Tensor-Based Multi-Modality Multi-Target Regression for Alzheimer's Disease Diagnosis

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Outline

- Background
- Proposed Method
- Results
- Q&A Session

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Background

- Alzheimer’s disease is concerned.
- Multi-modality data is available.
- Multi-target regression (MTR) is effective.

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Tensor-Based Multi-Modality MTR

- Regression models:

$$y_{i,k} = \langle \mathcal{W}^k, \mathcal{X} \rangle + \varepsilon_{i,k}, i = 1, \cdots, N, k = 1, \cdots, K$$

- Objective functions:

$$\min_{\mathcal{W}_r} \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} \left(\langle \mathcal{X}_i \otimes \mathbf{e}_k, \sum_{r=1}^{R} \mathcal{W}_r \rangle - y_{i,k} \right)^2 + \sum_{r=1}^{R} \lambda_r \|\mathcal{W}_r\|_1$$

$$\text{s.t.} \quad \text{CP-rank}(\mathcal{W}_r) \leq 1.$$

Where $\mathcal{W}_r = \mathbf{w}_r^{(1)} \otimes \cdots \otimes \mathbf{w}_r^{(M+1)}$ is a unit-rank defined based on CP decomposition.

Stage-Wise Learning Procedure

- Fast stagewise unit-rank tensor factorization (SURF) algorithm.
  - Rank-one pursuit

$$\min_{\mathcal{W}_r} \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} (\langle \mathcal{X}_i \otimes \mathbf{e}_k, \mathcal{W}_r \rangle - y_i^r)^2 + \lambda_r \|\mathcal{W}_r\|_1,$$
$$\text{s.t.} \quad \text{CP-rank}(\mathcal{W}_r) \leq 1.$$

  - Response residue

$$y_i^r := \begin{cases} y_i, & \text{if } r = 1 \\ y_i^{r-1} - \sum_{k=1}^{K} \langle \mathcal{X}_i \otimes \mathbf{e}_k, \mathcal{W}_{r-1} \rangle, & \text{otherwise,} \end{cases}$$

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Compared with Single Target Regression Methods

Feature Tensor	Assesment	Metrics	TMSTR	TMMTR
116×3	ADS	RMSE↓	0.316 ± 0.016	$\mathbf{0.307 \pm 0.009}$
		Sparsity↑	0.963 ± 0.007	$\mathbf{0.966 \pm 0.005}$
	ADAS-Cog 13	RMSE↓	0.165 ± 0.032	$\mathbf{0.145 \pm 0.019}$
		Sparsity↑	0.983 ± 0.005	$\mathbf{0.986 \pm 0.004}$
	MMSE	RMSE↓	0.216 ± 0.019	$\mathbf{0.142 \pm 0.011}$
		Sparsity↑	0.964 ± 0.003	$\mathbf{0.969 \pm 0.002}$
116×116	ADS	RMSE↓	$\mathbf{0.314 \pm 0.020}$	0.328 ± 0.010
		Sparsity↑	0.997 ± 0.001	$\mathbf{0.998 \pm 0.000}$
	ADAS-Cog 13	RMSE↓	0.160 ± 0.012	$\mathbf{0.148 \pm 0.031}$
		Sparsity↑	$\mathbf{0.999 \pm 0.000}$	$\mathbf{0.999 \pm 0.000}$
	MMSE	RMSE↓	0.194 ± 0.021	$\mathbf{0.153 \pm 0.016}$
		Sparsity↑	0.997 ± 0.001	$\mathbf{0.997 \pm 0.000}$
$116 \times 116 \times 3$	ADS	RMSE↓	0.281 ± 0.011	$\mathbf{0.273 \pm 0.010}$
		Sparsity↑	0.999 ± 0.001	$\mathbf{1.000 \pm 0.000}$
	ADAS-Cog 13	RMSE↓	0.143 ± 0.013	$\mathbf{0.141 \pm 0.013}$
		Sparsity↑	0.999 ± 0.001	$\mathbf{1.000 \pm 0.000}$
	MMSE	RMSE↓	0.184 ± 0.015	$\mathbf{0.146 \pm 0.011}$
		Sparsity↑	0.999 ± 0.000	$\mathbf{1.000 \pm 0.000}$

Q&A

- Thank You!

References

[1] Lifang He, Kun Chen, Wanwan Xu, Jiayu Zhou, and Fei Wang. “Boosted sparse and low-rank tensor regression." *Advances in Neural Information Processing Systems* 31 (2018).

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