

Template

Joshua T. Vogelstein*^{1,2}

¹Department of Biomedical Engineering, Institute for Computational Medicine, Kavli Neuroscience Discovery Institute, Johns Hopkins University

²University of Something Else

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 [1–3].

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:

$$e^{i\pi} - 1 = 0, \tag{1}$$

$$\chi = V - E + F \tag{2}$$

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.

*jovo@jhu.edu

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 Dependency Type	One-Dimensional			Ten-Dimensional		
	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 $(k, l) \in \mathbb{N} \times \mathbb{N}$.

```

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

```

References and Notes

- [1] Yali Amit and Donald Geman. Shape quantization and recognition with randomized trees. *Neural Computation*, 9(7):1545–1588, 1997. doi: 10.1162/neco.1997.9.7.1545. URL <http://dx.doi.org/10.1162/neco.1997.9.7.1545>.
- [2] Jimmy Ba, Geoffrey E Hinton, Volodymyr Mnih, Joel Z Leibo, and Catalin Ionescu. Using fast weights to attend to the recent past. In D D Lee, M Sugiyama, U V Luxburg, I Guyon, and R Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 4331–4339. Curran Associates, Inc., 2016.
- [3] Gökhan Bakir, Thomas Hofmann, and Bernhard Scholkopf. *Predicting structured data*. MIT press, 2007.
- [4] Anna Choromanska, Tony Jebara, Hyungtae Kim, Mahesh Mohan, and Claire Monteleoni. *Fast Spectral Clustering via the Nyström Method*, pages 367–381. Springer Berlin Heidelberg, Berlin, Heidelberg, 2013.
- [5] E.Aleskerov, B.Frelisleben, and B.Rao. Cardwatch: A neural network based database mining system for credit card fraud detection. In *Proceedings of IEEE Computational Intelligence for Financial Engineering*, pages 220–226, 1997.
- [6] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.
- [7] Patric Hagmann. *From diffusion MRI to brain connectomics*. PhD thesis, STI, Lausanne, 2005. URL <http://vpaa.epfl.ch/page14976.html>.
- [8] M. Tang, Y. Park, and C. E. Priebe. Out-of-sample extension for latent position graphs. Arxiv preprint at <http://arxiv.org/abs/1305.4893>, 2013.