfied

$$\underset{\omega,\rho,K}{\operatorname{argmax}} \left[\operatorname{corr}\left(\operatorname{corr}\left(\mu\left(\omega,\rho,K\right),\nu\left(\omega,\rho,K\right)\right),\theta\right)\right],$$

where corr(μ,ν) is the per-participant correlation between the upper triangles of the temporal correlation matrices of the video (μ) and recall (ν) trajectory, and θ is the per-participant hand-annotated memory performance. We searched over a grid of pre-specified values for each of these parameters; the resulting correlations are displayed in Figure S1. The optimal parameters were $\omega = 50$, $\rho = 10$, and $K = 100$.

The optimized model converged on 27 unique topics that were assigned non-zero weights over the course of the video. We provide a list of the top ten highest-weighted words from each topic in Figure S2.

Feature importance analyses

To determine the contribution of each feature to the structure of the video topic proportions, we conducted a "leave one out" analysis. Specifically, we compared the original video topic trajectory (created using all hand-annotated features from the 1000 hand-annotated scenes spanning the *Sherlock* episode; see *Methods* for a full list of features) with video trajectories created using all but one type of feature. We created temporal correlation matrices for each trajectory (using the topic proportions matrices) and correlated the upper triangles of each impoverished trajectory with the original feature-complete trajectory. Observing a lower correlation between an impoverished trajectory (holding out a particular feature) and the feature-complete trajectory would suggest that the given feature played a more prominent role in shaping the structure of the feature-complete trajectory. We found that hand-annotated narrative details provided the most structure to the feature-complete trajectory, whereas transcriptions of onscreen text provided the least structure (Fig. S3A).

We also carried out an analysis of which annotated features tended to shape aspects of the video topic trajectory that were preserved in participants' recalls. Specifically, we computed the timepoint-by-timepoint correlation matrix of the video topic trajectory, and correlated its upper triangle with that of the timepoint-by-timepoint correlation matrices of each participant's recall topic trajectory (resampled using linear interpolation to have the same number of timepoints as the video trajectory). This yielded a single correlation coefficient for each participant. We then repeated this analysis with each annotated feature held out in turn. Observing a lower correlation between the video and recall trajectories (when a given feature was held out) would indicate that the feature tends to be preserved in participants' recalls. We found that hand-annotated narrative details were the most preserved type of feature, whereas information about the camera angle tended not to influence participants' recalls (Fig. S3B).

Next, we wondered how the different types of features might relate. For example, knowing which characters are on screen during a given scene may also provide information about which characters are speaking. We computed video topic trajectories for each feature in turn, and then compared the temporal correlation matrices of all pairs of features. This provided additional confirmation that the shape of the full trajectory (including all types of features) was largely driven by narrative details. We also found that character-driven features (characters on screen, characters speaking, and characters in focus) were strongly correlated. Other details, such as the presence or absence of music, led to very different topic trajectories (Fig. S3C).

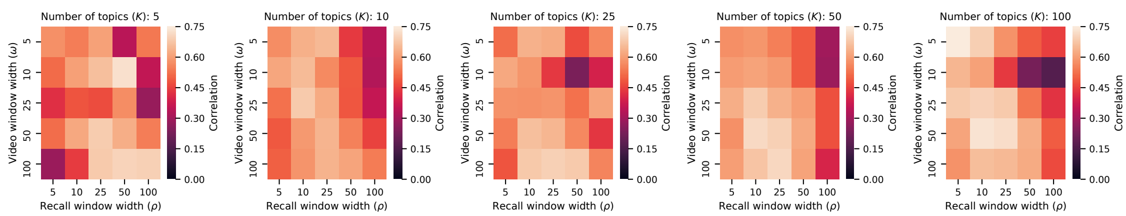

Figure S1: Optimizing topic model parameters. We performed a grid search over video sliding window length ($\omega \in \{5, 10, 25, 50, 100\}$), recall sliding window length ($\rho \in \{5, 10, 25, 50, 100\}$, and number of topics ($K \in \{5, 10, 25, 50, 100\}$. The reported correlations are between per-subject video-recall trajectory correlations and per-subject hand-annotated memory performance ratings.

Topic ID	Top 10 words	Topic description
1	sir, jeffrey, indoor, yes, office, building, aide, helen, lestrade, medium	The first death
2	sherlock, john, outdoor, taxi, yes, medium, road, says, phone, continues	John being followed (a)
3	sherlock, john, donovan, medium, lauriston, gardens, anderson, street, outdoor, lestrade	Discussing the fourth death
4	lestrade, donovan, room, indoor, press, conference, police, medium, reporter, reporters	Press conference (a)
5	john, man, yes, warehouse, indoor, medium, shoulder, says, hand, asks	Meeting with Mycroft (a)
6	sherlock, lestrade, john, indoor, medium, gardens, lauriston, room, floor, crime	Examining a body (a)
7	john, road, brixton, outdoor, phone, box, yes, medium, man, camera	John being followed (b)
8	john, sherlock, street, medium, baker, indoor, says, mrs, hudson, 221b	221b Baker St. (a)
9	john, donovan, lauriston, gardens, yes, street, medium, outdoor, shoulder, policeman	Consulting with the police
10	lestrade, donovan, indoor, room, medium, aide, press, conference, police, reporter	Press conference (b)
11	john, mike, lestrade, medium, donovan, park, indoor, square, russell, outdoor	Exposition
12	john, sherlock, medium, street, baker, anthea, indoor, yes, 221b, suite	Bringing John back
13	sherlock, john, st, bartholomew, hospital, indoor, medium, molly, mike, laboratory	John meets Sherlock (a)
14	john, man, yes, anthea, medium, warehouse, indoor, car, road, outdoor	Kidnapping John
15	john, mike, sherlock, medium, molly, park, russell, square, outdoor, bench	John runs into an old friend
16	jimmy, yes, indoor, donovan, medium, aide, gary, lestrade, press, conference	The second death (a)
17	sherlock, john, crime, scene, room, floor, lauriston, gardens, indoor, lestrade	Examining a body (b)
18	sherlock, john, mrs, hudson, baker, street, 221b, indoor, suite, yes	221b Baker St. (b)
19	john, jeffrey, sir, indoor, yes, medium, psychotherapist, helen, office, london	John's psychotherapy appointment
20	john, sherlock, yes, laboratory, indoor, hospital, bartholomew, st, medium, mike	John meets sherlock (b)
21	sherlock, lestrade, indoor, yes, room, floor, gardens, lauriston, scene, crime	Examining a body (c)
22	john, indoor, room, medium, psychotherapist, yes, soldiers, close, london, outdoor	John's PTSD
23	yes, jeffrey, sir, jimmy, aide, indoor, medium, woman, helen, man	Press conference (c)
24	sherlock, john, suite, street, 221b, baker, indoor, medium, says, asks	221b Baker St. (c)
25	man, john, warehouse, indoor, yes, shoulder, medium, says, continues, looks	Meeting with Mycroft (b)
26	jimmy, yes, gary, sir, jeffrey, medium, indoor, outdoor, psychotherapist, rain	The second death (b)
27	sherlock, john, indoor, street, baker, medium, 221b, suite, yes, phone	221b Baker St. (d)

Figure S2: Topics discovered in *Sherlock*. We applied a topic model to hand-annotated information about 1000 scenes spanning the 45 minute episode. We identified 27 unique topics with non-zero weights (we used $K = 100$ topics to fit the model). Each topic comprises a distribution of weights over all words in the vocabulary. For each topic, we show the words with the 10 largest weights, along with a suggested description of the topic.

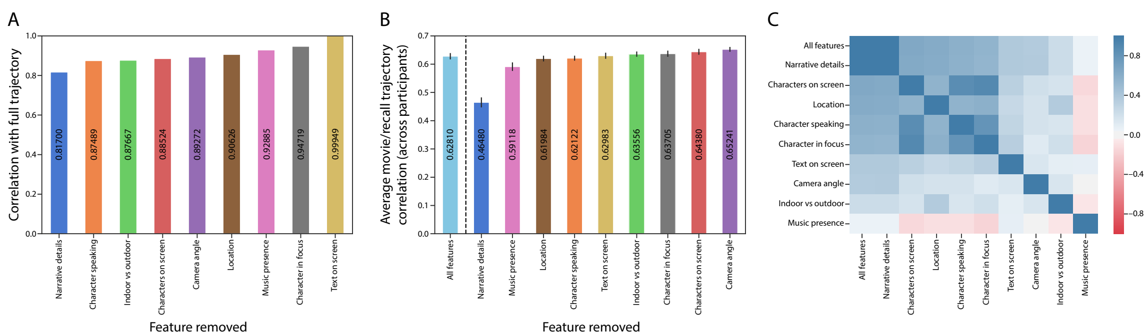

Figure S3: Feature importance analysis. A. Contributions of each feature type to the structure of the video trajectory. The bar heights reflect the correlation between the video trajectory computed using all features with a video trajectory computed using all features except the indicated feature. (Lower bars reflect features that contribute more substantially to the video trajectory's shape.) **B.** Which features are preserved during recall? The bar heights reflect the (average) across-participant correlations between the video and recall trajectories. Error bars denote bootstrap-estimated standard error of the mean. **C.** Feature correlation matrix. Each entry displays the correlation between video topic trajectories created using only the indicated (row/column) features.

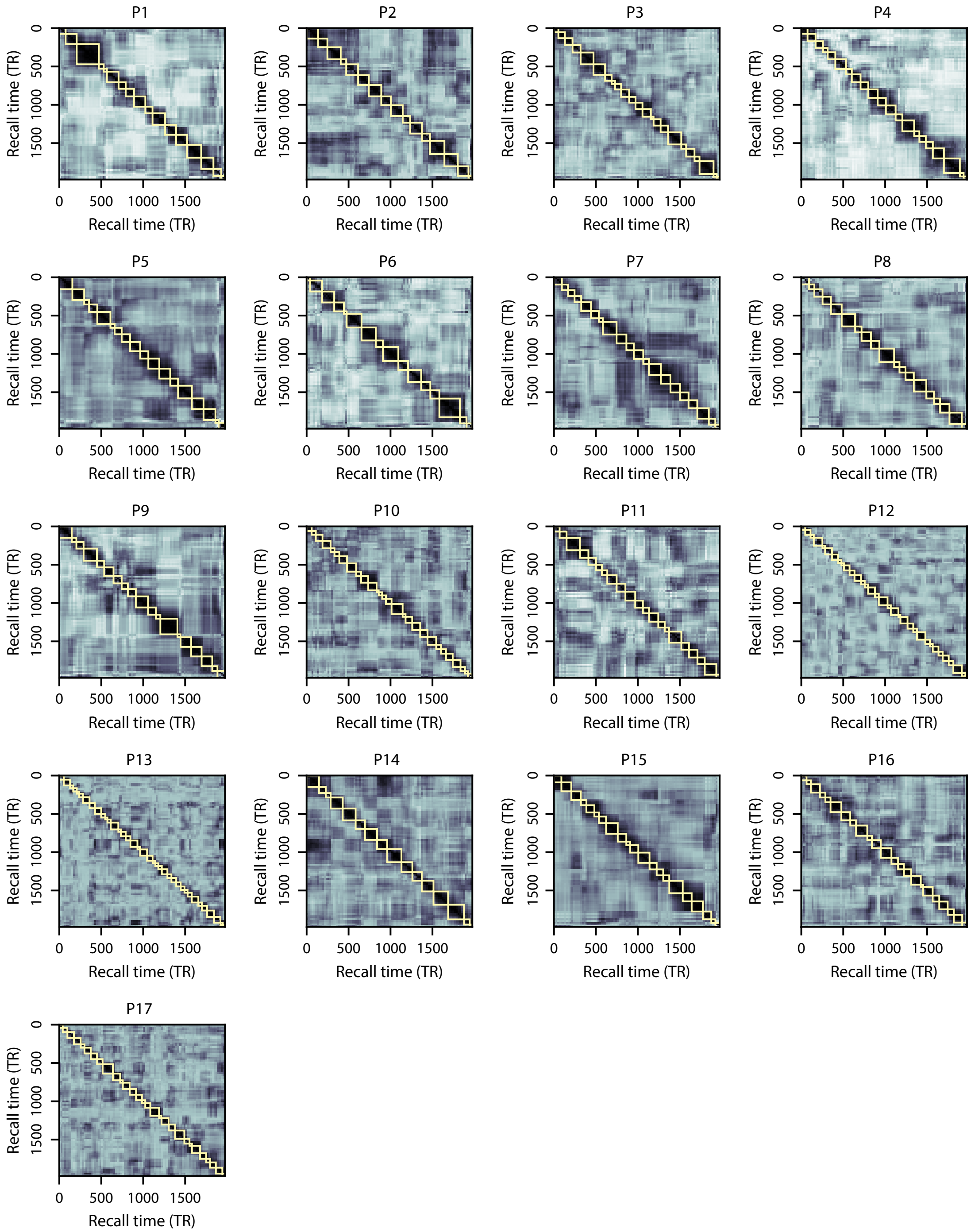

Figure S4: Recall trajectory temporal correlation matrices and event segmentation fits. Each panel is in the same format as Figure 2E in the main text. The yellow boxes indicate HMM-identified event boundaries.

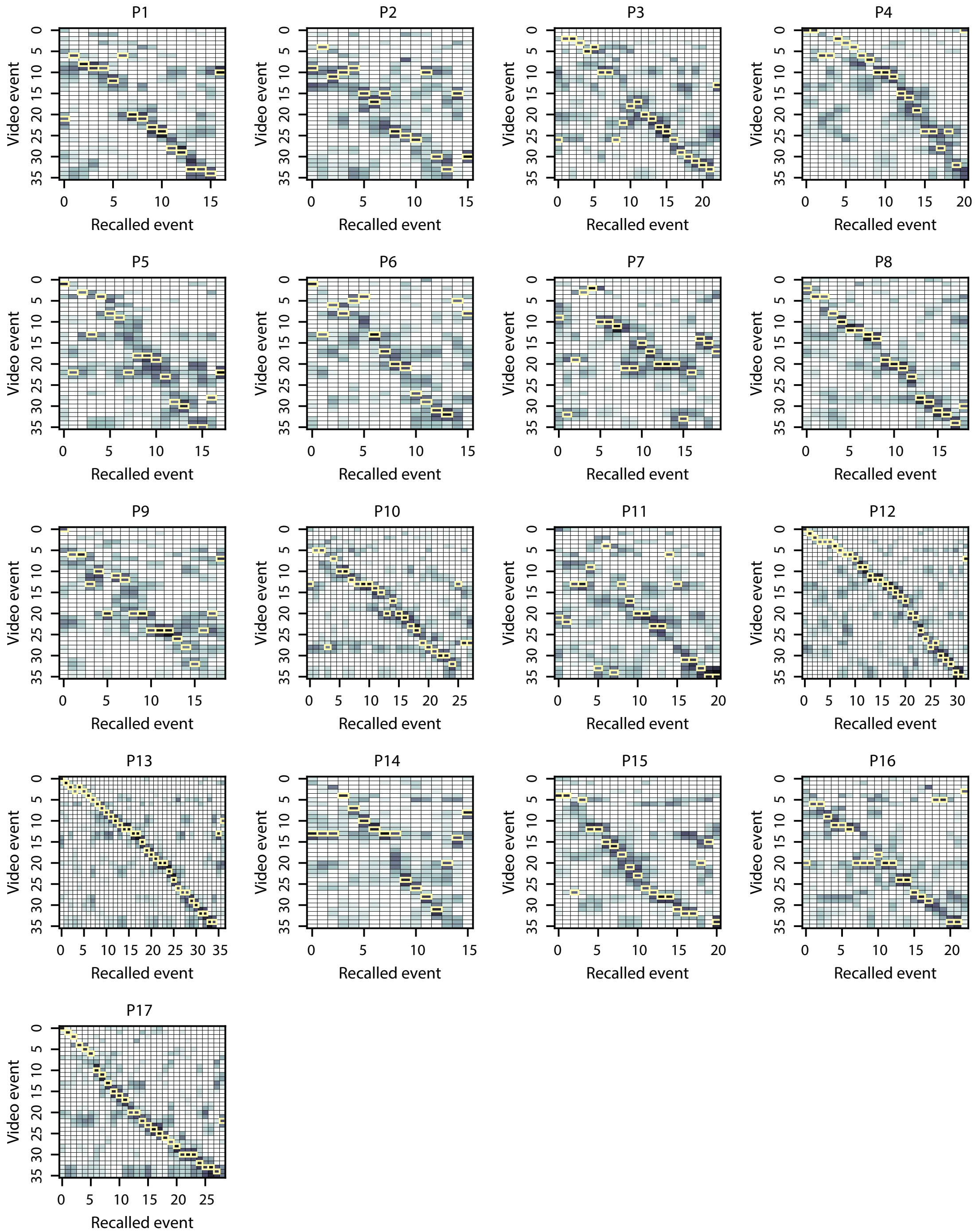

Figure S5: Video-recall event correlation matrices. Each panel is in the same format as Figure 2G in the main text. The yellow boxes mark the maximum correlation in each column.

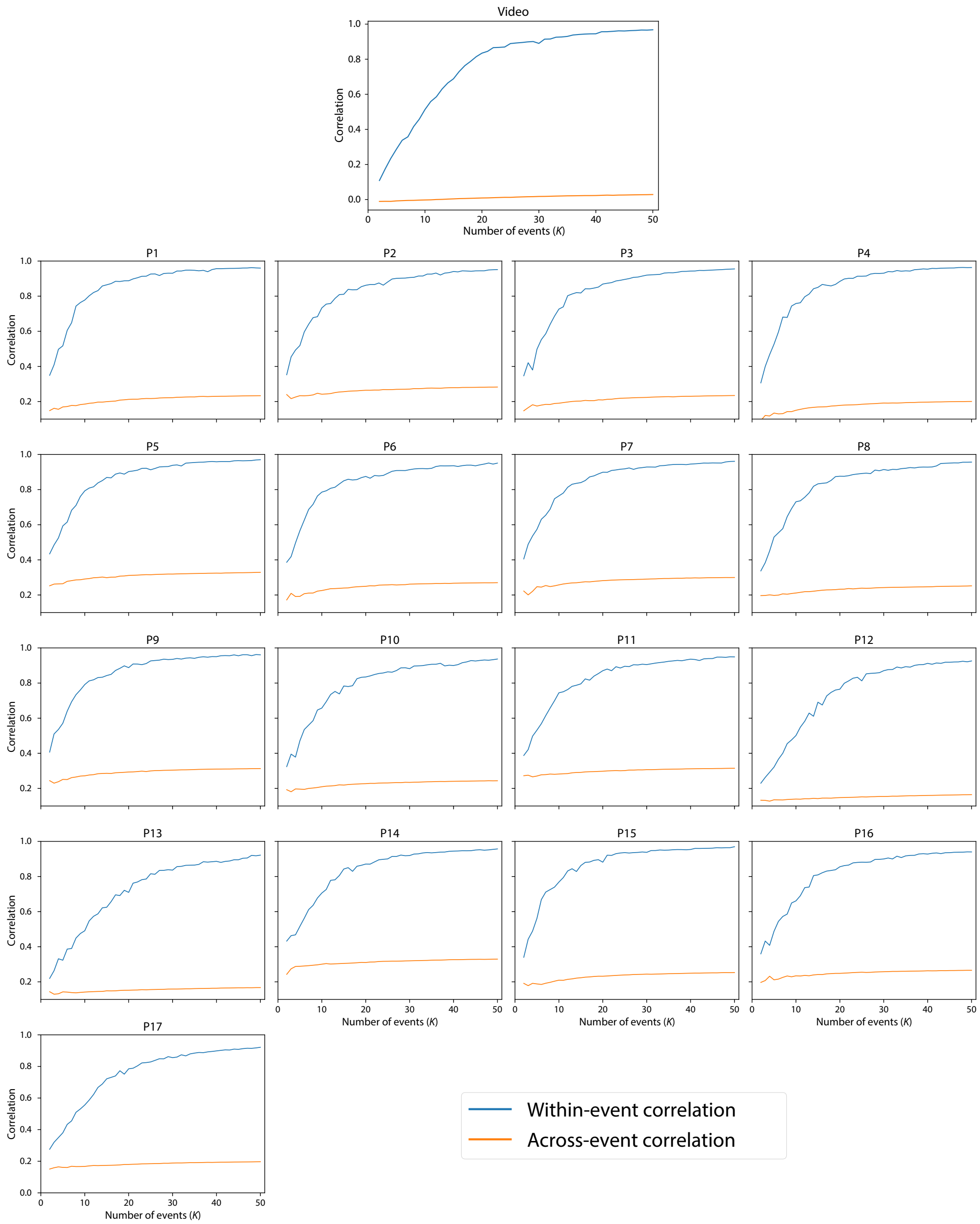

Figure S6: Within- and across-event correlations as a function of K. As part of the event-segmentation procedure, we searched over a range of possible K-values [2,50] (i.e., number of events) for the video and each recall topic trajectory, separately. For each K, we used an HMM to segment the trajectory into K-events. We then computed the average correlation between topic vectors at timepoints within the same event, and the average correlation between topic vectors at timepoints across different events.

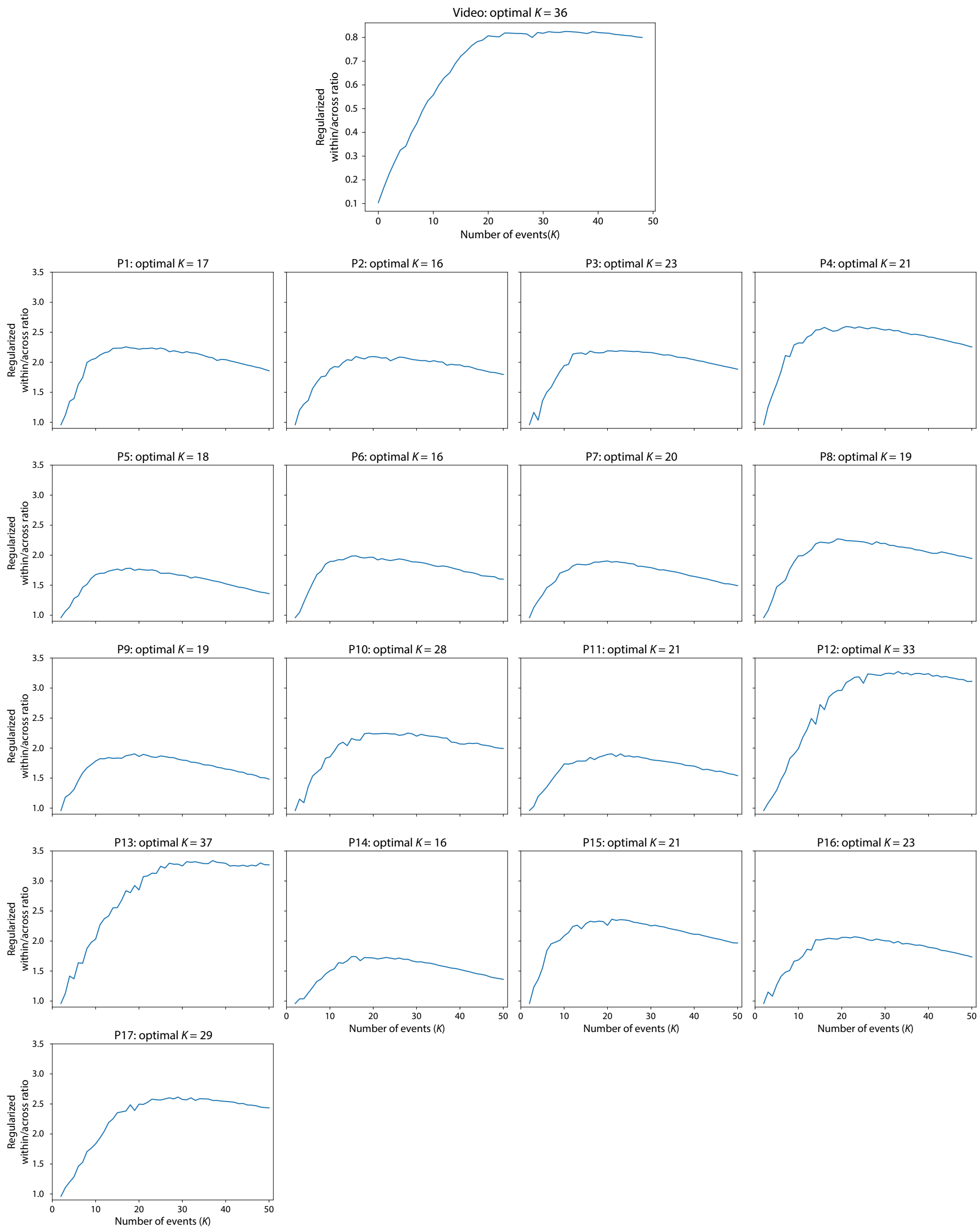

Figure S7: Video and recall trajectory *K*-optimization functions. We selected the optimal *K*-value for the video and each recall trajectory, using the formula described in *Methods*. This computation resulted in a curve for each trajectory, describing the regularized ratio of the average within-event topic vector correlation to the average across-event topic vector correlation, as a function of *K*.

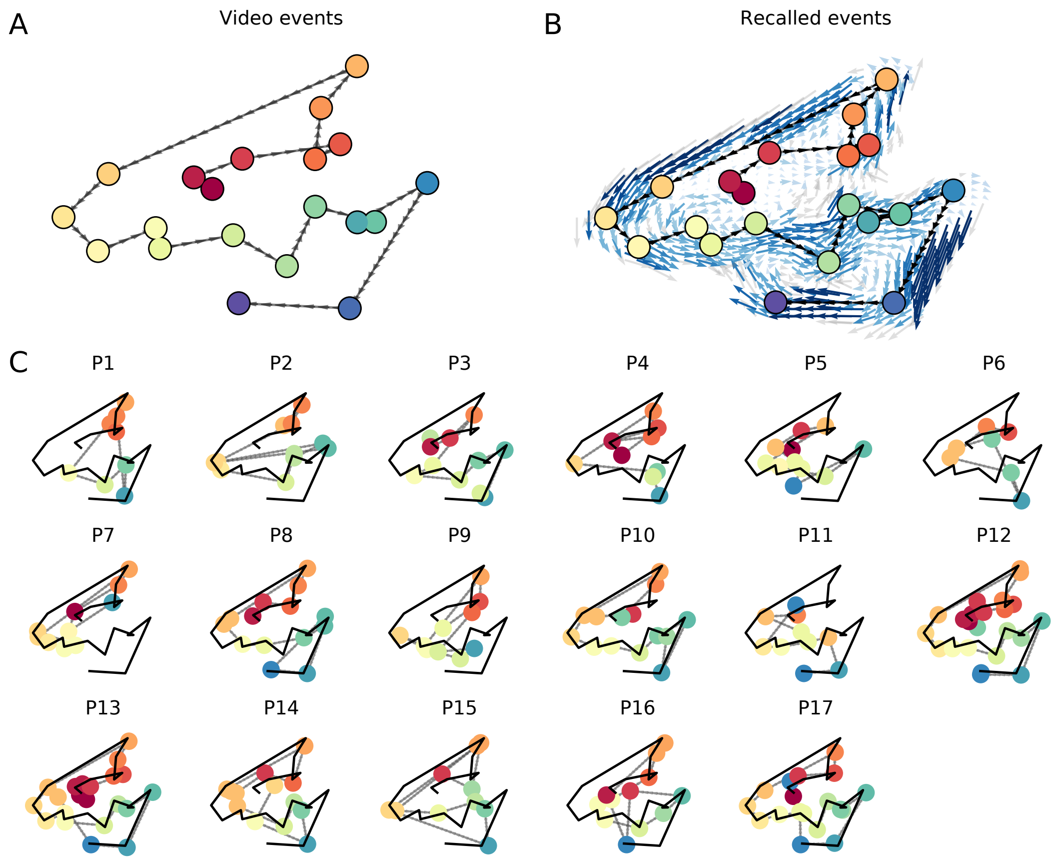

Figure S8: Trajectories using Wasserstein distance for choosing ***K*****.** We replicated the trajectory analysis using Wasserstein distance, a parameter-free procedure for choosing *K*. Overall, the pattern of findings is quite similar to our main approach, but resulted in a smaller number of events.