Me - Not Me - Or In Between?
Comparison of Causal Inference Models for Agency attribution in goal-directed actions

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Introduction

The perception of own actions is affected by both visual information and predictions derived from internal forward models [1]. Their integration depends critically on whether visual consequences are associated:

- with one's own action (sense of agency),
- with changes in the external world[2, 3],
- with accuracy of integrated signals [4, 5].

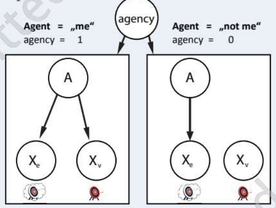
Attribution of percepts to consequences of own actions should depend on the consistency between internally predicted and actual visual signals.

The goal of this work is to develop quantitative theories for the influence of the sense of agency on the fusion of perceptual signals and predictions derived from internal forward models. Our work exploits *graphical models* as central theoretical framework.

Motivation

Goal: hit bullseye.

- **Miss**: correction to adapt one's action with next shot (for better result).
- **Standard approach**: fuse internal estimate and actual visual input to adapt.
- **Miss by external influence**: no cue fusion, no adaptation of action with next shot.



Causal inference model [2, 3].

- A: motor action.
- $\mathbf{X_v}$: visual feedback.
- $\mathbf{X_e}$: internal estimate.

Experiment

Virtual Reality Setup [9, 10].

- HMD, hand invisible.
- Fast out-back movement.
- Target directions chosen uniformly by the subject within first quadrant.
- Tracked direction μ_t.

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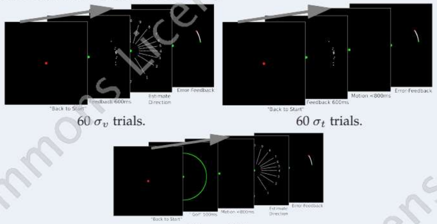
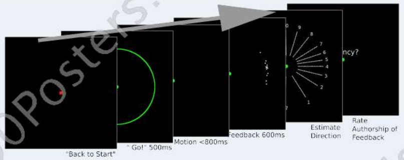
Experiment (continued)

- The experiment consisted of four blocks, focussing on different model parameters.
- The four blocks: 1) σ_V 2) σ_T 3) σ_e 4) *agency*.
- Block trial timeline sketches:



60 σ_v trials. 60 σ_t trials. 60 σ_e trials.



480 *agency* trials.

- Terminal visual feedback $\mathbf{X_v}$ of direction at fixed amplitude.
- $\mathbf{X_v}$ deviates from tracked direction $\boldsymbol{\mu_t}$.
- Offset angles (i.e. $0°, \pm7°, \pm15°, \pm30°, \pm60°$) in random order.

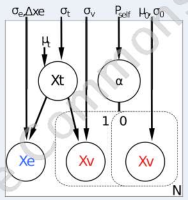
Participants had to answer 2 questions:

- 1. **Which direction did you point to?** $\rightarrow \mathbf{X_e}$
- 2. **Did you cause the observed direction of $\mathbf{X_v}$?** $\rightarrow$ **agency**

Models

A) Binary Agency

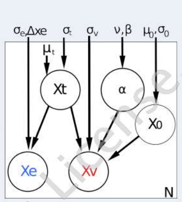
$$X_t \sim \mathcal{N}(\mu_t, \sigma_t^2)$$
$$X_e \sim \mathcal{N}(X_t + \Delta X_e, \sigma_e^2)$$
$$\alpha \sim \mathrm{Ber}(p_{self})$$
$$X_v|\alpha = 1 \sim \mathcal{N}(X_t, \sigma_v^2)$$
$$X_v|\alpha = 0 \sim \mathcal{N}(\mu_0, \sigma_0^2)$$



- **Causal Inference Model [2, 3]**
- $\Theta = \{p_{self}, \mu_0, \Delta X_e, \sigma_0^2, \sigma_e^2, \sigma_t^2, \sigma_v^2\}$
- Probability of attributing X_v to oneself.

B) Continuous Agency

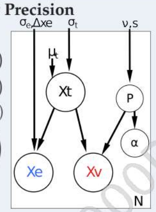
$$X_t \sim \mathcal{N}(\mu_t, \sigma_t^2)$$
$$X_e \sim \mathcal{N}(X_t + \Delta X_e, \sigma_e^2)$$
$$X_0 \sim \mathcal{N}(\mu_0, \sigma_0^2)$$
$$\alpha \sim \mathcal{B}(\nu, \beta)$$
$$\mu_v = \alpha X_t + (1 - \alpha) X_0$$
$$X_v \sim \mathcal{N}(\mu_v, \sigma_v^2)$$



- $\Theta = \{\nu, \beta, \mu_0, \sigma_0^2, \Delta X_e, \sigma_e^2, \sigma_t^2, \sigma_v^2\}$
- Expected agency weight for fusion of own movement direction μ_t with external X_0.

C) Continuous Agency Precision

$$X_t \sim \mathcal{N}(\mu_t, \sigma_t^2)$$
$$X_e \sim \mathcal{N}(X_t + \Delta X_e, \sigma_e^2)$$
$$P \sim \mathcal{B}(\nu, s)$$
$$X_v \sim \mathcal{N}\left(X_t, \frac{1}{P}\right)$$



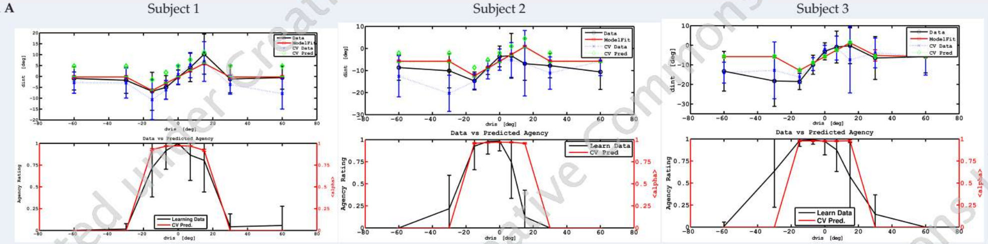
- $\Theta = \{\nu, s, \Delta X_e, \sigma_e^2, \sigma_t^2\}$
- Sigmoidal mapping from visual precision P to *agency*

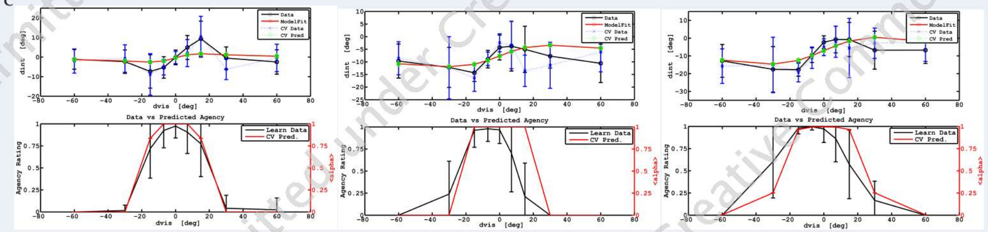
Maximizing Variational Lower Bound

$$\max_{\Theta} \mathcal{L} = \max_{\Theta} \sum_i < ll^i >_{q^i} - D_{KL}(q^i || p^i)$$

- ll Log-Likelihood
- D_{KL} is the Kullback-Leibler-Divergence.
- q^i are the posterior distributions for the latent variables for trial i, p^i the respective priors.
- EM-like variational maximization of $\mathcal{L}$ over the prior and posterior parameters.

Results





- Fits for Model A show good estimation of own movement direction.
- Fits for Model C show rather flat estimation of own movement direction.
- For large perturbations, the visual feedback is ignored and is not fused with the internal estimate.
- For small perturbations, the visual feedback and the internal estimate are fused to update the own movement estimate.

Results (continued)

- Both models A and C predict the agency attribution correctly, with a trend to overattribute the feedback to one's own action.
- Some participants showed a bias in the direction estimation.

Model Comparison

- 20% of the trials were randomly selected from each manipulation-bin for cross-validation.
- For comparison between models, we used the log-likelihood of the cross-validation data.
- A more positive log-likelihood score represents a stronger support of that model by the data.
- More positive scores are written in bold.

Subject	Model A	Model C
1	**-669.5**	-796.8
2	**-582.4**	-638.7
3	**-557.8**	-642.8
4	**-567.3**	-647.1
5	**-662.8**	-773.5
6	**-628.0**	-752.9
7	**-616.0**	-653.0

Table 1) Cross-Validation Loglikelihood scores.

Discussion

Summary.

- Models showed good own movement direction estimation.
  - Small perturbation $\rightarrow$ cue fusion.
  - Large perturbation $\rightarrow$ no cue fusion.
- Both models showed good prediction of agency attribution.
- Correct prediction of *agency* (belief that subject caused the visual feedback) by binary probabilistic model.

Model Comparison.

- **Model A**
  - Binary agency variable.
  - Showed good estimation of own motion direction and prediction of agency attribution.
- **Model B**
  - Fusing visual feedback with external input proved to be degenerate when learning parameters.
  - The degeneracy allowed adjusting the variance of the external input to such an extent, that visual feedback could be almost ignored and all movements explained by an external agent.
- **Model C**
  - Flat fusion trend, i.e. trend of participant to distrust the visual feedback.
  - Own movement estimation influenced by the visual feedback to a smaller degree than for model A.
  - This distrust of the visual feedback could result from the model only seeing accurate visual feedback in about 50% of the trials.

Conclusion

- Agency attribution of consequences to subjects' own actions was subject specific.
- Agency attribution depended on deviation between internal estimate and visual feedback.
- Correct prediction of *agency* by causal inference model.
- Model C showed tendency to distrust the visual feedback
- Model A with binary *agency* variable supported more strongly by data.

Current Work & Outlook

Variation of visual uncertainty σ_v

- Vary quality of visual stimulus.
- Increase distribution width of random stimulus dots.
- Effect of increasing σ_v:
  - Widening of agency posterior ($P(\alpha = 1|X_v, \mu_t, \Theta)$).
  - Widening of region of optimal cue fusion .
  - Flattening of curve, weaker influence of visual feedback onto internal estimate.

Instructed *agency* prior

- Train participant to different *agency* priors.
- Maintain same *agency* prior throughout experiment.
- Compare empirical data with model predictions.
- Effect of increasing *agency* prior:
  - Increase trust of visual feedback, stronger influence of visual feedback in cue fusion.
  - Widening of region of optimal cue fusion .

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