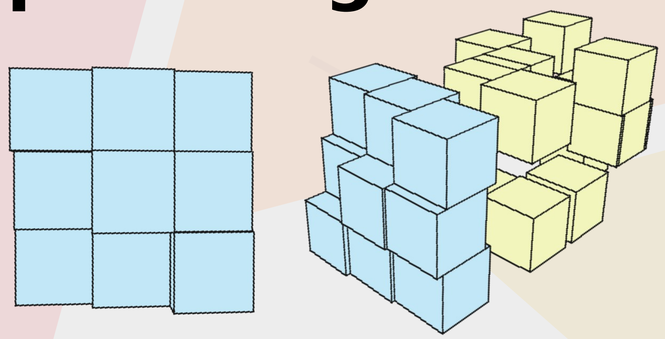
Social Attention Is All We Need

By Ahmad Khalidi

Natural language learned by variational encoder-decoder transformer with viewpoint regularization



for social driven responsible AI

Abstract

- Do data subjects have responsibilities about how their personal data are used in AI?
- Latest research in responsible AI is not asking that question. Primary responsibility lies within experts processing personal data [1].
- This work proposes an approach, where data subjects map their data on latent spaces..
- These latent spaces are regulated from data subjects personal subjective viewpoints (VP).
- The first approach uses variational encoder decoder transformer in a reinforcement setting.
- This study will try to prove that
  - Unregulated VPs are individual, noisy, entangled, and thus difficult to interpret,
  - Increase global and decrease local expense and
  - help developing responsible AI on large scale.

Methods

- Drawing from my personal experience and observations, Natural Language Processing (NLP) allows nuanced information exchange, thus motivating the adaption for this study.
- Transformers have shown great results in NLP and have been successfully trained with (self-) supervised and reinforcement learning [2, 3].
- The encoder and decoder models play the referential game [4] in a multi agent coopetitive Environment on the MARS service[5].
- The encoders learn to specifically address and exclude selected VPs of the decoders.
- Each training phase requires less reliance on the environment and participating agents.

Results

- Passing forward in BERT[6] and producing a covariance matrix is expensive.
- 8800 last hidden state tensors with labels and logits for four VPs (identity, add, mul, distribution) have been collected for offline training.
- Dynamic architectures in final dense layers are necessary to enable expensive policy.

Phase 1 Pre-Training

- Single Multi-Head Encoder-Decoder
- One or more heads represent a VP
- Training datapoints:
  - target VP
  - input params
- Decoder and Headers (VPs) are trained to fit datapoints by disregarding target VP
- Policy is trained to behave like the input and a normal Gaussian distribution.

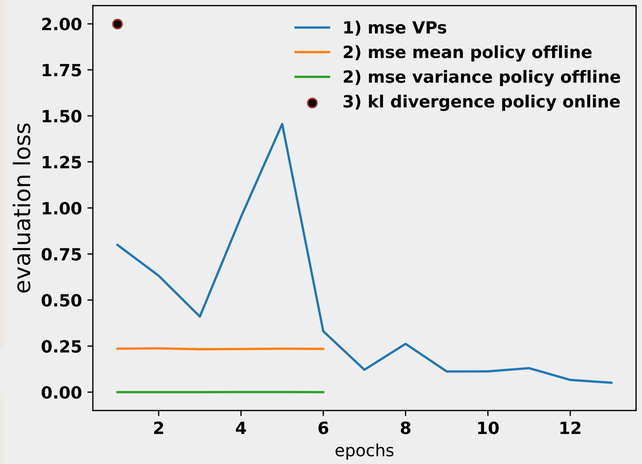
Phase 2 Encoder Policy

- Separate encoder from decoder
- Header for Encoder:
  - (Co-)Variances
  - Mean
- Sample latent space
- Reward of encoder is a weighted sum of the decoders losses
  - If target VP → negative margin loss
  - If not target VP → positive margin loss

Phase 3 Decoder Policy

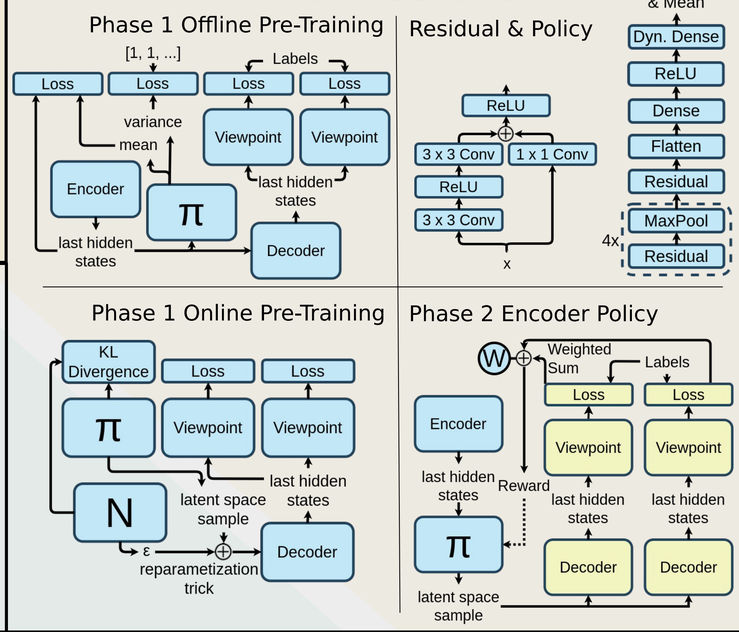
- Similar architecture to Encoder Policy
- Decoders learn what targets and strategy they use to interpret latent space samples

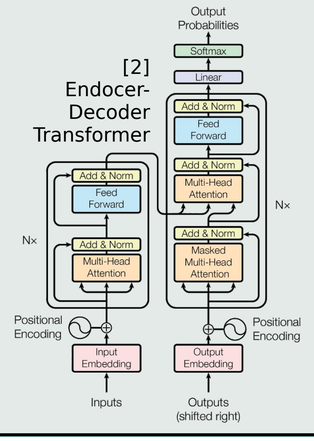
Phase 1 Pre-Training Progress



- VP's mse policy online: 200.0

Architectures





Bibliography

[1] Göllner, Sabrina et al. „Responsible Artificial Intelligence:Structured Literature Review“ (2023)
[2] Vaswani, Ashish et al. “Attention is All you Need“ (2017).
[3] Ziegler, Daniel M. et al.“Fine-Tuning Language Models from Human Preferences.” (2019)
[4] Lewis, David. “Convention: A Philosophical Study.” (1970).
[5] Hüning, Christian et al. „Modeling & Simulation as a Service with the Massive Multi-Agent System MARS“ (2016)
[6] Devlin, Jacob,et al. “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.”(2019)

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Further Research

- Find trade-off between accuracy and efficiency in policy architecture. Potential policy architectures are CNNs with residual blocks and multi head attention layer with down sampling.
- Experiment with phase 2 using PPO and clipped surrogate objective function.
- Research and apply evaluation metrics for the learned privacy enhancing techniques.