1 Abstract

The tigre package implements our methodology of Gaussian process differential equation models for analysis of gene expression time series from single input motif networks. The package can be used for inferring unobserved transcription factor (TF) protein concentrations from expression measurements of known target genes, or for ranking candidate targets of a TF.

2 Citing tigre

The tigre package is based on a body of methodological research. Citing tigre in publications will usually involve citing one or more of the methodology papers [1, 2, 3] that the software is based on as well as citing the software package itself [4].

3 Introductory example analysis - Drosophila development

In this section we introduce the main functions of the puma package by repeating some of the analysis from the PNAS paper [1].

3.1 Installing the tigre package

The recommended way to install tigre is to use the BiocManager::install function. Installing in this way should ensure that all appropriate dependencies are met.

```r
> if (!requireNamespace("BiocManager", quietly=TRUE))
> +   install.packages("BiocManager")
> BiocManager::install("tigre")
```

To load the package start R and run

```r
> library(tigre)
```
3.2 Loading the data

To get started, you need some preprocessed time series expression data. If the data originates from Affymetrix arrays, we highly recommend processing it with mmgmos from the puma package. This processing extracts error bars on the expression measurements directly from the array data to allow judging the reliability of individual measurements. This information is directly utilised by all the models in this package.

To start from scratch on Affymetrix data, the .CEL files from ftp://ftp.fruitfly.org/pub/embryo_tc_array_data/ may be processed using:

```r
> # Names of CEL files
> expfiles <- c(paste("embryo_tc_4_", 1:12, ".CEL", sep=""),
+ paste("embryo_tc_6_", 1:12, ".CEL", sep=""),
+ paste("embryo_tc_8_", 1:12, ".CEL", sep=""))
> # Load the CEL files
> expdata <- ReadAffy(filenames=expfiles,
+ celfile.path="embryo_tc_array_data")
> # Setup experimental data (observation times)
> pData(expdata) <- data.frame("time.h" = rep(1:12, 3),
+ row.names=rownames(pData(expdata)))
> # Run mmgMOS processing (requires several minutes to complete)
> drosophila_mmgmos_exprs <- mmgmos(expdata)
> drosophila_mmgmos_fragment <- drosophila_mmgmos_exprs
```

This data needs to be further processed to make it suitable for our models. This can be done using

```r
> drosophila_gpsim_fragment <-
+ processData(drosophila_mmgmos_fragment,
+ experiments=rep(1:3, each=12))
```

Here the last argument specifies that we have three independent time series of measurements.

In order to save time with the demos, a part of the result of this is included in this package and can be loaded using

```r
> data(drosophila_gpsim_fragment)
```

3.3 Learning individual models

Let us now recreate some the models shown in the plots of the PNAS paper [1]:

```r
> # FBgn names of target genes
> targets <- c('FBgn0003486', 'FBgn0033188', 'FBgn0035257')
> # Load gene annotations
+ library(annotate)
+ aliasMapping <- getAnnMap("ALIAS2PROBE",
+ annotation(drosophila_gpsim_fragment))
> # Get the probe identifier for TF 'twi'
+ twi <- get('twi', env=aliasMapping)
> # Load alternative gene annotations
+ fbgnMapping <- getAnnMap("FLYBASE2PROBE",
+" FBgn0003486", "FBgn0033188", "FBgn0035257")
```
# Get the probe identifiers for target genes
> targetProbes <- mget(targets, env=fbgnMapping)

# Learn single-target models for each gene individually
> for (i in seq(along=targetProbes)) {
+   st_models[[i]] <- GPLearn(drosophila_gpsim_fragment,
+                             TF=twi, targets=targetProbes[i],
+                             quiet=TRUE)
+ }

# Learn a joint model for all targets
> mt_model <- GPLearn(drosophila_gpsim_fragment, TF=twi,
+                      targets=targetProbes,
+                      quiet=TRUE)

# Display the joint model parameters
> show(mt_model)

Gaussian process driving input single input motif model:
Number of time points:
   Driving TF: 143396.at
Target genes (3):
   148227.at
   152715.at
   147995.at
Basal transcription rate:
   Gene 1: 40.6296427389947
   Gene 2: 0.00777689685567812
   Gene 3: 1.12067900718906e-06
Kernel:
   Multiple output block kernel:
     Block 1
     Normalised version of the kernel.
     RBF inverse width: 0.7719322 (length scale 1.138179)
     RBF variance: 1.754204
     Block 2
     Normalised version of the kernel
     DISIM decay: 0.07292779
     DISIM inverse width: 0.7719322 (length scale 1.138179)
     DISIM Variance: 1
     SIM decay: 2584.308
     SIM Variance: 0.00112408
     RBF Variance: 1.754204
     Block 3
     Normalised version of the kernel
     DISIM decay: 0.07292779
     DISIM inverse width: 0.7719322 (length scale 1.138179)
     DISIM Variance: 1
     SIM decay: 0.4982639
     SIM Variance: 0.03224426
     RBF Variance: 1.754204
     Block 4
Normalised version of the kernel
DISIM decay: 0.07292779
DISIM inverse width: 0.7719322 (length scale 1.138179)
DISIM Variance: 1
SIM decay: 0.0001855218
SIM Variance: 0.003264679
RBF Variance: 1.754204
Log-likelihood: -31.83826

> # Learn a model without TF mRNA and TF protein translation
> nt_model <- GPLearn(drosophila_gpsim_fragment,
+ targets=c(twi, targetProbes[1:2]), quiet=TRUE)

3.4 Visualising the models
The models can be plotted using commands like

> GPPlot(st_models[[1]], nameMapping=getAnnMap("FLYBASE",
+ annotation(drosophila_gpsim_fragment)))
> GPPlot(mt_model, nameMapping=getAnnMap("FLYBASE",
+ annotation(drosophila_gpsim_fragment)))
> GPPlot(nt_model, nameMapping=getAnnMap("FLYBASE",
+ annotation(drosophila_gpsim_fragment)))

3.5 Ranking the targets
Bulk ranking of candidate targets can be accomplished using

> ## Rank the targets, filtering weakly expressed genes with average
> ## expression z-score below 1.8
> scores <- GPRankTargets(drosophila_gpsim_fragment, TF=twi,
+ testTargets=targetProbes,
+ options=list(quiet=TRUE),
+ filterLimit=1.8)
> ## Sort the returned list according to log-likelihood
> scores <- sort(scores, decreasing=TRUE)
> write.scores(scores)

To save space, GPRankTargets does not return the models by default. If those are needed later e.g. for plotting, they can be recreated using the inferred parameters saved together with the ranking using

> topmodel <- generateModels(drosophila_gpsim_fragment,
+ scores[1])
> show(topmodel)
[[1]]
Figure 1: Single target models for the gene FBgn0003486. The models for each repeated time series are shown in different columns.

Gaussian process driving input single input motif model:
Number of time points:
Driving TF: 143396_at
Target genes (1):
147995_at
Basal transcription rate:
Gene 1: 0.00014225304681563
Kernel:
Multiple output block kernel:
Block 1
Normalised version of the kernel.
RBF inverse width: 0.761269 (length scale 1.146122)
RBF variance: 1.803157
Block 2
Normalised version of the kernel
DISIM decay: 0.02034749
DISIM inverse width: 0.761269 (length scale 1.146122)
DISIM Variance: 1
3.6 Ranking using known targets with multiple-target models

Ranking using known targets with multiple-target models can be accomplished simply by adding the `knownTargets` argument.

```R
> ## Rank the targets, filtering weakly expressed genes with average expression z-score below 1.8
> scores <- GPRankTargets(drosophila_gpsim_fragment, TF=twi,
+                      knownTargets=targetProbes[1],
+                      testTargets=targetProbes[2:3],
+                      options=list(quiet=TRUE),
+                      filterLimit=1.8)
> ## Sort the returned list according to log-likelihood
```
**Figure 3:** Multiple-target model without TF protein translation for selected example genes. The call creates independent figures for each repeated time series.

```r
> scores <- sort(scores, decreasing=TRUE)
> write.scores(scores)

"log-likelihood" "null_log-likelihood"
"152715_at" -28.1319196770648 -539.73619673943
"147995_at" -240.395472709229 -487.893231050121
```

### 3.7 Running ranking in a batch environment

`GPRankTargets` can be easily run in a batch environment using the argument `scoreSaveFile`. This indicates a file to which scores are saved after processing each gene. Thus one could, for example, split the data to, say, 3 separate blocks according to the reminder after division by 3 and run each of these independently. The first for loop could then be run in parallel (e.g. as separate jobs on a cluster), as each step is independent of the others. After these have all completed, the latter loop could be used to gather the results.

```r
> for (i in seq(1, 3)) {
+   targetIndices <- seq(i,
```
4 Experimental feature: Using non-Affymetrix data

Using non-Affymetrix data, or data without associated uncertainty information for the expression data in general, requires more because of two reasons

- noise variances need to be estimated together with other model parameters; and
- weakly expressed genes cannot be easily filtered a priori.

The first of these is automatically taken care of by all the above functions, but the latter requires some extra steps after fitting the models.

In order to get started, you need to create an ExpressionTimeSeries object of your data set. This can be accomplished with the function

```r
> procData <- processRawData(data, times=c(...),
+ experiments=c(...))
```

Filtering of weakly expressed genes requires more care and visualising the fitted models is highly recommended to avoid mistakes.

Based on initial experiments, it seems possible to perform the filtering based on the statistic

\[
\log \text{likelihood}(scores) - \text{baseloglikelihoods}(scores),
\]

but selection of suitable threshold is highly dataset specific.

5 Exporting results to an SQLite database

The results of the analysis can be stored to an SQLite database. The database can then be browsed and queried using the tigreBrowser result browser. The data is inserted to the database by using export.scores function.

An example of the usage of export.scores is given below

```r
> export.scores(scores, datasetName="Drosophila",
+ experimentSet="GPSIM/GPDISIM",
+ database='database.sqlite',
```
In this example, scores is the return value of GPRankTargets, ‘Drosophila’ is the name of a dataset in database and ‘GPsim/GPDISIM’ is the name of an experiment set in database. In general, results with the same dataset name are considered to be part of same dataset. That is, if no results with a given dataset are already in the database, a new dataset entry is created. On the other hand, if the database already contains results with the same dataset name, new results will be added to the old dataset.

Also, results from different experiments can be combined into a set of experiments by giving them the same experiment set name. This is useful as a result browser may display results depending on the experiment set.

database.sqlite is the filename of a database file. The file will be created if it does not exist already.

The function will create model figures and add them to the database if preprocessed data is given. In this example, models are given to the function as a parameter. This is not necessary, however, as the function can create models if preprocessed data is supplied. Nevertheless, the function will finish faster if it does not have to (re-)create models.

In addition to log likelihoods and z-scores, this function will also export different gene names and aliases to the database. By default, the function will read GENENAME, SYMBOL and ENTREZID datas from relevant annotations and insert those into the database. The function takes also aliasTypes argument which is used to define which annotation information is inserted. In the example above, FLYBASE gene numbers are also added to the genes in the database. The insertion of alias annotations and z-scores requires that the preprocessed data is supplied.

6 Session Info

> sessionInfo()

R version 4.4.0 beta (2024-04-15 r86425)
Platform: x86_64-pc-linux-gnu
Running under: Ubuntu 22.04.4 LTS

Matrix products: default
BLAS: /home/biocbuild/bbs-3.19-bioc/R/lib/libRblas.so
LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.10.0

locale:
[1] LC_CTYPE=en_US.UTF-8 LC_NUMERIC=C
[2] LC_COLLATE=en_US.UTF-8 LC_CTYPE=en_US.UTF-8
[5] LC_MONETARY=en_US.UTF-8 LC_MESSAGES=en_US.UTF-8
[7] LC_PAPER=en_US.UTF-8 LC_NAME=C
[9] LC_ADDRESS=C LC_TELEPHONE=C

time zone: America/New_York
tzcode source: system (glibc)

attached base packages:
- [1] stats4
- [2] stats
- [3] graphics
- [4] grDevices
- [5] utils
- [6] datasets
- [7] methods
- [8] base

other attached packages:
- [1] drosognome1.db_3.13.0
- [2] org.Dm.eg.db_3.19.1
- [3] annotate_1.82.0
- [4] XML_3.99-0.16.1
- [5] AnnotationDbi_1.66.0
- [6] IRanges_2.38.0
- [7] S4Vectors_0.42.0
- [8] tigre_1.58.0
- [9] Biobase_2.64.0
- [10] BiocGenerics_0.50.0

loaded via a namespace (and not attached):
- [1] bit_4.0.5
- [2] jsonlite_1.8.8
- [3] BiocStyle_2.32.0
- [4] compiler_4.4.0
- [5] BiocManager_1.30.22
- [6] crayon_1.5.2
- [7] gtools_3.9.5
- [8] blob_1.2.4
- [9] bitops_1.0-7
- [10] Biostrings_2.72.0
- [11] png_0.1-8
- [12] yaml_2.3.8
- [13] fastmap_1.1.1
- [14] R6_2.5.1
- [15] XVector_0.44.0
- [16] GenomeInfoDb_1.40.0
- [17] knitr_1.46
- [18] GenomeInfoDbData_1.2.12
- [19] DBI_1.2.2
- [20] rlang_1.1.3
- [21] KEGGREST_1.44.0
- [22] cachem_1.0.8
- [23] caTools_1.18.2
- [24] bit64_4.0.5
- [25] RSQLite_2.3.6
- [26] memoise_2.0.1
- [27] cli_3.6.2
- [28] zlibbioc_1.50.0
- [29] digest_0.6.35
- [30] xtable_1.8-4
- [31] vctrs_0.6.5
- [33] evaluate_0.23
- [34] rmarkdown_2.26
- [35] httptr_1.4.7
- [36] pkgconfig_2.0.3
- [37] gplots_3.1.3.1
- [38] tools_4.4.0
- [39] htmltools_0.5.8.1
- [40] UCSC.utils_1.0.0

References

