Basic Usage of **NetworkDistance** Package

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1. Load

Surely, the first thing we are always bound to do is to load the package,

```
library(NetworkDistance)
#> **-----**
#> ** NetworkDistance - Distance Measures for Networks
#> **
#> ** Version : 0.3.6 (2025)
#> ** Maintainer : Kisung You (kisung.you@outlook.com)
#> **
#> ** Please share any bugs or suggestions to the maintainer.
#> **------**
```

2. Computing Distances

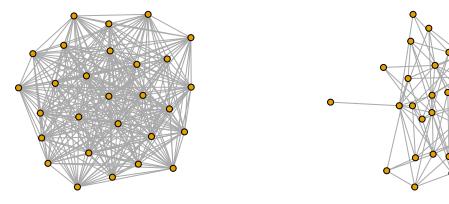
Suppose you have N network objects represented as square adjacency matrices. All the functions in the package require your data to be in a form of list whose elements are your adjacency matrices. Let's load example data graph 20.

```
data(graph20) # use `help(graph20)' to see more details.
typeof(graph20) # needs to be a list
#> [1] "list"
```

Before proceeding any further, since we have two types of graphs - densely and sparsely connected with p=0.8 and p=0.2 - we know that the distance matrix should show block-like pattern. Below is two example graphs from the dataset.

graph No.7

graph No.18

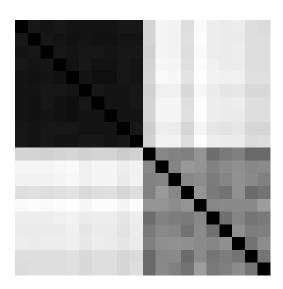


Once you have your data in such a form, all you've got is to run a single-line code to acquire distance numerics, resulting in either a dist class object or a square matrix. For example, let's compute graph diffusion distance by Hammond et al. (2013) on our example set.

```
dist.gdd <- nd.gdd(graph20) # return as a 'dist' object</pre>
```

and you can see the discriminating pattern from the distance matrix dist.gdd\$D with black represents 0 and white represents the largest positive number, indicating large deviation from 0.

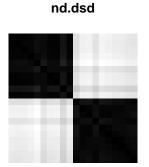
pairwise distance matrix

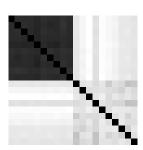


Finally, let's compare different methods as well.

```
dist.wsd <- nd.wsd(graph20)  # spectrum-weighted distance
dist.dsd <- nd.dsd(graph20, type="SLap") # discrete spectral measure
dist.nfd <- nd.nfd(graph20)  # network flow distance</pre>
```

nd.wsd



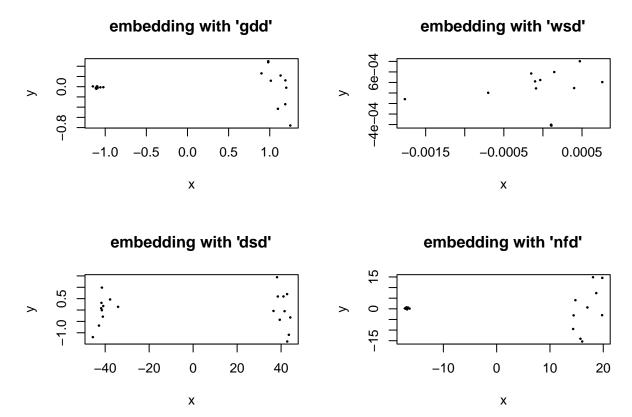


nd.nfd

3. One Application: Embedding Networks, Not Network Embedding

Our interest is focused on dealing with a collection of networks, **not** a single network. Therefore, the example we cover here is to **embed** multiple networks, not an embedding of single network and its nodes as points. We will use multidimensional scaling to embed 20 graphs we did before.

```
gdd2 = stats::cmdscale(dist.gdd$D, k=2)  # 2-d embedding from 'gdd' distance
wsd2 = stats::cmdscale(dist.wsd$D, k=2)  # 'wsd'
dsd2 = stats::cmdscale(dist.dsd$D, k=2)  # 'dsd'
nfd2 = stats::cmdscale(dist.nfd$D, k=2)  # 'nfd'
```



From the figure above, we can see that different measures/metrics reveal a variety of topological or network features. This necessitates the very existence of a package like ours to provide a set of tools for diverse perspectives on the space networks.