TPFN: Applying Outer Product along Time to Multimodal Sentiment Analysis Fusion on Incomplete Data


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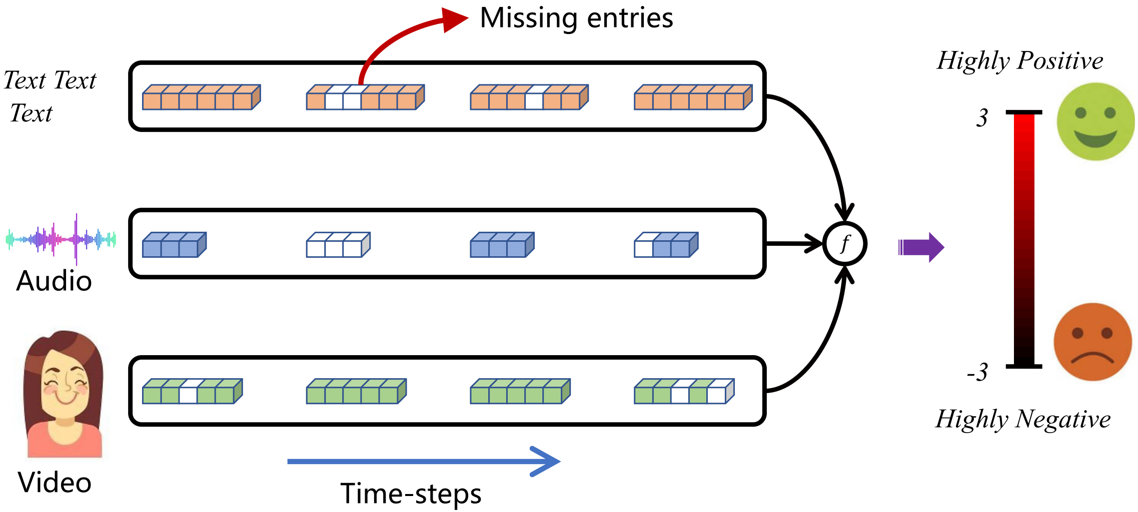
Multimodal Sentiment Analysis with Incomplete Data



Prior Arts

Out-product-based Methods: TFN (A. Zadeh et al, 2017), LMF (Z. Liu et al, 2018), HFFN (S. Mai et al, 2019), HPFN (M. Hou et al, 2019), T2FN (P.P. Liang et al 2019).

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Question

How to accurately give the prediction when the dataset (or features) are incomplete?

Cont'd

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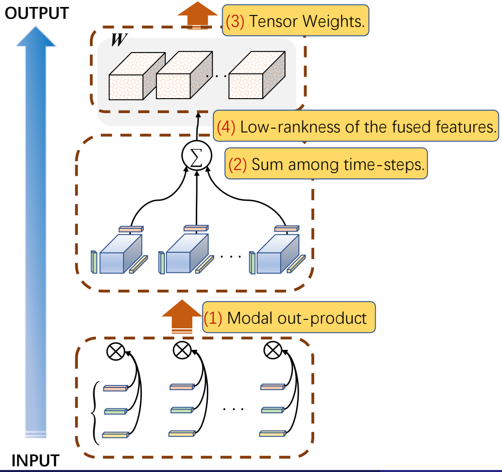

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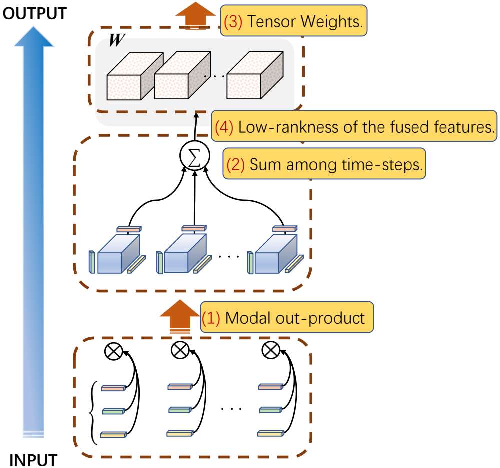

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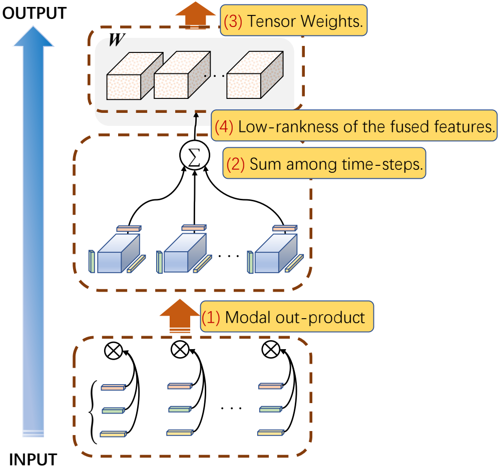

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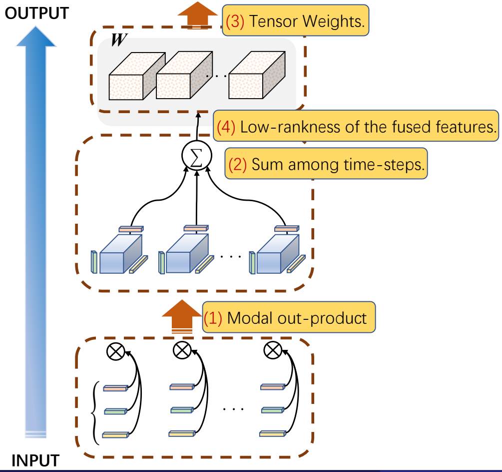

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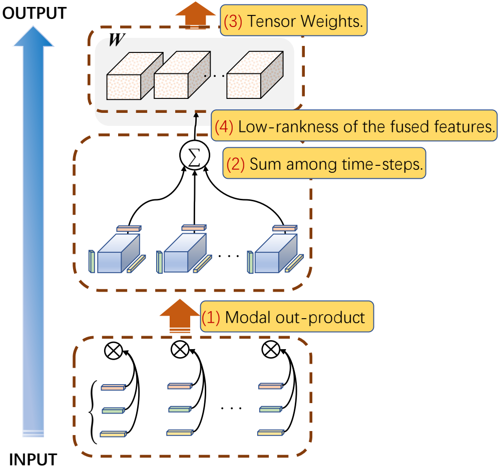

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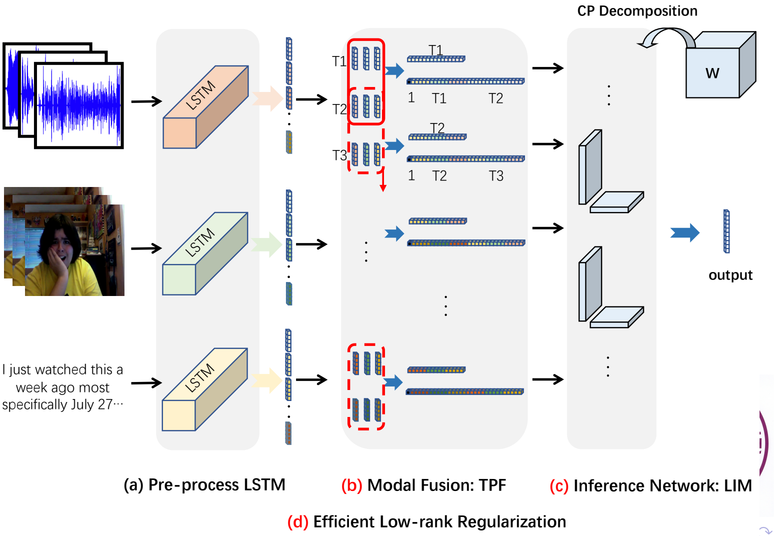
Goal of Our work

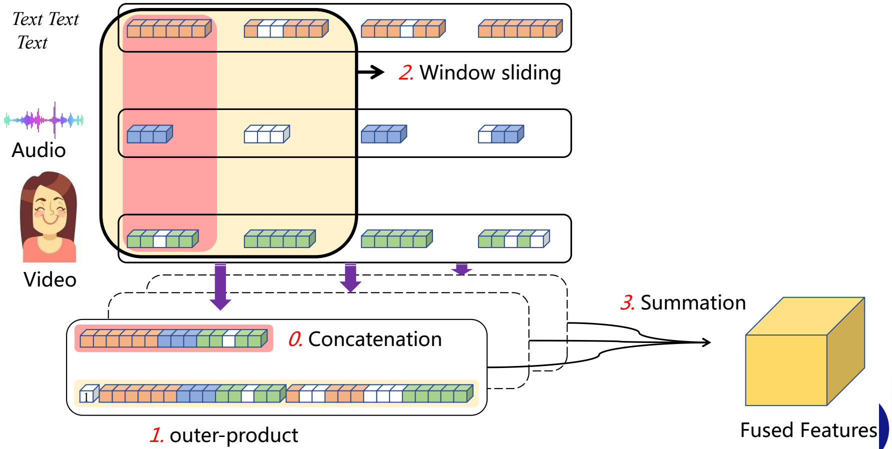
- Implicit out-product.
- Higher-order statistics of temporal dynamic.
- Dimension reduction of the tensor weights.

TPFN consists of:

(a) Pre-process LSTM
(b) Fusion: TPF
(c) Inference: LIM
(d) Low-rank regularization



TPF: Outer Product along Temporal Domain



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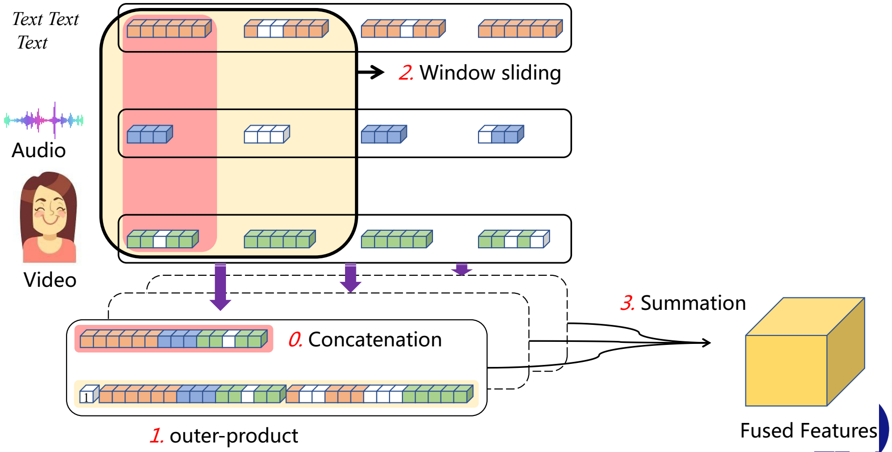
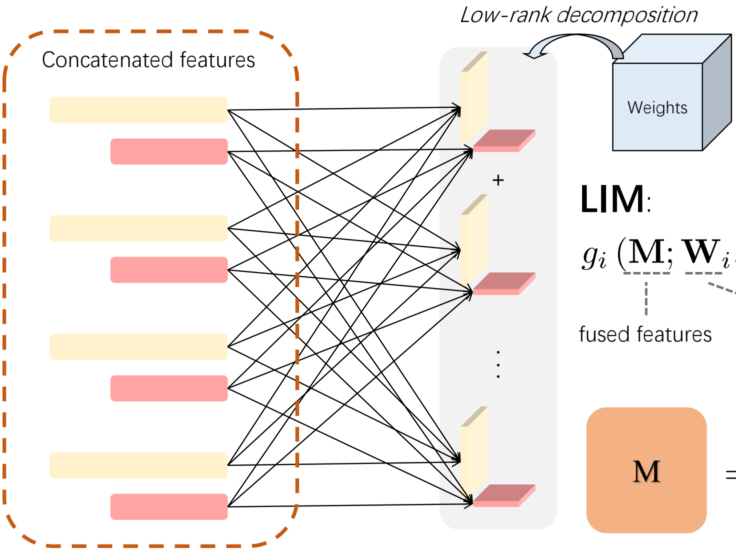


Are the explicit out-products really necessary?

The Answer Is *No.* – Low-rank Inference Module (LIM)



Complexity

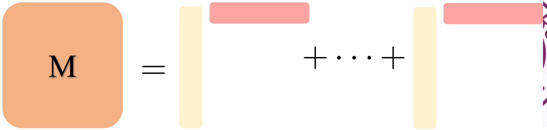
$\mathcal{O}(kNL^2) \rightarrow \mathcal{O}(kRNL)$

where $R \ll L$

Low-rank

LIM:

$$g_i\left(\underbrace{\mathbf{M}}_{\text{fused features}};\underbrace{\mathbf{W}_i}_{\text{weights}}, b_i\right) = \langle \mathbf{W}_i, \mathbf{M} \rangle + b_i$$



Low-rank Regularization before Outer-products

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Our Claim

Briefly speaking, the nuclear norm (i.e., convex surrogate of the rank) of $\mathbf{M}$ is upper-bounded by the Frobenius norm of the concatenated features from all modalities and time-steps.

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REMARK

The regularization term is applied before the outer-product. The explicit out-products is avoided in our model.

Experiments: Datasets and Settings

Datasets: **MOSI** (A. Zadeh et al, 2016) and **MOSEI** (A. Zadeh et al, 2018).

	Number of Samples			Size of Features		
	Train	**Val**	**Test**	**Acoustic**	**Visual**	**Language**
MOSEI	15,290	2,291	4,832	74	35	300
MOSI	1,284	229	686	5	20	300

Missing Pattern

- **Random Drop** (RD)
- **Structured Drop** (SR): Randomly drop the whole modalities from each time-step.

Performance (ACC-2) on CMU-MOSI

TFPN/reg: TPFN without low-rank regularization.

Task	Method	Low	Medium	High	Params
RD	TFN	0.7361	0.7172	0.4475	759,424
	LMF	0.7346	0.7317	0.5218	**2,288**
	HPFN	0.7565	0.6982	0.5568	4,622,039
	T2FN	0.7769	0.7113	0.5962	19,737
	TPFN/reg(ours)	0.7638	0.7594	0.5845	8,652
	TPFN(ours)	**0.7915**	**0.7609**	**0.6559**	19,488
SD	TFN	0.7317	0.6880	0.5758	390,784
	LMF	0.7346	0.7128	0.5976	**792**
	HPFN	0.7463	0.7186	0.6151	1,168,247
	T2FN	0.7478	0.7142	0.6137	19,737
	TPFN/reg(ours)	**0.7682**	0.7288	0.6151	11,360
	TPFN(ours)	0.7594	**0.7434**	**0.6516**	7,344

Performance (ACC-2) on CMU-MOSEI

TFPN/reg: TPFN without low-rank regularization.

Task	Method	Low	Medium	High	Params
RD	TFN	0.7195	0.7193	0.6705	1,353,856
	LMF	0.7307	0.7233	0.6684	**1,208**
	HPFN	0.7371	0.7189	0.7119	1,295,895
	T2FN	0.7394	**0.7382**	0.7104	18,785
	TPFN/reg(ours)	0.7375	0.7297	0.7156	14,240
	TPFN(ours)	**0.7411**	0.7367	**0.7334**	16,842
SD	TFN	0.7295	0.7121	0.6968	759,424
	LMF	0.7313	0.7067	0.7057	**1,304**
	HPFN	0.7311	0.7245	0.7003	1,296,423
	T2FN	0.7350	0.7295	0.7173	9,945
	TPFN/reg(ours)	**0.7437**	0.7301	0.7007	7,056
	TPFN(ours)	0.7386	**0.7382**	**0.7301**	5,796

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- The outer-product is important to obtain rich interaction among modalities.

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- The outer-product is important to obtain rich interaction among modalities.
- The benefit by outer-products is also given through time-steps.
- Low-rank tensor decomposition is a promising tool to tackle the dimension exploration issue by outer-products.
- The low-rank regularization on the fused features works well to cope with the incompleteness issue.

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