Template

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This is the abstract.

The bibliography file has a relatively recent copy of all neurodata pubs.

1 This is a section

The quick brown fox jumps over the lazy dog Eq. (1).

The quick brown fox jumps over the lazy dog [1–8].

The quick brown fox jumps over the lazy dog Figure 1.

The quick brown fox jumps over the lazy dog*. Amit and Geman [1]*

THE QUICK BROWN FOX JUMPS OVER THE LAZY DOG. Add cats

The quick brown fox jumps over the `lazy` dog.

The ~~quick~~ [~~brown~~ | chartreuse] fox jumps over the lazy [ass] dog

Aligned equation:

$$e^{i\pi} - 1 = 0, \quad (1)$$

$$\chi = V - E + F \quad (2)$$

Enumerate:

1. The quick brown fox jumps over the lazy dog
2. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog.

Itemize:

- The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog.
- The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog.

Description:

The The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog.
Quick brown fox jumps over the lazy dog. The quick brown fox jumps over the lazy dog.

1.1 This is a subsection

The quick brown fox jumps over the lazy dog.

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Table 1: Table.

Metrics	Sub	**Phase 1**	**Phase 2**
1			
The	quick	brown	fox

Table 2: The median sample size for each method to achieve power 85% at type 1 error level 0.05, grouped into monotone (type 1-5) and non-monotone simulations (type 6-19) for both one- and ten-dimensional settings, normalized by the number of samples required by MGC. In other words, a 2.0 indicates that the method requires double the sample size to achieve 85% power relative to MGC. PEARSON, RV, and CCA all achieve the same performance, as do SPEARMAN and KENDALL. MGC requires the fewest number of samples in all settings, and on average for high-dimensional settings, all other methods require about two to three times more samples than MGC.

Dimensionality	One-Dimensional			Ten-Dimensional		
Dependency Type	Monotone	Non-Mono	Average	Monotone	Non-Mono	Average
MGC	**1**	**1**	**1**	**1**	**1**	**1**
DCORR	**1**	2.6	2.2	**1**	3.2	2.6
MCORR	**1**	2.8	2.4	**1**	3.1	2.6
HHG	1.4	**1**	1.1	1.7	1.9	1.8
HSIC	1.4	1.1	1.2	1.7	2.4	2.2
MANTEL	1.4	1.8	1.7	3	1.6	1.9
PEARSON / RV / CCA	**1**	>10	>10	**0.8**	>10	>10
SPEARMAN / KENDALL	**1**	>10	>10	n/a	n/a	n/a
MIC	2.4	2	2.1	n/a	n/a	n/a

1.1.1 This is a subsubsection

The quick brown fox jumps over the lazy dog.

This is a paragraph The quick brown fox jumps over the lazy dog.

This is a subparagraph The quick brown fox jumps over the lazy dog.

Figure 1: Lion is awesome.

Algorithm 1 MGC test statistic. This algorithm computes all local correlations, take the smoothed maximum, and reports the (k, l) pair that achieves it. For the smoothing step, it: (i) finds the largest connected region in the correlation map, such that each correlation is significant, i.e., larger than a certain threshold to avoid correlation inflation by sample noise, (ii) take the largest correlation in the region, (iii) if the region area is too small, or the smoothed maximum is no larger than the global correlation, the global correlation is used instead. The running time is $\mathcal{O}(n^2)$.

Input: A pair of distance matrices $(A, B) \in \mathbb{R}^{n\times n} \times \mathbb{R}^{n\times n}$.
Output: The MGC statistic $c^* \in \mathbb{R}$, all local statistics $\mathcal{C} \in \mathbb{R}^{n\times n}$, and the corresponding local scale $(k, l) \in \mathbb{N} \times \mathbb{N}$.

function MGCSampleStat(A, B)
  $\mathcal{C} = \text{MGCAllLocal}(A, B)$ ▷ All local correlations
  $\tau = \text{Thresholding}(\mathcal{C})$ ▷ find a threshold to determine large local correlations
  for $i, j := 1, \ldots, n$ **do** $r_{ij} \leftarrow \mathbb{I}(c^{ij} > \tau)$ **end for** ▷ identify all scales with large correlation
  $\mathcal{R} \leftarrow \{r_{ij} : i, j = 1, \ldots, n\}$ ▷ binary map encoding scales with large correlation
  $\mathcal{R} = \text{Connected}(\mathcal{R})$ ▷ largest connected component of the binary matrix
  $c^* \leftarrow \mathcal{C}(n, n)$ ▷ use the global correlation by default
  $k \leftarrow n, l \leftarrow n$
  if $\left(\sum_{i,j} r_{ij}\right) \geq 2n$ **then** ▷ proceed when the significant region is sufficiently large
    $[c^*, k, l] \leftarrow \max(\mathcal{C} \circ \mathcal{R})$ ▷ find the smoothed maximum and the respective scale
  end if
end function

References and Notes

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