Efficient Large-scale Independent Vector Analysis using Self-Referenced IVA (SRIVA)

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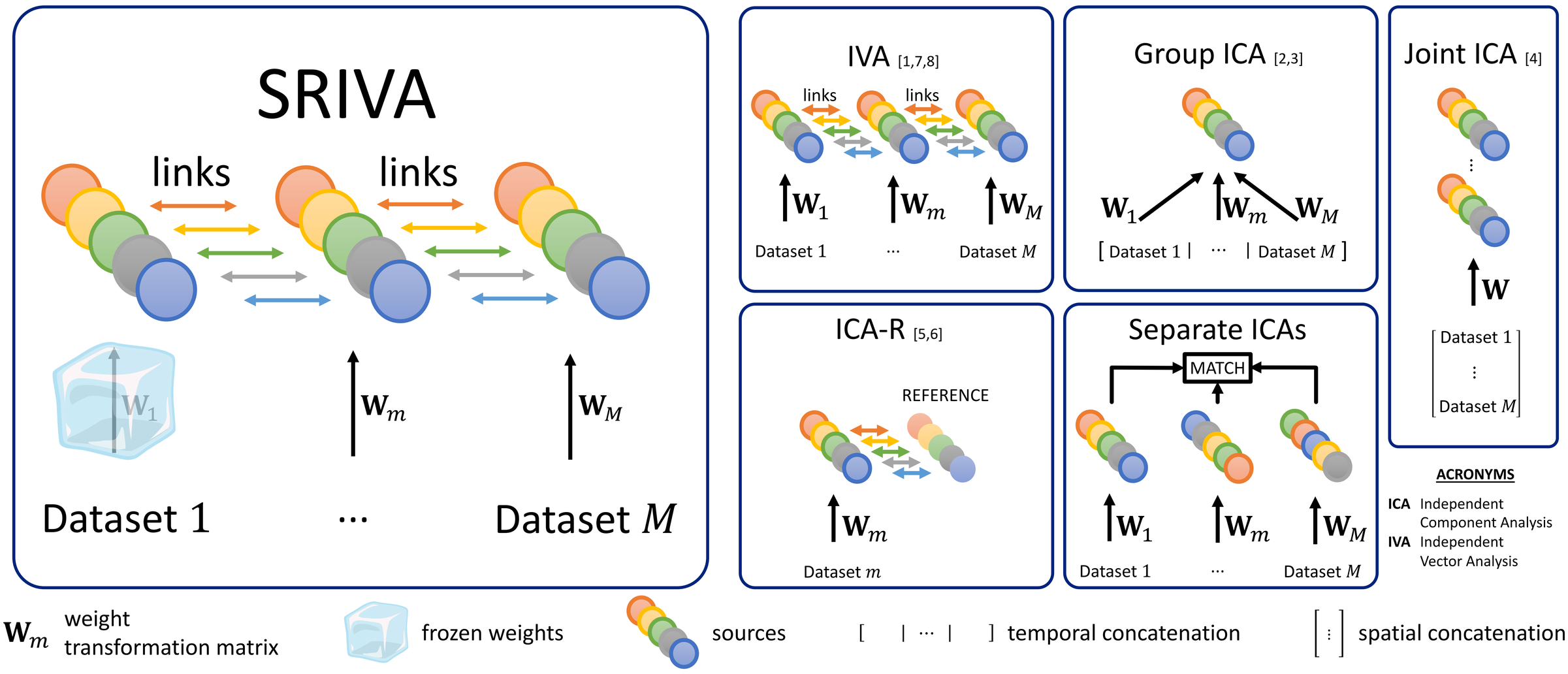
Latent Linkage Detection Strategies



Self-Referenced IVA (SRIVA)

Goals

- *capture dataset-specific variability*
- *no sharing* source/loading sets, and *no reference*
- *highly efficient large-scale IVA*

Strategy

- weight freezing sources act as a reference and still contribute to estimation in other datasets
- frozen results from subset guides and aligns remaining sets

Steps

1. IVA on subset of the datasets and freeze final weights
2. add new subset and use SRIVA

Benefits

- ✓ efficiency: smaller model and parallelizable
- ✓ multiple datasets as simultaneous references (pooling)
- ✓ no additional modeling, regularization, cost optimization, or parameter tuning
- ✓ no external references are necessary, but could be included too
- ✓ IVA-Kotz model from MISA Toolbox efficiently utilizes all-order statistics

	IVA	ICA-R	Separate ICAs	Joint ICA	Group ICA
Principle	process datasets ***together*** to find their underlying similarity *structure*	processes datasets ***separately*** while pushing for similarity with external reference	process datasets ***separately*** match post-hoc	sharing ***same*** **W**	sharing ***same*** sources
Limitation	not scalable (high-dimensional distributions)	prone to overfit depends highly on reference quality	not scalable (matching) noisy estimates	subjects ***must*** have similar temporal basis	multiple subjects treated as one single individual

Experiments

Setup

- M = 16 datasets
- C = 50 sources per dataset
- 1:1 SNR
- Square mixing A, cond(A) = 5
- References from GICA

Dependence (same cross-correlations)

SOS only:

- Gaussian dependence with Laplace marginals
- N = 10000 observations

AOS:

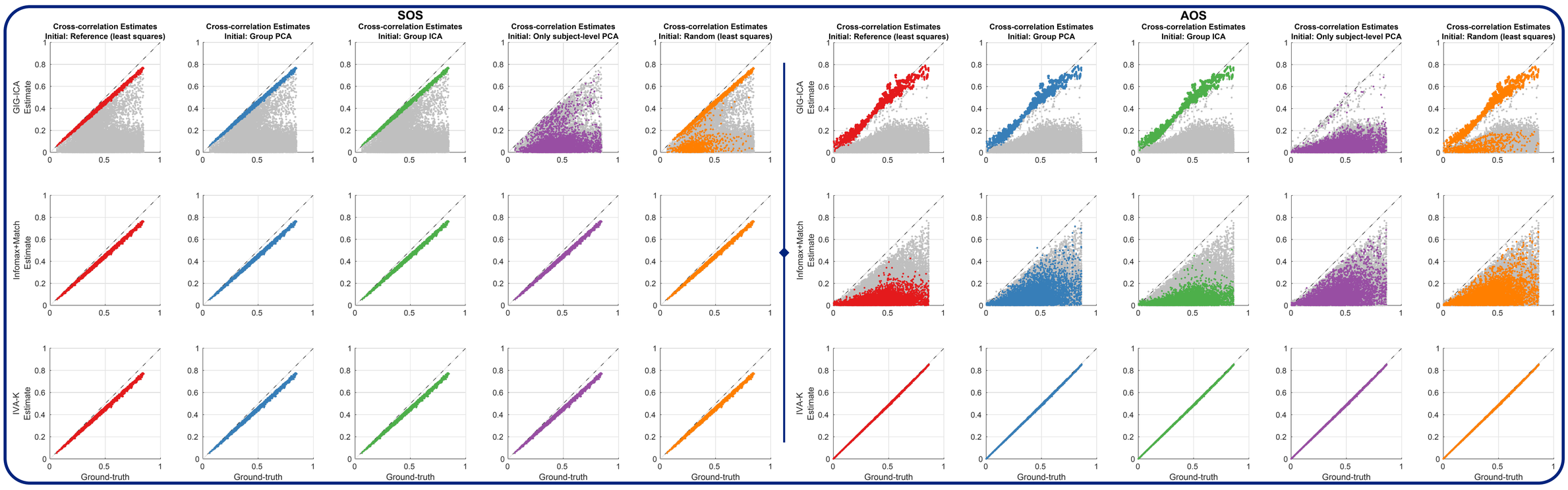
- Multivariate Laplace
- N = 32968 observations

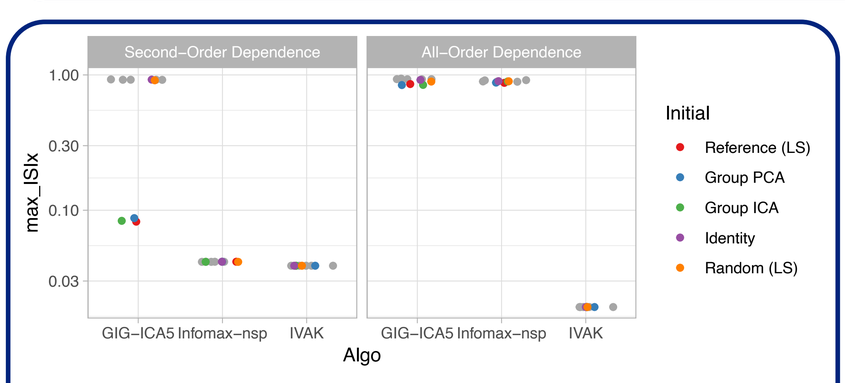
Initializations

- Reference (least squares)
- Group PCA
- Group ICA
- Identity (Only subject-level PCA)
- Random (least squares)
- Random (orthogonal)

Algorithms

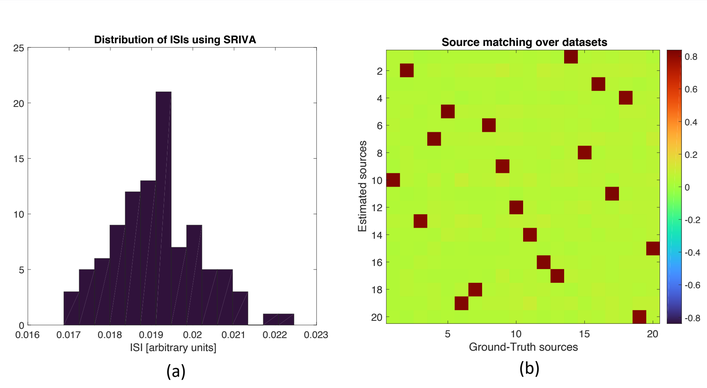
- GIG-ICA (α=0.5)
- Separate ICAs + Match
- IVA-Kotz





max_ISIx: largest ISI over 5 worst source estimates (smaller is better)

- ✓ IVA-K is robust to initialization and dependence type
- ✓ IVA-K is not dependent on the quality of the reference
- ✓ GIG-ICA (ICA-R) is highly dependent on reference quality (not robust to initialization)
- ✓ GIG-ICA and separate ICAs do not recover higher-order dependences well



The utility of SRIVA

M = 100 simulated datasets, C = 20 sources per dataset linked at various correlations levels across datasets.
A single IVA model with 20 100-dimensional sources would take hours to complete.
SRIVA completes in 10 minutes.

(a) The distribution of intersymbol interference (ISI) coefficients measured on each dataset after SRIVA completion. ISI < 0.1 indicates successful recovery. The global ISI = 0.0633 indicates sources were aligned correctly across datasets.
(b) Evidence of source alignment in SRIVA.

Conclusion

- IVA yields higher accuracy than current approaches for multisubject analysis but is computationally intensive.
- SRIVA can rip the benefits of IVA at scale and without massive computational costs.
- It does not require additional modeling and tuning of regularizers.
- The MISA [1] implementation of IVA-K uses second- and higher-order statistics.
- Current efforts are being carried out to assess the utility of the approach for large real datasets and multisite studies.

References:

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