

# A Study of Cycle Length Spectra: Connecting Homotopy to Network Science

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## Abstract

- We highlight the connection between **nonbacktracking walks (NBWs)** and **homotopy theory** from algebraic topology.
- We show how **NBWs track structural graph measures** such as the degree distribution and clustering coefficient.
- We propose a **graph distance measure based on NBWs**.

## Nonbacktracking Matrix

- Given a graph  $G$  with  $m$  edges, the **nonbacktracking matrix  $B$**  is a  $2m \times 2m$  matrix.
- Each edge in  $G$  is represented by two rows in  $B$ , one per orientation:  $u \rightarrow v$  and  $v \rightarrow u$ .
- For two edges  $u \rightarrow v$  and  $k \rightarrow l$ ,  $B$  is given by

$$B_{k \rightarrow l, u \rightarrow v} = \delta_{vk}(1 - \delta_{ul})$$

where  $\delta_{ij}$  is the Kronecker delta.

- Example: There is a 1 in the entry indexed by row  $u \rightarrow v$  and column  $k \rightarrow l$  when  $u \neq l$  and  $v = k$ ; and a 0 otherwise.

## 1 Computing $B$ and its Properties

- We compute  $B$  in two steps  
Step 1: compute

$M_{x,u \rightarrow v}^+ = \delta_{xu}$	$O(m)$
$M_{x,u \rightarrow v}^- = \delta_{xv}$	$O(m)$
$C = (M^+)^T M^-$	$O(n \langle k^2 \rangle)$

- Step 2: compute  $B$  entrywise:

$$C_{k \rightarrow l, u \rightarrow v} = \delta_{vk}$$

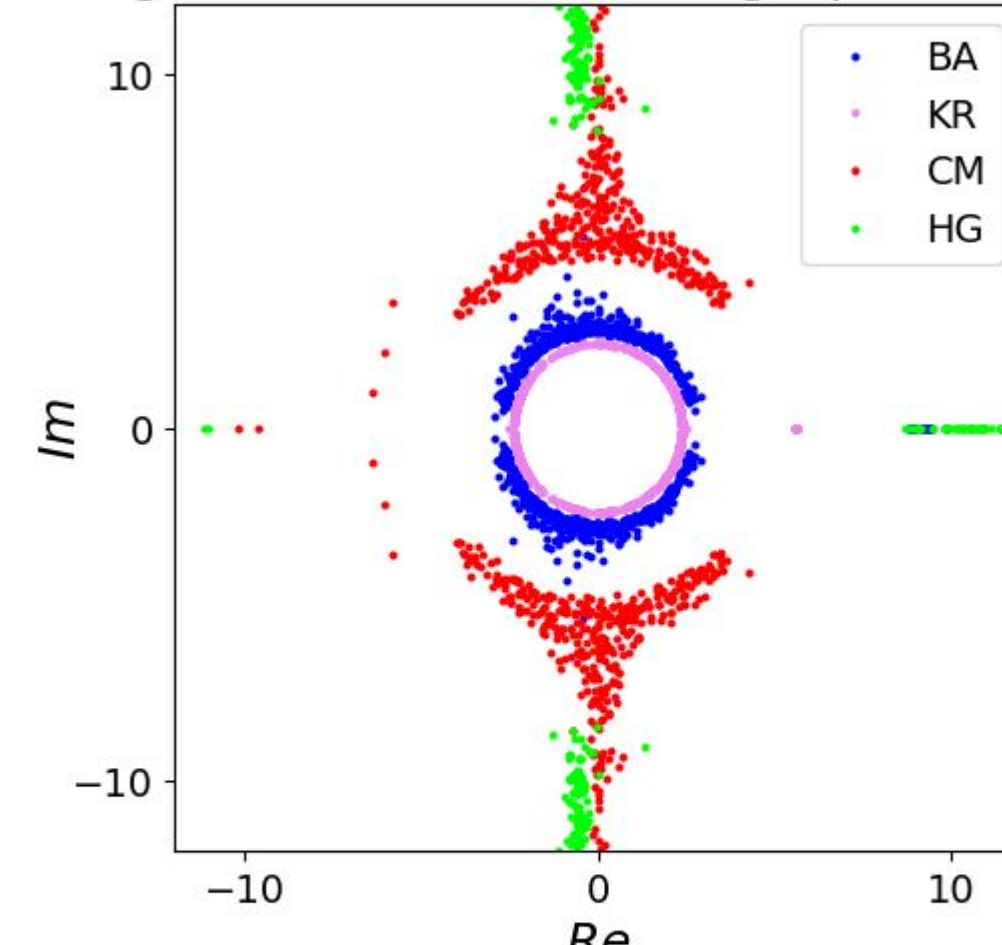
$$B_{k \rightarrow l, u \rightarrow v} = C_{k \rightarrow l, u \rightarrow v} (1 - C_{u \rightarrow v, k \rightarrow l})$$

- Time complexity**  $O(m + n \langle k^2 \rangle)$ .
- For homogeneous networks:  $O(m + n)$ .
- For power-law degree distributions: between  $O(m + n)$  and  $O(n^2)$ .
- The number of non-zero elements of  $B$  is related to the **degree distribution**:  $nnz(B) = n \langle k^2 \rangle - n \langle k \rangle$ .
- If  $\lambda_k = \alpha_k + i\beta_k$  are the **eigenvalues** of  $B$ , then the **number of triangles** is

$$tr(B^3) = \sum_k a_k (a_k^2 - 3b_k^2)$$

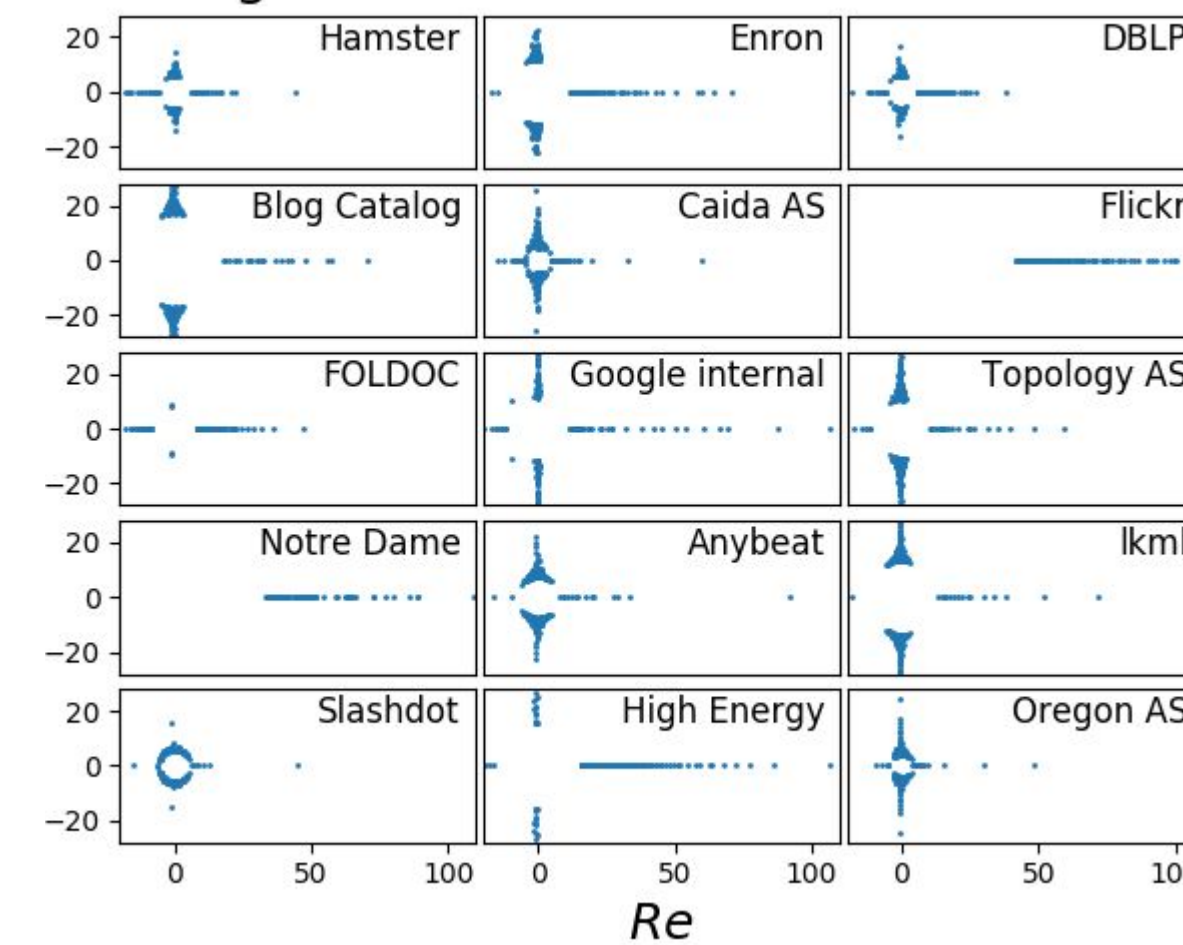
- If  $(\sum_k a_k^2)$  is large and  $(\sum_k b_k^2)$  is small, then number of triangles is large.

Eigenvalues of random graph models



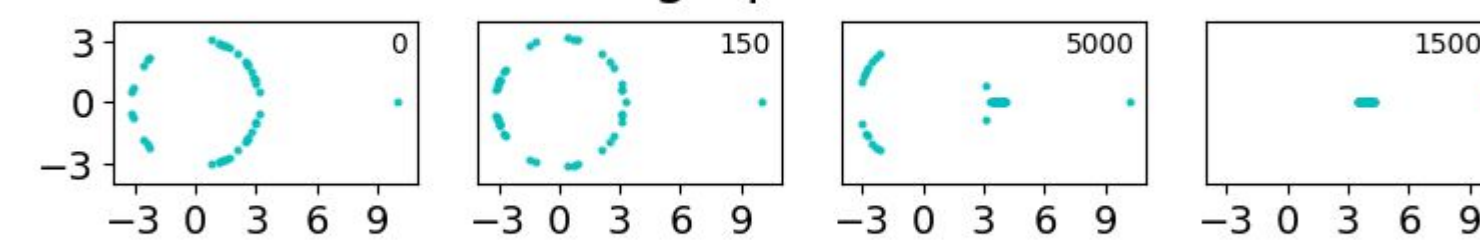
Shown are the largest 40 eigenvalues of  $B$  of 20 random graphs of each model. BA: Barabási-Albert, KR: Kronecker Graph, CM: Configuration Model, HG: Hyperbolic Graph. CM and HG generated with power law degree distribution with exponent  $\gamma = 2.1$ . All graphs have  $n = 10^4$  nodes and approximately  $\langle k \rangle = 10$ .

Eigenvalues of Real Networks



Top 100 eigenvalues of  $B$  for real networks of diverse domains: social (Hamster, Blog Catalog, Anybeat, Flickr), communications (Enron, IkmI), scientific citations (DBLP, High Energy), autonomous systems of the internet (Caida AS, Oregon AS, Topology AS), web graphs (Notre Dame, Google Internal, FOLDOC).

Change in eigenvalues as triangles are added to a ER graph ( $N = 10^4$ ,  $\langle k \rangle = 10$ )

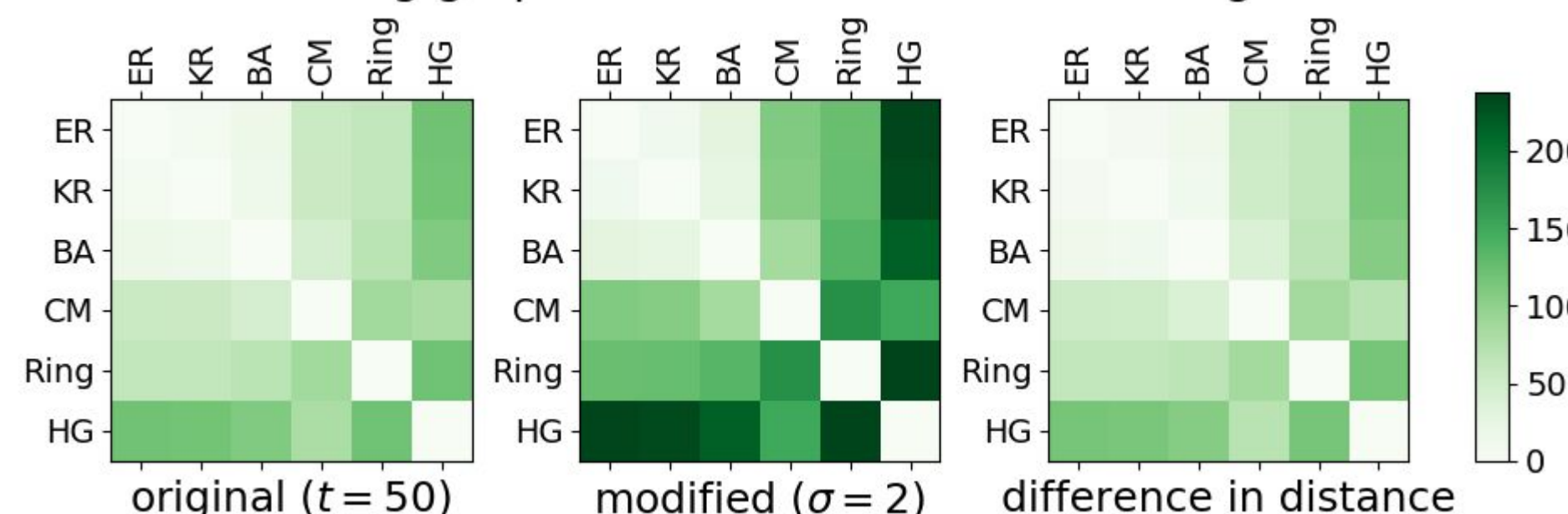


As more triangles are added to the network,  $B$ 's eigenvalues move further right and closer to the horizontal axis. If  $\lambda_k = a_k + ib_k$ , then  $a_k^2$  increases and  $b_k^2$  decreases.

## 2 A Measure of Graph Distance

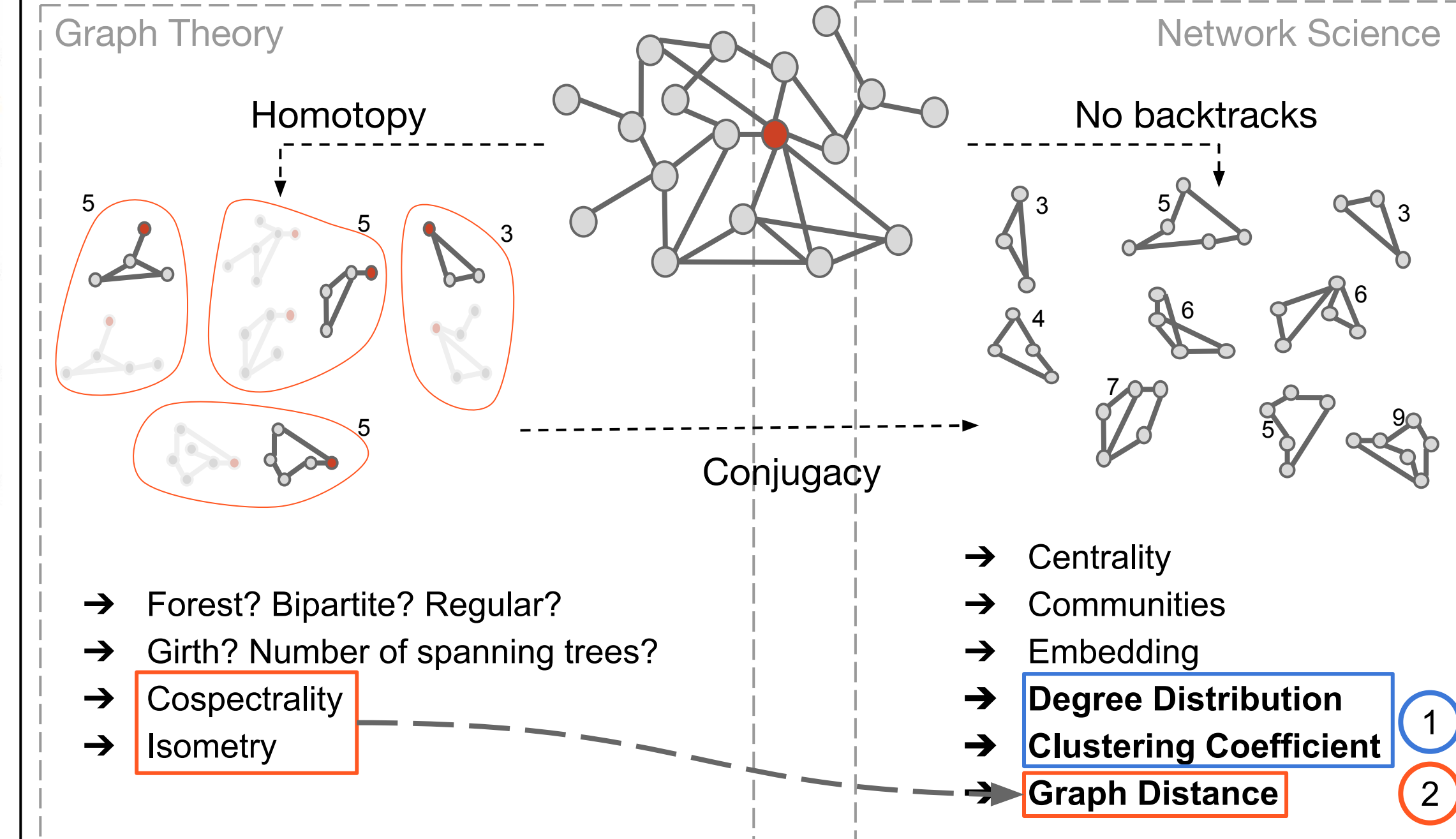
Graph	$G_1$	$G_2$
Eigenvalues	$\lambda_k = a_k + ib_k, k = 1..t$	$\mu_k = \alpha_k + i\beta_k, k = 1..t$
Features	$(a_1, \dots, a_t, b_1, \dots, b_t) = (a, b)$	$(\alpha, \beta)$
Fine-tuned	$(\sigma a, b/\sigma)$	$(\sigma \alpha, \beta/\sigma)$

Fine tuning graph distance to number of triangles



Left: distance between the mean feature vector of several random graph models. Models are ordered in increasing number of triangles from left to right. Center: distance between mean modified feature vector. Right: difference in previous two distances. Observe that elements away from the diagonal have a larger difference in number of triangles, which are amplified accordingly. ER: Erdos-Renyi, KR: Kronecker Graph, BA: Barabasi-Albert, CM: Configuration Model, Ring: ring lattice, HG: Hyperbolic Graph.

## Homotopy Theory



## Discussion

We propose  $B$  as a better alternative for computing graph distance because it:

- carries information about important features such as degrees and triangles,
- can be fine tuned to be more or less sensitive to such features,
- is backed by the **cospectrality and isometry results from homotopy theory**.

To our knowledge, the **connection between NBWs and homotopy theory** hasn't been fully realized in the Network Science literature.

## Open Questions and Future Research

- How best to take advantage of **homotopy theory** in the study of **complex networks**?
- What other **structural and dynamic graph measures** are stored in NBWs and  $B$ ?
- Can **algebraic-topological features** be used to define a metric on the space of all graphs?
- What other **graph mining tasks** can we improve by the use of NBWs and  $B$ ?