The psychological arrow of time drives temporal asymmetries in inferring unobserved past and future events

Xinming Xu[1], Ziyan Zhu[2], Xueyao Zheng[3], and Jeremy R. Manning[1,⋆]

[1]Dartmouth College, Hanover, NH, USA

[2]Peking University, Beijing, China

[3]University of California at Davis, CA, USA

[⋆]Address correspondence to jeremy.r.manning@dartmouth.edu

September 13, 2023

Abstract

How much can we infer about the past and future, given our knowledge of the present? Unlike temporally symmetric inferences about simple sequences, inferences about our own lives are asymmetric: we are better able to infer the past than the future, since we remember our past but not our future (i.e., the psychological arrow of time). What happens when both the past and future are unobserved, as when we make inferences about *other* people's lives? We had participants in two experiments view segments of two character-driven television dramas. They wrote out what would happen just before or after each just-watched segment. Participants were better at inferring past (versus future) events. This asymmetry was driven by participants' reliance on characters' conversational references in the narrative, which tended to favor the past. We also carried out a meta analysis to estimate the prevalence of these asymmetries in hundreds of millions of dialogues from television shows, popular movies, novels, and written and spoken natural conversations. We found that, on average, references to the past are roughly 1.5–2 times more prevalent than references to the future. Our work reveals a temporal asymmetry in how observations of other people's behaviors can inform us about the past and future.

Keywords: arrow of time, prediction, retrodiction, narrative, conversation

Introduction

What we experience in the current moment tells us about *now*– but what does it tell us about the past or future? And does the current moment tell us, as human observers, *more* about the past or about the future? One way of examining these questions is to consider highly simplified scenarios that are artificially constructed in the laboratory (e.g., Maheu et al., 2022). At one extreme, for deterministic sequences with *known* rules, knowing the current state provides the observer with sufficient information to exactly reconstruct the entire past and future history of the stimulus. At another extreme, for purely random sequences, observing the current state provides no information about the past *or* future.

Sequences generated by stochastic processes fall somewhere between these two extremes. For Markov processes, where each state is solely dependent on the immediately preceding state, Shannon entropy may be used to quantify the uncertainty of the past and future states, given the present state. Cover (1994) showed that, for any stationary process (i.e., processes in equilibrium), Markov or otherwise, the present state provides equal information (i.e., mutual information) about past and future states (also see Bialek et al., 2001; Ellison et al., 2009). Further, there is some evidence that humans are similarly adept at inferring the most likely previous and next items in sequences governed by stochastic Markov processes (Jones and Pashler, 2007).

Deterministic, random, and probabilistic sequences (in equilibrium) are all symmetric: the present state of these sequences is equally informative about past versus future states. In contrast, our subjective experience in everyday life is that we know more about our own past than our future (e.g., Horwich, 1987). We have memories of our past that we carry with us into the present moment, but we do not have memories of our yet-to-be-experienced future. This temporal asymmetry imposes an "arrow of time" on our subjective experience, known as the *psychological arrow of time* (e.g., Hawking, 1985).

Although the psychological arrow of time implies that we should be better able to infer our past than our future, how generally does this temporal asymmetry hold? And does the asymmetry hold only for our own experiences (due to our memories), or is the asymmetry a general property

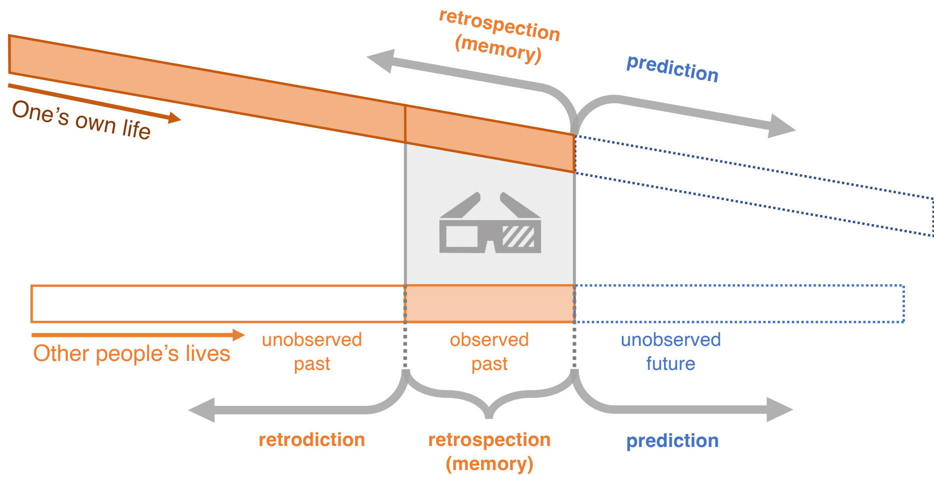

Figure 1: Retrodiction, retrospection, and prediction. In one's own life, one may draw on memory to retrospect (i.e., review or re-evaluate) the past or predict the future. This process is time-asymmetric, since our own past is (typically) observed whereas our future is not. When we make inferences about *other* people's lives, however, we often have uncertainty about both their past and future, since we may have observed neither. We may *retrodict* the unobserved past and predict the unobserved future of other people's lives.

of any real-life event sequence? In real-world situations (and narratives) where we are *equally* ignorant of the past and future, as for *other* people's lives where we lack memories of the relevant past, are our inferences about the past and future symmetric or asymmetric? For example, imagine that you are meeting a stranger for the first time. At the moment of your meeting, you lack both memories of their past and knowledge about what they might do in the future. After your first encounter with the stranger, would you be able to more accurately or easily form inferences about what had happened in their past (*retrodiction*) or what will happen in their future (*prediction*; Fig. 1)? Or suppose you started watching a movie partway through. Again, you would enter the moment of watching without memories of prior parts of the movie. Given your observations in the present, would your guesses about what had happened before you started watching be more (or less) accurate than your guesses about what will happen next? In general, when the past and future are *both* unobserved, are we better at inferring the past or the future in real-world settings? Narrative stimuli, such as stories and movies, can provide a useful testbed for exploring several of these questions.

Although narratives are unlikely to be confused with one's own experiences, narratives mirror some of the structure of real-world experiences. Character behaviors and interactions are often designed in a way that helps the audience connect with or relate to the characters. Events in narratives also unfold in ways that are intended to build rapport or engagement with the audience. This might be accomplished by having events follow a believable structure that is reminiscent of real-world experiences, or by designing the audience's experiences in ways that communicate clear "rules" or "features" that help to immerse the audience in the narrative's universe. The characters in a realistic narrative can also be written to behave in ways reminiscent of real-world people. These same aspects of narratives that authors use to drive engagement with events and characters can lead narratives to replicate some core aspects of real-world experiences that are typically lost or overlooked in traditional sequence learning paradigms. Narratives can drive the audience to build situation models (Radvansky and Copeland, 2006; Zwaan and Radvansky, 1998) of the narrative's universe, or to form a theory of mind of and make predictions about the characters (Tamir and Thornton, 2018; Koster-Hale and Saxe, 2013). Events in narratives may unfold in a consistent or logical way, but they also exhibit complex and meaningful interactions across events reminiscent of real-world experiences (but not necessarily the simple sequences traditionally used in the statistical learning literature).

One key difference between simple artificial sequences and more naturalistic (real or narrative) sequences is that naturalistic sequences often incorporate other people. Despite the past and future being equally unknown to *the observer* prior to the current moment, other people, and realistic characters in narratives, have their own psychological arrows of time. Specifically, they have memories of their own pasts. Other people's asymmetric knowledge about their *own* pasts and futures might affect their behaviors (e.g., conversations). In turn, this might provide time-asymmetric clues that favor the past (e.g., other people might talk more about their own pasts than their futures; Demiray et al., 2018). If observers leverage these clues from other people's asymmetric knowledge, then observers should also be better at inferring the past (versus the future) of other people's lives. Alternatively, if inferences about other people's lives are more like inferences about artificial statistical sequences (e.g., perhaps solely relying on statistical regularities like event schemas, scripts, or situation models Radvansky and Copeland, 2006; Zwaan and Radvansky, 1998; Bower et al., 1979; Ranganath and Ritchey, 2012; Baldassano et al., 2018), then the accuracy of inferences about the past and the future of others' lives should be approximately equal.

We designed a naturalistic paradigm for exposing participants to scenarios where the past and future were equally unobserved. We asked our participants to watch a series of movie segments drawn from a character-driven dramatic television show. Across the conditions and trials in the experiment, participants made free-form text responses to either retrodict what had happened in the previous segment, predict what would happen in the next segment, or recall what happened in the just-watched segment. We used manual annotations and sentence-level natural language processing models to characterize participants' responses. To foreshadow our results, we found that participants were overall better at retrodicting the past than predicting the future. This appeared to be driven by two main factors. First, characters more often referred to past events than future (e.g., planned) events, and this influenced participants' responses. Second, associations and dependencies between temporally adjacent events enabled participants to form estimates about nearby events (e.g., to a just-watched scene or a past or future event referenced in an observed conversation). We also ran a pre-registered replication study to confirm that these findings generalized to another television show and group of participants. Finally, we ran a meta analysis using natural language processing to estimate the prevelance of references to past and future events in hundreds of millions of dialogues drawn from television shows, popular movies, novels, and written and spoken natural conversations. Taken together, our work reveals a temporal asymmetry in how observations of other humans' behaviors inform us about the past versus the future.

Results

Participants in our main experiment ($n = 36$) watched segments from two storylines, drawn from the CBS television show *Why Women Kill*. Each storyline comprised 11 segments (mean duration: 2.05 min; range: 0.97–3.87 min, Table S1). We asked participants to use free-form (typed) text responses to retrodict what had happened prior to a just-watched segment, predict what would happen next, or recall what they had just watched (Fig. 2, *Task design*). We referred to the to-be-retrodicted, to-be-predicted, or to-be-recalled segment as the *target segment* for each response. We systematically varied whether participants watched the segments in forward or reverse chronological order, and how many segments they had seen prior to making a response (see *Methods*).

We asked participants in our main experiment to generate four types of responses after watching each video segment: uncued responses, character-cued responses, updated responses, and recalls (Fig. 2, *Data overview*). To generate *uncued* responses, we asked participants to either retrodict (uncued retrodiction; *u-R*) what happened shortly before or predict (uncued prediction; *u-P*) what happened shortly after the just-watched segment. To generate *character-cued* responses, we asked participants to retrodict (character-cued retrodiction; *c-R*) or predict (character-cued prediction; *c-P*) what came before or after the just-watched segment, but we provided additional information to the participant about which character(s) would be present in the target (to-be-retrodicted or to-be-predicted) segment. We hypothesized that character-cued responses should be more accurate than uncued responses, to the extent that participants incorporate the character information we provided to them into their retrodictions and predictions. To generate updated responses, we asked participants to watch an additional segment that came just prior to or just after the target segment, and then to update their retrodiction (*c-RP*) or prediction (*c-PR*) about the target segment. Results on updated responses are not reported in this paper. Finally, we also asked participants to *recall* what happened in the just-watched segment. We labeled these responses according to which other segments participants had watched prior to the just-watched target. Retrodiction-matched recall (*re(R)*) responses were made during the retrodiction sequences (B1 and B2; Fig. 2), whereas prediction-matched recall (*re(P)*) responses were made during the prediction sequences (A1 and A2; Fig. 2). Whereas retrodiction and prediction responses reflect what participants *estimate* they would remember after watching the (inferred) target segment, recall responses provide a benchmark for comparison by measuring what they *actually* remember about the target segment. Our replication

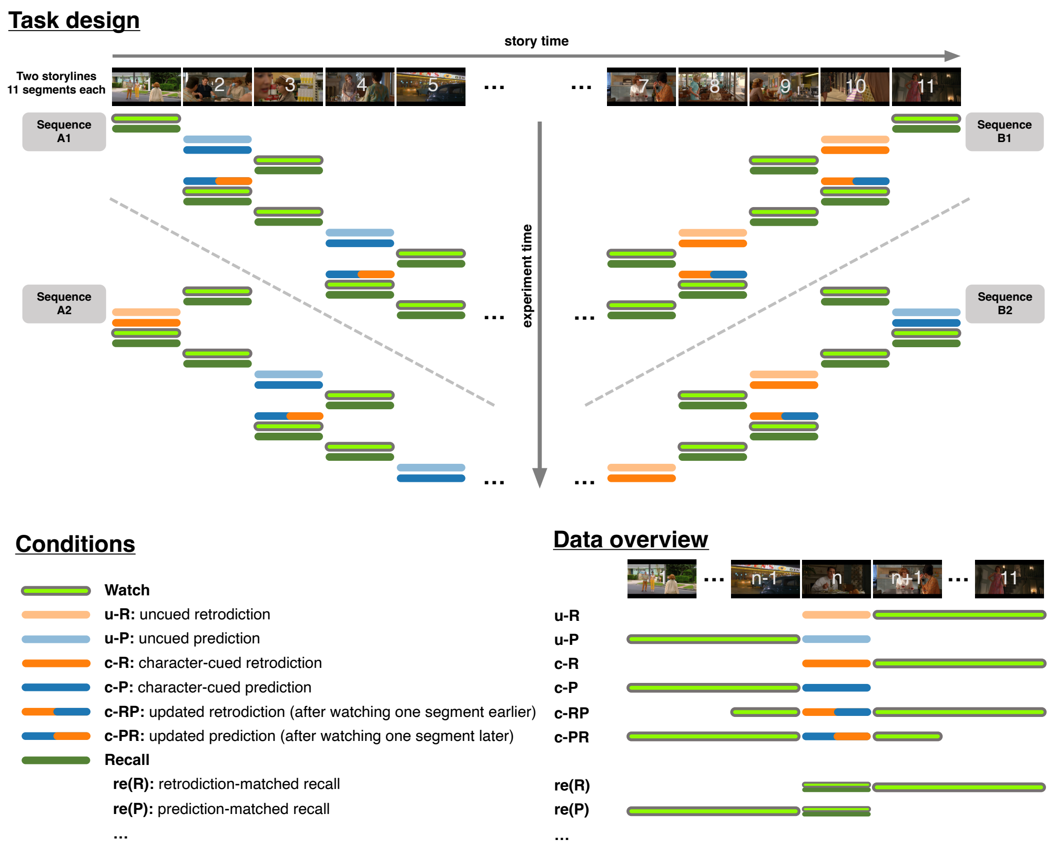

Figure 2: Task overview. Participants in our main experiment watched segments of two storylines from the television series *Why Women Kill*. They made free-form text responses to either retrodict what had happened in the previous segment, predict what would happen in the next segment, or recall what happened in the just-watched segment. Across four counterbalanced sequences, we systematically varied whether participants watched the segments in forward or reverse chronological order, whether (or not) responses were cued using the main characters in the target segment, and which other segments participants had watched prior to making a response. For each segment, we collected several retrodiction, prediction, and/or recall responses across different experimental conditions. Experiment time is denoted along the vertical axis, storyline segments are indicated along the horizontal axis, and the colors denote experimental tasks (conditions). For an analogous depiction of our replication experiment's design, see Fig. S4.

experiment (Fig. S4) used a similar design, but did not have participants generate recall, re(R), or re(P) responses.

For each retrodiction and prediction, participants were asked to generate at least one, and not more than three, responses that constituted "the sorts of things [the participant would] expect to have remembered if [they] had watched the [target] segment." They were asked to generate multiple responses only if those additional responses were (in their judgement) of equal likelihood to occur. On average, participants generated 1.08 responses per prompt; therefore we chose to consider only participants' first ("most probable" or "most important") responses to each prompt. We also discarded a small number ($n = 20$) of character-cued responses that did not contain references to all cued characters, along with one additional response due to the participant's misunderstanding of the task instructions during that trial. We carried out our analyses on the remaining 2084 retrodiction, prediction, and recall responses.

We used two general approaches to assess the quality of participants' responses (see *Methods*, Figs. 3A). One approach entailed manually annotating events in the video and counting the number of matched events in participants' responses. We identified a total of 117 unique events reflected across the 22 video segments (range: 3–9 per segment; see *Methods*, Table S1). We assigned one "point" to each of these video events. We also identified 23 additional events in participants' responses that were either summaries of several events or that were partial matches to the manually identified video events. We assigned 0.5 point to each of these additional events. This point system enabled us to compute the numbers and proportions (*hit rates*) of correctly retrodicted, predicted, and recalled events contained in each response. Our second approach entailed using a natural language processing model (Cer et al., 2018) to embed annotations and responses in a 512-dimensional feature space. This approach was designed to capture conceptual overlap between responses that were not necessarily tied to specific events. To quantify this conceptual overlap, we computed the similarities between the embeddings of different sets of responses. Following Heusser et al. (2021), we defined the *precision* of each participants' retrodictions or predictions about a target segment as the median cosine similarities between the embeddings of (a) the participant's retrodiction or prediction response for the target segment and (b) each

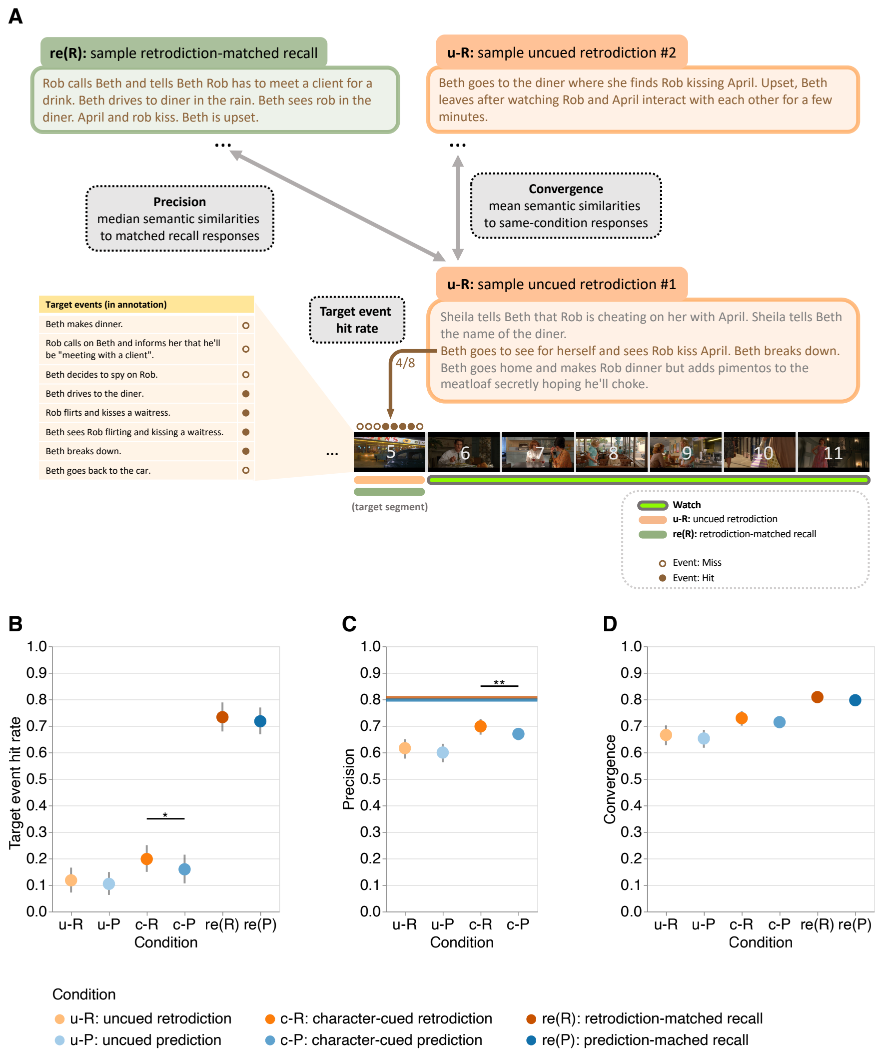

Figure 3: Retrodiction, prediction, and recall performance by experimental condition. A. Methods schematic. For each retrodiction, prediction, and recall response, we calculated the hit rate for events in the target segment, the response precision (see *Methods*), and the response convergence across participants (see *Methods*). **B. Target event hit rate.** Mean proportions of target events that were contained in participants' responses, for each response type, averaged across target segments. **C. Response precision.** Mean precisions of participants' responses, for each response type, averaged across target segments. The horizontal lines denote the mean pairwise semantic similarities (see *Methods*) across recall responses (re(R): orange; re(P): blue). **D. Response convergence.** Mean (across-participant) convergence of participants' responses, for each response type, averaged across target segments. All panels: error bars denote bootstrapped 95% confidence intervals. Asterisks indicate significance in the (generalized) linear mixed models: * denotes $p < 0.05$ and ** denotes $p < 0.01$. See Figure S5for analogous results from our replication experiment.

other participant's recalls of the same segment. In other words, precision is designed to measure the extent to which retrodictions and predictions captured the conceptual content that (other) participants remembered. We also developed a related measure, which we call *convergence*, to characterize response similarities across participants. In particular, we defined convergence as the mean cosine similarity between the embeddings of a participant's responses to a target segment and all other participants' responses (of the same type) to the same segment. We analyzed the data using generalized linear mixed models, with participant and stimulus (e.g., target segment) identities as crossed random effects (see *Methods*).

First we sought to validate a main effect of response type (i.e., uncued responses, character-cued responses, and recalls), irrespective of the temporal direction (retrodiction versus prediction). Across these three types of responses, participants have access to increasing amounts of information about the target segment. Therefore, across these response types, we hypothesized that participants' responses should become both more accurate and more convergent across individuals. Consistent with this hypothesis, participants' character-cued retrodictions and predictions were associated with higher target event hit rates than uncued retrodictions and predictions (odds ratio (OR): 2.65, $Z = 4.24$, $p < 0.001$, 95% confidence interval (CI): 1.69 to 4.16; Fig. 3B). These character-cued responses were also more precise ($b = 0.13$, $t(18.1) = 9.43$, $p < 0.001$, CI: 0.10 to 0.16; Fig. 3C) and convergent across individuals ($b = 0.11$, $t(18.6) = 6.21$, $p < 0.001$, CI: 0.07 to 0.15; Fig. 3D). Relative to character-cued responses, participants' recalls showed higher target event hit rates (OR = 21.83, $Z = 10.61$, $p < 0.001$, CI: 12.35 to 38.59) and were more convergence across individuals ($b = 0.20$, $t(19.4) = 9.10$, $p < 0.001$, CI: 0.16 to 0.25). These results are consistent with the common-sense notion that access to more information about a target segment yields better performance (i.e., higher hit rates, precision, and convergence across individuals). These findings also held for our replication experiment (Fig. S5; hit rates of character-cued vs. uncued responses: OR: XXX, $Z = XXX$, $p = XXX$, 95% confidence interval (CI): XXX to XXX; precisions of character-cued vs. uncued responses: $b = XXX$, $t(XXX) = XXX$, $p = XXX$, CI: XXX to XXX; convergence of character-cued vs. uncued responses: $b = XXX$, $t(XXX) = XXX$, $p = XXX$, CI: XXX to XXX).

Next we carried out a series of analyses specifically aimed at characterizing temporal direction effects— i.e, the relative quality of retrodictions versus predictions across different types of responses. We hoped that these analyses might provide insights into our central question about whether inferences about the past and future are equally accurate. Across both uncued and character-cued responses in our main experiment (Fig. 2), retrodictions had numerically higher hit rates than predictions (Fig. 3B). However, these differences were only statistically reliable for character-cued responses (uncued responses: OR = 1.17, $Z = 0.35$, $p = 0.73$, CI: 0.47 to 2.92; character-cued responses: OR = 1.93, $Z = 2.15$, $p = 0.03$, CI: 1.06 to 3.52). We observed a similar pattern of results for the precisions of participants' responses (Fig. 3C). Specifically, their responses tended to be numerically more precise for retrodictions versus predictions, but the differences were only statistically reliable for character-cued responses (uncued responses: $b = 0.03$, $t(20.9) = 1.09$, $p = 0.29$, CI: -0.03 to 0.10; character-cued responses: $b = 0.06$, $t(20.8) = 3.01$, $p = 0.007$, CI: 0.02 to 0.11). We also consistently observed numerically higher convergence across participants for retrodictions versus predictions (Fig. 3D), but neither of these differences were statistically reliable (uncued responses: $b = 0.03$, $t(17.9) = 0.75$, $p = 0.46$, CI: -0.05 to 0.11; character-cued responses: $b = 0.04$, $t(17.4) = 1.46$, $p = 0.16$, CI: -0.02 to 0.09). In our replication experiment (Fig. S5), participants were numerically better at making *predictions* than retrodictions, but none of these differences were statistically reliable (hit rate for uncued responses: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; hit rate for character-cued responses: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; precision for uncued response: $b = XXX$, $t(XXX) = XXX$, $p = XXX$, CI: XXX to XXX; precision for character-cued responses: $b = XXX$, $t(XXX) = XXX$, $p = XXX$, CI: XXX to XXX; convergence for uncued responses: $b = XXX$, $t(XXX) = XXX$, $p = XXX$, CI: XXX to XXX; convergence for character-cued responses: $b = XXX$, $t(XXX) = XXX$, $p = XXX$, CI: XXX to XXX). Taken together, our results across our main and replication experiment suggest that whether participants are better at retrodicting versus predicting the immediate past or future may be somewhat stimulus specific. We also verified that this was not solely a consequence of how participants' memory performance might have been affected by watching different segments (or making different responses to other segments) across conditions by comparing recall responses in the retrodiction-matched recall (*re(R)*) and prediction-matched recall (*re(P)*) conditions. Recall performance in our main experiment was similar in both conditions (target event hit rate: OR = 1.12, Z = 1.07, p = 0.29, CI: 0.91 to 1.39; convergence: b = 0.03, $t(19.3)$ = 1.89, p = 0.07, CI: 0.00 to 0.07). (We did not collect recall responses in our replication experiment.)

The above analyses were focused solely on the target segment (i.e., retrodiction of segment n after watching segments $(n+1)$...11, or prediction of segment n after watching segments 1...$(n-1)$). We wondered whether participants' responses might also contain longer-range information about preceding or proceeding events. In order to carry out this analysis properly, we reasoned that participants might reference past or future events that were *implied* to have occurred offscreen, but not explicitly shown onscreen. For example, a character in location A during one scene might appear in location B during the immediately following scene. Although it wasn't shown onscreen, we can infer that the character traveled between locations A and B sometime between the time intervals separating the scenes (Bordwell, 2008). In all, we manually identified a set of 74 *implicit* offscreen events that were implied to have occurred given what was (explicitly) depicted onscreen (Fig. 4A), plus one additional partial event and one additional summary event. We defined the just-watched segment as having a *lag* of 0. We assigned the target segment of a participant's retrodiction or prediction (i.e., the immediately preceding or proceeding segment) a lag of -1 or +1, respectively. The segment following the next was assigned a lag of 2, and so on. We tagged offscreen events using half steps. For example, an offscreen event that occurred after the prior segment but before the just-watched segment would be assigned a lag of -0.5.

Because there is no "ground truth" number of offscreen events, we could not compute the hit rates for offscreen events. Instead, we counted up the absolute *number* of retrodicted or predicted events as a function of lag. In other words, given that the participant had just watched segment i, we asked how many events from segment $i + lag$ they retrodicted or predicted, on average, given that they were aiming to retrodict or predict events at lags of ±1. We also counted the numbers of *unmatched* events in participants' responses that did not correspond to any events in the relevant segments of the narrative. We focused specifically on *uncued* retrodictions and predictions, which we hypothesized would provide the cleanest characterizations of participants' initial estimates of the unobserved past and future (i.e., without potential biases introduced by additional character

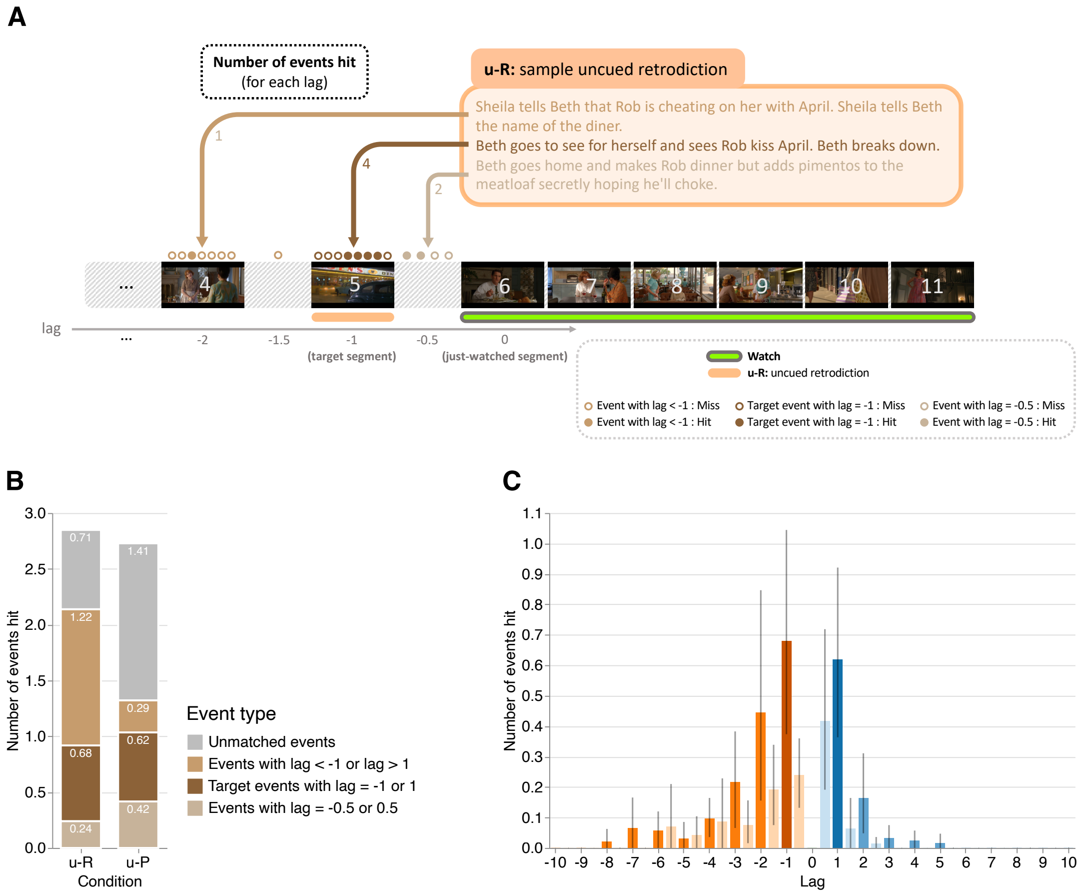

Figure 4: Retrodictions and predictions of temporally near and distant events. A. Illustration of annotation approach. For each uncued retrodiction and prediction response in our main experiment, we calculated the number of (retrodicted or predicted) events as a function of temporal distance from the target segment, or *lag*. Onscreen (explicit) events are tagged using integer-valued lags, whereas offscreen (implicit) events are tagged using half-step lags (±0.5, ±1.5, etc.). **B. Number of events hit in participants' uncued retrodictions and predictions for each event type.** Here we separated events we identified in participants' responses according to whether they occurred in the target segment (lags of ±1), during the interval between the target segment and the just-watched segment (lags of ±0.5), at longer temporal distances (|lag| > 1), or were incorrect (unmatched with any past or future events in the narrative). The counts displayed in the panel are averaged across just-watched segments. **C. Number of events hit as a function of temporal distance.** Here the (across-segment) mean numbers of events hit in participants' uncued retrodictions (orange) and predictions (blue) are displayed as a function of temporal distance to the just-watched segment (lag). Error bars denote bootstrapped 95% confidence intervals. Colors denote temporal direction (orange: past; blue: future) and distance (darker shading: onscreen events from segments adjacent to the target segment; lighter shading: offscreen events). See Figure S6for an analogous presentation of results from our replication study.

information, as in the character-cued responses). For participants in our main experiment, the numbers of uncued retrodicted and predicted target (lag = ±1) events were not reliably different (OR = 0.92, $Z = -0.15$, $p = 0.88$, CI: 0.30 to 2.84). In other words, uncued retrodictions and predictions over short timescales did not exhibit reliable asymmetries. This "null result" also held in our replication study (OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX). However, when retrodicting, participants in both experiments mentioned events from the distant past (lag < -1) more often than participants predicted events from the distant future (lag > 1; main experiment: OR = 9.10, $Z = 3.80$, $p < 0.001$, CI: 2.92 to 28.39; Fig. 4B, C; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; Fig. S6; for results from the character-cued conditions, see Fig. S2). Despite this asymmetry in the accuracies of participants' long-range retrodictions versus predictions, there were no reliable differences in the *numbers* of uncued retrodicted versus predicted events (across all lags; main experiment: OR = 1.05, $Z = 0.75$, $p = 0.45$, CI: 0.93 to 1.18; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$). Nor did we find any reliable differences in the numbers of offscreen events immediately before or after the just-watched segment ($lag = \pm 0.5$; main experiment: OR = 0.75, $Z = -0.36$, $p = 0.72$, CI: 0.15 to 3.59; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX). The apparent discrepancy between participants' asymmetric accuracy but symmetric event counts was due to participants' tendencies to reference "unmatched" events (i.e., events that did not correspond to any explicit or implicit event in the story) more in their predictions than retrodictions (main experiment: OR = 0.36, $Z = -4.53$, $p < 0.001$, CI: 0.23 to 0.56; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX). We confirmed that the retrodiction advantage held when controlling for absolute lag (main experiment: OR = 34.31, $Z = 3.28$, $p = 0.001$, CI: 4.16 to 283.20; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX), for onscreen events alone (main experiment: OR = 47.54, $Z = 3.74$, $p < 0.001$, CI: 6.27 to 360.60; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX), and marginally for offscreen events alone (main experiment: OR = 24.76, $Z = 1.71$, $p = 0.09$, CI: 0.63 to 975.27; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX). Taken together, these analyses show that (in generating uncued responses) participants tend to reach "further" into the unobserved past, and with greater accuracy, than the unobserved future.

What might be driving participants to retrodict further and more accurately into the unobserved past, compared with their predictions of the unobserved future? By inspecting the video content, we noticed that characters in the television show frequently referenced both past events and (planned or predicted) future events in their spoken conversations. We wondered whether the characters' references might show temporal asymmetries that might explain participants' behaviors. Across all of the characters' conversations, and across all of the video segments, we manually identified a total of 82 references to past or future events (i.e., that occurred onscreen or offscreen before or after the events depicted in the current segment; Figs. 5A, S3A, S7). Characters in our main experiment's stimulus tended to reference the past (52 references) more than the future (30 references), consistent with previous work (Demiray et al., 2018). References to the past were also skewed to more temporally distant events compared with references to the future (Figs. 5B, S3B, S7). These asymmetries also held for characters in the replication experiment's stimulus (Fig. 8). These observations indicate that the characters in the stimulus display a preference for the past (versus future) in their conversations. Might this asymmetry be driving the asymmetries in participants' retrodictions versus predictions?

Controlling for temporal distance (lag), past and future events that story characters referenced in their conversations were associated with higher hit rates than unreferenced events in our main experiment (uncued retrodiction: OR = 12.70, $Z = 10.94$, $p < 0.001$, CI: 8.06 to 20.03; uncued prediction: OR = 8.29, $Z = 6.83$, $p < 0.001$, CI: 4.52 to 15.20; Fig. 5E). This indicates that participants' responses are at least partially influenced by the characters' conversations. To estimate the contributions of characters' references on hit rates, we computed the difference in hit rates between all events (which comprised both referenced and unreferenced events) and unreferenced events, as a function of lag. These differences exhibited a temporal asymmetry in favor of retrodiction (Figs. 5C). This indicates that the asymmetries in participants' retrodictions versus predictions are also at least partially influenced by the characters' conversations. However, these temporal asymmetries in participants' retrodictions and predictions persisted even for events that characters never referenced in their conversations (hit rates of uncued retrodicted versus predicted

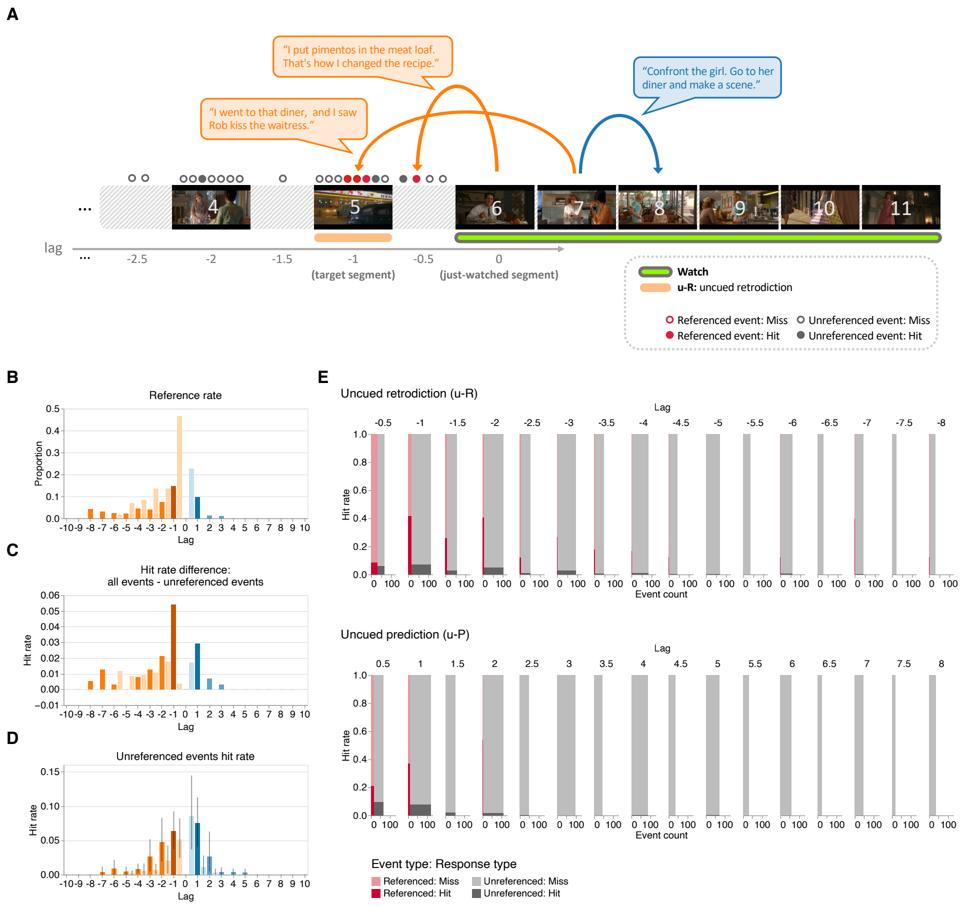

Figure 5: Characters' references drive participants' retrodiction and prediction performance. A. Illustration of annotation approach. We manually annotated references to events in past or future segments in characters' spoken conversations. We matched each such reference with its corresponding storyline event (and its corresponding segment number for onscreen events, or half-step segment number for offscreen events). We then tracked the hit rate separately for referenced versus unreferenced events in participants' uncued retrodictions and predictions. **B. Reference rate as a function of lag.** Across all possible just-watched segments (lag 0), the bar heights denote the average proportions of events referenced in other past (orange, negative lags) or future (blue, positive lags) segments in our main experiment's stimulus. **C. Difference in hit rates between all events and unreferenced events.** To highlight the effect of characters' references to past and future events on participants' retrodictions and predictions, here we display the difference in across-segment mean hit rates between all events and unreferenced events, as a function of temporal distance (lag) to the just-watched segment. **D. Hit rates for unreferenced events.** The average response hit rates for unreferenced events are displayed as a function of temporal distance to the just-watched segment. Error bars denote bootstrapped 95% confidence intervals. Panels B–D: colors are described in the Figure 4 caption. **E. Hit rates and counts of referenced and unreferenced events.** As a function of temporal distance to the just-watched segment, the sub-panels display the across-segment mean numbers (x-axes) and hit rates (y-axes) of referenced (red) and unreferenced (gray) events that participants hit (darker shading) or missed (lighter shading) in their uncued retrodictions (top sub-panel) and uncued predictions (bottom sub-panel). For an analogous presentation of results from the replication experiment, see Fig. S7.

unreferenced events: OR = 2.00, $Z = 2.40$, $p = 0.02$, CI: 1.14 to 3.51; Fig. 5D). When we further separated the unreferenced events into onscreen events and offscreen events, we found that these asymmetries held only for the onscreen events (onscreen: OR = 2.65, $Z = 2.59$, $p = 0.01$, CI: 1.27 to 5.54; offscreen: OR = 1.50, $Z = 0.91$, $p = 0.36$, CI: 0.63 to 3.62). We found similar patterns in our replication experiment (Fig. S7; hit rates of uncued retrodictions for referenced events: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; uncued predictions for referenced events: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; hit rates of uncued retrodcitions for *unreferenced* events: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; for predicted events: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX). Taken together, these analyses suggest that asymmetries in the number of references characters make to past and future events partially (but not entirely) explain why participants tend to retrodict the past further and more accurately than they predict the future.

If characters' direct references cannot fully account for the temporal asymmetry in retrodicting the unobserved past versus predicting the unobserved future, what other factors might explain this phenomenon? The results above indicate that characters' references to specific unobserved events in the past or future boost participants' estimates of these events. But might characters' references have other effects on participants' responses *beyond* the referenced events? For example, real-world experiences and events in realistic narratives are often characterized by temporal autocorrelations (i.e., what is "happening now" will likely relate to what happens "a moment from now," and so on). Real-world experiences and realistic narratives are also often structured into "schemas" whereby experiences unfold according to a predictable pattern or formula that characterizes a particular situation, such as going to a restaurant or catching a flight at the airport (Baldassano et al., 2018). If there are associations or temporal dependencies between temporally nearby events in the television show participants watched, participants might be able to pick up on these patterns in forming their responses. This would be reflected in an inference "boost" for events that were *nearby in time* to events that characters referred to in their conversations, in addition to the referenced events themselves (Fig. 6A).

Because characters tended to refer to past events more often than future events, the proportions of unreferenced events that were adjacent to referenced events should show a similar temporal

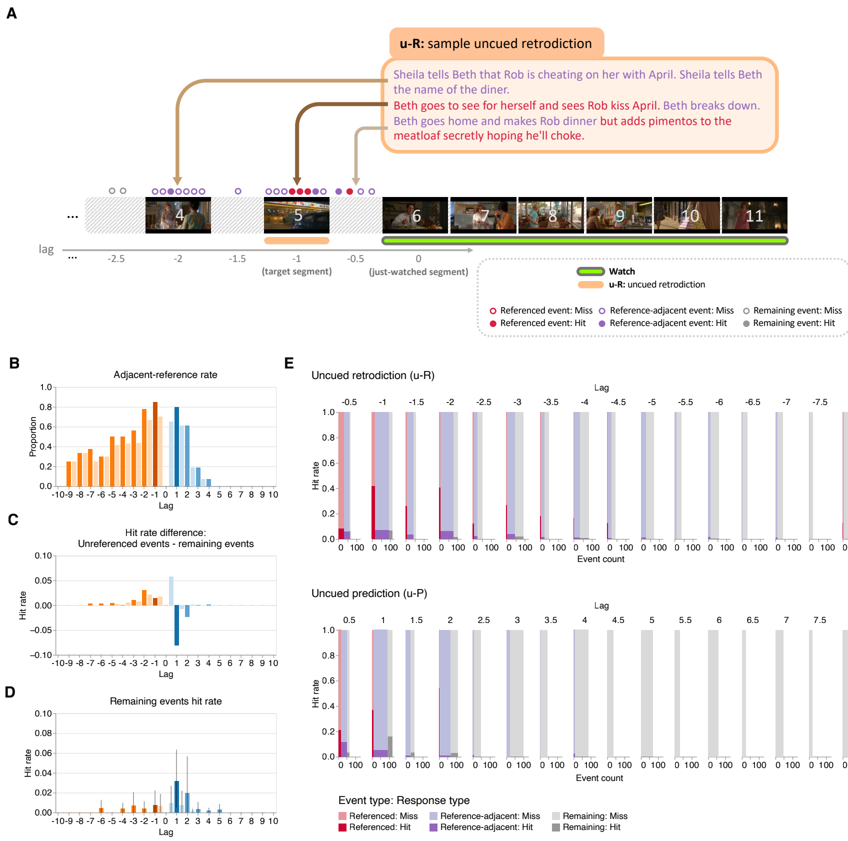

Figure 6: Reference-adjacent events are associated with higher hit rates (main experiment). A. Illustration of annotation approach. We extended the annotation procedure depicted in Figure 5A to also label unreferenced events that were either temporally adjacent to (i.e., immediately preceding or proceeding) a referenced event (reference-adjacent events) or not (remaining events). **B. Adjacent reference rate for unreferenced events as a function of lag.** Across all possible just-watched segments (lag 0), the bar heights denote the average proportion of unreferenced events in other past (orange, negative lags) or future (blue, positive lags) segments that were temporally adjacent to any referenced event. **C. Difference in hit rates between unreferenced events and remaining events.** To highlight the effect of reference adjacency on retrodiction and prediction of unreferenced events, here we display the difference in across-segment mean hit rates between unreferenced events and remaining events, as a function of temporal distance (lag) to the just-watched segment. **D. Hit rates for remaining events.** The across-segment mean response hit rates for unreferenced events that were *not* temporally adjacent to any referenced events are displayed as a function of temporal distance to the just-watched segment. Error bars denote bootstrapped 95% confidence intervals. Panels B–D: colors are described in the Figure 4 caption. **E. Hit rates and counts of referenced, reference-adjacent, and remaining events.** As a function of temporal distance to the just-watched segment, the sub-panels display the numbers (x-axes) and proportions (y-axes) of referenced (red), reference-adjacent (purple), and remaining (gray) events that participants hit (darker shading) or missed (lighter shading) in their uncued retrodictions (top sub-panel) and uncued predictions (bottom sub-panel). For an analogous depiction of results from our replication experiment see Fig. S8.

asymmetry in favor of the past. We tested this intuition by computing the proportions of unreferenced events in the stimulus that were temporally adjacent to past or future events referenced by the characters during a given segment. Here we defined *temporally adjacent* as any event within an absolute lag of one relative to a referenced onscreen event, or within an absolute lag of 0.5 to a referenced offscreen event. We also defined *remaining* events as unreferenced events that were not temporally adjacent to any referenced events. As shown in Figure 6B, in our main experiment we observed higher proportions of unreferenced past than future events that were temporally adjacent to referenced events. Further, these reference-adjacent events had higher hit rates than remaining events after controlling for absolute lag (uncued retrodiction: OR = 7.15, $Z = 2.40$, $p = 0.02$, CI: 1.44 to 35.58; uncued prediction: OR = 3.11, $Z = 2.30$, $p = 0.02$, CI: 1.18 to 8.21; Fig. 6E). These findings also held in our replication experiment (uncued retrodiction: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; uncued prediction: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; Fig. S8). To estimate the contributions of reference adjacency on hit rates, we computed the difference in hit rates between unreferenced events (which comprised both reference-adjacent and remaining events) and remaining events, as a function of lag. These differences exhibited a temporal asymmetry in favor of retrodiction. This suggests that reference-adjacent events also contribute to participants' retrodiction advantage. Remaining events did *not* exhibit a reliable temporal asymmetry (main experiment: OR = 0.75, $Z = 0.33$, $p = 0.74$, CI: 0.14 to 4.08, Fig. 6D; replication experiment: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX, Fig. S8D), suggesting that, after accounting for temporal adjacency, character's references to past and future events can explain participants' retrodiction advantage.

The preceding analyses show that when characters reference past or future events, those referenced events, and other events that are temporally adjacent to the referenced events, are more likely to be retrodicted and predicted. In other words, referring to a past or future event in conversation leads to a "boost" in that event's hit rate. We wondered whether this boost was bi-directional. In particular: when a character refers (during a *referring event*) to another event (i.e., the *referenced event*), does this boost only the referenced event's hit rate, or does the referring event also receive a boost? We labeled each event as a "referring event," a "referenced event," or a "other event" (i.e.,

Figure 7: Referenced events are associated with higher hit rates, but referring events are not. A. Illustration of annotation approach. We extended the annotation procedure depicted in Figure 5A to also label which events in our main experiment's stimuli *contained* references to events in other segments. **B. Referenced versus referring events.** During event i, when a character makes a reference to another event (j), we define i as the *referring* event and j as the *referenced* event. **C. Referring rate as a function of lag.** Across all possible just-watched segments (lag 0), the bar heights denote the across-segment mean proportions of events containing references to events in other past (orange, negative lags) or future (blue, positive lags) segments. The bar colors are described in the Figure 4 caption. **D. Hit rates and counts of referenced, referring, and other events.** As a function of temporal distance to the just-watched segment, the sub-panels display the numbers (x-axes) and hit rates (y-axes) of referenced (red), referring (green), and other (gray) events that participants hit (darker shading) or missed (lighter shading) in their uncued retrodictions (top sub-panel) and uncued predictions (bottom sub-panel). For a display of analogous results from our replication experiment see Figure S9.

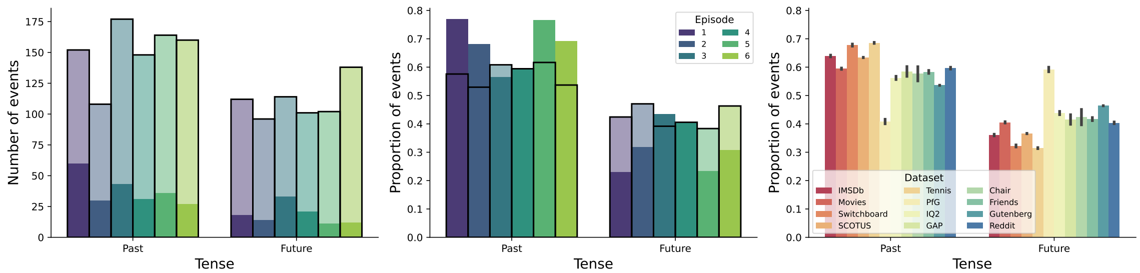

Figure 8: Meta analysis

not referring or referenced; Fig. 7A, B). We limited our analysis to references to onscreen (explicit) events. Consistent with our analysis of the proportions of referenced events (Fig. 5B), the proportions of *referring* events exhibited a *forward* temporal asymmetry (Fig. 7C). Controlling for absolute lag, we found that referring events were associated with lower hit rates than referenced events in our main experiment (uncued retrodiction: OR = 0.03, $Z = -4.81$, $p < 0.001$, CI: 0.01 to 0.11; uncued prediction: OR = 0.04, $Z = -5.84$, $p < 0.001$, CI: 0.01 to 0.12; Fig. 7D) and had no reliable differences in hit rates compared with other events (uncued retrodiction: OR = 0.37, $Z = -1.46$, $p = 0.15$, CI: 0.10 to 1.41; uncued prediction: OR = 2.16, $Z = 1.68$, $p = 0.09$, CI: 0.88 to 5.30). We also observed this phenomenon in our replication experiment (referenced events, uncued retrodiction: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; referenced events, uncued prediction: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; other events, uncued retrodiction: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX; other events, uncued prediction: OR = XXX, $Z = XXX$, $p = XXX$, CI: XXX to XXX;Fig. S9). Taken together, this indicates that only referenced events received a hit rate boost (relative to other events), suggesting that the retrodictive and predictive benefits of references are directed (i.e., asymmetric).

JRM STOPPED HERE

Discussion

We asked participants to watch sequences of movie segments from a character-driven television drama and then either retrodict what had happened prior to a just-watched segment, predict what

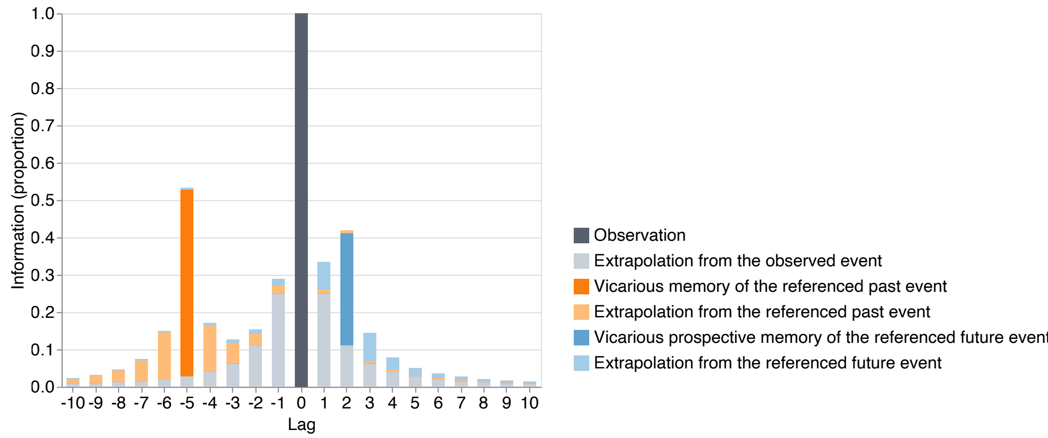

Figure 9: How much information about the past and future can be inferred by observing the present? By definition, let us say that the present moment (lag 0) contains all information about itself (dark gray). Given learned statistical regularities, one might extrapolate from the present moment into the past or future (light gray). As illustrated in this schematic, the information contained in the present about other moments in time falls off with absolute lag. This falloff is approximately time-symmetric. References in the present to past events (dark orange) or future events (dark blue) provide additional information about those referenced moments in time, beyond what could be inferred solely from statistical regularities. This additional information about those referenced moments can also be extrapolated to other moments that are temporally nearby to *them* (light orange and blue).

would happen next, or recall what they had just watched. We found that participants tended to more accurately and more readily retrodict the unobserved past than predict the unobserved future. We traced this temporal asymmetry to (a) characters' tendencies to refer to past events more than future events in their ongoing conversations, and (b) associations between temporally proximal events (Fig. 9). Essentially, associations between temporally proximal events serve to enhance asymmetries in inferences driven by conversational references (light orange and blue bars in Fig. 9). Our findings show that other peoples' psychological arrows of time can affect external observers' inferences about the unobserved past and future.

When people communicate through language or other observable behaviors, they can transmit their knowledge and memories to others (Hirst and Echterhoff, 2012; Mahr and Csibra, 2018; Dessalles, 2007; Zadbood et al., 2017). A consequence of this sharing across people is that biases or limitations in one person's knowledge and memories may also be transmitted to external observers.

Although people *can* communicate their intentions and future plans (i.e., information about their future), because people know *more* about their pasts than their futures, the knowledge transmitted to observers is inherently biased in favor of the past (Fig. 9; Demiray et al., 2018). Since observers leverage communicated knowledge to reconstruct the unobserved past and future, this explains why observers' inferences about observed people's lives also favor the past.

People's knowledge asymmetries are not always directly observable. For example, in a conversation where someone talks exclusively about their future plans, a passive observer might gain more insight into the speaker's unobserved future than their unobserved past. However, because the speaker is also guided by their own psychological arrow of time, the "upper limit" of knowledge about their past is still higher than that of their future. Therefore, after accounting for knowledge that *could* be revealed through active participation in the conversation, the seemingly future-biased conversation masks an underlying knowledge asymmetry in favor of the past. This hypothesized "unmasking" effect of interaction implies that the influence of other people's psychological arrows of time should be more robust when the receiver is an active participant in the conversation. Other social dimensions, such as trust, motivation or level of engagement, personal goals, and beliefs, might serve to modulate the effective "gain" of the communication channel– i.e., how much the speaker's knowledge influences the observer's knowledge.

In typical statistical sequences used in laboratory studies, there is no temporal asymmetry, either theoretically (Cover, 1994; Bialek et al., 2001; Ellison et al., 2009), or empirically (Jones and Pashler, 2007). What makes narratives and real-world event sequences time-asymmetric? Of course there are many superficial differences between simple laboratory-manufactured sequences and real-world experiences. As one example, real-world experiences often involve other people who have their own memories and goals. At a deeper level, however, are our subjective experiences essentially more complicated versions of laboratory-manufactured sequences? Or are there fundamental differences? One possibility is that real-life event sequences are not stationary (i.e., not in equilibrium, Cover, 1994). For example, real-life events might start from a special initial condition (Albert, 2000; Feynman, 1965; Cover, 1994) and proceed through a series of transitions from more-ordered to less-ordered states, thus exhibiting an arrow time. When we retrodict, it is possible that we only consider possible past events that are compatible with the highly-ordered special initial state (Carroll, 2010, 2016). For example, when we see a broken egg we might infer that the egg had been intact at some point in the past. But it would be difficult to guess at what states or forms the broken egg might take in the future (Carroll, 2010, 2016). In other words, the procession from order to disorder might result in better retrodiction performance compared with that of (implicitly less-restricted) prediction tasks. The special initial state might also explain why we remember the past, but not the future. Some recent work suggests that the psychological arrow of time might be explained by a related concept in the statistical physics literature, termed the "thermodynamic" arrow of time (Mlodinow and Brun, 2014; Rovelli, 2022). However, the relation between the thermodynamic and psychological arrows of time is still under debate (Gołosz, 2021; Hemmo and Shenker, 2019).

In our study, we explicitly designed participants' experiences such that both the past and future were unobserved. How representative is this scenario of everyday life? For example, we might try to speculate about the unobserved future when making plans or goals, but when might we encounter situations where the past is unobserved but still useful for us to speculate about? Real-life events have long-range dependencies. In general, because the future depends on what happened in the past, discovering or estimating information about the unobserved past can help us form predictions about the future. We illustrate this point in Figure 9 by showing that the additional information contributed by a referenced past event can also extend into the future (light orange bars at lags > 0). This might explain why humans devote substantial effort and resources to attempting to figure out what happened in the unobserved past: history, anthropology, geology, detective and forensic science, and other related fields are each primarily focused on understanding, retrodicting, or reconstructing unobserved past events.

Methods

Participants

A total of 36 participants (25 female, mean age 21.47 years, range 19–50 years) were recruited from the Dartmouth College community. All participants had self-reported normal or corrected-to-normal vision, hearing, and memory, and had not watched any episodes of *Why Women Kill* before the experiment. Participants gave written consent to enroll in the study under a protocol approved by the Committee for the Protection of Human Subjects at Dartmouth College. Participants received course credit or monetary compensation for their time. Two participants completed only the first half of the study and one participant's data from the second half of their testing session was lost due to a technical error. All available data were used in the analyses.

Stimuli

The stimulus used in the study were segments of the CBS television series *Why Women Kill* Season 1. The TV series contained three distinct storylines depicting three women's marital relationships. The three storylines, which took place in the 1960s, 1980s, and 2019, were shown in an interleaved fashion in the original episodes. The first 11 segments from the 1960s and 1980s storylines, across the first and second episodes, were used in our study. Segments were divided based on major scene cuts, which primarily corresponded to storyline shifts in the original episodes. The mean length of the segments was 2.05 min (range 0.97–3.87 min). We chose this TV series based on its strictly linear storytelling (within each storyline) and its realistic settings where most events depicted everyday life. The plots were focused on the main characters (Beth in storyline 1 and Simone in storyline 2), who were present in all the segments in the corresponding storylines.

Task design and procedure

Our experimental paradigm was divided across two testing sessions. In each session, participants performed a sequence of tasks on segments from one storyline (Fig. 2). For each storyline, there were four different task sequences: two forward chronological order sequences and two backward chronological order sequences. Participants completed one task sequence in forward chronological order for one storyline, and one in backward chronological order for the other storyline. The order of the two sessions (forward chronological order sequence first or backward chronological order sequence first), and the pairing of task sequences with storylines, were counterbalanced across participants.

Tasks in each sequence alternated between watching, recall, and retrodiction or prediction, with the specific order of tasks differing across the four sequences. For example, in sequence A1, participants first watched segment 1, followed by an immediate recall of segment 1. Then they predicted what would happen in segment 2 (first uncued and then character-cued). Participants then watched segment 3 and recalled segment 3. After that, participants guessed what happened in segment 2 again, which we termed "updated prediction". Then they watched segment 2, recalled segment 2, and so on as depicted in Figure 2. This procedure was repeated to cover all possible segments. We also note several edge cases at the start and end of the narrative sequences. Since no segments precede the first segment, participants could never make "prediction" responses with the first segment as their target. For analogous reasons, participants never made "retrodiction" responses with the last segment as their target. Another edge case occurred in task sequences B2 and A2 (Fig. 2). In the A1 and A2 sequences, participants experience the narrative in the original (forward) order, predicting one segment ahead along the way. In the B1 and B2 sequences, participants experience the narrative in the reverse order, retrodicting one segment ahead along the way. However, because A2 and B2 are offset from A1 and B2 by one segment, the initial A2 responses are *retro*dictions, and the initial B2 responses are *pre*dictions (i.e., they conflict with the temporal directions of the remaining responses in those conditions). We therefore excluded from our analysis those initial retrodiction responses from the A2 condition, and the initial prediction responses from the B2 condition.

Before watching each segment, participants were given the following task instructions. After watching the video, participants were instructed to type their responses (retrodiction, prediction, or recall) in 1–4 sentences. Participants were also asked to specify the characters' names in their responses, i.e., avoiding use of characters' pronouns. For the recall task, the names of the characters in the recall segment were displayed, and participants were asked to summarize the major plot points in the present tense. For the retrodiction and prediction tasks, participants were instructed to retrodict or predict the major plot points of the segment (also in the present tense), as though they had watched the segment and were writing a plot synopsis. They were also instructed to avoid speculation words (e.g., "I *think* Beth will..."). For the uncued retrodiction and prediction tasks, participants made retrodictions or predictions without any cues provided, so they had to guess which of the characters would be present in the segment. For character-cued retrodictions and predictions, the characters in the target segment were revealed on the screen, alongside participants' previous responses. Participants were instructed to include or incorporate those characters into their character-cued responses, if their previous responses did not contain all the characters provided. They were also told that the characters were not necessarily listed in their order of appearance in the segment, and that only the main characters would be given. Also, the characters given did not necessarily interact with each other in that segment, and they could appear in successive events in that segment. If participants' previous responses included all the characters given, then they could directly proceed to the next task without updating their responses. For all of the prediction and retrodiction tasks, participants were instructed to provide at least one response, but they were given the opportunity enter up to three responses if they felt that multiple possibilities were more or less equally likely. Each response (including recall) was followed by a confidence rating on a 1–5 point scale. However, these confidence data were not analyzed in the present study.

Before their first testing session, participants were given a practice session, where they watched the first segment of storyline 3 followed by a recall trial, an uncued prediction trial, and a character-cued prediction trial. Participants' responses were checked by the experimenter to ensure compliance with the instructions. To provide participants with sufficient background information about the storyline (especially for the backward chronological sequences), at the beginning of each session, participants were shown the time, location, and the main characters (with pictures) of the storyline. The first session was approximately 1.5 h long and the second session was approximately

1 h long. We allowed participants, at their own discretion and convenience, to sign up for two consecutive testing time-slots (i.e., with their testing sessions occurring in immediate succession), or for testing sessions on two different days. The mean inter-session interval was 0.73 days (range: 0–4 days). The experiment was conducted in a sound- and light-attenuated testing room. Videos were displayed using a 27-inch iMac desktop computer (resolution: 5120 × 2880) and sound was presented using the iMac's built-in speakers. The experiment was implemented using jsPsych (de Leeuw, 2015) and JATOS (Lange et al., 2015).

Video annotation

Events in the first 11 segments of the two storylines were identified by the first author (X.X.), corresponding to major plot points (total: 117; mean: 5.32 per segment; range 3–9). Additionally, 74 offscreen events were identified. Of these 74 offscreen events, 43 events were identified from references in conversations during onscreen events. Another 16 events were identified based on characters' implied movements and travels. For example, if in segment 1 character A was in place A and in segment 2 she was in place B, then the transit from place A to B for character A would be identified as an offscreen event. The remaining 15 offscreen events were identified based on logical inferences. For example, if a photograph was shown in an onscreen event (but not the act of the photograph being taken), then the action that someone took the photograph would be identified as an offscreen event. Offscreen events always occurred between two contiguous segments, or before the first segment. The purpose of identifying offscreen events was to match participants' responses to video events; thus our identification of these offscreen events was not intended to be exhaustive.

Response analyses

Participants' retrodiction, prediction, and recall responses were minimally processed to correct obvious typos (e.g., in characters' names) and remove speculation descriptions (e.g., "I predict that..."). All responses were manually coded and matched to events from the video annotations.

Retrodiction and prediction responses were coded by two coders (X.X. and Z.Z.). Recall responses were coded by one coder (X.X.). While most responses were clearly identifiable as either matching specific storyline events or as not matching any storyline events, several ambiguous cases arose. First, some responses combined or summarized over several (distinct) storyline events. Second, some responses lacked any specific detail (e.g., "character A and B talk" without describing the specific topic(s) of conversation or providing other relevant details). Based on participants' responses, in addition to the original 117 onscreen events and 74 offscreen events, we added 25 new events (23 onscreen, 2 offscreen) that either summarized across several events or partially matched the annotated events. Whereas the original events were each assigned a value of one point, we assigned these additional events a half point. This point system enabled us to directly match events in participants' responses to the annotated events. In our analyses of retrodictions, predictions, and recalls, we added up the number of points earned for each response to estimate participants' event hit rates.

We coded only the first retrodiction or prediction response in each trial. For these responses, we also only considered storyline events that were in the same temporal direction as the target segment. For example, if a participant was asked to retrodict what happened in segment n, only events from segments $1...n$ were considered in our analysis. When coding recall responses, we considered only events from the target segment.

An additional ambiguous case arose in one participant's responses pertaining to segment 12, storyline 2, whereby the participant correctly identified an onscreen event that had not been included in our original annotations. To account for this participant's response, we retroactively added that event to our annotations of that segment. We also identified and counted unmatched events in participants' responses (i.e., events that did not match any annotated events). Cases where the two coders' independent scoring disagreed were resolved through discussions between the two coders.

To estimate the semantic similarities between pairs of responses, we first transformed each response into a 512-dimensional vector (embedding) using the Universal Sentence Encoder (Transformer USE, Cer et al., 2018). We defined *similarity* as the cosine of the angle formed by the responses' vectors. Following Heusser et al. (2021), we defined the *precision* of participants' responses as the median similarity between that response's vector and the embedding vectors for all other participants' recalls of the target segment. We defined the *convergence* of a given response as the mean similarity between that response's vector and all other participants' responses to the corresponding segment, in the same condition. To compute these median or mean similarities we first applied the Fisher z-transformation to the similarity values, then took the median or mean of the z-transformed similarities, and finally applied the inverse z-transformation to obtain the precision or convergence score.

To test the validity and reliability of the USE embeddings, we performed a classification analysis of recall responses using a leave-one-out approach. For each recall response, we calculated its semantic similarity with all other recall responses for the same storyline. We took the segment with the highest median semantic similarity (to the recall response) as the "predicted" segment. Across all responses, the predicted segments matched the true recalled segments' labels 98.6% of the time (1088 out of 1103 predictions; chance level: 9%).

Reference coding

Two coders (X.X. and Z.Z.) identified character dialogues in the narrative that referred to past events or future (onscreen or offscreen) events. Only references to events that occurred in a different segment were included in this tagging procedure. For each reference, the source (referring) segment and the referred event number were recorded. A total of 82 references were identified. Of these, 30 referred to onscreen events and 52 referred to offscreen events. For these referenced events, their corresponding summary events or partial events were also labelled as referenced. In instances where the coders disagreed about a given tag, disagreements were resolved through discussions between the two coders. In our analyses, each storyline event was coded according to whether or not it had been referenced in the segment(s) that the participant had viewed thus far in the experiment.

In principle, a given event could receive multiple labels. For example, during event A, a character might speak about another event, B, during which a reference to a third event (C) was made. In this scenario, event B could be both a "referring event" ($B \to C$) *and* a referenced event ($A \to B$). In practice, however, this scenario was quite rare, accounting for only one out of a total of 30 onscreen events.

Statistical analysis

We used (generalized) linear mixed models to analyze the hit rates and numbers of events retrodicted, predicted, and recalled, as well as the precisions and convergences of participants' responses. Our models were implemented in `R` using the `afex` package. We carried out comparisons or contrasts, and extracted *p*-values, using the `emmeans` package. Participants and stimuli (e.g., segment identity) were modeled as crossed random effects (as specified below). Random effects were selected as the maximal structure that allowed model convergence. All of our statistical tests were two-sided.

For our tests of the target event hit rates across four `levels` (uncued, character-cued, updated, and recall; Fig. 3B), we fit a generalized linear mixed model with a binomial link function:

```
cbind(thp, ttp - thp) ~ direction * level * seg_cnt * storyline +
(direction * level | target) +
(direction * level * seg_cnt | subject)
```

where `thp` was the number of points hit for the target segment, `ttp` was the total number of points for the target segment (from its annotations), `direction` was either retrodiction or prediction, `level` had four levels (uncued, character-cued, updated, and recall), `seg_cnt` represented the number of segments in the storyline that had been watched (1–10, centered), `storyline` had two levels (1 or 2), and `target` had 22 levels according to the identity of the target segment. For our tests of precision and convergence (Fig. 3C, D), we fit linear mixed models using the same formula. To test the effect of `direction` (retrodiction or prediction) on target event hit rates, precision, and convergence, we fit a (generalized) linear mixed model separately for each of the three levels (uncued, character-cued, and recall).

For our tests comparing the numbers of hits for different types of events (Fig. 4B), we fit generalized linear mixed models using the same formula, but with a Poisson link function. For these models, we manually doubled the point counts to ensure that half points were mapped onto integers, ensuring compatibility with the Poisson link function.

For our analyses of the numbers of events hit, controlling for lag (Fig. 4C), we fit a generalized linear mixed model with a Poisson link function:

```
hp_lag ~ direction * full_stp * lag * storyline +
(direction | base_seg) + (1 | base_seg_pair) +
(direction * full_stp * lag * storyline | subject)
```

where `hp_lag` is the number of "points" earned (for each lag) in each trial (we manually doubled the point counts to ensure that half points were mapped onto integers, for compatibility with the Poisson link function), `full_stp` denoted whether the given events (of the given lag) were onscreen (i.e., full step) or offscreen (i.e., half step), `lag` denotes the (centered) absolute lag, `base_seg` denotes the identity of the just-watched segment (22 levels), and `base_seg_pair` denotes the pairing of the just-watched segment and the segment at each lag (440 levels).

For our analyses of the proportions of events hit for referenced versus unreferenced events (Fig. 5D, E), we fit a generalized linear model with a binomial link function:

```
cbind(hp_lag, tp_lag - hp_lag) ~ direction * reference * full_stp +
lag + (direction | base_seg) +
(1 | base_seg_pair) +
(direction * reference * full_stp + lag | subject)
```

where `hp_lag` denotes the number of earned hit points for each reference type (referenced or unreferenced) at each lag, `tp_lag` denotes the total number of possible hit points for each reference type at each lag, and the other variables adhered to the same notation used in the above formulas.

For our tests of the proportions of events hit for all three reference types (referenced, reference-adjacent, and remaining: Fig. 6D, E; or referenced, referring, and other: Fig. 7D), we fit a generalized linear mixed model using the same formula as above, but with three (rather than two) `reference` levels.

Code and data availability

All of the code and data generated for the current manuscript are available online at:

https://github.com/ContextLab/prediction-retrodiction-paper

References

Albert, D. Z. (2000). *Time and chance*. Harvard University Press, Cambridge, Mass.

Baldassano, C., Hasson, U., and Norman, K. A. (2018). Representation of real-world event schemas during narrative perception. *The Journal of Neuroscience*, 38(45):9689–9699.

Bialek, W., Nemenman, I., and Tishby, N. (2001). Predictability, complexity, and learning. *Neural Computation*, 13(11):2409–2463.

Bordwell, D. (2008). *Poetics of cinema*, chapter Three dimensions of film narrative, pages 85–134. Routledge.

Bower, G. H., Black, J. B., and Turner, T. J. (1979). Scripts in memory for text. *Cognitive Psychology*, 11(2):177–220.

Carroll, S. (2010). *From eternity to here: the quest for the ultimate theory of time*. Penguin.

Carroll, S. (2016). *The big picture: on the origins of life, meaning, and the universe itself*. Dutton.

Cer, D., Yang, Y., Kong, S. Y., Hua, N., Limtiaco, N., John, R. S., Constant, N., Guajardo-Cespedes, M., Yuan, S., Tar, C., Sung, Y.-H., Strope, B., and Kurzweil, R. (2018). Universal sentence encoder. *arXiv*, 1803.11175.

Cover, T. M. (1994). Which processes satisfy the second law? In Halliwell, J. J., Pérez-Mercader, J., and Zurek, W. H., editors, *Physical Origins of Time Asymmetry*, pages 98–107. Cambridge University Press, Cambridge, UK.

de Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a web browser. *Behavior Research Methods*, 47(1):1–12.

Demiray, B., Mehl, M. R., and Martin, M. (2018). Conversational time travel: evidence of a retrospective bias in real life conversations. *Frontiers in Psychology*, 9:2160.

Dessalles, J.-L. (2007). Storing events to retell them. *Behavioral and Brain Sciences*, 30(3):321–322.

Ellison, C. J., Mahoney, J. R., and Crutchfield, J. P. (2009). Prediction, retrodiction, and the amount of information stored in the present. *Journal of Statistical Physics*, 136(1005):doi.org/10.1007/s10955–009–9808–z.

Feynman, R. (1965). *The character of physical law*. MIT Press.

Gołosz, J. (2021). Entropy and the direction of time. *Entropy*, 23(4):388.

Hawking, S. W. (1985). Arrow of time in cosmology. *Physical Review D*, 32(10):2489–2495.

Hemmo, M. and Shenker, O. (2019). The second law of thermodynamics and the psychological arrow of time. *The British Journal for the Philosophy of Science*.

Heusser, A. C., Fitzpatrick, P. C., and Manning, J. R. (2021). Geometric models reveal behavioral and neural signatures of transforming naturalistic experiences into episodic memories. *Nature Human Behavior*, 5:905–919.

Hirst, W. and Echterhoff, G. (2012). Remembering in conversations: the social sharing and reshaping of memories. *Annual Review of Psychology*, 63(1):55–79.

Horwich, P. (1987). *Asymmetries in time: problems in the philosophy of science*. MIT Press.

Jones, J. and Pashler, H. (2007). Is the mind inherently forward looking? comparing prediction and retrodiction. *Psychonomic Bulletin and Review*, 14(2):295–300.

Koster-Hale, J. and Saxe, B. (2013). Theory of mind: A neural prediction problem. *Neuron*, 79(5):836–848.

Lange, K., Kühn, S., and Filevich, E. (2015). ”Just Another Tool for Online Studies” (JATOS): an easy solution for setup and management of web servers supporting online studies. *PLoS One*, 10(6):e0130834.

Maheu, M., Meyniel, F., and Dehaene, S. (2022). Rational arbitration between statistics and rules in human sequence processing. *Nature Human Behaviour*, pages 1–17.

Mahr, J. B. and Csibra, G. (2018). Why do we remember? the communicative function of episodic memory. *Behavioral and Brain Sciences*, 41:e1.

Mlodinow, L. and Brun, T. A. (2014). Relation between the psychological and thermodynamic arrows of time. *Physical Review E*, 89(5):052102.

Radvansky, G. A. and Copeland, D. E. (2006). Walking through doorways causes forgetting: situation models and experienced space. *Memory and Cognition*, 34(5):1150–1156.

Ranganath, C. and Ritchey, M. (2012). Two cortical systems for memory-guided behavior. *Nature Reviews Neuroscience*, 13:713–726.

Rovelli, C. (2022). Memory and entropy. *Entropy*, 24(8):1022.

Tamir, D. I. and Thornton, M. A. (2018). Modeling the predictive social mind. *Trends in Cognitive Sciences*, 22(3):201–212.

Zadbood, A., Chen, J., Leong, Y. C., Norman, K. A., and Hasson, U. (2017). How we transmit memories to other brains: constructing shared neural representations via communication. *Cerebral Cortex*, 27(10):4988–5000.

Zwaan, R. A. and Radvansky, G. A. (1998). Situation models in language comprehension and memory. *Psychological Bulletin*, 123(2):162–185.

Acknowledgements

We thank Luke Chang, Yi Fang, Paxton Fitzpatrick, Caroline Lee, Meghan Meyer, Lucy Owen, and Kirsten Ziman for feedback and scientific discussions. Our work was supported in part by NSF CAREER Award Number 2145172 to J.R.M. The content is solely the responsibility of the authors and does not necessarily represent the official views of our supporting organizations. The funders

had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Author contributions

Conceptualization: X.X. and J.R.M.; Methodology: X.X. and J.R.M.; Software: X.X.; Analysis: X.X. and Z.Z.; Writing, Reviewing, and Editing: X.X., Z.Z., and J.R.M.; Supervision: J.R.M.

Competing interests

The authors declare no competing interests.