What you didn't see 👀: Prevention and generation in continuous time causal induction

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Background

- How do people use temporal information to make causal inferences?
- We investigate whether people can infer causal structures involving both **generative** and **preventative** relationships.
- We compare two models to human judgments.

Conclusion

- People are able to use rich information in continuous time to infer causal structure including prevention.
- Their performance is better explained by a feature-based model based on ***delay*** and ***count*** heuristic cues.

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Download the full paper

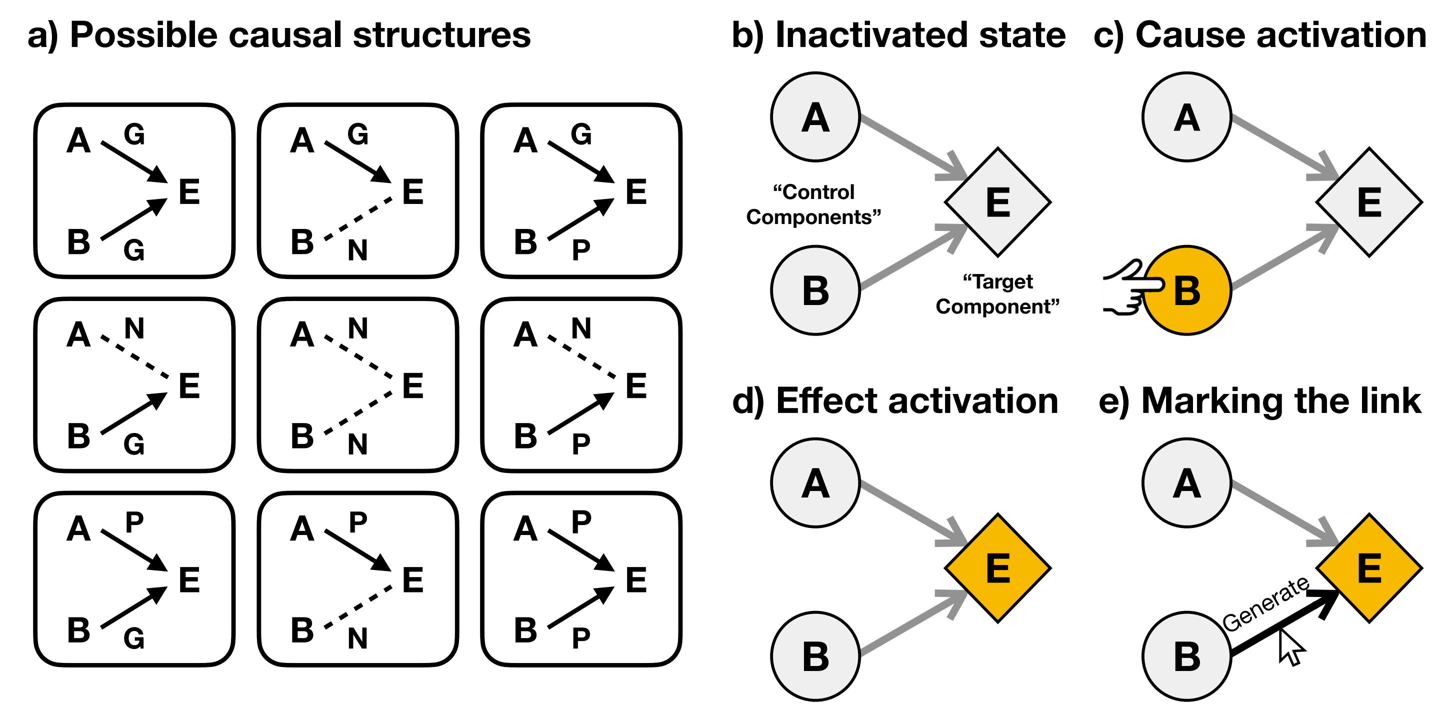
Gong, T., & Bramley, N. R.(2020). What you didn't see: Prevention and generation in continuous time causal induction. In *Proceedings of the 42th annual conference of the cognitive science society*.

https://www.bramleylab.ppls.ed.ac.uk/pdfs/gong2020what.pdf

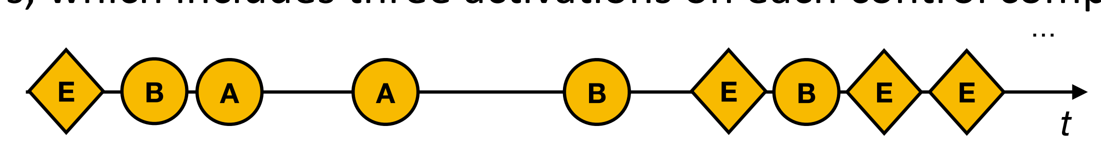
Learning Problem

- Participants learn structure of several causal "devices" by ***watching*** their patterns of activation over time.

- Generative links: produce an activation of the effect component after 1.5±0.5 s.
- Preventative links: block any activations of the effect component within 3±0.5 s.
- The effect component also has a base rate (i.e. self-activates semi-periodically) 5±0.5 s.

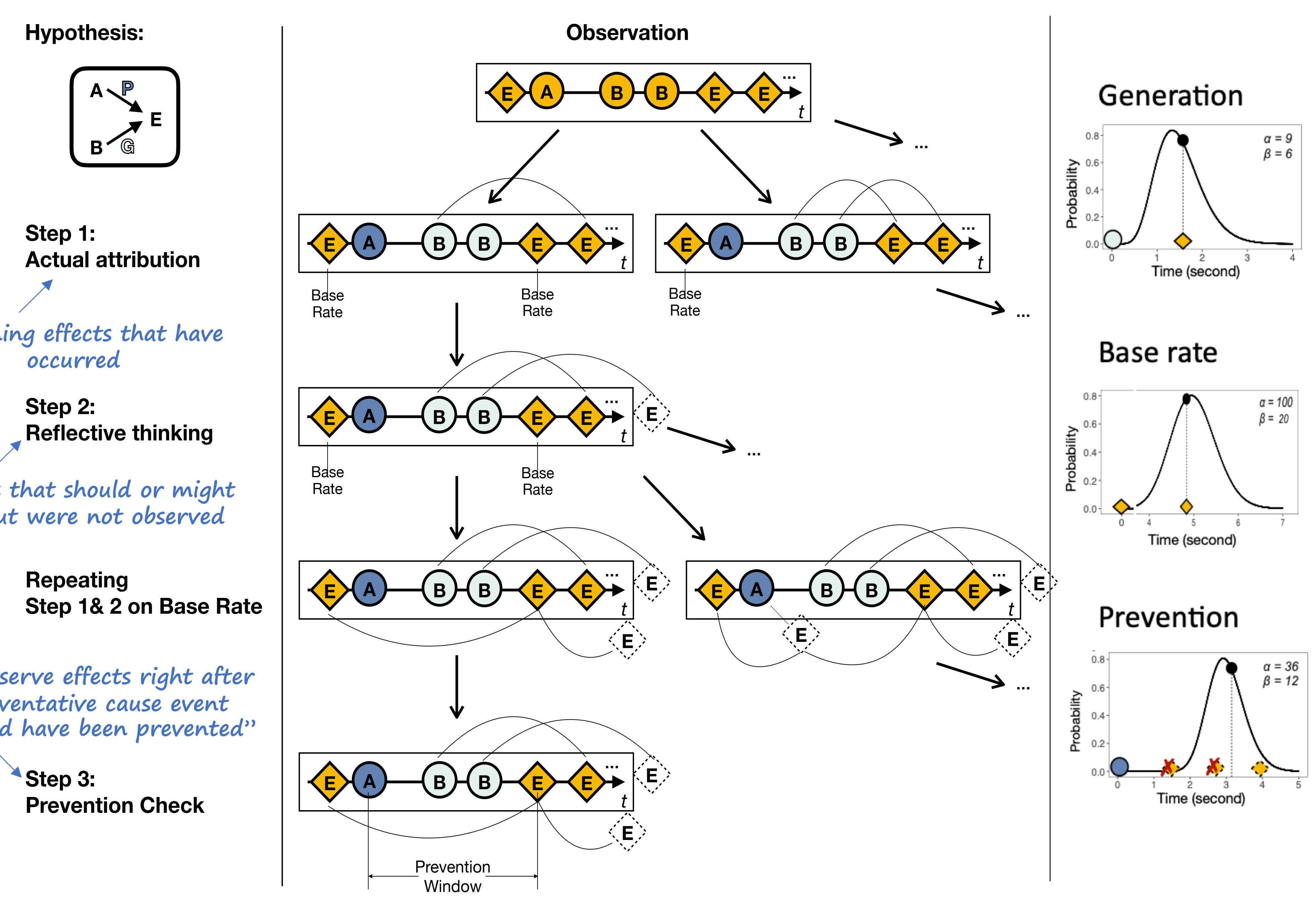


- Each clip lasts 20 s, which includes three activations on each control component (A and B) e.g.:



Normative Bayesian Reasoner

- Considers all possible causal paths that could describe what actually happened conditional on each possible structural hypothesis (Bramley et al., 2017).

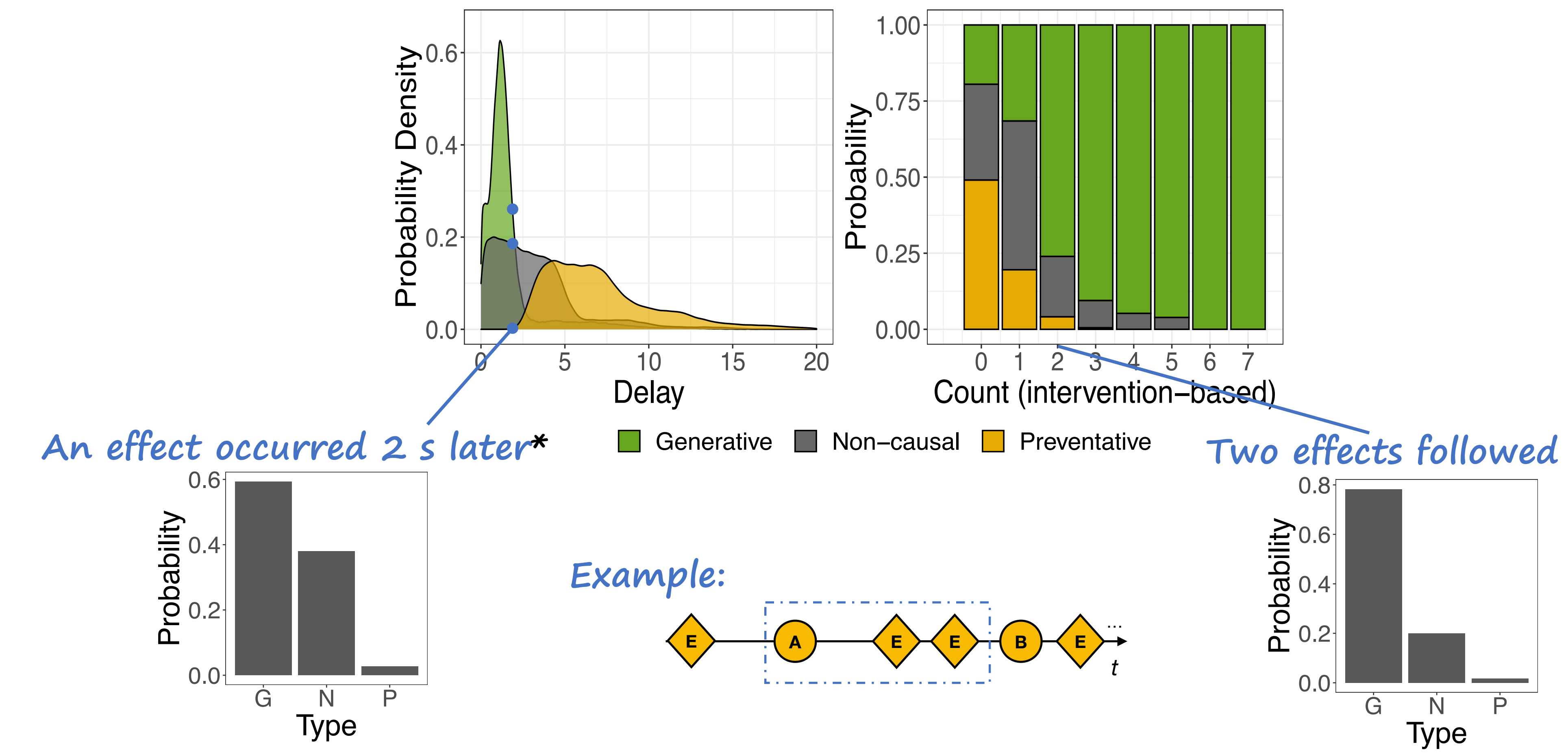


References
Bramley, N. R., Mayrhofer, R., Gerstenberg, T., & Lagnado, D. A. (2017). Causal learning from interventions and dynamics in continuous time. In *Proceedings of the 39th annual conference of the cognitive science society* (pp. 150–155).
Ullman, T. D., Stuhlmüller, A., Goodman, N. D., & Tenenbaum, J. B. (2018). Learning physical parameters from dynamic scenes. *Cognitive psychology*, 104, 57–82.

Feature-based Approximation

- Simulates situations under different causal structures and derives statistical "cues", then favors whatever hypothesis has closest match to the observed data in terms of these cues (Ullman et al., 2018).

- Delay: the interval between each control component activation and the subsequent target component activation.
- Count: the number of subsequent target component activations after the control component's activation.



*We used empirical distributions based on values averaged from all interventions in the same simulated sequences for demonstration in the paper (Fig. 5), but used distributions that treat each intervention as a data point (this figure) in real inference processes.

Human Preference

- **Participants:** Sixty participants (26 female, aged 40 ± 13) were recruited via MTurk.
- **Procedure:** Participants watched clips from 18 devices and judge the causal structure of each device.
- **Results:** The accuracy at the device level was 56 ± 22%, substantially higher than chance (11%), $t(59) = 15.70$, $p < .001$. The accuracy per connection was 73 ± 17% (Generative: 80%, non-causal: 62%, preventative: 76%).

Model	Accuracy	Parameters	BIC	N Best
Normative	83-95%	λ:2.67; θ:3	3378	10/60
Feature-Based				**45/60**
delay	60%	λ:3.62	3431	(23)
count	43%	λ:5.49	3548	(12)
combine	43-60%	λ_d:2.36; λ_c:3.03	**3239**	(10)
Random	11%		4768	5/60