REPRODUCIBILITY IN JOINT BLIND SOURCE SEPARATION: APPLICATION TO FMRI ANALYSIS

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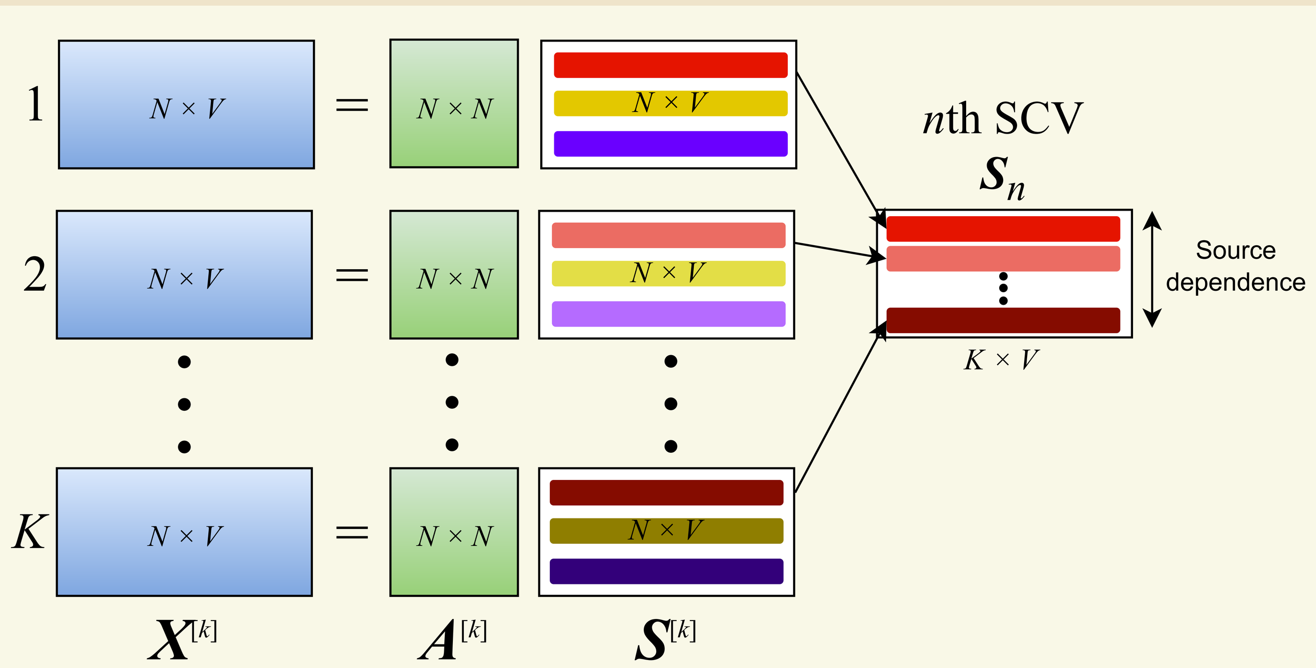
Introduction

- Blind source separation (BSS) techniques have been successfully applied to a wide array of domains including fMRI data analysis
- Joint BSS (JBSS) techniques are implemented to leverage the joint information across multiple datasets
- JBSS results present high variability:
  - Cost functions of most JBSS algorithms are non-convex
  - Closed-form solutions do not exist for these problems – iterative solutions
  - No unique and perfect initialization – random initialization
- Reproducibility assessment of JBSS has been limited in the literature
- Highly consistent results do not guarantee a low bias in the estimates

Contributions

- Evaluate the computational reproducibility of a JBSS algorithm: **constrained independent vector analysis (cIVA)**
- Propose a normalized measure related to the cost function to evaluate cIVA performance in practical scenarios
- Present a new mechanism for selecting the model complexity based on reproducibility and accuracy metrics
- Show that the model orders that balance accuracy and reproducibility metrics provide the most meaningful and interpretable results from analyzing real fMRI data

Independent Vector Analysis (IVA)



- IVA cost function

$$\mathcal{J}_{\text{IVA}}(\mathcal{W}) = \sum_{n=1}^{N}\left(\sum_{k=1}^{K}\mathcal{H}(y_n^{[k]}) - \mathcal{I}(y_n)\right) - \sum_{k=1}^{K}\log|\det(W^{[k]})|$$

where $\mathcal{W} = \{W^{[1]}, \ldots, W^{[K]}\}$ are the demixing matrices of the K datasets, y_n is the nth estimated SCV, $\mathcal{I}(y_n)$ is the mutual information of y_n and $\mathcal{H}(y_n^{[k]})$ is the entropy of the nth estimated source for the kth dataset

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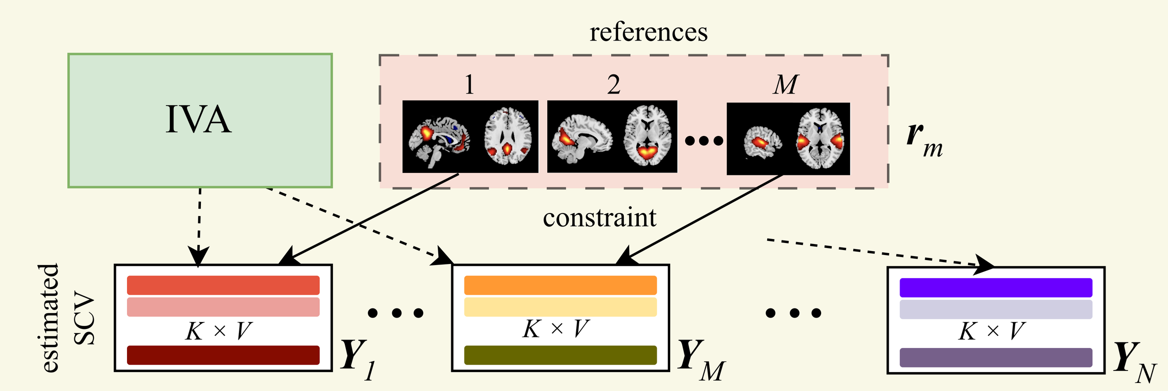
Constrained IVA



- The augmented cost function

$$\mathcal{L}_\lambda(\mathcal{W}) = \mathcal{J}_{\text{IVA}}(\mathcal{W}) + \frac{\lambda}{2}\sum_{m=1}^{M}\sum_{k=1}^{K}\left(\sum_{\substack{n=1\\n\neq m}}^{M}\epsilon^2(r_m, y_n^{[k]}) - \epsilon^2(r_m, y_m^{[k]})\right)$$

Reproducibility and Accuracy Metrics

- In real applications the ground truth is unknown
- **Reproducibilty: cross-joint-ISI**
  - Let $G^{[k]} = A^{[k]}W^{[k]}$ and $G = 1/K\sum_{k=1}^{K}|G^{[k]}|$ then

$$\text{ISI}(G) = \frac{\sum_{i=1}^{N}\left(\frac{\sum_{j=1}^{N}|G_{ij}|}{\max_p|G_{ip}|} - 1\right) + \sum_{j=1}^{N}\left(\frac{\sum_{i=1}^{N}|G_{ij}|}{\max_p|G_{pj}|} - 1\right)}{2N(N-1)}$$

  - Let $W_r^{[k]}$ be the kth demixing matrix of the rth run and $P_{ij} = 1/K\sum_{k=1}^{K}|(W_i^{[k]})^{-1}W_j^{[k]}|$ then

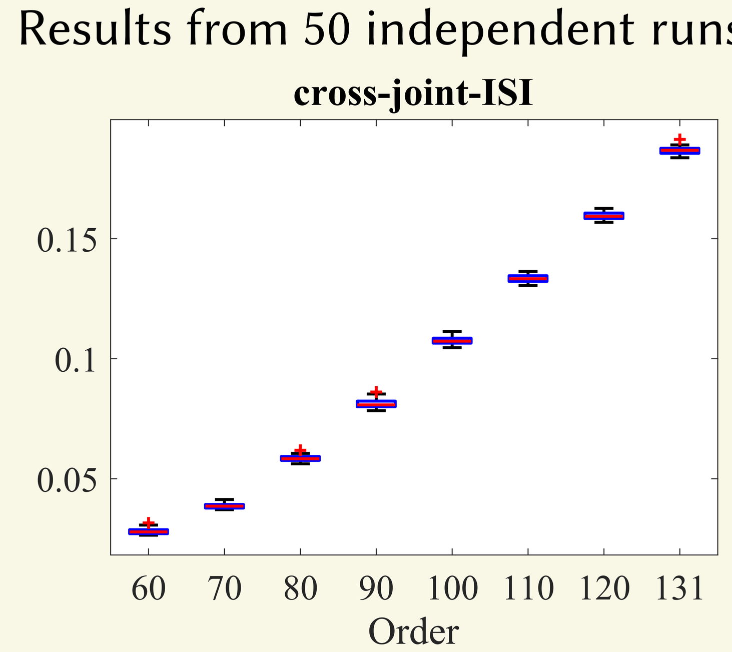
$$\text{cross-joint-ISI}_i = \frac{1}{R}\sum_{j=1, j\neq i}^{R}\text{ISI}(P_{ij})$$

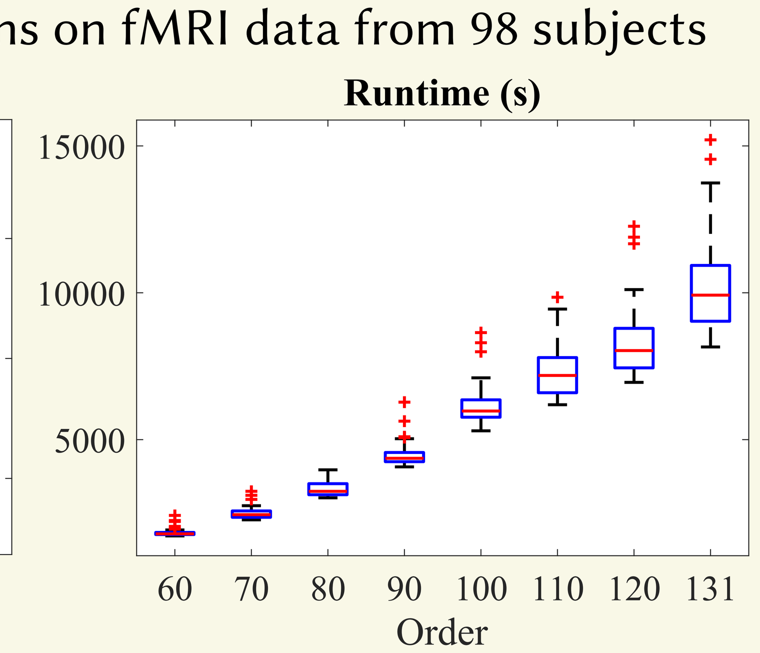
- **Accuracy: Pairwise normalized mutual information**
  - Let $I(y_i^{[k]}, y_j^{[k]})$ be the mutual information between two estimated components

$$\text{N-MI}_r = \frac{2}{KN(N-1)}\sum_{k=1}^{K}\sum_{i=1, i\neq j}^{N}\sum_{j>i}^{N}\frac{2I(y_i^{[k]}, y_j^{[k]})}{I(y_i^{[k]}, y_i^{[k]}) + I(y_j^{[k]}, y_j^{[k]})}$$

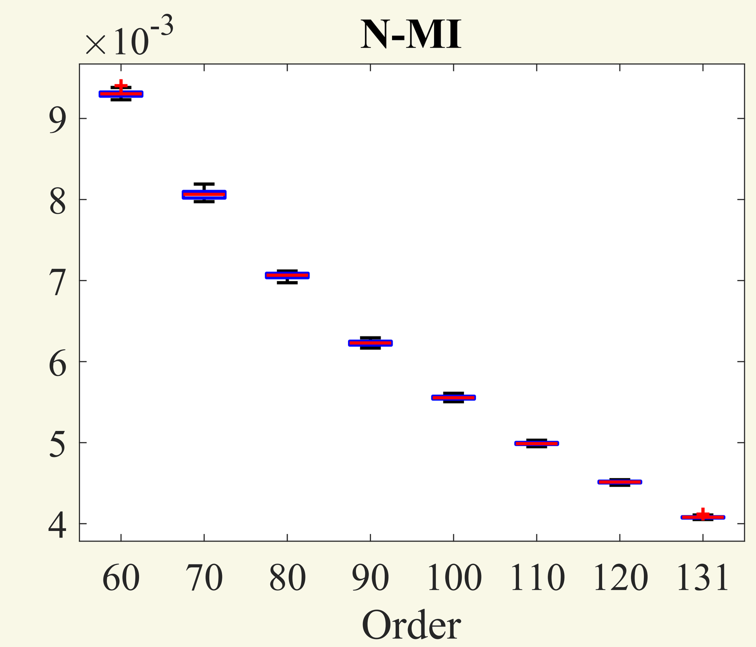
Experimental Results

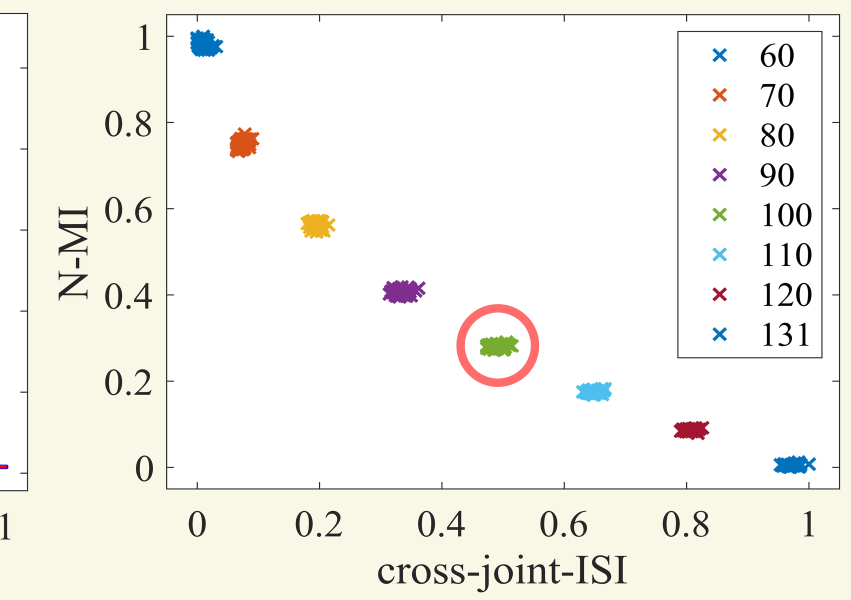
- Results from 50 independent runs on fMRI data from 98 subjects





Experimental Results (continued)

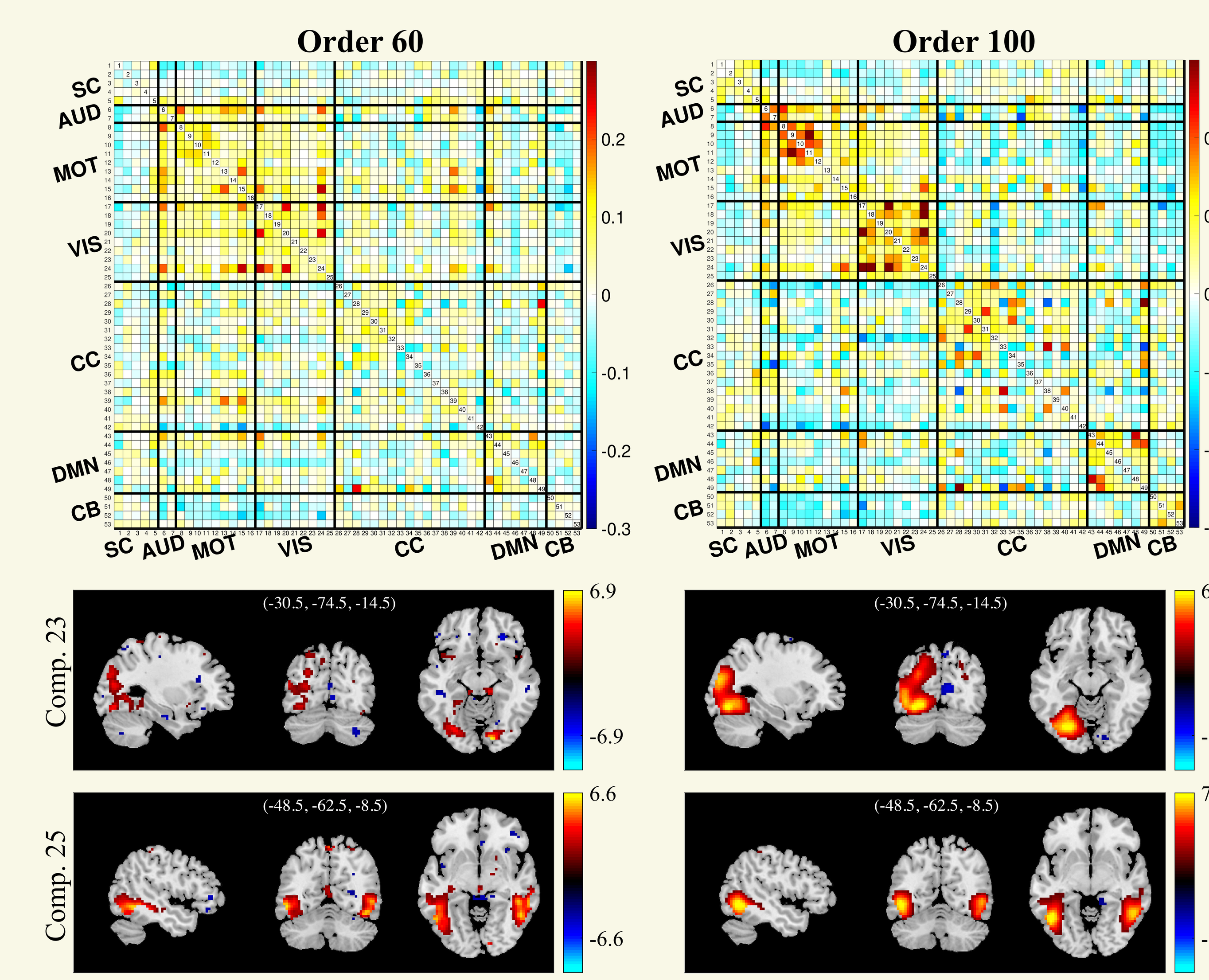




- Cross-joint-ISI increases with the model order while N-MI decreases – Bias and Variance dilemma
- Model orders balancing cross-joint-ISI and N-MI show clearer spatial maps, higher temporal correlations within functional domains, and higher power ratios

	60	80	90	100	120
Power Ratio	3.74±2	3.89±2.35	3.92±2.54	4±2.82	3.97±2.83

Table: Power ratio values for different model orders



Summary

- Model order selection should be guided by both reproducibility and accuracy metrics
- Model orders that balance the bias-variance tradeoff provide a better model match and more interpretable and meaningful results in fMRI data