

Introduction to the pageRank Package

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1 Introduction

1.1 Background

The *pageRank* package provides implementations of temporal PageRank as defined by [1], as well as multiplex PageRank as defined by [2]. As the extension of original steady-state PageRank [3,4] in temporal networks, temporal PageRank ranks nodes based on their connections that change over time. Multiplex PageRank, on the other hand, extends PageRank analysis to multiplex networks. In such networks, the same nodes might interact with one another in different layers. Multiplex PageRank is calculated according to the topology of a predefined

base network, with regular PageRank of other supplemental networks as edge weights and personalization vector.

PageRank-related approaches can be applied to prioritize key transcriptional factors (TFs) in gene regulatory networks (GRNs). Specifically, the *pageRank* package provides functions for generating temporal GRNs from corresponding static counterparts. The *pageRank* package also provides functions for converting multi-omics, e.g. gene expression, chromatin accessibility and chromosome conformation profiles to multiplex GRNs. Such temporal and multiplex GRNs can thus be used for temporal and multiplex PageRank-based TF prioritization, respectively.

1.2 Installation

pageRank requires the R version 4.0 or later, packages *BSgenome.Hsapiens.UCSC.hg19*, *TxDb.Hsapiens.UCSC.lorg.Hs.eg.db*, *annotate*, *GenomicFeatures*, *JASPAR2018*, *TFBSTools* and *bcellViper*, to run the examples. After installing R, all required components can be obtained with:

```
if (!requireNamespace("BiocManager", quietly=TRUE)) install.packages("BiocManager")
BiocManager::install("BSgenome.Hsapiens.UCSC.hg19")
BiocManager::install("TxDb.Hsapiens.UCSC.hg19.knownGene")
BiocManager::install("org.Hs.eg.db")
BiocManager::install("annotate")
BiocManager::install("GenomicFeatures")
BiocManager::install("JASPAR2018")
BiocManager::install("TFBSTools")
BiocManager::install("bcellViper")
```

2 PageRank Analysis

2.1 Temporal PageRank

We applied `diff_graph()` to calculate temporal PageRank. This is a simplified version of temporal PageRank described by [1] by only analyzing temporally adjacent graph pairs.

```
> library(pageRank)
> set.seed(1)
> graph1 <- igraph::erdos.renyi.game(100, 0.01, directed = TRUE)
> igraph::V(graph1)$name <- 1:100
> #the 1st graph with name as vertex attributes
> set.seed(2)
> graph2 <- igraph::erdos.renyi.game(100, 0.01, directed = TRUE)
> igraph::V(graph2)$name <- 1:100
> #the 2nd graph with name as vertex attributes
> diff_graph(graph1, graph2)
```

```

IGRAPH 7bd991f DN-- 98 190 --
+ attr: name (v/c), pagerank (v/n), moi (e/n)
+ edges from 7bd991f (vertex names):
  [1] 1 ->60  2 ->15  2 ->57  3 ->10  3 ->16  3 ->84  4 ->43  5 ->20  5 ->60
 [10] 5 ->72  5 ->81  5 ->91  6 ->25  6 ->50  7 ->37  7 ->67  7 ->73  7 ->80
 [19] 8 ->80  9 ->90 10->26 11->6  11->100 12->70 12->82 12->92 13->30
 [28] 13->48 13->51 13->61 15->74 15->77 16->85 17->31 17->32 17->30
 [37] 17->50 17->58 19->17 19->96 20->23 20->79 20->87 21->41 21->40
 [46] 22->4  22->41 23->57 24->61 25->66 26->34 26->39 26->72 27->20
 [55] 27->43 28->98 29->95 30->84 32->49 33->10 34->16 34->99 35->80
 [64] 36->17 36->33 36->45 36->53 36->77 37->33 37->54 38->6  38->10
+ ... omitted several edges

```

Differential graph graph1-graph2 will be outputed. The Differential graph has "moi (mode of interaction, 1 and -1 for interactions gained and losed in graph1, respectively)" as edge attribute. The Differential graph has "pagerank" and "name" as vertex attributes.

2.2 Multiplex PageRank

We applied `multiplex_page_rank()` to calculate multiplex PageRank following definition by [2].

```

> set.seed(1)
> graph1 <- igraph::erdos.renyi.game(100, 0.01, directed = TRUE)
> igraph::V(graph1)$name <- 1:100
> igraph::V(graph1)$pagerank <- igraph::page_rank(graph1)$vector
> #the base graph with pagerank and name as vertex attributes.
> set.seed(2)
> graph2 <- igraph::erdos.renyi.game(100, 0.01, directed = TRUE)
> igraph::V(graph2)$name <- 1:100
> igraph::V(graph2)$pagerank <- igraph::page_rank(graph2)$vector
> #the supplemental graph with pagerank and name as vertex attributes.
> multiplex_page_rank(graph1, graph2)

```

| | | | | | |
|-------------|-------------|-------------|-------------|-------------|-------------|
| 1 | 2 | 3 | 4 | 5 | 6 |
| 0.024486930 | 0.003587882 | 0.003269234 | 0.025062625 | 0.002517812 | 0.014031152 |
| 7 | 8 | 9 | 10 | 11 | 12 |
| 0.019560780 | 0.002517812 | 0.010657975 | 0.024750578 | 0.003587882 | 0.002517812 |
| 13 | 14 | 15 | 16 | 17 | 18 |
| 0.002517812 | 0.002517812 | 0.012543315 | 0.011993811 | 0.011752012 | 0.002517812 |
| 19 | 20 | 21 | 22 | 23 | 24 |
| 0.002517812 | 0.005019851 | 0.005073934 | 0.019579420 | 0.010917862 | 0.006654581 |
| 25 | 26 | 27 | 28 | 29 | 30 |

| | | | | | |
|-------------|-------------|-------------|-------------|-------------|-------------|
| 0.008481052 | 0.024875556 | 0.018813575 | 0.012145212 | 0.002517812 | 0.005371332 |
| 31 | 32 | 33 | 34 | 35 | 36 |
| 0.028390794 | 0.003870287 | 0.022958947 | 0.007132217 | 0.026500261 | 0.014220612 |
| 37 | 38 | 39 | 40 | 41 | 42 |
| 0.003894189 | 0.014025489 | 0.007048515 | 0.006489236 | 0.009884435 | 0.011620308 |
| 43 | 44 | 45 | 46 | 47 | 48 |
| 0.021776702 | 0.005804823 | 0.007274354 | 0.005973955 | 0.002517812 | 0.003231192 |
| 49 | 50 | 51 | 52 | 53 | 54 |
| 0.008363678 | 0.018470262 | 0.007252872 | 0.007734145 | 0.007333127 | 0.008132101 |
| 55 | 56 | 57 | 58 | 59 | 60 |
| 0.002517812 | 0.009882306 | 0.012570845 | 0.005099961 | 0.009773330 | 0.005728022 |
| 61 | 62 | 63 | 64 | 65 | 66 |
| 0.008887585 | 0.009392001 | 0.002517812 | 0.012318772 | 0.002517812 | 0.012403356 |
| 67 | 68 | 69 | 70 | 71 | 72 |
| 0.003894189 | 0.008046953 | 0.006637398 | 0.012164635 | 0.004952221 | 0.025846022 |
| 73 | 74 | 75 | 76 | 77 | 78 |
| 0.007717015 | 0.017071807 | 0.004497441 | 0.031878419 | 0.006205317 | 0.006125093 |
| 79 | 80 | 81 | 82 | 83 | 84 |
| 0.007674159 | 0.004657952 | 0.036708345 | 0.004133414 | 0.003587882 | 0.008317756 |
| 85 | 86 | 87 | 88 | 89 | 90 |
| 0.019805589 | 0.003587882 | 0.010071696 | 0.003779210 | 0.002517812 | 0.010708381 |
| 91 | 92 | 93 | 94 | 95 | 96 |
| 0.009826976 | 0.006014406 | 0.020117463 | 0.010635582 | 0.006048082 | 0.004657952 |
| 97 | 98 | 99 | 100 | | |
| 0.012988768 | 0.015761377 | 0.004243860 | 0.003249976 | | |

Multiplex PageRank values corresponded to nodes in graph1 (base network) will be outputed.

2.3 Adjusting PageRank Calculations

The `clean_graph()` can remove nodes by residing subgraph sizes, vertex names and PageRank values. We thus can adjust graphs for PageRank calculation.

```
> set.seed(1)
> graph <- igraph::erdos.renyi.game(100, 0.01, directed = TRUE)
> igraph::V(graph)$name <- 1:100
> igraph::V(graph)$pagerank <- igraph::page_rank(graph)$vector
> #the graph to be cleaned, with pagerank and name as vertex attributes.
> clean_graph(graph, size=5)
```

```
IGRAPH 5b4d428 DN-- 82 96 -- Erdos-Renyi (gnp) graph
+ attr: name (g/c), type (g/c), loops (g/l), p (g/n), name (v/n),
| pagerank (v/n)
```

```
+ edges from 5b4d428 (vertex names):
[1] 72-> 1 88-> 3 22-> 4 11-> 6 65-> 6 87-> 6 60-> 7 85->
[9] 84-> 9 33-> 10 100-> 10 11->100 2-> 15 40-> 15 3-> 16 34->
[17] 19-> 17 46-> 17 5-> 20 69-> 20 100-> 20 92-> 21 27-> 22 83->
[25] 42-> 24 6-> 25 10-> 26 74-> 27 94-> 27 43-> 31 36-> 33 38->
[33] 59-> 35 90-> 35 60-> 36 70-> 36 53-> 38 26-> 39 46-> 40 88->
[41] 21-> 41 71-> 41 49-> 42 65-> 42 77-> 42 87-> 43 100-> 43 52->
[49] 21-> 45 54-> 46 32-> 49 92-> 49 6-> 50 17-> 50 43-> 52 54->
+ ... omitted several edges
```

Adjusted graph will be outputed, with "pagerank" and "name" as vertex attributes.

The `adjust_graph()` can re-calculate PageRank with updated damping factor, personalized vector and edge weights.

```
> set.seed(1)
> graph <- igraph::erdos.renyi.game(100, 0.01, directed = TRUE)
> igraph::V(graph)$name <- 1:100
> igraph::V(graph)$pagerank <- igraph::page_rank(graph, damping=0.85)$vector
> #the graph to be adjusted, with pagerank and name as vertex attributes.
> adjust_graph(graph, damping=0.1)
```

```
IGRAPH c0ff5a9 DN-- 100 98 -- Erdos-Renyi (gnp) graph
+ attr: name (g/c), type (g/c), loops (g/l), p (g/n), name (v/n),
| pagerank (v/n)
+ edges from c0ff5a9 (vertex names):
[1] 72-> 1 88-> 3 22-> 4 11-> 6 65-> 6 87-> 6 60-> 7 85->
[9] 84-> 9 33-> 10 100-> 10 11->100 2-> 15 40-> 15 3-> 16 34->
[17] 19-> 17 46-> 17 5-> 20 69-> 20 100-> 20 92-> 21 27-> 22 83->
[25] 42-> 24 6-> 25 10-> 26 74-> 27 94-> 27 63-> 30 43-> 31 36->
[33] 38-> 35 59-> 35 90-> 35 60-> 36 70-> 36 53-> 38 26-> 39 46->
[41] 88-> 40 21-> 41 71-> 41 49-> 42 65-> 42 77-> 42 87-> 43 100->
[49] 52-> 44 21-> 45 54-> 46 32-> 49 92-> 49 6-> 50 17-> 50 13->
+ ... omitted several edges
```

Adjusted graph will be outputed, with updated "pagerank" and "name" as vertex attributes.

Please note `diff_graph()`, `multiplex_page_rank()`, `clean_graph()` and `adjust_graph()` can be used in combination for customized PageRank analysis tasks.

3 Prioritizing TFs in GRNs

3.1 Generating GRNs from Multi-Omics Profiles

The `aracne_network()` can re-format ARACNe network in regulon object for PageRank analysis. It can also handle GRNs reverse engineered using other algorithms, as long as such

GRNs are written in regulon object.

```
> library(bcellViper)
> data(bcellViper)
> head(aracne_network(regulon[1:10]))
```

| | reg | target | direction |
|---|------|----------|-----------|
| 1 | AATF | SAMM50 | 1 |
| 2 | AATF | DRG1 | 1 |
| 3 | AATF | ATIC | 1 |
| 4 | AATF | SMARCC1 | 1 |
| 5 | AATF | AHCY | 1 |
| 6 | AATF | HSD17B10 | 1 |

The `accessibility_network()` can build network from accessibility, e.g. ATAC-Seq peaks.

```
> table <- data.frame(Chr=c("chr1", "chr1"), Start=c(713689, 856337), End=
+                      row.names=c("A", "B"), stringsAsFactors=FALSE)
> regulators=c("FOXF2", "MZF1")
> #peaks and regulators to be analyzed
>
> library(GenomicRanges)
> library(GenomicFeatures)
> library(TxDb.Hsapiens.UCSC.hg19.knownGene)
> library(org.Hs.eg.db)
> library(annotate)
> promoter <- promoters(genes(TxDb.Hsapiens.UCSC.hg19.knownGene))
> names(promoter) <- getSYMBOL(names(promoter), data="org.Hs.eg")
> promoter <- promoter[!is.na(names(promoter))]
> #get promoter regions
>
> library(JASPAR2018)
> library(TFBSTools)
> library(motifmatchr)
> pfm <- getMatrixSet(JASPAR2018, list(species="Homo sapiens"))
> pfm <- pfm[unlist(lapply(pfm, function(x) name(x))) %in% regulators]
> #get regulator position frequency matrix (PFM) list
>
> library(BSgenome.Hsapiens.UCSC.hg19)
> accessibility_network(table, promoter, pfm, "BSgenome.Hsapiens.UCSC.hg19")

      target    reg
1  LINC01409 FOXF2
```

```

2      LINC01409  MZF1
3      LINC02593  FOXF2
4 LOC107985728  FOXF2
5          SAMD11  FOXF2
6      LINC02593  MZF1
7 LOC107985728  MZF1
8          SAMD11  MZF1

```

The `conformation_network()` can build network from conformation, e.g. HiChIP records.

```

> table <- data.frame(Chr1=c("chr1", "chr1"), Position1=c(569265, 713603),
+                      Chr2=c("chr4", "chr1"), Position2=c(206628, 715110),
+                      row.names=c("A", "B"), stringsAsFactors=FALSE)
> regulators=c("FOXF2", "MZF1")
> #peaks and regulators to be analyzed
>
> promoter <- promoters(genes(TxDb.Hsapiens.UCSC.hg19.knownGene))
> names(promoter) <- getSYMBOL(names(promoter), data="org.Hs.eg")
> promoter <- promoter[!is.na(names(promoter))]
> #get promoter regions
>
> pfm <- getMatrixSet(JASPAR2018, list(species="Homo sapiens"))
> pfm <- pfm[unlist(lapply(pfm, function(x) name(x))) %in% regulators]
> #get regulator position frequency matrix (PFM) list
>
> conformation_network(table, promoter, pfm, "BSgenome.Hsapiens.UCSC.hg19",
+
+      target  reg
1 ZNF876P MZF1

```

3.2 Filter GRNs with Expression Profiles

The `P_graph()` can filter GRNs by quantifying joint and margin probability distributions of regulator-target pairs. Statistically significant non-random regulator-target pairs will be kept.

```

> dset <- exprs(dset)
> net <- do.call(rbind, lapply(1:10, function(i, regulon){
+   data.frame(reg=rep(names(regulon)[i], 10),
+               target=names(regulon[[i]][[1]])[1:10],
+               stringsAsFactors = FALSE)}, regulon=regulon))
> P_graph(dset, net, method="difference", null=NULL, threshold=0.05)

```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]


```

|
|=====
|
|=====
|
|=====
|
|=====
|
|=====
|
|=====
|
+ attr: name (v/c), pagerank (v/n), pvalue (e/n)
+ edges from feb9856 (vertex names):
[1] PPM1G ->AATF    CTBP2 ->APP    TAGLN ->APP    MTSS1 ->APP    JMJD1C->AR

```

3.3 Session Information

```

> sessionInfo()

R Under development (unstable) (2025-11-04 r88984)
Platform: aarch64-apple-darwin20
Running under: macOS Ventura 13.7.8

Matrix products: default
BLAS:   /System/Library/Frameworks/Accelerate.framework/Versions/A/Framework
LAPACK: /Library/Frameworks/R.framework/Versions/4.6-arm64/Resources/lib/l

locale:
[1] C/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

time zone: America/New_York
tzcode source: internal

attached base packages:
[1] stats4      stats      graphics  grDevices  utils      datasets  methods
[8] base

other attached packages:
[1] BSgenome.Hsapiens.UCSC.hg19_1.4.3
[2] BSgenome_1.79.1
[3] rtracklayer_1.71.1
[4] BiocIO_1.21.0

```

```

[5] Biostrings_2.79.2
[6] XVector_0.51.0
[7] motifmatchr_1.33.0
[8] TFBSTools_1.49.0
[9] JASPAR2018_1.1.1
[10] annotate_1.89.0
[11] XML_3.99-0.20
[12] org.Hs.eg.db_3.22.0
[13] TxDb.Hsapiens.UCSC.hg19.knownGene_3.22.1
[14] GenomicFeatures_1.63.1
[15] AnnotationDbi_1.73.0
[16] GenomicRanges_1.63.1
[17] Seqinfo_1.1.0
[18] IRanges_2.45.0
[19] S4Vectors_0.49.0
[20] bcellViper_1.47.0
[21] Biobase_2.71.0
[22] BiocGenerics_0.57.0
[23] generics_0.1.4
[24] pageRank_1.21.0

```

loaded via a namespace (and not attached):

```

[1] KEGGREST_1.51.1           DirichletMultinomial_1.53.0
[3] SummarizedExperiment_1.41.0 rjson_0.2.23
[5] caTools_1.18.3            lattice_0.22-7
[7] vctrs_0.6.5               tools_4.6.0
[9] bitops_1.0-9              curl_7.0.0
[11] parallel_4.6.0            RSQLite_2.4.5
[13] blob_1.2.4                pkgconfig_2.0.3
[15] Matrix_1.7-4              cigarillo_1.1.0
[17] lifecycle_1.0.4           compiler_4.6.0
[19] Rsamtools_2.27.0          codetools_0.2-20
[21] RCurl_1.98-1.17           yaml_2.3.12
[23] crayon_1.5.3              BiocParallel_1.45.0
[25] DelayedArray_0.37.0       cachem_1.1.0
[27] abind_1.4-8               gtools_3.9.5
[29] restfulr_0.0.16           fastmap_1.2.0
[31] grid_4.6.0                cli_3.6.5
[33] SparseArray_1.11.8        magrittr_2.0.4
[35] S4Arrays_1.11.1           TFMPvalue_0.0.9
[37] bit64_4.6.0-1            pwalgn_1.7.0
[39] httr_1.4.7                matrixStats_1.5.0

```

| | | |
|------|--------------------------|-----------------------|
| [41] | igraph_2.2.1 | bit_4.6.0 |
| [43] | png_0.1-8 | memoise_2.0.1 |
| [45] | rlang_1.1.6 | Rcpp_1.1.0.8.1 |
| [47] | xtable_1.8-4 | glue_1.8.0 |
| [49] | DBI_1.2.3 | seqLogo_1.77.0 |
| [51] | R6_2.6.1 | MatrixGenerics_1.23.0 |
| [53] | GenomicAlignments_1.47.0 | |

4 References

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3. Brin, Sergey, and Lawrence Page. "The anatomy of a large-scale hypertextual web search engine." (1998).
4. Page, Lawrence, et al. The pagerank citation ranking: Bringing order to the web. Stanford InfoLab, 1999.