Masked Prediction Task a parameter identifiability view

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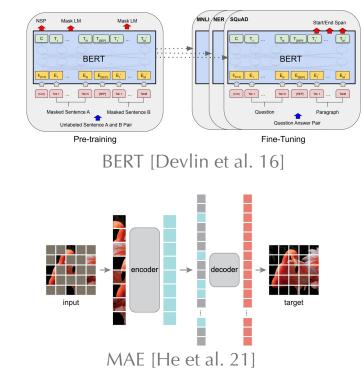




Masked Prediction

Task: train a model by predicting the missing part of the input.

- Empirically successful: good features for downstream tasks.
 - NLP: Word2vec [Milokov et al. 13], BERT [Devlin et al. 16]
 - Vision: Context Encoder [Pathak et al.16], MAE [He et al. 21]
- Theoretically studied [Lee et al. 21, Wei et al. 21]



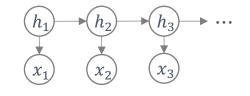
Evaluation metrics

- Downstream performance unclear which downstream tasks to use.
- Parameter identifiability: a natural quality measure; e.g. common in graphical models.

Masked Prediction – parameter identifiability

Setup: sequential data generated by a latent-variable model with known parametric form.

HMM: discrete latents $\{h_t\}$, discrete or continuous observables $\{x_t\}$.



$$P(h_{t+1} = i|h_t = j) = T_{ij},$$
(discrete case)
$$P(h_{t+1} = i|h_t = j) = T_{ij},$$
(parameters)
$$P(x_t = x|h_t = j) \propto \exp\left(-\frac{||x - \mu_i||^2}{2}\right).$$
(continuous case)

Identifiability: *when* can we *read off* the parameters from an optimal predictor with the *correct form*?

Identifiability

Are the HMM parameters identifiable from an optimal predictor?

A masked prediction task is identifiable, if for two HMMs with (0, T) and (\tilde{O}, \tilde{T}) , matching the predictor means $O = \tilde{O}\Pi, T = \Pi^{\top}\tilde{T}\Pi$ for some permutation matrix Π .

e.g. discrete case, pairwise prediction: $\begin{bmatrix} \phi(x) \end{bmatrix}_{j} \text{ (posterior distr on } h \text{ given } x)$ $f^{2|1}(x) = \mathbb{E}[x_{2}|x_{1} = x] = \sum_{i \in [k]} \sum_{j \in [k]} O_{i}T_{ij} \frac{O_{x,j}}{\sum_{l \in [k]} O_{x,l}}$

$$= \sum_{i \in [k]} \sum_{j \in [k]} \tilde{O}_i \tilde{T}_{ij} \quad \frac{\tilde{O}_{x,j}}{\sum_{l \in [k]} \tilde{O}_{x,l}} = \tilde{f}^{2|1}(x)$$

Results overview

Are the HMM parameters identifiable from an optimal predictor – Task & model dependent.

Identifiable: matching the predictor $\rightarrow 0 = \tilde{0}\Pi, T = \Pi^{\top}\tilde{T}\Pi$ for some permutation Π .

	$x_i \mid x_j$	$x_i \otimes x_j x_k$
HMM	×	
(discrete)	rotation problem (matrix)	Tensor
G-HMM	more informative posterior	decomposition
(cond Gaussian)		

Discrete case

transition matrix $T \in \mathbb{R}^{k \times k}$ emission matrix $0 \in \mathbb{R}^{d \times k}$

Pairwise prediction: non-identifiable due to rotation.

(Thm 4) There exist parameters $\tilde{0}, 0$ such that $\tilde{0} \neq 0$ (up to permutation), yet the predictors for $x_2|x_1, x_1|x_2, x_3|x_1, x_1|x_3$ are the same.

Triplet prediction: identifiable due to the uniqueness of tensor decomposition (Kruskal's theorem).

(Thm 5) *O*, *T* are identifiable from the predictor for $x_{t_2} \otimes x_{t_3} | x_{t_1}$, for t_1, t_2, t_3 being any permutation of {1,2,3}.

Continuous case (conditionally Gaussian)

transition matrix $T \in \mathbb{R}^{k \times k}$ means $M \coloneqq [\mu_1, \dots, \mu_k] \in \mathbb{R}^{d \times k}$

Pairwise prediction: identifiable:

(Thm 3) *M*, *T* are identifiable from the predictor for $x_2 \mid x_1$.

Intuition: the nonlinearity gives a more informative posterior ϕ (over *h*, given *x*).

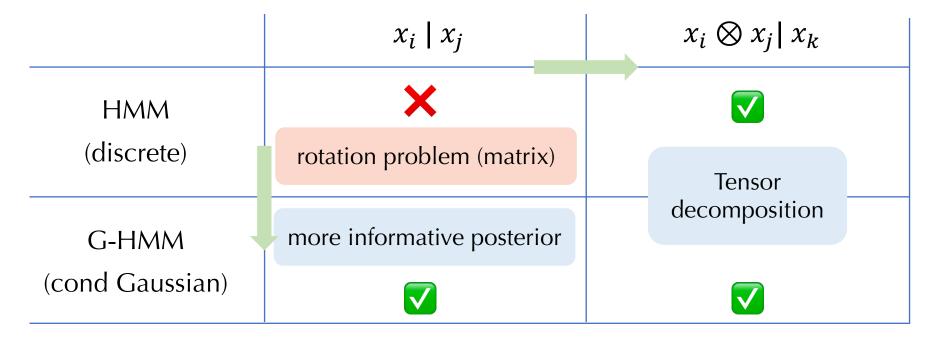
(Lem 1) For 2 parameters M, \widetilde{M} , if $\phi = \widetilde{\phi}$, then

•
$$\widetilde{M} = M \coloneqq [\mu_1, \dots, \mu_k],$$

• or $\widetilde{M} = HM$, where *H* is a Householder transformation.

Contributions

Q: *when* can we *read off* the parameters from an optimal predictor with the *correct form*? A: highly specific to the task & model:



• Open: condition on more tokens? robustness / sample complexity? More general families?