Learning Representations from Imperfect Time Series Data via Tensor Rank Regularization

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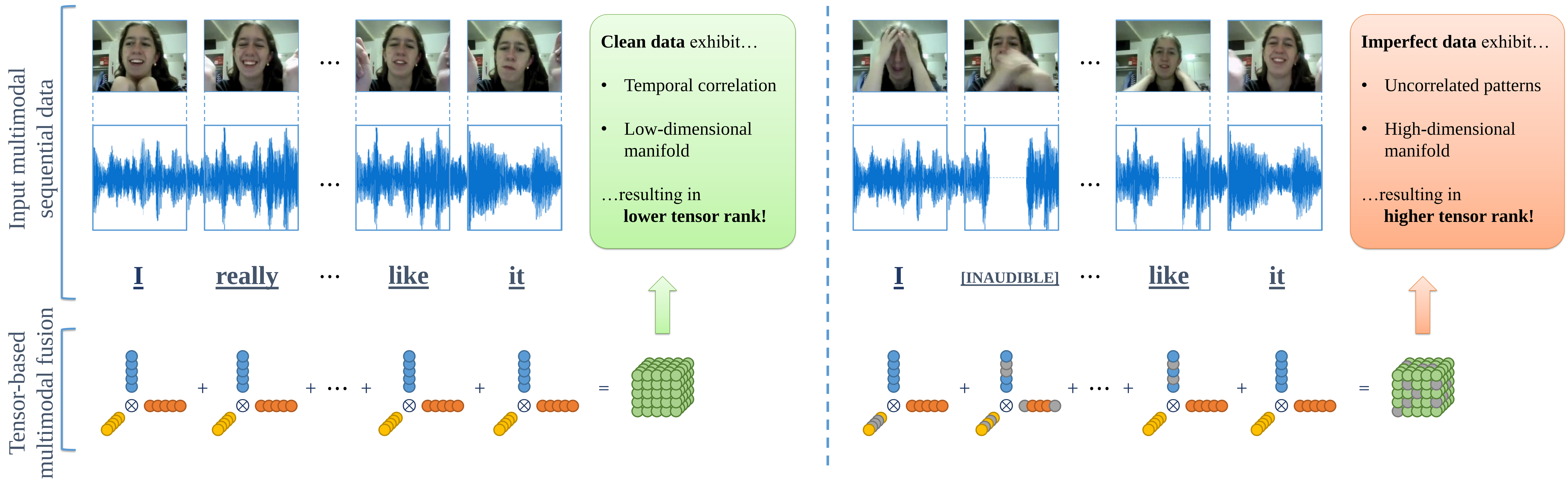
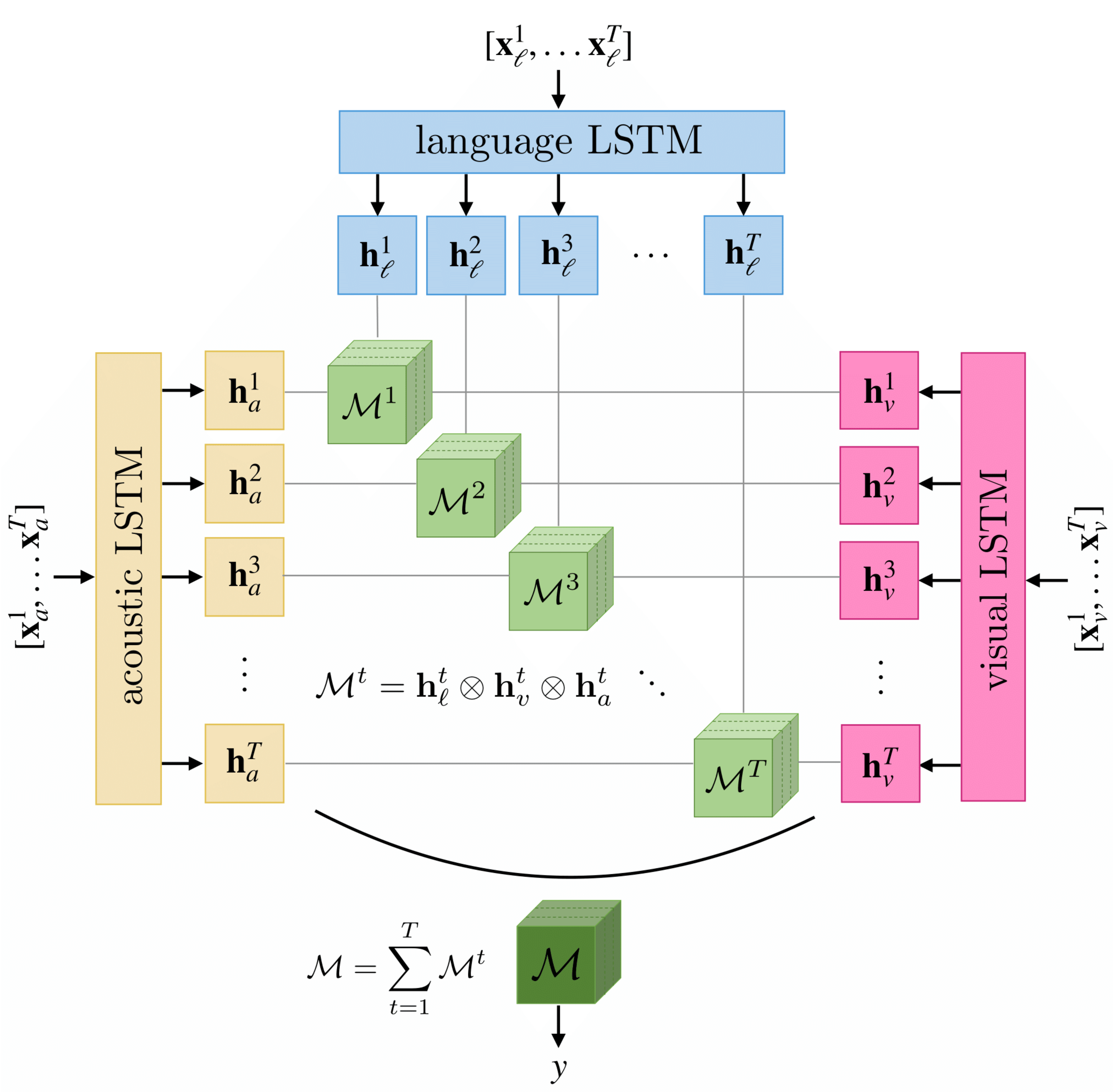
Introduction



Our Proposed Model: Temporal Tensor Fusion Networks (T2FN)



Definition of **tensor rank of** tensor $\mathcal{M} \in \mathbb{R}^{d_1 \times \cdots \times d_M}$:

$$r_{\mathcal{M}} = \inf\{r \mid \exists \mathbf{w}_m^1 \in \mathbb{R}^{d_1}, \cdots, \mathbf{w}_m^r \in \mathbb{R}^{d_M} \ s.t. \ \mathcal{M} = \sum_{i=1}^{r} \bigotimes_{m=1}^{M} \mathbf{w}_m^i\}$$

Problem: Exact calculation of **tensor rank** is **NP-hard**

Solution: Adopt **efficient upper bound** instead:

$$r_{\mathcal{M}} \leq \underbrace{\sqrt{\frac{\prod_{i=1}^{M} d_i}{\max\{d_1, \dots, d_M\}}}}_{\text{Constant for all input}} \underbrace{\|\mathcal{M}\|_F}_{\text{Frobenius norm}}$$

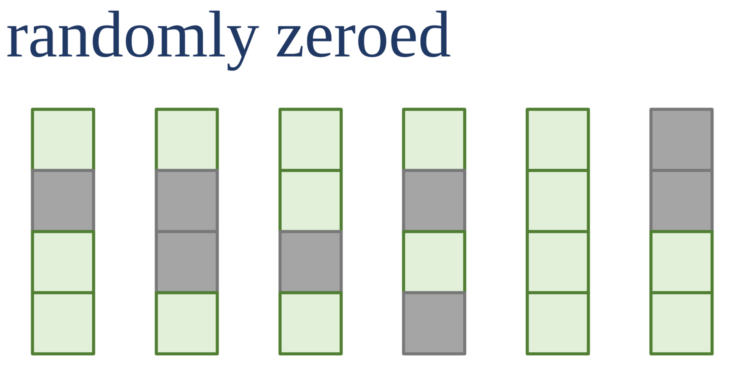
Loss function of T2FN: $\mathcal{L} = \underbrace{\ell(\hat{y}, y)}_{\text{Task loss}} + \lambda \cdot \underbrace{\|\mathcal{M}\|_{\mathcal{F}}}_{\text{Tensor rank regularizer}}$

Experiments and Results

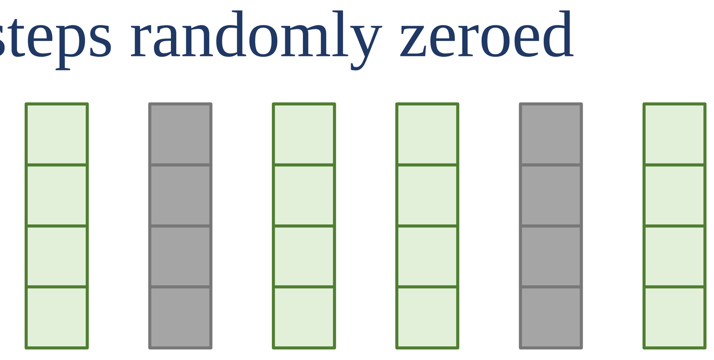
Two imperfect data settings

** original entry*   ** zeroed entry*

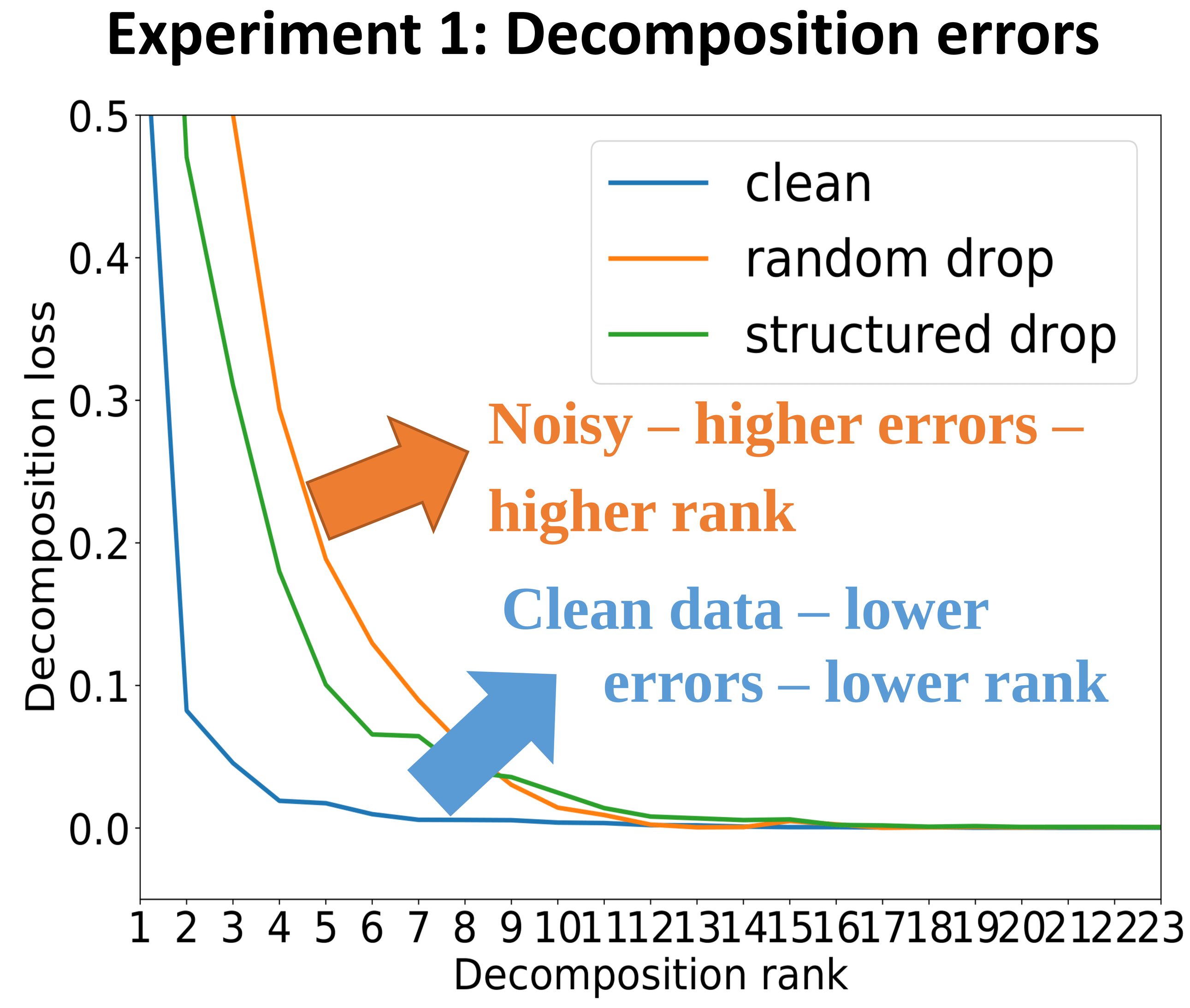
1. ***Random drop***: entries randomly zeroed



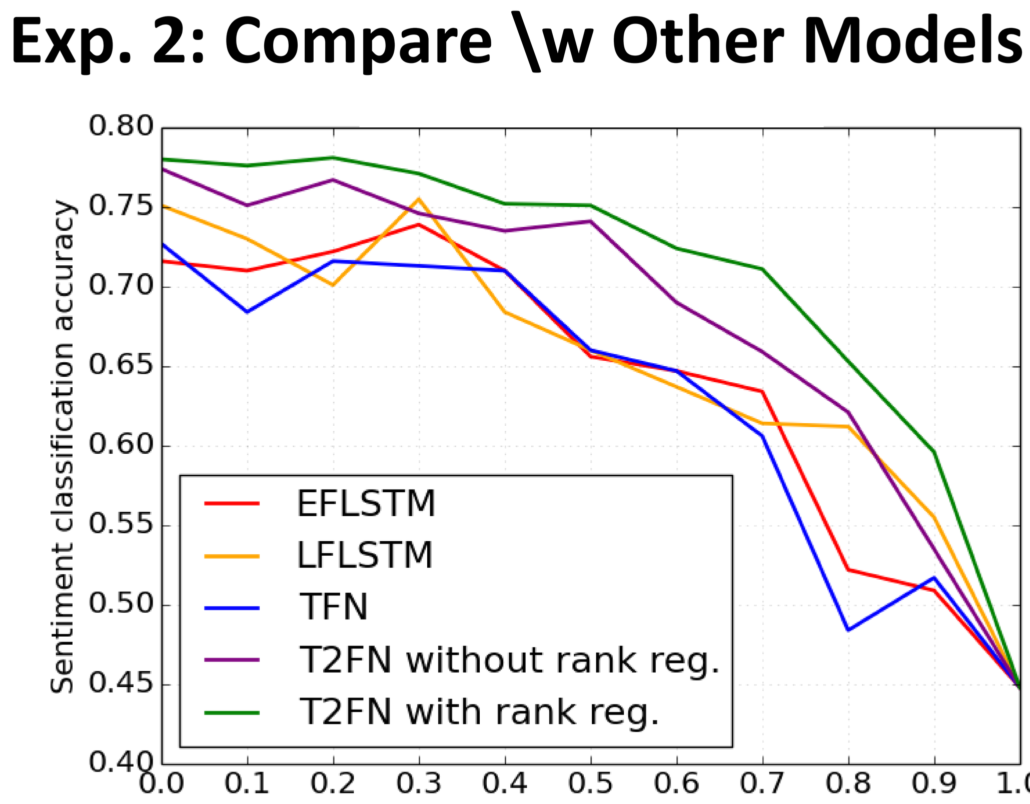
2. ***Structured drop***: time steps randomly zeroed



Experiment 1: Decomposition errors



Exp. 2: Compare \w Other Models



Conclusion: Tensor rank regularization consistently improves performance at various levels of imperfect data.