Interview for PhD Position on Synthesizing Digital Humans

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Outline

"Resolving uncertainty in a social world". O FeldmanHall, A Shenhav. Nature human behaviour, 2019.

Summary

Features

- Described the nature of uncertainty in social inferring.
- Integrated findings from distinct fields to offer a holistic framework.
- Proposed a generalized model of how uncertainty is minimized.
- Assessed the trade-offs and consequences of the intrinsic desire to minimize uncertainty.
- Supported the laid arguments with relevant examples, cases and research evidences.

Key arguments

1. People tend to minimize the uncertainty induced aversion.
2. This minimization occurs iteratively through inference and learning.
3. The prediction of one's own states based on others follows the Bayesian inference.

The proposed framework explains the social uncertainty using Shannon's entropy, where the distribution with outcomes having equal likelihood has highest uncertainty.

The total uncertainty in one's actions (a), given their current state (s) and another individual's state (i_z) can be given as-

$$H(a|sy, i_z) = -\sum_j \sum_i \sum_z Pr(a_j|s_y, i_z) \cdot log_2(Pr(a_j|s_y, i_z)) \cdot Pr(s_y, i_z)$$

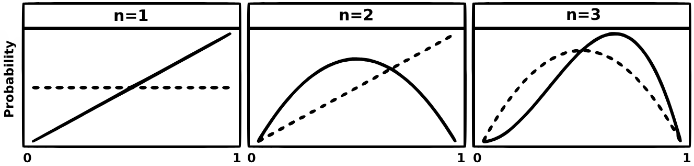

Figure: The bayesian updating of probability distribution of prior (dotted) and posterior (solid) impression formation where 0 refers to negative impression and 1 refers to positive impression.

Research questions

- How **uncertainty minimization** is the **underlying principle** for a range of dynamics in the social environment?
- How uncertainty is **induced**, **responded** and **managed** through mechanisms of **inference** and **learning** in different contexts?
- What **outward** and **inward implications** can the **intrinsic desire** cause?

Methodology

The presented work offers a fresh **composite** perspective by emphasizing on the importance of uncertainty through the means of-

- a **theoretical framework** validated against generalized examples, and
- the **review of articles** from diverse fields such as social psychology, neuroscience, statistics, cognitive science, information theory, economics, among others.

Significance

- The work intends to **stimulate discussion** by providing **foundational groundwork** and **encourage development** in the direction of social uncertainty.
- Social cognition has been investigated from distinct perspectives [1] since late 1980s [2], however, the efforts towards **integration** have been **minimal**. The present paper adopts an eceletic approach to account for mechanisms motivating social cognition and action.
- Lately, with the emergence of functional Positron Emission Tomography (PET) [3], majority of the research have centered their models around **neuroscientific methods** [4] whereas the present work, being conceptual and statistical in nature, has a **wider scope** for future research under limited resources without compromising its reliability.

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[1] P. A. Van Lange and E. T. Higgins (2011). "Handbook of theories of social psychology". In: *Handbook of Theories of Social Psychology*, pp. 73–374

[2] A. Bandura (1986). "Social foundations of thought and action". In: *Englewood Cliffs, NJ* 1986.23-28

[3] M. D. Lieberman (2012). "A geographical history of social cognitive neuroscience". In: *NeuroImage* 61.2, pp. 432–436

[4] B. A. Nosek and C. B. Hawkins (2011). "Implicit social cognition: From measures to mechanisms". In: *Trends in cognitive sciences* 15.4, pp. 152–159

Limitations

- The proposed model is grounded on **assumptions** (people tend to reduce uncertainty induced aversion) that are **cognitive** in nature. Future research will be bound to rely upon qualitative research techniques which will **impact** the **validity** of the theory. Such assumptions are also prone to biases which, in turn, will make the theory **fallible**.
- While the authors explain the behaviour of people with **high risk appetite** that actively **seek uncertainty** (explore-exploit dilemma), the arguments stay in contrast with a number of studies that claim the endogeneous [5] and irrational [6] nature of risk.
- The article fails to discuss the directions for **operationalizing** the future research work as well as hardly sheds light on the **correlation** between aversion and social uncertainty.
- The idea of reducing aversion (or uncertainty) and actively searching information has been **popularized** in various **other fields** as information-foraging theory (behavioral ecology), cognitive load minimization (user experience research), utility maximization (microeconomics), etc. which have **failed** to **capture** the **complexity** of behaviour.

[5] J. Danielsson, H. S. Shin, and J.-P. Zigrand (2010). *Risk appetite and endogenous risk*. Financial Markets Group

[6] P. Jackson (2018). "Risk accountability and risk appetite: enhancing risk culture". In: *Journal of Financial Perspectives* 5.1

"Towards robust and adaptive motion forecasting: A causal representation perspective".
Liu, Yuejiang et al. CVPR, 2022.

Summary

Features

- Bifurcated the forecasting problem into a three group dynamic process.
- Formulated optimal methods to independently address causal-invariant and non-causal spurious shifts.
- Implemented a modular architecture to account for latent variables in different environments along with the causal learning.
- Evaluated the model with respect to synthetic and real datasets.

Key arguments

1. Conventional methods (i) only look for patterns by modelling correlations between latent variables as well as (ii) neglect inherent differences in the datasets.
2. Causal learning with a structured representation learning is more robust and adaptive.

To generalize the motion forecasting problem to every distribution shifts, firstly the spurious correlations are suppressed using gradient norm penalty (ref Eq.3), secondly a modular architecture is introduced to capture style shifts using style contrastive learning (ref Eq.5), and lastly, the refinement occurs through a self-supervisory signal in the test environment[7].

$$\min_{\phi,g} \quad \frac{1}{|\mathcal{E}|} \sum_{e \in \mathcal{E}} \left[\mathcal{R}^e(\phi, g) + \lambda \|\nabla_g \mathcal{R}^e(\phi, g)\|_2^2 \right]. \tag{3}$$

$$\mathcal{L}_{\text{style}} = -\log \frac{\exp(\text{sim}(\boldsymbol{p}_i, \boldsymbol{p}_j)/\tau)}{\sum_k \mathbb{1}_{[k=j \vee \boldsymbol{e}_k \neq \boldsymbol{e}_i]} \exp(\text{sim}(\boldsymbol{p}_i, \boldsymbol{p}_k)/\tau)}, \tag{5}$$

[7] The experiments are performed over real data from ETH-UCY datasets [8] and synthetic data generated from ORCA, a multi-agent simulation [9].

Methodology

- ADE 8/12 were used to compare the performance of the model with Vanilla ERM and Counterfactual Analysis.
- ETH-UCY dataset was used for invariant bloss while ORCA data was used for style shifts.
- Zero-shot transfer (IID and OOD) and low-shot transfer was used to evaluate the model in presence of style shifts.
- The effects of modular adaptation and test-time refinement was assessed by fine-tuning different style-related parameters.

Results

- With the domain parameter $\alpha \in (8, 64]$, the invariant learning performed better, especially the hyperparameter $\lambda = 10$.
- For IID and OOD, the modular and causal with modular preforms better respectively with respect to ADE 8/12.
- Fine-tuning only the style modulator instead of all style-related parameters yields higher efficiency and refinement leads to further error reduction.

Significance

- Despite the current work emphasizes on causal representations, it also advances to address the spurious non-causal shifts present in the test environment by making the model adaptive through iteratively adjusting the feature $\overline{z}$.
- The model has emphasized on a different architecture instead of using distinct novel models [10] as well as used conventional STGAT model for fair comparison.
- The authors have exhaustively justified their use of particular attributes of their proposed framework by comparing to other related work and literature.
- The experiments were well-structured in the sense that the individual assessment of every group of the framework was evaluated and compared with other models.

[10] M.-Y. Chen, H.-S. Chiang, E. Lughofer, and E. Egrioglu (2020). "Deep learning: Emerging trends, applications and research challenges". In: *Soft Computing* 24, pp. 7835–7838

Limitations

- Final Displacement Error (FDE) which helps in determining endpoint accuracy,task-specific relevance, and decision-making and planning was only computed for the low-shot transfer.
- The non-spurious test-time refinement appears over-promising as it utilizes the style contrastive loss instead of a distinct module within the architecture itself.
- The problem when extended to different forecasting problems may suffer from change in the invariancy (i.e., the basic physical laws or natural instincts).
- Models similar to causal representations like Physics informed Neural Nets (PINNs) have attempted to combine the strengths of deep learning with the physical laws and constraints of a given problem, however, they largely overlook the fine-grained structure of the problem.

Thanks for your attention.
A digital version of this presentation can be found here:

`https://github.com/vyasnatansh/tudelft`

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