Causal Explanations for Sequential Decision-Making in Multi-Agent Systems

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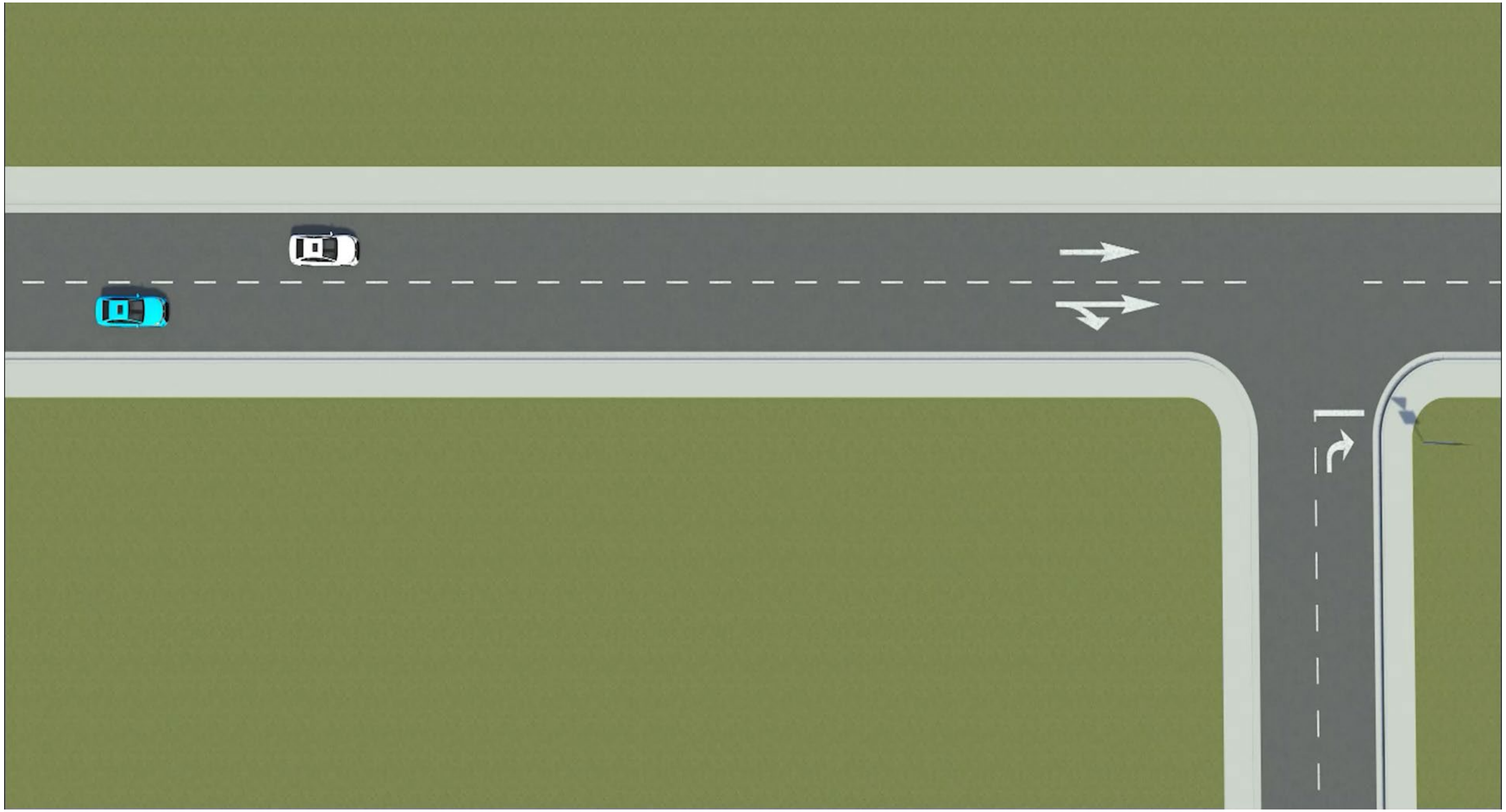
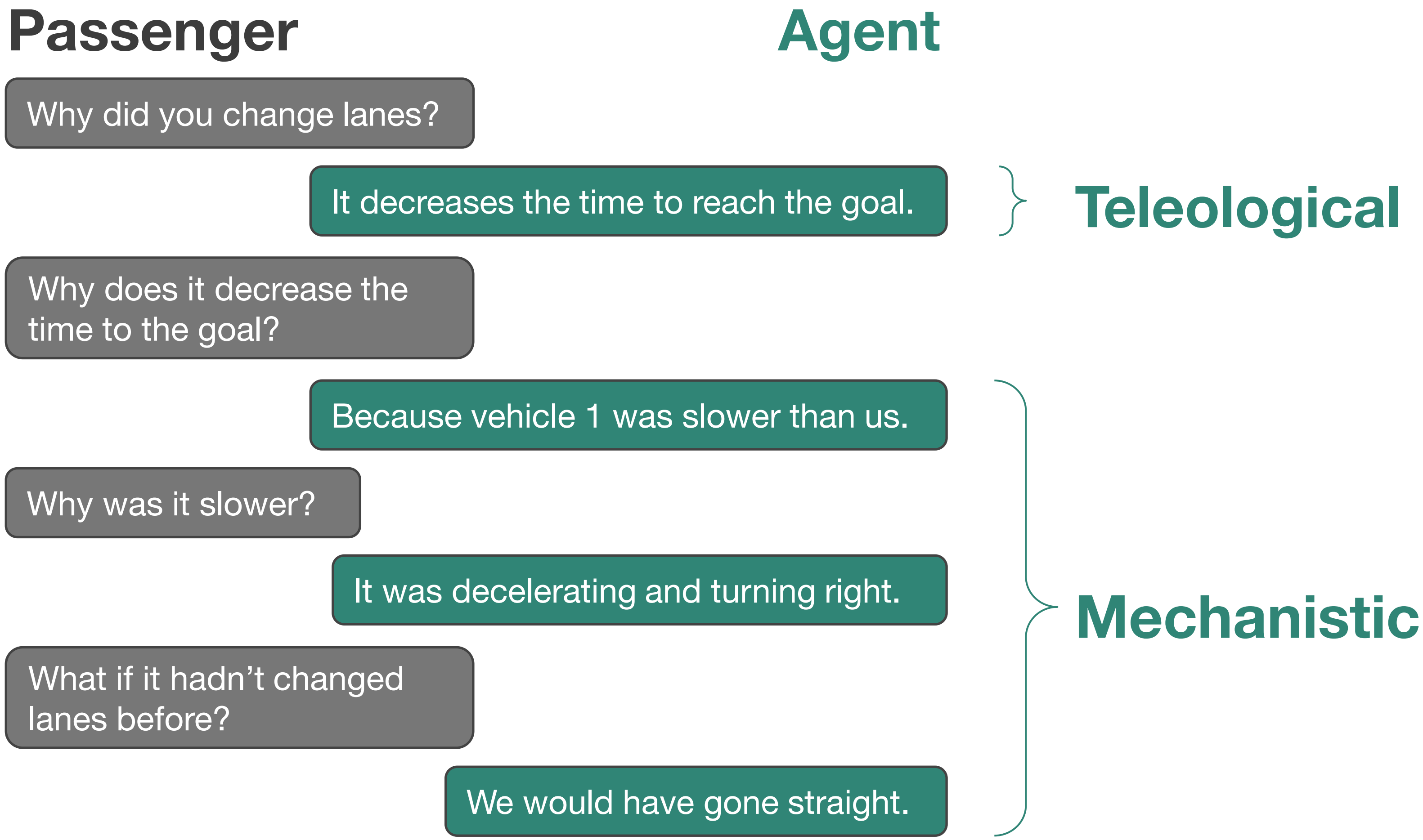
explainable AI · human-centric design · multi-agent systems · cognitive science · natural language processing

ILLUSTRATIVE SCENARIO



EXAMPLE INTERACTION



Passenger **Agent**

Passenger: Why did you change lanes?

Agent: It decreases the time to reach the goal.

Passenger: Why does it decrease the time to the goal?

Agent: Because vehicle 1 was slower than us.

Passenger: Why was it slower?

Agent: It was decelerating and turning right.

Passenger: What if it hadn’t changed lanes before?

Agent: We would have gone straight.

Teleological

Mechanistic

CAUSAL EXPLANATIONS FOR MULTI-AGENT SYSTEMS (CEMA)

CEMA

Causal **E**xplanations for **M**ulti-**A**gent Systems

WHY MULTI-AGENT SYSTEMS?

Why multi-agent systems?

Coupled interactions;

Conflicting goals;

Partial observability;

Communication;

Often difficult to explain, even for humans.

WHY DO WE WANT EXPLANATIONS?

Critical environments:

Socially: Others react to our agents and change their behaviour;

Epistemically: Partial observability and shared rules;

Safety: Actions can harm agents/humans/environment;

Explanations help:

Explain confusing behaviour;

Highlight occluded information;

Calibrate trust.

HUMAN-CENTRED EXPLANATIONS

Theory tells us that explanations should be:

Causal;

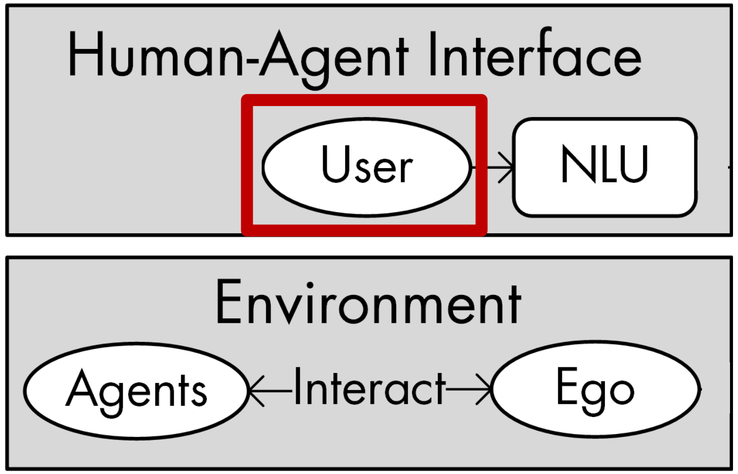
Contrastive;

Selected;

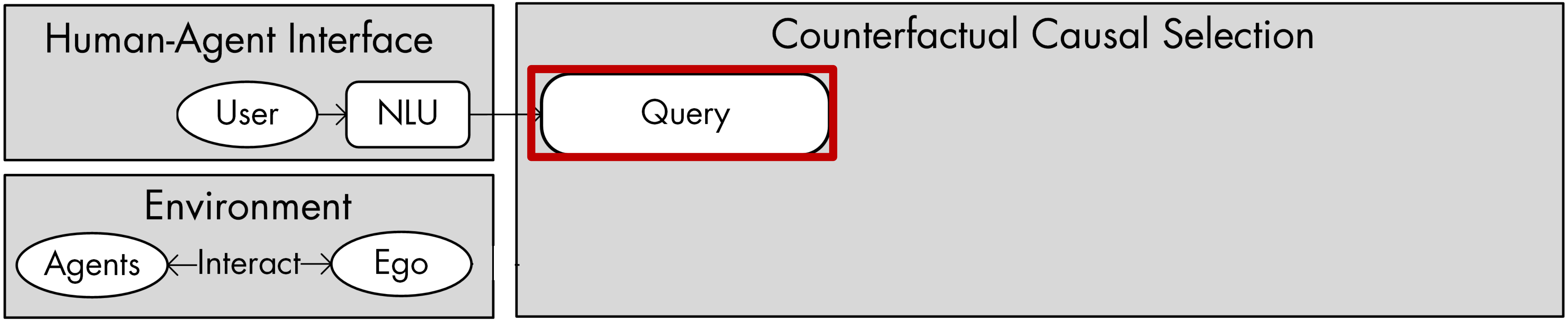
Conversational;

[2] Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences.

How does CEMA work?



How does CEMA work?



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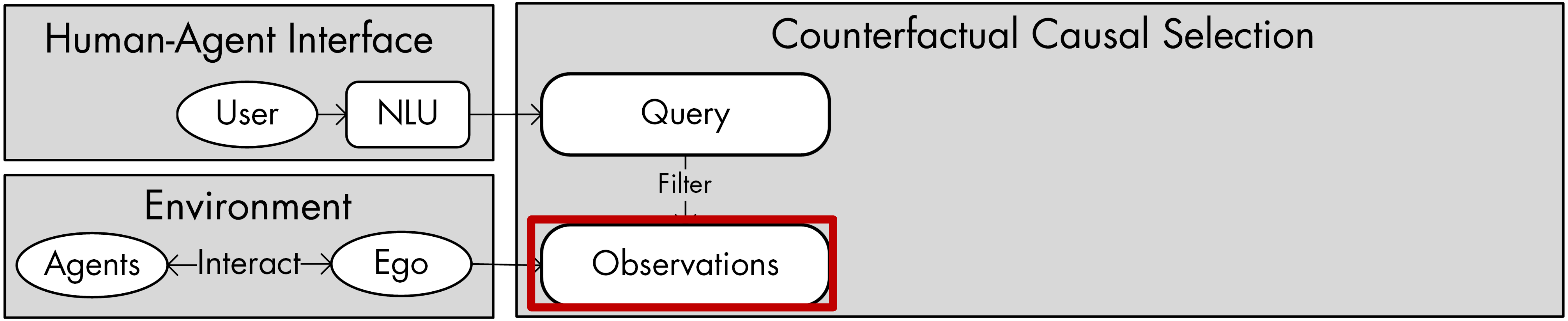
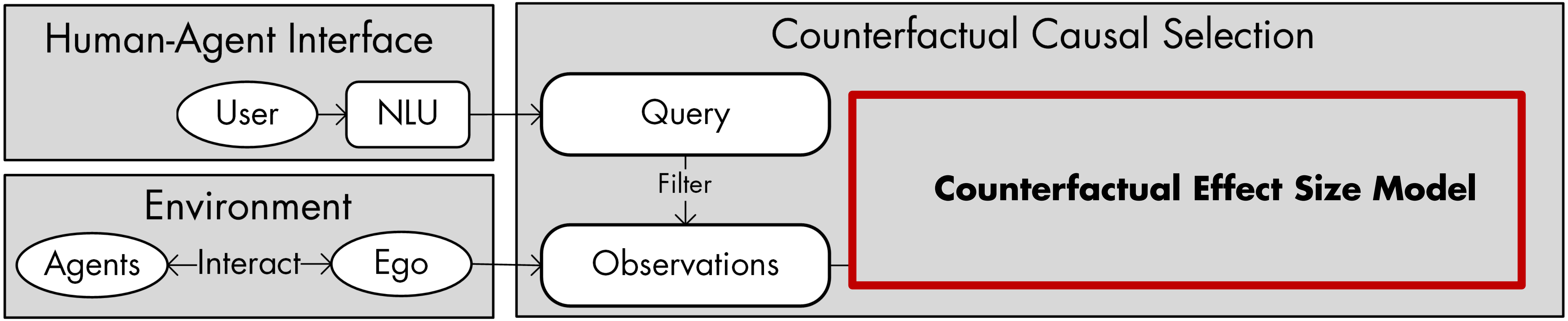


How does CEMA work?



COUNTERFACTUAL EFFECT SIZE MODEL (CESM)

Based on how people could select causes to explain;

People simulate worlds to select causes:

Using some prior (cognitive) distribution;
But anchored to observations;

People use correlation to select among causes:

C caused E if C is highly correlated with E across worlds.

[1] Quillien, T., & Lucas, C. G. (2023, June 8). *Counterfactuals and the Logic of Causal Selection.*

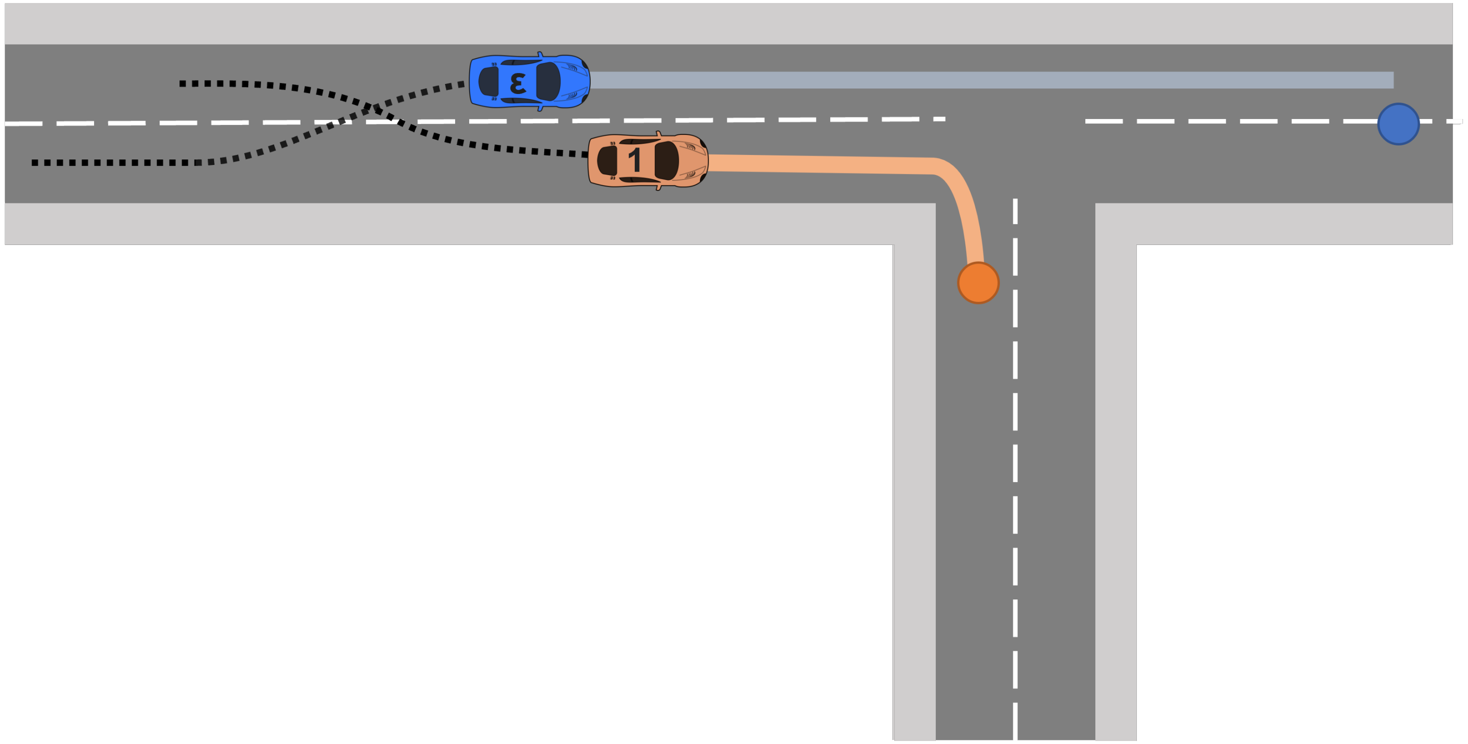
CEMA – THREE-STEP APPROACH

Counterfactual Effect Size Model in CEMA

Rollback → Simulate → Correlate

CEMA – ROLLBACK

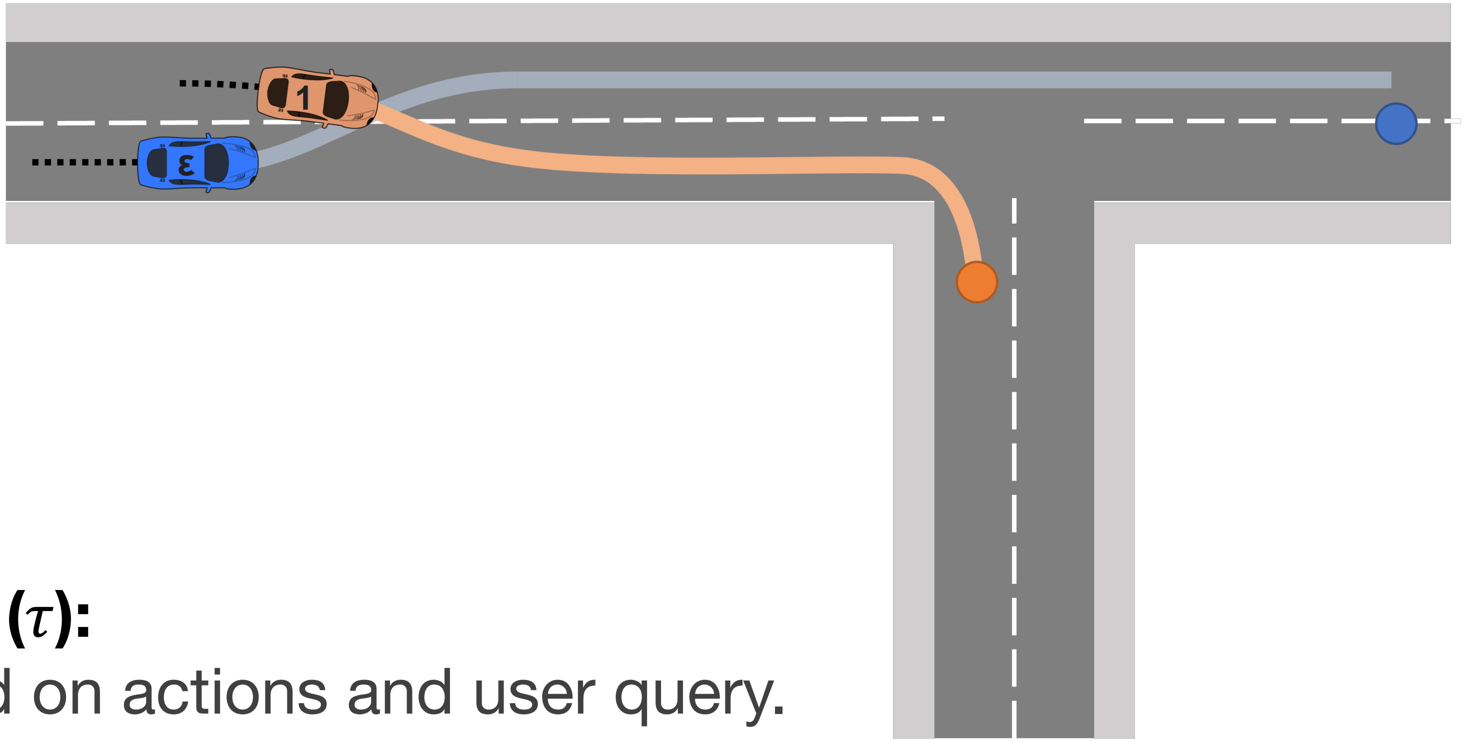
Observed trajectory: $s_{1:t}$



Rollback → Simulate → Correlate

CEMA – ROLLBACK

Rolled back trajectory: $s_{1:\tau}$



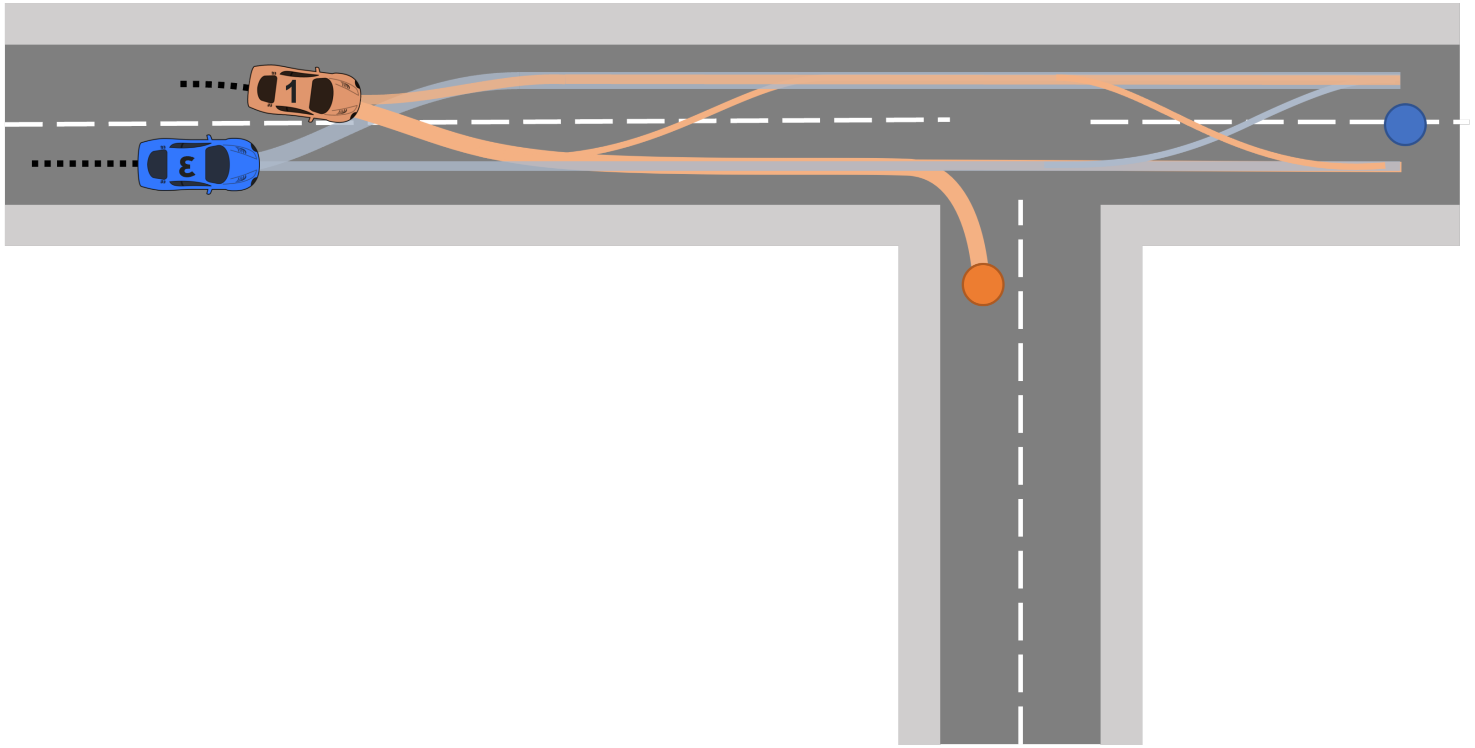
Rollback time (τ):

Selected based on actions and user query.

Rollback → Simulate → Correlate

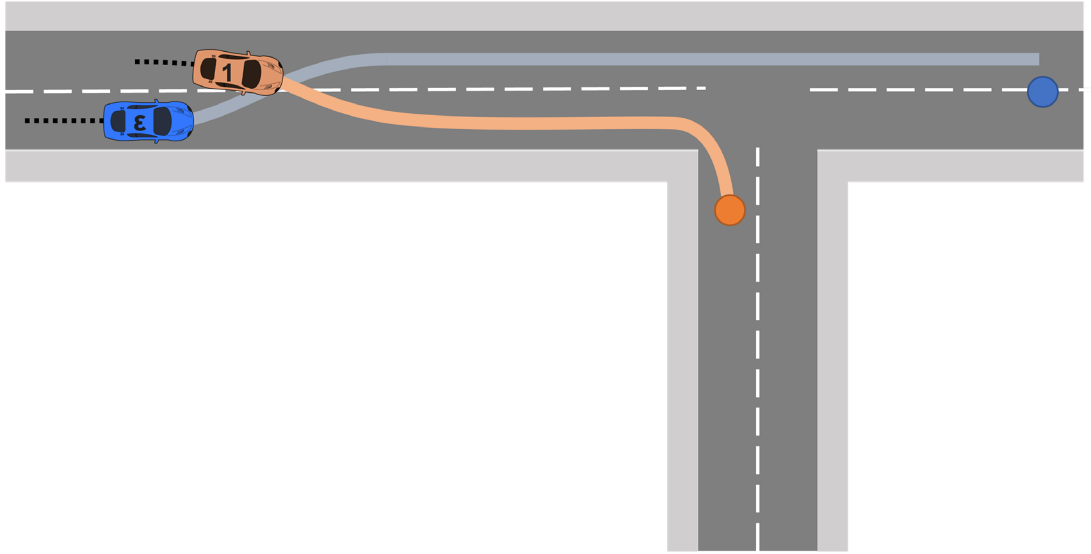
CEMA – SIMULATE (COUNTER)FACTUALS

Simulate (counter)factual worlds



Rollback → **Simulate** → Correlate

CEMA – SIMULATE FACTUAL



Action presence:

Lane change (1)

Rewards:

Time-to-goal: 7 s

Comfort (jerk): 0.5 m/s^3

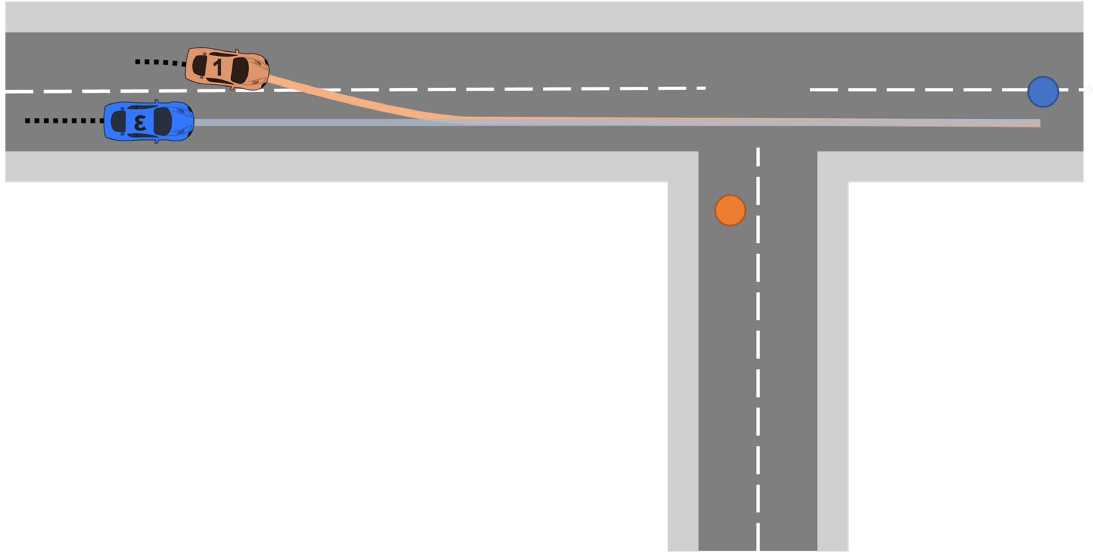
Collision: No

Features from trajectory:

{Decelerate, Turn, Slower, etc…}

Rollback → **Simulate** → Correlate

CEMA – SIMULATE COUNTERFACTUAL



Action presence:

No lane change (0)

Rewards:

Time-to-goal: 5 s
Comfort (jerk): 0.1 m/s^3
Collision: No

Features from trajectory:

{Accelerate, Continue, Faster, etc…}

Rollback → **Simulate** → Correlate

CEMA – CORRELATE – TELEOLOGICAL CAUSES

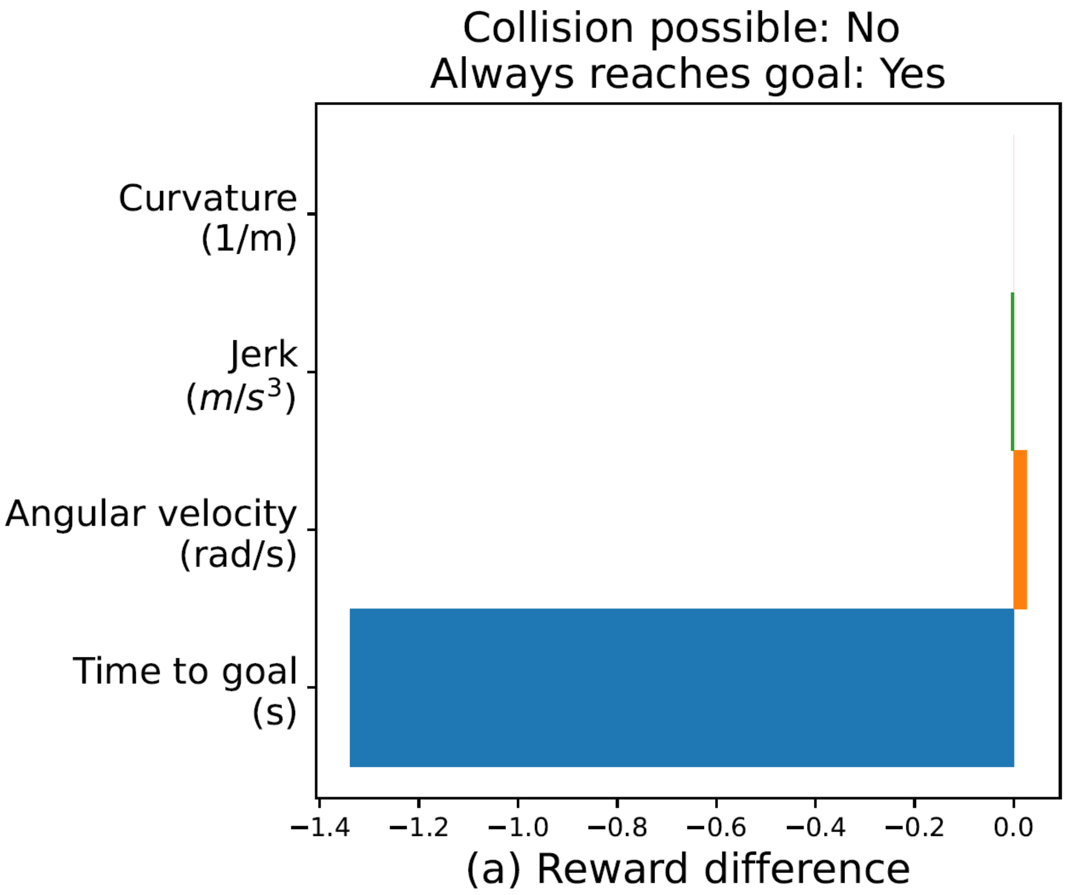
Process for teleological causes;

Difference of expected rewards between:

Worlds where queried action happened;
Where queried action did not happen.

Rollback → Sample → **Correlate**

CEMA – CORRELATE – TELEOLOGICAL CAUSES



Rollback → Sample → **Correlate**

CEMA – CORRELATE – MECHANISTIC CAUSES

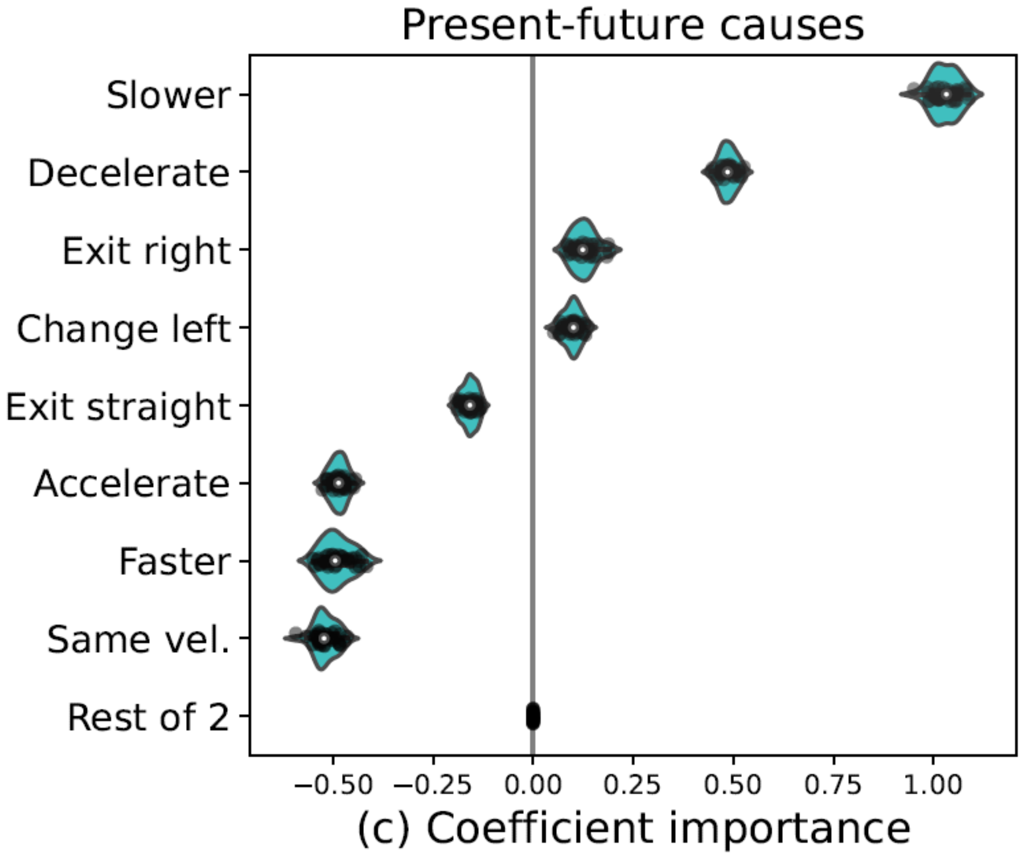
Process for mechanistic causes:

1. Fit interpretable model to trajectory features;
2. Predict presence of queried action;
3. Extract feature importance;

Counterfactual effect size of features.

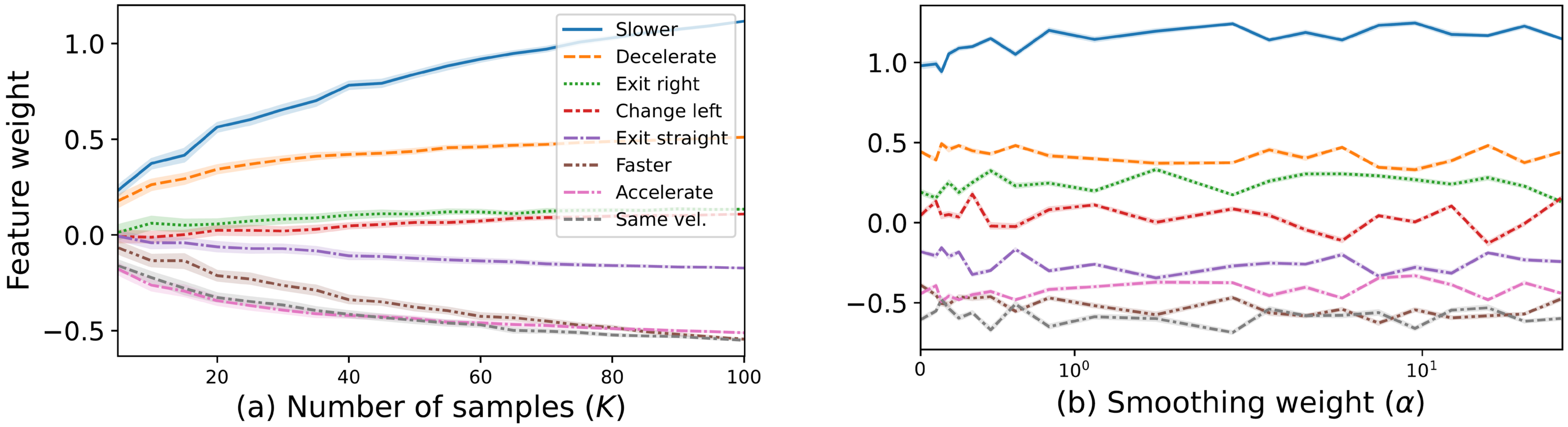
Rollback → Sample → **Correlate**

CEMA – CORRELATE – MECHANISTIC CAUSES



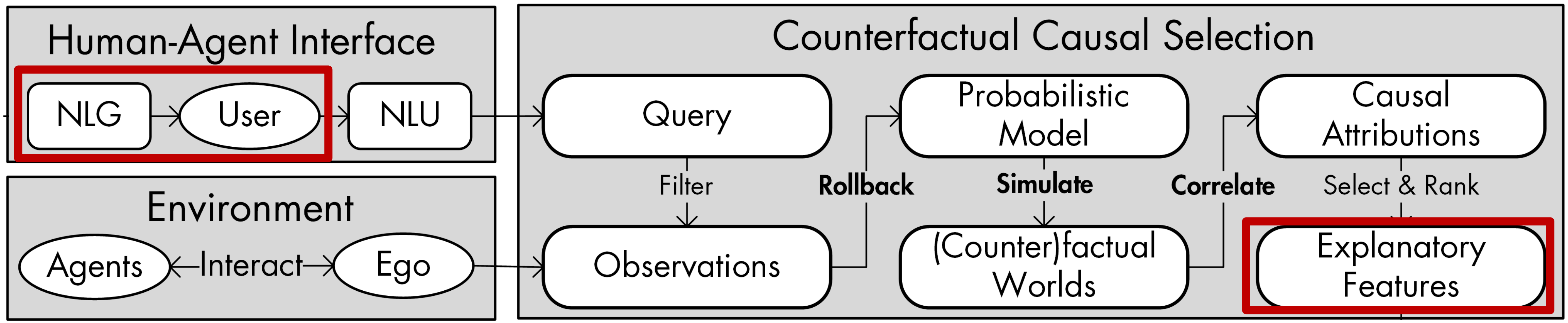
Rollback → Sample → **Calculate**

CEMA is robust

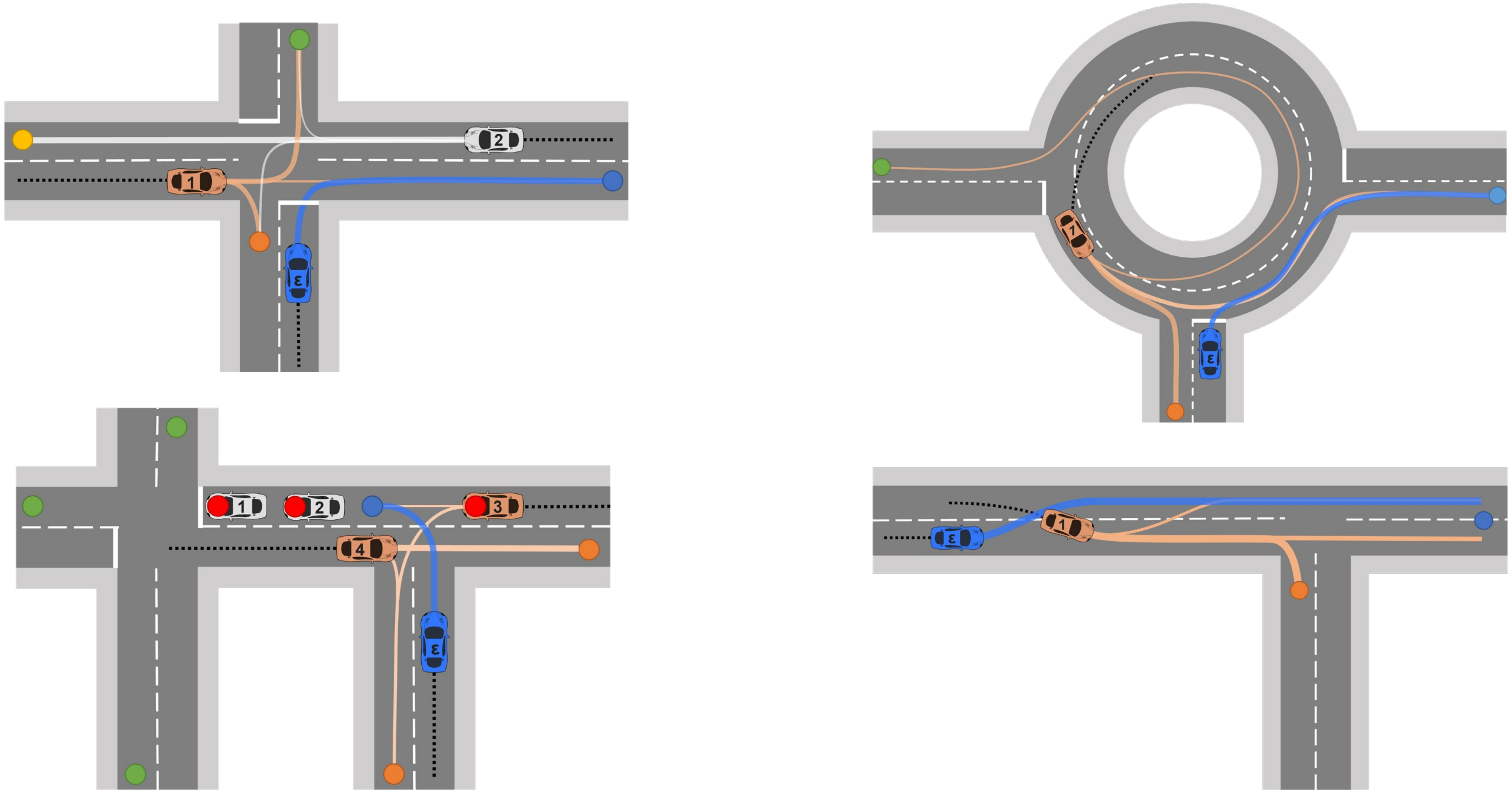


Rollback → Sample → **Calculate**

CEMA – STRUCTURE OF CEMA



FOUR SCENARIOS



CEMA – HUMAN EVALUATION

User study:

Generate human-like explanations at least as good as human-written explanations;

Method:

1. Elicit explanations from people (*HEADD: Human Explanations for AD Decisions* dataset [3]);
2. Compare human explanations to CEMA.

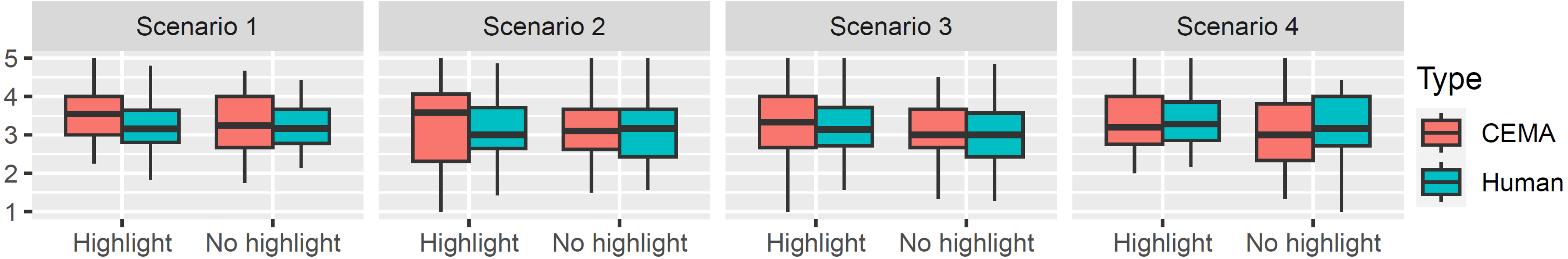
[3] **Gyevnar, B.**, et al. (2024) *People Attribute Purpose to Autonomous Vehicles When Explaining Their Behavior*. (arXiv:2402.10086).

Independent variables:

Scenarios (1-4)

Explanation type (CEMA/Human)

Highlighting CEMA (Y/N)



CEMA – BENEFITS

- **Generally applicable simple (3-step) framework;**
- **No explicit assumption on causal structure:**
  No need to model world with DAGs;
- **Robust causal selection based on CESM;**
- **Works for large number of agents:**
  Tested with up to 20 agents in 4 scenarios.

Causal Explanations for Sequential Decision-Making in Multi-Agent Systems

https://arxiv.org/abs/2302.10809

Contributions:

- **CEMA:** General framework for causal explanations of behaviour: Rollback time → Simulate worlds → Correlate variables with outcomes;
- Robustly generated intelligible explanations through natural language.

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Autonomous Agents Research Group