3Mformer: Multi-order Multi-mode Transformer for Skeletal Action Recognition

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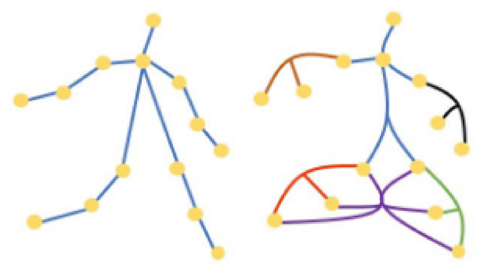
Motivation

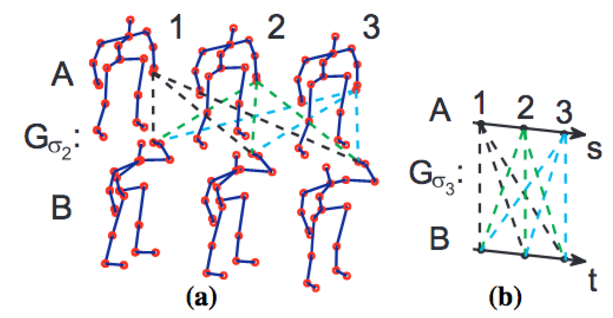


Existing GCN-based action recognition models:

- represent human body joints based on physical connectivity
- limited receptive fields & one-/few-hop neighbourhood aggregation
- ignore dependency between body joints non-connected by body parts

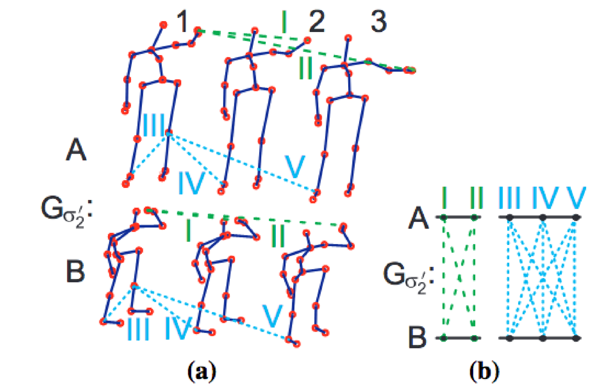
Human actions are associated with interaction groups of skeletal joints:

- the impact of groups of joints on each action differs
- the degree of influence of each joint should be learned
- design a better model for skeleton data (topology of skeleton graph)



Inspired by our tensor representations[1]:

- *sequence compatibility kernel* (SCK) & *dynamics compatibility kernel* (DCK)
- incorporate multi-modal inputs & compactly capture complex interplay
- operate on subsequences / capture local-global interplay of correlations



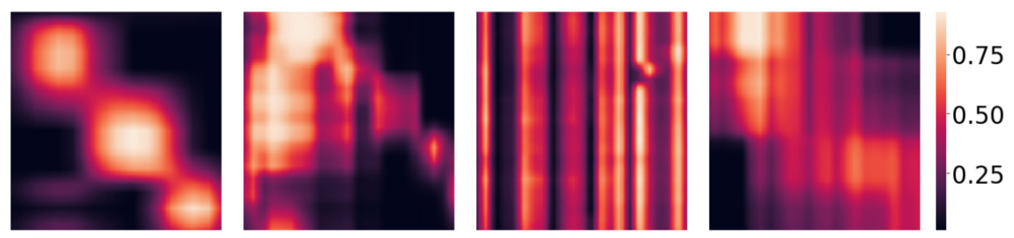
[1]Koniusz, P., Wang, L., Cherian, A. (2021). **Tensor representations for action recognition**. *IEEE TPAMI*, 44(2), 648-665.

Key ideas

We use hypergraph higher-order relations of hyper-edges. We use hypergraph transformer[2] output $\mathcal{M} \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_r}$, and apply mode-$m$ matricization $\mathbf{M} \equiv \mathcal{M}_{(m)}^{\top} \in \mathbb{R}^{(I_1 \ldots I_{m-1} I_{m+1} \ldots I_r) \times I_m}$ to form coupled-token: 'channel-temporal block', 'channel-body joint', 'channel-hyper-edge (any order)', and 'channel-only' pairs.

Coupled-mode Self-Attention (CmSA):

- shows diagonal & vertical patterns
- patterns are consistent with the patterns of attention matrices found in standard Transformer, *e.g.*, NLP

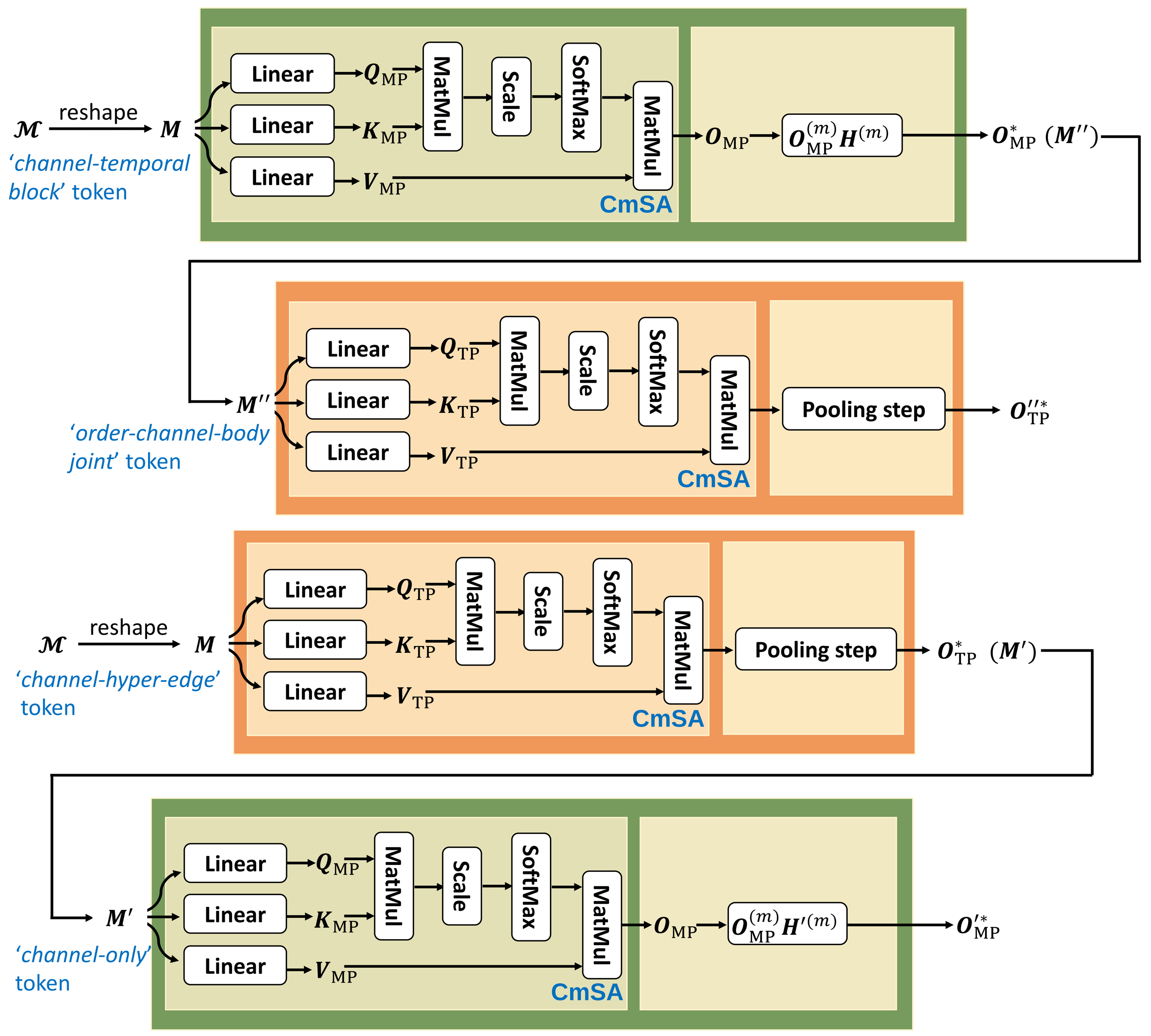


We propose a **Multi-order Multi-mode Transformer (3Mformer)**, which uses coupled-mode tokens to jointly learn various higher-order motion dynamics.

We have building modules:

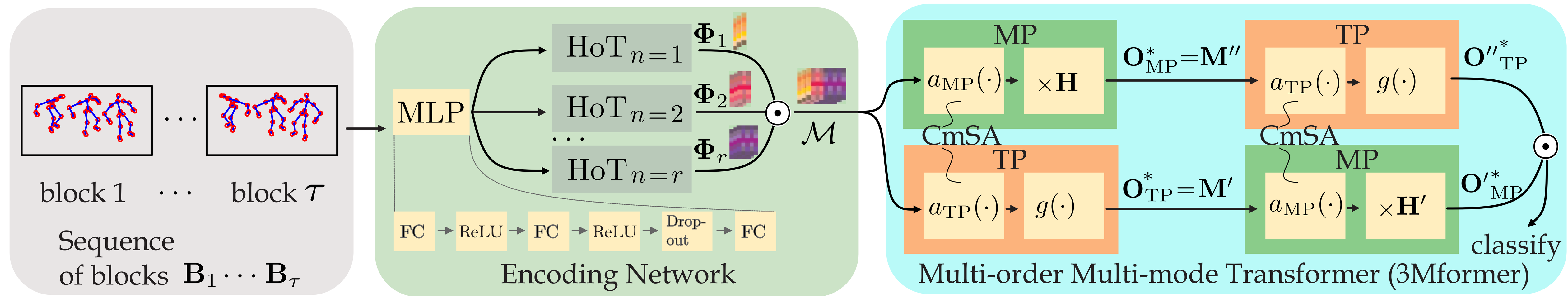
- Multi-order Pooling (MP):
  - combine information flow **block-wise**
  - **coupled-mode** tokens help improve results
  - **different focus** of each attention mechanism
- Temporal block Pooling (TP):
  - each sequence may contain a different number of blocks
  - aggregation via popular pooling: rank-, first-, second- or higher-order pooling

We form **multi-head** CmSA.



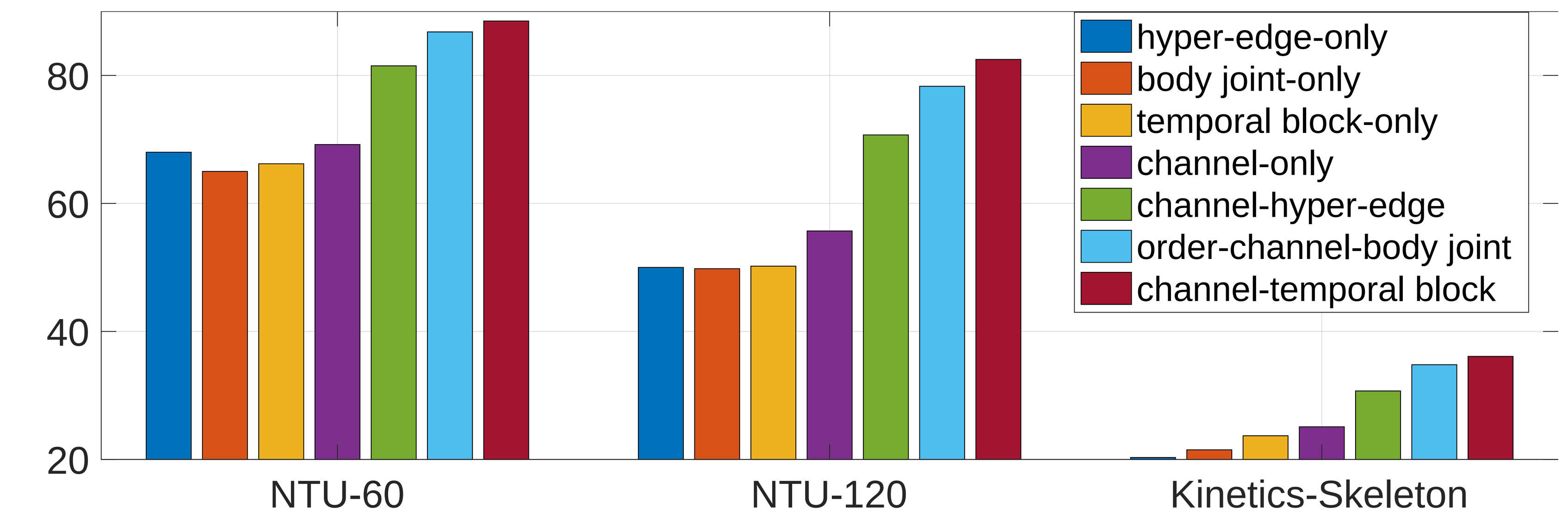
[2] Jinwoo Kim *et al.*, A. (2021). **Transformers generalize deepsets and can be extended to graphs & hypergraphs**. *NeurIPS*, 21.

The pipeline



- Each sequence is split into τ temporal blocks $\mathbf{B}_1, \ldots, \mathbf{B}_\tau$
- Each block is embedded by a simple MLP into $\mathbf{X}_1, \ldots, \mathbf{X}_\tau$
- $\mathbf{X}_1, \ldots, \mathbf{X}_\tau$ are passed to HoTs ($n = 1, \ldots, r$) for feature tensors $\mathbf{\Phi}_1, \ldots, \mathbf{\Phi}_\tau$
- Subsequently concatenated by $\odot$ along the hyper-edge mode into tensor $\mathbf{M}$
- **3Mformer contains two complementary branches**: MP→TP & TP→MP
- Outputs are concatenated by $\odot$ and passed to the classifier
- MP & TP perform attention with the so-called **coupled-mode tokens**
- MP contains **weighted pooling along hyper-edge mode** by learnable matrix $\mathbf{H}$ (& $\mathbf{H}'$ in another branch).
- TP contains **block-temporal pooling** denoted by $g(\cdot)$ to capture block-temporal order with pooling

Results



	Method	Venue	NTU-60 X-Sub	NTU-60 X-View	NTU-120 X-Sub	NTU-120 X-Set	Kinetics-Skeleton Top-1	Kinetics-Skeleton Top-5
Graph-based	ST-GCN	AAAI'18	81.5	88.3	70.7	73.2	30.7	52.8
	AS-GCN	CVPR'19	86.8	94.2	78.3	79.8	34.8	56.5
	2S-AGCN	CVPR'19	88.5	95.1	82.5	84.2	36.1	58.7
	NAS-GCN	AAAI'20	89.4	95.7	-	-	37.1	60.1
	Sym-GNN	TPAMI'22	90.1	96.4	-	-	37.2	58.1
	Shift-GCN	CVPR'20	90.7	96.5	85.9	87.6	-	-
	MS-G3D	CVPR'20	91.5	96.2	86.9	88.4	38.0	60.9
	CTR-GCN	ICCV'21	92.4	96.8	88.9	90.6	-	-
	InfoGCN	CVPR'22	93.0	97.1	89.8	91.2	-	-
	PoseConv3D	CVPR'22	94.1	97.1	86.9	90.3	**47.7**	-
Hypergraph-based	Hyper-GNN	TIP'21	89.5	95.7	-	-	37.1	60.0
	SD-HGCN	ICONIP'21	90.9	96.7	87.0	88.2	37.4	60.5
Transformer-based	ST-TR	CVIU'21	90.3	96.3	85.1	87.1	38.0	60.5
	STST	ACM MM'21	91.9	96.8	-	-	38.3	61.2
	3Mformer (with max-pool, *ours*)		92.1	97.8	-	-	-	-
	3Mformer (with attn-pool, *ours*)		**94.2**	**98.5**	89.7	92.4	45.7	67.6
	3Mformer (with tri-pool, *ours*)		94.0	**98.5**	**91.2**	**92.7**	**47.7**	**71.9**
	3Mformer (with rank-pool, *ours*)		**94.8**	**98.7**	**92.0**	**93.8**	**48.3**	**72.3**