



SOFTWARE TOOL ARTICLE

REVISED Using singscore to predict mutation status in acute myeloid leukemia from transcriptomic signatures [version 3; peer review: 2 approved]

Previously titled: Using singscore to predict mutations in acute myeloid leukemia from transcriptomic signatures

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Abstract

Advances in RNA sequencing (RNA-seq) technologies that measure the transcriptome of biological samples have revolutionised our ability to understand transcriptional regulatory programs that underpin diseases such as cancer. We recently published singscore - a single sample, rank-based gene set scoring method which quantifies how concordant the transcriptional profile of individual samples are relative to specific gene sets of interest. Here we demonstrate the application of singscore to investigate transcriptional profiles associated with specific mutations or genetic lesions in acute myeloid leukemia. Using matched genomic and transcriptomic data available through the TCGA we show that scoring of appropriate signatures can distinguish samples with corresponding mutations, reflecting the ability of these mutations to drive aberrant transcriptional programs involved in leukemogenesis. We believe the singscore method is particularly useful for studying heterogeneity within a specific subsets of cancers, and as demonstrated, we show the ability of singscore to identify where alternative mutations appear to drive similar transcriptional programs.

Keywords

single sample, gene set scoring, signature scoring, AML mutations, NPM1c mutation, mutation prediction, TCGA

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REVISED Amendments from Version 2

The updated workflow includes additional guidance on how to interpret results from singscore, especially in an unsupervised setting where labels for data are unavailable and further context on how this relates to alternative approaches. We also demonstrate the ability of our visualisation functions to label individual samples, further assisting in result interpretation

Any further responses from the reviewers can be found at the end of the article

Introduction

The development of microarrays and more recently the rapid uptake of RNA-sequencing technologies have provided a platform to examine the transcriptional profile (or transcriptome) of biological samples¹. Transcriptomic analyses have traditionally focused on ‘differential expression’ of genes between sets of samples, however with the rapid growth of publicly available RNA data there has been increasing usage of ‘relative approaches’, which quantify the relative concordance of a sample or samples with a specific gene signature¹. While sequencing of genomic mutations has been important for classifying different tumour subsets based upon the presence of mutations or fusion genes, and identifying genetic lesions which may act as drivers of cancer progression, transcriptomic profiling can provide further information on the state or phenotype of cells carrying these mutations. Cancers are a heterogeneous set of diseases with a number of clinical and pathological subtypes. In diseases such as breast cancer the primary clinical classifications relate to the expression of hormone receptors (estrogen receptor: ER; and progesterone receptor: PR) or the overexpression of Erb-B2 receptor tyrosine kinase (*HER2*), as these features can be directly targeted with therapeutic agents. A common example of transcriptomic or gene expression data informing clinical practice is the use of prediction analysis of microarray 50 (PAM50) signatures for distinguishing the intrinsic breast cancer subtypes [2, Cieřlik and Chinnaiyan¹]. For many other cancers, subtype classification has largely relied upon identifying sets of recurrent mutations across large patient cohorts, with whole genome or whole exome sequencing studies helping to resolve the clinically significant subtypes [3, Papaemmanuil *et al.*⁴].

Perhaps the most well-known ‘relative approach’ is single-sample gene set enrichment analysis (ssGSEA)⁵, often used through the [GenePattern web-tool](#). Another common approach is [gene set variation analysis \(GSVA\)](#)⁶ which is available as an R/Bioconductor package that also includes functionality for ssGSEA, an alternative approach known as PLAGE⁷, and a z-score based approach⁸. Both ssGSEA and GSVA use a Kolmogorov-Smirnov like random-walk statistic to convert normalised gene ranks to the resulting score, however this normalisation procedure means that the scores are not truly ‘single-sample’, and variations in the overall sample composition for a study (e.g. variations in the presence or relative frequency of different cancer subtypes) can lead to unexpected changes in sample scores. Furthermore, the resultant scores from these methods can vary in their range and absolute value, making them difficult to interpret without further processing. To overcome this, we have developed a single-sample gene set scoring method [singscore](#)⁹ which simply uses the ranks of genes within a given set, normalised relative to the maximum and minimum theoretical scores for a gene set of a given size.

Through large scale efforts such as The Cancer Genome Atlas (TCGA), transcriptomic data are available for thousands of clinical samples, often together with corresponding genomic or epigenomic (often DNA methylation) data. These transcriptomic data can help to characterise the functional effects of corresponding mutations, and provide a window to study the heterogeneity which arises within different subtypes of cancer due to epigenetic and transcriptional regulatory programs which can also influence cell behaviour. Here, we demonstrate that the single-sample gene set scoring method [singscore](#)⁹ can be used to classify TCGA AML samples using transcriptional ‘gene signatures’ for the NPM1c mutation, *KMT2A (MLL)* gene fusions, and *PML-RARA* gene fusions that were derived from independent studies. Without any need for parameter fitting or estimation, we show that gene set scoring with [singscore](#) can distinguish samples carrying these mutations. The case studies we present demonstrate the application of gene set scoring to examine not only the differences, but also the relative similarities between established subtypes of AML that impact clinical outcome. This workflow is available as a bioconductor workflow package from <https://bioconductor.org/packages/release/workflows/html/SingscoreAMLMutations.html>.

Description of the biological problem

As with most cancers, acute myeloid leukemia (AML) is a heterogeneous disease with a number of classified subtypes. Analysis of TCGA AML genomic data identified a number of subtypes based upon the presence or absence of specific ‘driver mutations’; recapitulating and expanding upon previously identified clinical subsets³. A more recent study which focused primarily on genomic data has further refined the clinically significant AML subtypes⁴, highlighting a number of co-occurring as well as mutually exclusive mutations. As the identification of putative driver fusions/mutations continues, work has also been directed towards how these lesions interact with each other and other features (e.g. cellular proliferation, changes due to phenotypic plasticity, or variation in post-transcriptional regulators such as microRNAs) to drive transcriptional changes as discussed in a recent review¹⁰.

Of note for this work, one of the most common mutations in clinical AML samples is a frameshift mutation within exon 12 of the nucleophosmin (*NPM1*) gene⁴. This mutation leads to aberrant localisation of nucleophosmin with cytoplasmic accumulation rather than localising to the nucleolus, and accordingly this mutation is often referred to as the NPM1c mutation¹¹. As noted by Verhaak *et al.*¹², the NPM1c mutation is associated with dysregulated activity of the homeobox domain (Hox) family of transcription factors which are essential for developmental patterning. The effects of this mutation in disease progression have been further demonstrated in recent work which showed that loss of NPM1c leads to differentiation of AML cells¹¹.

Further recurrent genetic lesions in AML relevant for this work include lysine methyl transferase 2A (*KMT2A*; previously known as *MLL*) fusion genes, partial tandem duplications within *KMT2A* (*KMT2A-PTD*), and fusion genes between promyelocytic leukemia and retinoic acid receptor alpha (*PML-RARA*). Given the role of NPM1c in dysregulating the Hox gene family, it is interesting to note that AML samples with *MLL* fusion genes also show dysregulated expression of Hox family genes [13, Ross *et al.*¹⁴]; however, samples with *MLL-PTD* appear to show a relatively distinct phenotype from *MLL*-fusion samples¹⁴. While there is good evidence demonstrating the role of NPM1c mutations and other genetic lesions in blocking AML cell differentiation, the *PML-RARA* fusion subset is diagnostic for a specific subset of AML known as acute promyelocytic leukemia (APL). This clinically distinct subtype of AML is associated with a specific morphology under the French-American-British (FAB) classification of AML, FAB-M3, with cells showing a distinct morphology due to a differentiation block at the promyelocyte stage¹⁵.

In this workflow we demonstrate the ability of the singscore method for single sample gene set scoring⁹ to classify tumour ‘driver mutations’ from transcriptomic data. We use a previously identified gene signature for the NPM1c mutation¹². We also use signatures for *PML-RARA* gene fusions and *MLL*-fusions that were derived using pediatric AML samples but shown to work well for classifying adult AML samples with similar lesions¹⁴, although we note that there is evidence of relatively large differences in the mutational profiles of adult and pediatric cancers¹⁶. Using these signatures, which are included within the molecular signatures database (MSigDB)¹⁷, we demonstrate that a bi-directional scoring approach can classify TCGA AML samples with corresponding mutations with a good precision and recall. A particularly useful feature of gene set scoring is the ability to project samples onto 2D or higher-order landscapes defined by corresponding phenotypic signatures. Accordingly, by comparing scores for both the NPM1c and *KMT2A-MLL*-fusion signatures, we show that this classification likely arises through the shared downstream biological effects of Hox family dysregulation. We also compare the NPM1c mutation signature to the *PML-RARA* signature and show a clear separation of these subtypes reflecting their divergent phenotypes and the mutually exclusive nature of these mutations.

While we demonstrate that singscore is capable of inferring mutation status from the transcriptional profile of AML samples, we note that it is best used to supplement alternative data which can provide a more definitive resolution of these lesions. Processing of raw RNA seq data will directly identify the presence of gene fusion products or mutations within protein-coding regions, although for many large data sets the quantified transcript abundance data are much easier to obtain without access agreements. The method can also be applied to legacy microarray data sets where genome and RNA sequencing data are unavailable. As such singscore provides a useful approach to supplement established methods for the study of genetic lesions in cancer. By exploring associations between different genomic and phenotypically relevant signatures, it may also help to better characterise true driver mutations which exert consistent effects on the transcriptome of AML samples and other cancers.

Downloading and preparing the data

Data from TCGA project is made available through the Genomic Data Commons (GDC). Open access data from the project can be accessed in multiple pre-processed formats. Transcriptomic data can be downloaded either at the count level or as FPKM transformed abundance, before or after upper quantile normalisation. Other pre-processed version can be found from sources such as the [cBioPortal](#) and [FireBrowse](#). The GDC data used STAR to perform a two-pass alignment followed by quantification using HTSeq. Data from the GDC can be downloaded using the [GDC data transfer tool](#) which allows users to select the specific files of interest using the GDC portal. These files then have to be read, merged, annotated and processed into a data structure that simplifies downstream analysis. Alternatively, all the above mentioned steps, including the download, can be performed using the R package [TCGAbiolinks](#)¹⁸. The package supports data download using the GDC API and the GDC client. We will use the TCGAbiolinks package to download, annotate and process the data into a SummarizedExperiment R object.

The following steps need to be performed to prepare the data:

1. Create a query to select the files to download
2. Execute the query and download the data
3. Read the data into R
4. Filter out genes with low expression
5. Normalise the data for compositional bias and transform to account for gene-length biases as outlined in the [singscore manuscript](#)⁹

Querying the GDC database

The first step in any analysis should be to determine and report the data version and the service used to download the data. The `getGDCInfo()` function returns the release date of all data on the GDC along with a version.

```
library(SingscoreAMLMutations)
library(TCGAbiolinks)

#get GDC version information
gdc_info = getGDCInfo()
gdc_info

## $commit
## [1] "b18b2385b1e916597856067dc6437f3c20b46bca"
##
## $data_release
## [1] "Data Release 19.0 - September 17, 2019"
##
## $status
## [1] "OK"
##
## $tag
## [1] "1.22.0"
##
## $version
## [1] 1
```

A query then needs to be run, using the GDC to identify the specific files for download. This step is similar to generating a *MANIFEST* file using the GDC portal. The first parameter of the query specifies the project - available projects can be accessed using `getGDCprojects()` or from <https://portal.gdc.cancer.gov/projects>. The TCGA acute myeloid leukemia data is part of the TCGA-LAML project. Following this, the data category, data type and workflow type need to be specified. The query formed below selects files containing the count level transcriptomic measurements. Values for different parameters of the query can be identified from “searching

arguments” section of the “query” vignette: `vignette("query", package = "TCGAbiolinks")`. The result of this query will be a dataframe containing filenames and additional annotations related to the files.

Read count level data are selected instead of the processed FPKM data as one of the downstream pre-processing analysis results in filtering out of genes. A general recommendation is to compute FPKM values after filtering genes out so as to ensure counts are normalised by the corresponding library sizes. In cases where count-level data is not available, filtering can be performed directly on FPKM values, provided that the library size is large enough.

```
#form a query for the RNAseq data
query_rna = GDCquery(
  #getGDCprojects()
  project = 'TCGA-LAML',
  #TCGAbiolinks:::getProjectSummary('TCGA-LAML')
  data.category = 'Transcriptome Profiling',
  data.type = 'Gene Expression Quantification',
  workflow.type = 'HTSeq - Counts'
)

#extract results of the query
rnaseq_res = getResults(query_rna)
dim(rnaseq_res)
```

```
## [1] 151 28
```

```
colnames(rnaseq_res)
```

```
## [1] "data_release"           "data_type"
## [3] "updated_datetime"      "file_name"
## [5] "submitter_id"          "file_id"
## [7] "file_size"             "cases"
## [9] "id"                    "created_datetime"
## [11] "md5sum"                "data_format"
## [13] "access"                "state"
## [15] "version"               "data_category"
## [17] "type"                  "experimental_strategy"
## [19] "project"               "analysis_id"
## [21] "analysis_updated_datetime" "analysis_created_datetime"
## [23] "analysis_submitter_id"  "analysis_state"
## [25] "analysis_workflow_link" "analysis_workflow_type"
## [27] "analysis_workflow_version" "tissue.definition"
```

Downloading the TCGA AML RNA-seq read counts

The `GDCdownload` function then executes the query on the GDC database and begins downloading the data using the GDC API. The download method should be changed to “client”, if the size of the data is expected to be large, e.g for RNA-seq read data or methylation data. It is good practice to specify the directory for data storage - we store all the data in the “GDCdata” directory in the temporary directory. Users should store their data in a permanent storage to retain the data. The function downloads the data and organises it into the folder based on parameters specified in the query. This allows multiple different levels and types of data to be stored in the same directory structure. Files with counts are stored at *TEMPDIR/GDCdata/TCGA-LAML/harmonized/Transcriptome_Profiling/Gene_Expression_Quantification/*.

```
datapath = file.path(tempdir(), 'GDCdata')
GDCdownload(query_rna, directory = datapath) #(size: 39MB)
```

Reading count-level data into R

The `GDCprepare` function reads and processes the downloaded data into a `RangedSummarizedExperiment` object from the `SummarizedExperiment` package which allows patient annotations, gene annotations and count data to be stored in one object. Patient annotations are downloaded upon calling this function and subsequently mapped and attached to the resulting object. A `RangedSummarizedExperiment` object is similar to an `ExpressionSet` object but provides added functionality such as indexing with genomic coordinates and storing multiple data matrices with the same structure. Feature annotations used to annotate the data are stored in an `RDA/RDATA` file.

```
aml_se = GDCprepare(query_rna, directory = datapath)
```

The object contains data for 56,925 features and 151 samples. The original data files contain 60,483 features, some of which (3,881) could not be mapped to ENSEMBL GRCh38.p12. Feature and sample annotations can be accessed using `rowData(se)` and `colData(se)`, respectively, and the counts data can be accessed using `assay(se)`. TCGA data usually contains some formalin-fixed paraffin-embedded (FFPE) samples which should be discarded from the analysis as the protocol introduces biological artefacts. This procedure is only performed on solid tumours and not leukemias, therefore, no filtering is required for this data set.

```
aml se
```

```
## class: RangedSummarizedExperiment
## dim: 56512 151
## metadata(1): data_release
## assays(1): HTSeq - Counts
## rownames(56512): ENSG000000000003 ENSG000000000005 ...
##   ENSG00000281912 ENSG00000281920
## rowData names(3): ensembl_gene_id external_gene_name
##   original_ensembl_gene_id
## colnames(151): TCGA-AB-3001-03A-01T-0736-13
##   TCGA-AB-2853-03A-01T-0734-13 ... TCGA-AB-2977-03B-01T-0760-13
##   TCGA-AB-2995-03A-01T-0735-13
## colData names(61): sample patient ... name is_ffpe
```

Filter out genes with low counts

The `edgeR` package contains methods that assist in the data normalisation and transformation required for filtering and subsequent steps. The methods require a `DGEList` object therefore we begin by creating a `DGEList` for the AML data from the `SummarizedExperiment`.

```
library(SummarizedExperiment)
library(edgeR)

aml_dge = DGEList(counts = assay(aml_se), genes = rowData(aml_se))
```

Genes with low counts across most samples are discarded from the analysis. This is a standard step in differential expression analysis as inclusion of such genes in the analysis could skew estimates of dispersion. It is also motivated in rank-based analysis, such as with `singscore`, to avoid rank duplication. Rank duplication reduces the discriminant power of scores as the number of unique ranks is reduced. A commonly used filter is to select only those genes that have CPMs above a certain threshold across a proportion of samples. Filtering is performed on the CPMs rather than raw counts as the former accounts for variation in library sizes, therefore, is unbiased. For instance, a CPM of 1 would equate to read counts between 19 and 50 for samples in the AML data where library sizes vary between 18.6 and 49.7 million reads. Here, we retain genes that have a CPM > 1 across more than 50% of the samples. Other methods to filter out genes with low counts exist and may be preferable in specific applications. Chen *et al.*¹⁹ and Law *et al.*²⁰ filter genes based on the experimental design whereby the proportion of samples with enough read counts are evaluated per experimental group. As the AML data have many samples, filtering is performed across all samples rather than within sub-groups. Group specific filtering would be recommended for the study of rare groups. The distribution of `logCPMs` is much closer to the expected log-normal distribution after filtering out genes with low counts as seen in [Figure 1](#).

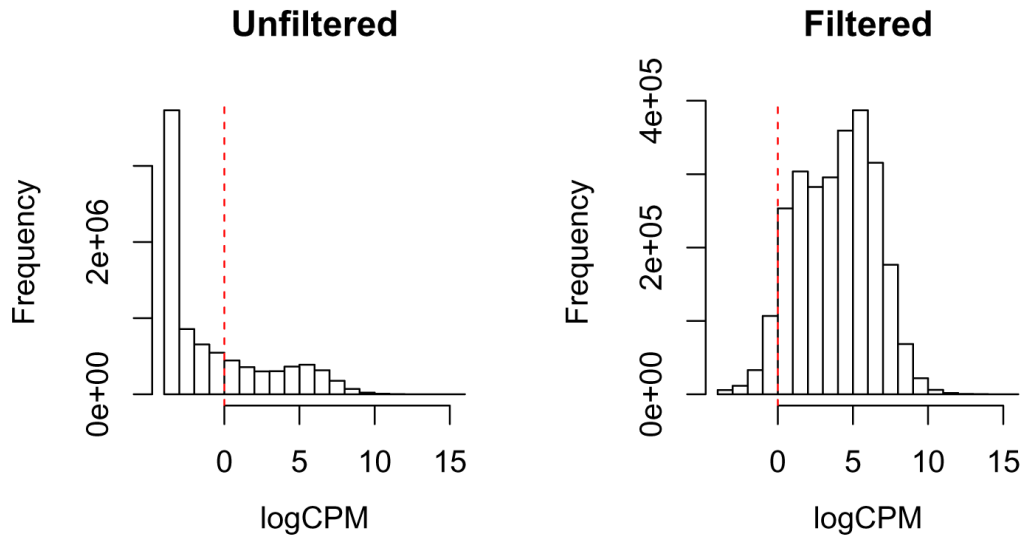


Figure 1. Histogram of logCPM values for the AML data before and after filtering. Filtering results in fewer zeros in the data. Most genes with CPM less than 1, $\log\text{CPM} < 0$; (red line) across the majority of samples get discarded, resulting in an approximately log-normal distribution.

```
prop_expressed = rowMeans(cpm(aml_dge) > 1)
keep = prop_expressed > 0.5

op = par(no.readonly = TRUE)
par(mfrow = c(1, 2))
hist(cpm(aml_dge, log = TRUE), main = 'Unfiltered', xlab = 'logCPM')
abline(v = log(1), lty = 2, col = 2)
hist(cpm(aml_dge[keep, ], log = TRUE), main = 'Filtered', xlab = 'logCPM')
abline(v = log(1), lty = 2, col = 2)
```

```
par(op)
```

```
#subset the data
aml_dge = aml_dge[keep, , keep.lib.sizes = FALSE]
aml_se = aml_se[keep, ]
```

Transformation to FPKM values and normalisation

Singscore requires gene expression measurements to be comparable between genes within a sample, therefore, correction for gene length bias needs to be performed²¹. Transformations such as transcripts per million (TPM) and reads/fragments per kilobase per million (RPKM/FPKM), that normalise by gene length, may be used. Both TPM and RPKM/FPKM values should produce similar results when applying singscore provided that the library size is large enough, which they are here. RPKM values are generally computed after correcting for compositional biases. The `calcNormFactors` function in edgeR provides three methods to do so, TMM normalisation being the default. Chen *et al.*¹⁹ and Law *et al.*²⁰ discuss the implications of normalisation prior to down-stream processing such as differential expression analysis. Normalisation is generally performed for cross-sample analysis where samples need to be comparable. Singscores are invariant to data normalisation as the analysis is contained within the sample of interest. The idea extends to any transformation that preserves the relative ranks of genes within a sample such as a log transformation. Here, we use TMM normalisation solely for visualisation purposes.

Data transformation to TPM or RPKM/FPKM requires the lengths for all genes to be calculated. Gene lengths need to be computed based on the alignment and quantification parameters. The TCGA transcriptomic data has been aligned using STAR and quantified using HTSeq (details of the pipeline available at https://docs.gdc.cancer.gov/Data/Bioinformatics_Pipelines/Expression_mRNA_Pipeline/).

HTSeq quantifies reads mapping to the exons of each gene, therefore, effective gene lengths can be calculated as the sum of all exons spanning the gene. The GENCODE v22 annotation file was used for quantification therefore the same file needs to be used to compute gene lengths.

```
#download v22 of the GENCODE annotation
gencode_file = 'gencode.v22.annotation.gtf.gz'
gencode_link = paste(
  'ftp://ftp.ebi.ac.uk/pub/databases/gencode/Gencode_human/release_22',
  gencode_file,
  sep = '/'
)
download.file(gencode_link, gencode_file, method = 'libcurl') #(size: 39MB)
```

The rtracklayer R package provides functions to help parse GTF files.

```
library(rtracklayer)
library(plyr)

gtf = import.gff(gencode_file, format = 'gtf', genome = 'GRCm38.71', feature.type = 'exon')
#split records by gene to group exons of the same gene
grl = reduce(split(gtf, elementMetadata(gtf)$gene_id))
gene_lengths = ldply(grl, function(x) {
  #sum up the length of individual exons
  return(c('gene_length' = sum(width(x))))
}, .id = 'ensembl_gene_id')
```

Genes are also annotated with their biotype for further analysis. The annotation file uses Ensembl IDs with versions as keys to records, which then need to be converted to Ensembl IDs. This is simply achieved by truncating the trailing version number.

```
#extract information on gene biotype
genetype = unique(elementMetadata(gtf)[, c('gene_id', 'gene_type')])
colnames(genetype)[1] = 'ensembl_gene_id'
gene_lengths = merge(genetype, gene_lengths)

#remove ENSEMBL ID version numbers
gene_lengths$ensembl_gene_id = gsub('\\.[0-9]*', '', gene_lengths$ensembl_gene_id)
saveRDS(gene_lengths, file = 'gene_lengths_HTSeq_gencodev22.rds')
gene_lengths
```

```
## DataFrame with 60483 rows and 3 columns
##      ensembl_gene_id      gene_type gene_length
##      <character>      <character> <integer>
## 1  ENSG00000000003  protein_coding      4535
## 2  ENSG00000000005  protein_coding      1610
## 3  ENSG00000000419  protein_coding      1207
## 4  ENSG00000000457  protein_coding      6883
## 5  ENSG00000000460  protein_coding      5967
## ...                ...                ...
## 60479 ENSGR0000275287      misc_RNA      290
## 60480 ENSGR0000276543      miRNA      68
## 60481 ENSGR0000277120      miRNA      64
## 60482 ENSGR0000280767      lincRNA     515
## 60483 ENSGR0000281849      antisense     484
```

The SummarizedExperiment object allows feature annotations to be stored, therefore, information on gene length and biotypes should be added to the existing annotations. Similarly, annotations need to be added to the DGEList object. The column containing lengths should include “length” in its name.

```
#allocate rownames for ease of indexing
rownames(gene_lengths) = gene_lengths$ensembl_gene_id
rowData(aml_se)$gene_length = gene_lengths[rownames(aml_se), 'gene_length']
rowData(aml_se)$gene_biotype = gene_lengths[rownames(aml_se), 'gene_type']

#annotate gene lengths for the DGE object
aml_dge$genes$length = gene_lengths[rownames(aml_dge), 'gene_length']
```

RPKM/FPKM values can now be calculated with the computed gene lengths after computing the normalisation factors. The SummarizedExperiment object can store multiple levels of the data simultaneously, provided that the number of features and samples remains the same across measurements. As such, FPKM values are appended to the existing object.

```
aml_dge_tmm = calcNormFactors(aml_dge, method = 'TMM')

#compute FPKM values and append to assays
assay(aml_se, 'logFPKM_TMM') = rpkm(aml_dge_tmm, log = TRUE)
aml_se
```

```
## class: RangedSummarizedExperiment
## dim: 17412 151
## metadata(1): data_release
## assays(2): HTSeq - Counts logFPKM_TMM
## rownames(17412): ENSG00000000419 ENSG00000000457 ...
##   ENSG00000281772 ENSG00000281896
## rowData names(5): ensembl_gene_id external_gene_name
##   original_ensembl_gene_id gene_length gene_biotype
## colnames(151): TCGA-AB-3001-03A-01T-0736-13
##   TCGA-AB-2853-03A-01T-0734-13 ... TCGA-AB-2977-03B-01T-0760-13
##   TCGA-AB-2995-03A-01T-0735-13
## colData names(61): sample patient ... name is_ffpe
```

Annotate samples with mutation data

For this analysis we have used the curated mutation list from the original TCGA AML publication³ (Supplemental Table 01 at <https://gdc.cancer.gov/node/876>) rather than variant calls from the standard TCGA pipeline (available through the [National Cancer Institute Genomic Data Commons](#)) and readers should note that there are some discrepancies between these. For genetic lesions of interest (NPM1c, *KMT2A-MLL*, *KMT2A-PTD* and *PML-RARA*), patients were identified by the following criteria:

- **Patient ID:** The 'TCGA Patient ID' column was extracted directly
- **NPM1c:** TRUE if the 'NPM1' column contains the strings 'p.W287fs' or 'p.W288fs'
- **KMT2A-fusion:** TRUE if the 'MLL-partner' column contains the string 'MLL-' or '-MLL' (note that the official gene symbol for *MLL* is now *KMT2A*)
- **KMT2A-PTD:** TRUE if the 'MLL-PTD' column contains the string 'exons'
- **PML-RARA:** TRUE if the 'PML-RARA' column contains the string 'PML-RARA'

```
data(AMLPatientMutationsTCGA)
patient_mutations = AMLPatientMutationsTCGA
patient_mutations = patient_mutations[colnames(aml_se), ] # order samples
aml_mutations = colnames(patient_mutations) # get mutation labels
colData(aml_se) = cbind(colData(aml_se), patient_mutations)
colData(aml_se)[, aml_mutations]
```

```
## DataFrame with 151 rows and 4 columns
##           NPM1c.Mut KMT2A.Fusion KMT2A.PTD PML.RARA
##           <logical> <logical> <logical> <logical>
## TCGA-AB-3001-03A-01T-0736-13 FALSE FALSE FALSE TRUE
## TCGA-AB-2853-03A-01T-0734-13 TRUE FALSE FALSE FALSE
## TCGA-AB-2929-03A-01T-0735-13 FALSE FALSE FALSE FALSE
## TCGA-AB-2939-03A-01T-0740-13 FALSE FALSE FALSE FALSE
## TCGA-AB-2982-03B-01T-0748-13 FALSE FALSE FALSE TRUE
## ...
## TCGA-AB-2815-03A-01T-0734-13 FALSE FALSE FALSE FALSE
## TCGA-AB-3000-03A-01T-0736-13 FALSE FALSE FALSE FALSE
## TCGA-AB-2919-03A-01T-0740-13 TRUE FALSE FALSE FALSE
## TCGA-AB-2977-03B-01T-0760-13 FALSE FALSE TRUE FALSE
## TCGA-AB-2995-03A-01T-0735-13 FALSE FALSE FALSE FALSE
```

Map Ensembl IDs to Entrez IDs

Ensembl annotations (Ensembl IDs) have higher coverage of the genome which may be useful in applications such as variant calling and similar exploratory analysis²². However, RefSeq annotations (Entrez IDs) may be better suited to RNA-seq analyses which require a stable reference annotation for comparison²³. As such, we choose to map Ensembl IDs to Entrez IDs and discard any unmapped features.

Mapping can be performed using the Ensembl Biomart service, which can be queried using the biomaRt bioconductor package. This would provide the most up to date annotations. Alternatively, mapping could be performed with the bi-annually updated `org.Hs.eg.db` annotation R package which provides a stable set of annotations, thereby enhancing reproducibility. Mapping is performed with the `mapIds` function in the `AnnotationDbi` R package.

```
library(org.Hs.eg.db)

rowData(aml_se)$entrezgene = mapIds(
  org.Hs.eg.db,
  keys = rownames(aml_se),
  keytype = 'ENSEMBL',
  column = 'ENTREZID',
  multiVals = 'asNA'
)
gene_annot = rowData(aml_se)
```

Multimapped Ensembl IDs are replaced by NAs, then discarded to enforce unique mapping. Similarly, Entrez IDs that map to multiple Ensembl IDs are identified from the mapping, and discarded. Only features with unique Ensembl ID to Entrez ID mappings remain.

```
#select genes with mapped Entrez IDs
keep = !is.na(gene_annot$entrezgene)

#select genes with unique Entrez IDs
dup_entrez = gene_annot$entrezgene[duplicated(gene_annot$entrezgene)]
keep = keep & !gene_annot$entrezgene %in% dup_entrez

#Biotype of discarded genes (due to non-unique mapping)
head(sort(table(gene_annot[!keep, 'gene_biotype']), decreasing = TRUE), n = 10)
```

```
##
##           processed_pseudogene           antisense
##                   1017                   903
##                   lincRNA                   TEC
##                   451                   263
```

```
##           sense_intronic           protein_coding
##                249                138
##   unprocessed_pseudogene transcribed_unprocessed_pseudogene
##                128                93
##   processed_transcript   transcribed_processed_pseudogene
##                72                72

#subset the data
aml_se = aml_se[keep, ]
```

Transcriptional signatures to predict mutation status

The signature by Verhaak *et al.*¹² is now used to predict the mutation status of the NPM1c mutation. This is done by quantifying the concordance of genes in the signature with their expression in each sample. As such, high expression of up-regulated genes and low expression of down-regulated genes would result in higher scores. This single value can then be used to predict the mutation status of individual samples if these data were unavailable.

The signatures of interest are first downloaded from the MSigDB and read into *GeneSet* objects from the *GSEABase* R package. We then use the *singscore* R/Bioconductor package to quantify each sample for the Verhaak signature. Some of the visualisation and diagnostic tools within the *singscore* package are used to interpret the signatures and scores. Finally, we use a simple logistic regression model on the scores to predict the mutation status.

Download signature and load into R

The Verhaak *et al.*¹² signature is composed of an up-regulated and a down-regulated gene set. Many signatures are developed in such a manner to improve discrimination of samples. MSigDB stores such signatures using names with suffixes “_UP” and “_DN” representing the independent components of the signature. Here, we form the download links for the signature with the base name “VERHAAK_AML_WITH_NPM1_MUTATED”.

```
#create signature names
verhaak_names = paste('VERHAAK_AML_WITH_NPM1_MUTATED', c('UP', 'DN'), sep = '_')
verhaak_names

## [1] "VERHAAK_AML_WITH_NPM1_MUTATED_UP" "VERHAAK_AML_WITH_NPM1_MUTATED_DN"
```

The signatures are then downloaded using the links, resulting in an XML file for each component of the signature. The *mapply* function is used to run the download function on all pairs of link-output arguments.

```
#generate URLs
verhaak_links = paste0(
  'http://software.broadinstitute.org/gsea/msigdb/download_geneset.jsp?geneSetName=',
  verhaak_names,
  '&fileType=xml'
)

#download files
verhaak_files = paste0(verhaak_names, '.xml')
mapply(download.file, verhaak_links, verhaak_files, method = 'libcurl')
```

Functions in the *GSEABase* package help with reading, parsing and processing the signatures. Signatures from an MSigDB XML file can be read using the *getBroadSets* function which results in a *GeneSet* object. Gene symbols, Entrez IDs and affymetrix chip IDs from the original experiment (HG-U133A in this case) are stored in the XML file. Entrez IDs are read from the file as these can be mapped directly to our data. Conversions to other identifiers can be achieved using the *mapIdentifiers* function from *GSEABase* and an annotation package that contains the mappings. The advantage of using this function instead of the *mapIds* function from the *AnnotationDbi* package is that the former retains the *GeneSet* object after conversion of IDs.

```
library(GSEABase)

verhaak_sigs = getBroadSets(verhaak_files, membersId = 'MEMBERS_EZID')
verhaak_sigs

## GeneSetCollection
## names: VERHAAK_AML_WITH_NPM1_MUTATED_UP, VERHAAK_AML_WITH_NPM1_MUTATED_DN (2 total)
## unique identifiers: 10051, 10135, ..., 9828 (435 total)
## types in collection:
## geneIdType: SymbolIdentifier (1 total)
## collectionType: BroadCollection (1 total)
```

To make data indexing easier during signature scoring, row names of the SummarisedExperiment object are changed to Entrez IDs which are already part of the row annotations.

```
rownames(aml_se) = rowData(aml_se)$entrezgene
```

Score TCGA AML samples using the Verhaak signature

Singscore is a rank based metric of gene set enrichment in single samples. Scores for multiple signatures make use of the same ranked expression per sample. As such, it makes sense to compute the ranks only once and re-use them for scoring different signatures. The implementation separates these two phases of the analysis to reduce the computational cost of scoring. The rankGenes function will compute ranks from expression data in the form of either a numeric matrix, numeric data frame, ExpressionSet object, DGEList object or a SummarizedExperiment object. Users also have to specify what method should be used to break ties. The default is 'min' and we recommend this be used for RNA-seq data which may have many genes with zero counts. This will reduce the effect of zeros in the scores, however, appropriate pre-filtering of genes with low counts will still be required.

```
library(singscore)

#apply the rankGenes method to each version of the dataset, excluding counts
aml_ranked = rankGenes(assay(aml_se, 'logFPKM_TMM'))
```

Singscores can be computed using three modes, depending on the properties of the gene signature. The first mode of operation is applied when two directed gene sets (expected up- and down-regulated gene sets) form the transcriptomic signature. Many signatures in the MSigDB, including the Verhaak *et al.*¹² signature come in such pairs. This mode can be invoked by passing the up- and down-regulated gene sets to the arguments upSet and downSet respectively. In some cases, only one set of genes forms the signature. If all genes in the gene set are up-regulated or all down-regulated, the second mode of operation applies and is invoked by passing the gene set to the upSet argument. For sets of down-regulated genes, the score would simply be inverted (-score if scores are centered, 1 - score otherwise). Finally, if the user is unsure of the composition of genes in the gene-set, such that, the gene set may contain both up- and down- regulated genes, the final mode of singscore applies. The gene set is passed to the upSet argument similar to the previous mode with the additional argument knownDirection set to FALSE.

By default, singscores are centered such that the range of scores is [-1, 1] and [-0.5, 0.5] for the first two modes respectively. Negative scores indicate an inverse enrichment of signatures, that is, expected up-regulated genes are in fact down-regulated and vice-versa. Scores from the last mode can not be centered and have the range [0, 1]. In this mode, high scores are obtained when ranks of genes are distant from the median and low scores obtained when ranks converge to the median rank. If scores are centered in this scenario, it would lead to the conclusion that a negative score shows inverted enrichment, which is not the case. Score centering only serves the purpose of easing interpretation for users, a simple linear transformation is applied to achieve it.

Scores for the NPM1c mutation signature are computed using the default settings, with the first mode of operation being used due to the presence of an up- and down- regulated gene set. The function returns a data frame reporting the score and dispersion of ranks for the up-regulated gene set, down-regulated gene set and the combination of both. Dispersion of the combined gene set in this mode is simply the mean of the independent

dispersion estimates. If any gene names/IDs are present in the signature but missing in the expression data, a warning will be reported.

```
#apply the scoring function
verhaak_scores = simpleScore(aml_ranked,
                             upSet = verhaak_sigs[[1]],
                             downSet = verhaak_sigs[[2]])

## Warning in checkGenes(upSet, rownames(rankData)): 24 genes missing: 10265,
## 108, 10924, 11025, 11026, 1672, 200315, 2212, 2215, 3215, 3216, 3569, 3627,
## 3759, 50486, 6346, 6364, 6967, 8337, 861, 8843, 9518, 9627, 9997

## Warning in checkGenes(downSet, rownames(rankData)): 29 genes missing:
## 10232, 10267, 11217, 2122, 221981, 2258, 23532, 24141, 25907, 2697, 28526,
## 28638, 3047, 3386, 3848, 3934, 4070, 445, 4680, 4681, 5457, 5790, 6091,
## 653067, 653145, 7441, 8277, 862, 8788
```

It should be noted that singscores are composed of two components, an enrichment score and a dispersion estimate of ranks. The quantity of interest in gene set enrichment is the distribution of the expression or ranks of genes in the signature. In an ideal scenario, all expected up-regulated genes would have high expression therefore higher values of ranks. As such, ranks would be distributed on the higher end of the entire rank spectrum. Singscore aims to quantify this distribution of ranks, therefore, computes and reports the average and dispersion of ranks of genes in the signature relative to all other genes. The first quantity is similar to scores computed from all other single sample scoring methods. We determined a two component score to be a more appropriate and accurate representation of the distribution of ranks of signature genes. The default and recommended measure of dispersion is the median absolute deviation (MAD) due to its non-parametric property. Other appropriate measure of dispersion could be the inter-quartile range (IQR) and can be used by passing the IQR function as an argument to the dispersionFun argument.

```
head(verhaak_scores)
```

	TotalScore	TotalDispersion	UpScore
## TCGA-AB-3001-03A-01T-0736-13	-0.09161242	5256.929	-0.0768291807
## TCGA-AB-2853-03A-01T-0734-13	0.19605308	4882.943	0.0353047490
## TCGA-AB-2929-03A-01T-0735-13	-0.07106828	5443.737	0.0006426157
## TCGA-AB-2939-03A-01T-0740-13	-0.09795161	5697.632	-0.0599342558
## TCGA-AB-2982-03B-01T-0748-13	-0.11011396	5464.122	-0.0986913016
## TCGA-AB-2813-03A-01T-0736-13	0.15487900	4694.653	0.1385452964
	UpDispersion	DownScore	DownDispersion
## TCGA-AB-3001-03A-01T-0736-13	4513.034	-0.01478324	6000.823
## TCGA-AB-2853-03A-01T-0734-13	5868.872	0.16074833	3897.014
## TCGA-AB-2929-03A-01T-0735-13	5152.035	-0.07171089	5735.438
## TCGA-AB-2939-03A-01T-0740-13	4977.829	-0.03801735	6417.434
## TCGA-AB-2982-03B-01T-0748-13	5024.531	-0.01142266	5903.713
## TCGA-AB-2813-03A-01T-0736-13	4332.157	0.01633370	5057.149

Diagnosics of the Verhaak signature

The singscore package provides a set of visualisation tools that enable diagnostics of the gene signature. For instance, these tools may be used to determine the importance of each component for a bidirectional signature (up- and down-regulated gene sets) to the total score, determine the importance of each gene of a signature in discriminating between the classes of interest, and to investigate the relationship between the final score and the dispersion of signature gene ranks. Sample annotations of interest (e.g. clinical annotations) can be colour coded on each plot. Singscore supports both continuous and categorical annotations, which can either be input as a vector, or as a string specifying a column within the score data frame. We begin by investigating the relationship between the score and dispersion of ranks for the up-regulated gene signature, down-regulated gene signature and the full signature. The plotDispersion functions generates a diagnostic plot with annotations overlaid. Annotations can be discrete or continuous, and can be passed as independent variables, or as a column name when

the data is appended to the score data frame. It should be noted that all plotting functions in `singscore` can be made interactive by setting the `isInteractive` argument to `TRUE`.

```
#relative size of text in the figure
relSize = 0.7

#create annotation
mutated_gene = rep('Other', ncol(aml_se))
mutated_gene[aml_se$NPM1c.Mut] = 'NPM1c Mut'
mutated_gene[aml_se$KMT2A.Fusion | aml_se$KMT2A.PTD] = 'MLL Fusion/PTD'
p1 = plotDispersion(verhaak_scores, annot = mutated_gene, textSize = relSize)
p1
```

Figure 2 shows that the set of down-regulated genes has more discriminant power in separating NPM1c mutated samples from those those without. Moreover, the signature is able to discriminate *MLL (KMT2A)* fusions and PTDs from the other samples. NPM1c mutations produce higher scores for the down-regulated gene set while *MLL* fusions and PTDs produce moderate scores. Similar trends are observed with the set of upregulated genes; however, despite the range of scores increasing, the discriminant power drops moderately. In fact, the signature of up-regulated genes is able to discriminate samples without the genomic changes of interest ('Other') better by producing negative scores for most of these samples. Negative scores for the expected up-regulated gene set indicate that these genes are expressed below median expression, therefore, likely down-regulated within corresponding samples. Another observation from these plots is based on the trend of the dispersion (MAD). The dispersion is generally expected to be higher for scores close to zero. Zero scores are achieved in three possible scenarios: when genes are expressed at median expression level; when genes are evenly distributed at both ends of the expression spectrum; or, the more likely scenario whereby the rank of expression of all genes are uniformly distributed. The last two scenarios would result in a high dispersion. To explain these ideas, we select 3 samples and plot the ranks of genes in both signatures. The sample with the highest total score, lowest total score and highest dispersion are chosen.

```
library(gridExtra)

#select samples with the properties required
select_samples = c(
  'Max Total Score' = which.max(verhaak_scores$TotalScore),
  'Min Total Score' = which.min(verhaak_scores$TotalScore),
  'Max Dispersion' = which.max(verhaak_scores$TotalDispersion)
)

#plotRankDensity applied to each sample
rank_plots = lapply(names(select_samples), function(x) {
  #get the sample index
  aml_sample = select_samples[x]
  #drop = FALSE is required to ensure the data.frame is intact
  p1 = plotRankDensity(rankData = aml_ranked[, aml_sample, drop = FALSE],
    upSet = verhaak_sigs[[1]],
    downSet = verhaak_sigs[[2]],
    textSize = relSize)

  #overwrite title of the plot with the description of the sample
  #this is possible because singscore uses ggplot2
  p1 = p1 + ggtitle(paste(x, mutated_gene[aml_sample], sep = '\n')) +
    guides(colour = guide_legend(ncol = 1))

  return(p1)
})

#create a multipanel plot
grid.arrange(grobs = rank_plots, nrow = 1)
```

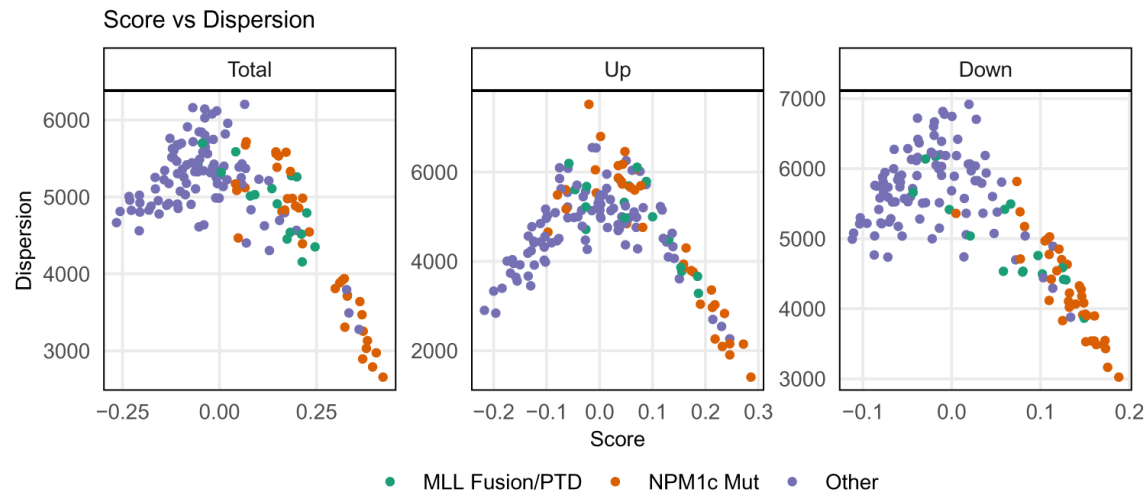



Figure 2. NPM1c signature scores from the up- and down-regulated gene sets, both combined (Total) and independently, can separate samples with NPM1c mutations or MLL fusions/PTDs from samples not bearing these genomic lesions. Scores are plotted against the median absolute deviation (MAD) of the ranks of genes in each gene set forming the NPM1c signature. The plots also reveal that scores close to 0 result in higher MADs.

Figure 3 shows that both the up- and down-regulated gene sets contribute to the score of the top scoring sample as these genes are at the extremes ends of the rank spectrum. Similarly, the lowest scoring sample has the ranks of genes in each set inverted. As observed in the previous plot, the up-regulated genes improve discrimination between NPM1c mutated samples and other samples and may be a stronger indicator of wild-type NPM1c samples than the down-regulated genes. Finally, the sample with the maximum dispersion exhibits uniformly distributed down-regulated gene ranks and a bimodal distribution of the up-regulated gene ranks with the modes at the extremes of the spectrum.

Combined, these plots show that both the up- and down-regulated genes play an important role in discriminating between NPM1c mutated (and *MLL* fusion/PTD samples), and wild-type samples. These diagnostic plots help in determining the importance of genes in signatures with respect to the samples of interest and should be used prior to application of signatures. In some cases, signatures may have been developed in specific contexts due to inherent biases in datasets and yet, described or applied in a generalised setting. These diagnostic plots may help in validating their application in specific contexts and possibly assist in characterising the contexts of all existing signatures.

Predicting NPM1c mutation status using the Verhaak signature

Mutation status can be predicted from singscores using a logistic regression model with a “logit” link function. The benefits of this model over one where each gene in the signature is used as a term in the model is the simplicity of the model. The Verhaak *et al.*¹² signature consists of 429 genes which would result in a regression model with 429 predictors. As there are fewer samples than the predictors, some feature selection method would be required which may result in the loss of information. Moreover, automating model development on a larger selection of gene signatures would be limited with gene-level models. Additionally, models trained using singscore would inherit its non-parametric properties to some extent. For instance, such models would be invariant to all data transformations that retain within sample ranks of genes. The main limitation of such models would be the loss of accuracy due to summarisation of the data (information on 429 genes is summarised into a two-component score).

In any case, our aim here is not to discuss the various models that can be used to predict mutation status, but to exhibit the discriminant power of singscore and transcriptomic signatures. consequently, the data used to train the model are used to evaluate the basic performance properties. We begin by combining the scores with mutation annotations.

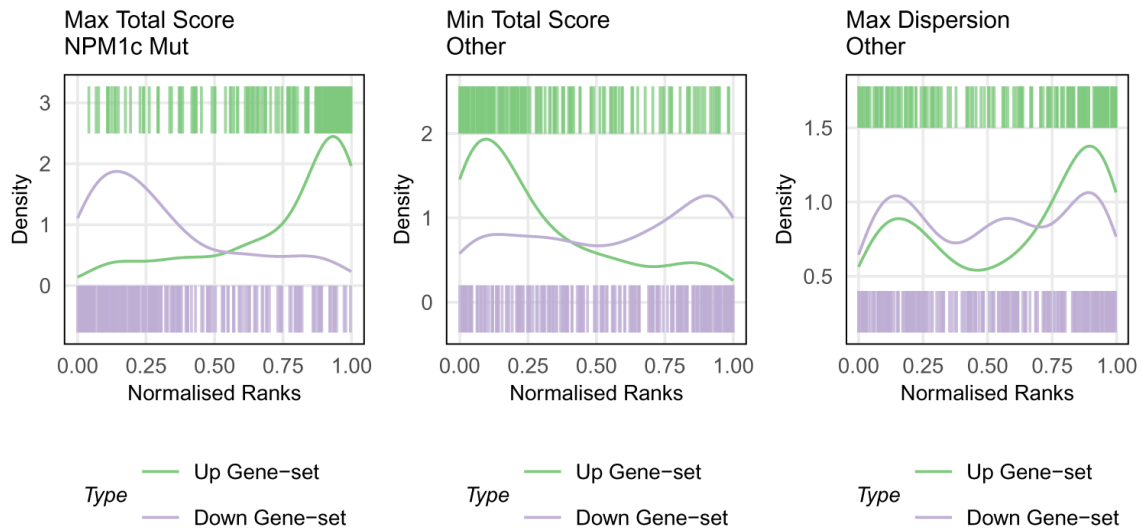


Figure 3. Rank distribution of genes reveals that expected up-regulated genes are up-regulated in high scoring samples and down-regulated in low-scoring samples with a similar, but inverse, observation for the expected down-regulated genes. Samples with the highest score, lowest score and highest dispersion (MAD) are show from left to right. The barcode plot for ranks of genes in each signature along with the density of the ranks is shown in each plot. Up-regulated genes are represented in green and down-regulated genes in purple. Gaussian distributions are observed at the extremes for the lowest and highest scores. High dispersion results in scores close to 0 because all genes are either evenly distributed (down-regulated gene set) or bi-modally distributed at the extrema (up-regulated gene set).

```
#create a dataframe with the data required: scores and mutations
scoredf = as.data.frame(colData(aml_se)[, aml_mutations])
scoredf$Score = verhaak_scores$TotalScore
scoredf$Dispersion = verhaak_scores$TotalDispersion
```

Before training a model, we can visualise how well scores resulting from the Verhaak *et al.*¹² signature separates the mutants from wild-type samples for some genes of interest. Figure 4 shows that NPM1c signature scores can discriminate between NPM1c wild-type and mutants. Similar observations are made for *MLL (KMT2A)* fusions and *PML-RARA* fusions.

```
#restructure the data for plotting
plotdf = melt(
  scoredf,
  id.var = c('Score', 'Dispersion'),
  variable.name = 'Mutation',
  value.name = 'Status'
)
#convert TRUE-FALSE values to Mut-WT
plotdf$Status = factor(plotdf$Status, labels = c('WT', 'Mut'))
p1 = ggplot(plotdf, aes(Mutation, Score, fill = Status)) +
  geom_boxplot(position = 'dodge', alpha = 0.6) +
  scale_fill_brewer(palette = 'Set2') +
  current_theme +
  theme(axis.text.x = element_text(angle = 45, vjust = 0.5))
p1
```

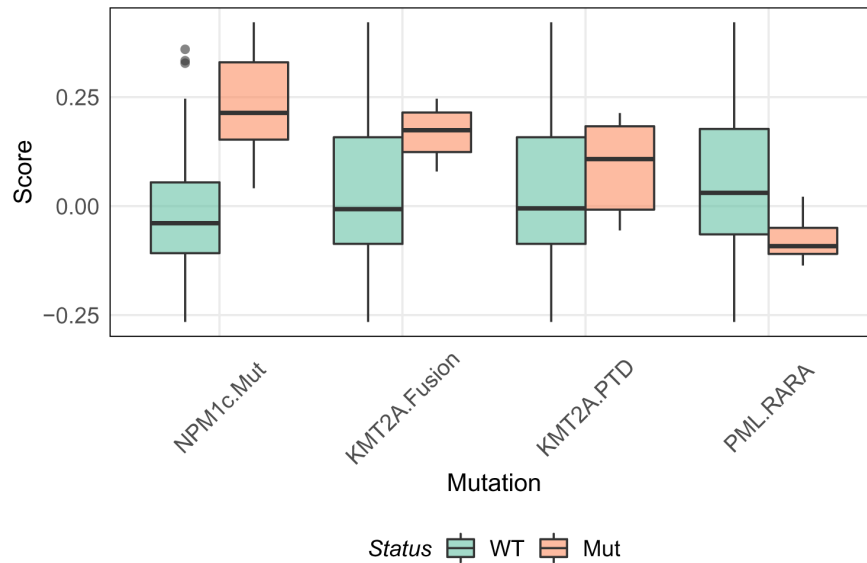


Figure 4. NPM1c signature scores are able to separate mutants from wild-types. Boxplot of scores from the NPM1c signature split by different types of mutations.

To quantify the above observations, we fit logistic regression models with each genomic lesion as the response variable and the score as the predictor. Coefficient estimates, standard errors, z-statistics, and *p*-values of each model are listed below.

```
#fit GLMs to each mutation
glms = lapply(aml_mutations, function(x) {
  #generate a formula for the fit
  form = as.formula(paste0(x, '~ Score'))
  glm1 = glm(form, data = scoredf, family = binomial(link = 'logit'))
  return(glm1)
})
names(glms) = aml_mutations

#extract coefficients
coefs = lapply(glms, function(x) coef(summary(x)))
ldply(coefs, function(x) x[2, ], .id = 'Mutation')
```

##	Mutation	Estimate	Std. Error	z value	Pr(> z)
## 1	NPM1c.Mut	13.276945	2.209811	6.0081806	1.876167e-09
## 2	KMT2A.Fusion	4.442768	2.151409	2.0650505	3.891822e-02
## 3	KMT2A.PTD	1.646183	2.089950	0.7876661	4.308921e-01
## 4	PML.RARA	-6.780992	2.414752	-2.8081526	4.982661e-03

NPM1c mutations are significantly associated with the score. Samples carrying a *MLL* gene fusion are also associated with the score reflecting their shared effects on Hox gene dysregulation, although with a lower significance. Interestingly the *PML-RARA* fusion carries a negative coefficient, likely reflecting the distinct cellular morphology/phenotype of acute promyelocytic leukemia relative to other subsets of AML, as noted above.

Evaluate prediction model performance

The above statistics give insight on the models trained but not on their performance. Precision and recall provide insight on a models predictive performance. The `dcanr` package provides functions to compute these metrics along with other measures of performance.

```
library(dcanr)

#assess sensitivity and specificity
prec_rec = ldply(glms, function(glm1) {
  #predict mutations for the data used in training and convert to binary format
  prediction = as.numeric(predict(glm1) > 0)
  observed = glm1$y
  prec = performanceMeasure(prediction, observed, 'precision')
  recall = performanceMeasure(prediction, observed, 'recall')
  f1 = performanceMeasure(prediction, observed)
  return(c('Precision' = prec, 'Recall' = recall, 'F1' = f1))
}, .id = 'Mutation')
prec_rec
```

```
##      Mutation Precision   Recall      F1
## 1   NPM1c.Mut      0.7 0.5675676 0.6268657
## 2  KMT2A.Fusion    NaN 0.0000000 0.0000000
## 3   KMT2A.PTD     NaN 0.0000000 0.0000000
## 4    PML.RARA     NaN 0.0000000 0.0000000
```

Precision for predictions of all genomic changes other than NPM1c is undefined because all samples are predicted to be wild-types. Consequently, their recall is zero. Precision, recall and the F1 score of the NPM1c mutation model are high as expected. As singscores are two-components scores, performance may be further improved by including the dispersion of ranks. This is observed in [Figure 2](#).

As observed from the model below, using both components of singscores significantly improves the predictive performance.

```
#include dispersion in the model
glm_npmlc = glm('NPM1c.Mut ~ Score + Dispersion',
               data = scoredf,
               family = binomial(link = 'logit'))

#evaluate performance of the new model
prediction = as.numeric(predict(glm_npmlc) > 0)
observed = glm_npmlc$y
c(
  'Precision' = performanceMeasure(prediction, observed, 'precision'),
  'Recall' = performanceMeasure(prediction, observed, 'recall'),
  'F1' = performanceMeasure(prediction, observed)
)
```

```
## Precision   Recall      F1
## 0.7631579 0.7837838 0.7733333
```

Unsupervised classification of mutations

There may be some cases where sample annotation is not available. In such scenarios, we are unable to build regression models to interpret scores. A higher singscore would provide stronger evidence for the signature but the magnitude is difficult to interpret without a reference. One approach to deal with this situation is to compare

scores to those from other datasets where the mutations status is known. An alternative approach would be to compare scores within the dataset using unsupervised learning methods.

Here we demonstrate the use of three clustering methods (Gaussian mixture decomposition, k-means clustering, and hierarchical clustering) to stratify samples, and as we have done previously²⁴ use the adjusted Rand index (ARI) to compare classifications. As expected, supervised (GLM) classification results in the best prediction. This is followed by clustering based on the score using Gaussian mixture decomposition. Any other classification algorithm along with prior knowledge could be used to decompose scores into groups. The important characteristic of singscores is that they maintain the discriminant power of gene signatures therefore can be coupled with supervised, semi-supervised or unsupervised algorithms to perform stratification.

```
library(mclust)

#Gaussian mixture model
m1 = Mclust(scoredf$Score, G = 2, verbose = FALSE)
#k-means clustering
m2 = kmeans(scoredf[, 5:6], centers = 2, nstart = 100)
#hierarchical clustering
m3 = hclust(dist(scoredf[, 5:6]))

mutation_inference = cbind(
  'GLM' = prediction,
  'mclust' = m1$classification,
  'k-means' = m2$cluster,
  'hclust' = cutree(m3, k = 2)
)
apply(mutation_inference, 2, adjustedRandIndex, scoredf$NPM1c.Mut)

##          GLM      mclust    k-means    hclust
## 0.5712724 0.4451106 0.3298026 0.3725541
```

Signature landscapes with multiple signatures

Often, we are interested in the relationship between two dependent or independent phenotypes, for instance, the epithelial and mesenchymal phenotypes. The role of most signatures is to estimate an unobservable molecular phenotype so they may be considered as proxies of phenotypes. As such, we could investigate the relationship between two phenotypes using corresponding signatures. Foroutan *et al.*²⁵ first introduced the idea of molecular signature landscapes to investigate the relationship between signatures related to the epithelial-mesenchymal transition (EMT) and TGF β -induced EMT. Subsequently, Cursons *et al.*²⁶ computed epithelial and mesenchymal phenotype signature singscores and demonstrated an epithelial phenotype shift following miR-200c transfection into a mesenchymal cell line using a signature landscape. Foroutan *et al.*⁹ used signature landscapes to stratify breast cancer subtypes along the epithelial-mesenchymal axis and included it as part of the `singscore` package. Here, we show how such landscapes can be used beyond the current application of the epithelial-mesenchymal axis. We demonstrate how transcriptomic signatures of different mutations can be used to stratify AML samples.

Ross MLL fusion signature vs. Verhaak signature landscape

We now use the Ross *et al.*¹⁴ MLL-fusion signatures to score the TCGA AML samples. Unlike the NPM1c signature, this signature is composed of genes that discriminate samples with MLL-fusion genes. We download and parse the signature as demonstrated with the NPM1c signature.

```
#create signature names
rossmll_name = 'ROSS_AML_WITH_MLL_FUSIONS'
#generate URLs
rossmll_link = paste0(
  'http://software.broadinstitute.org/gsea/msigdb/download_geneset.jsp?geneSetName=',
  rossmll_name,
  '&fileType=xml'
)

#download files
rossmll_file = paste0(rossmll_name, '.xml')
download.file(rossmll_link, rossmll_file, method = 'libcurl')
rossmll_sig = getBroadSets(rossmll_file, membersId = 'MEMBERS_EZID')
rossmll_sig
```

```
## GeneSetCollection
##  names: ROSS_AML_WITH_MLL_FUSIONS (1 total)
##  unique identifiers: 10113, 10479, ..., 9961 (81 total)
##  types in collection:
##    geneIdType: SymbolIdentifier (1 total)
##    collectionType: BroadCollection (1 total)
```

The gene set is a composition of both up- and down-regulated genes as genes were selected based on their ability to discriminate mutants from wild-types. We use the third mode of `singscore`, which does not require the direction of genes in the gene set to be known. The `knownDirection` parameter of the `simpleScore` function is set to `FALSE` to induce this mode. Ranks computed previously can be reused to compute scores with the new signature.

```
rossmll_scores = simpleScore(aml_ranked, rossmll_sig[[1]], knownDirection = FALSE)
```

The `plotScoreLandscape` function plots a hexbin plot to visualise the two-dimensional distribution of scores. Scores computed using the Verhaak *et al.*¹² signature and the Ross *et al.*¹⁴ *MLL*-fusions signature are passed as arguments. Both scores should have been computed on the same samples with the order of samples retained. Names of the scores should be passed as arguments to the `scorenames` argument. The `textSize` argument can be used to specify the size of all text relative to the plot size. This may prove useful when plots are being generated for scientific posters, publications and presentations, all of which require different image sizes.

```
p_mll_npm1c = plotScoreLandscape(
  verhaak_scores,
  rossmll_scores,
  scorenames = c('VERHAAK_AML_WITH_NPM1_MUTATED', 'ROSS_AML_WITH_MLL_FUSIONS'),
  textSize = relSize
)
p_mll_npm1c
```

Figure 5 shows a strong positive association between scores from the two signatures (Spearman's $\rho = 0.628$) despite only 16 genes being shared across the two signatures (signature sizes are 78 and 429 genes). In such an analysis, we may be interested in projecting new data points onto the landscape as done by Cursons *et al.*²⁶. Alternatively, we may want to overlay some existing data points to investigate sample stratification using scores. Here, we overlay *MLL* fusions, *MLL* PTDs, *PML-RARA* fusions and *NPM1c* mutations onto the landscape. First, we build the annotation vector.

```
#new annotation - modify previously used annotations
mutated_gene[aml_se$KMT2A.Fusion] = 'MLL Fusion'
mutated_gene[aml_se$KMT2A.PTD] = 'MLL PTD'
mutated_gene[aml_se$PML.RARA] = 'PML-RARA'
```

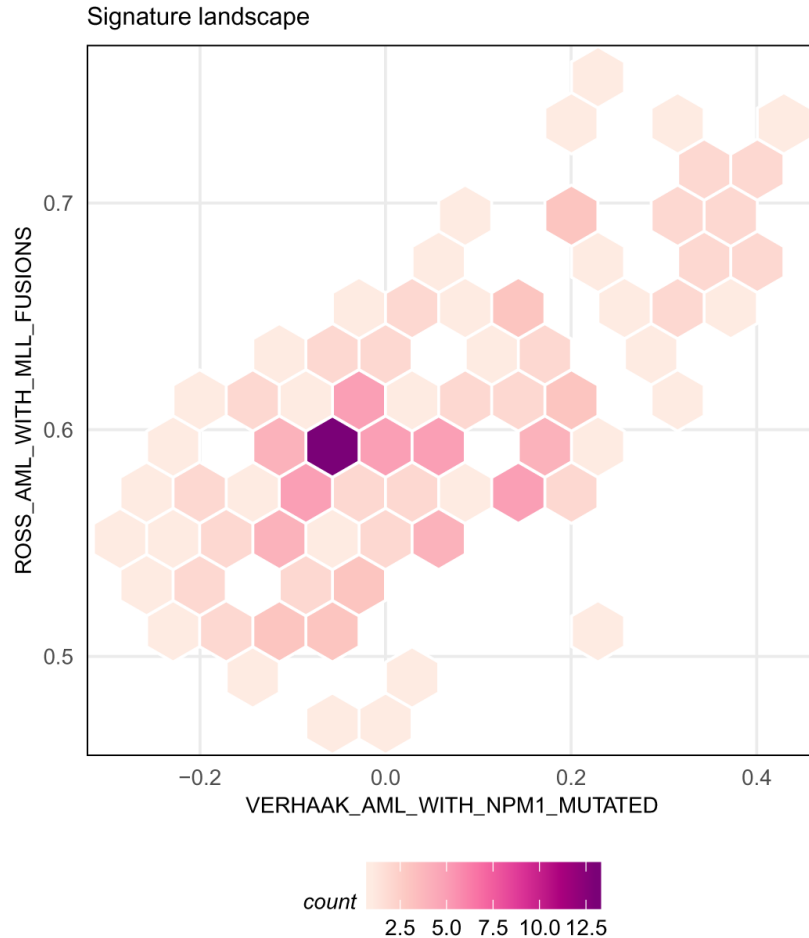


Figure 5. Signature landscape between the MLL fusion and NPM1c signatures. A positive association is revealed between the two signatures in AML.

Points are projected onto an existing landscape using the `projectScoreLandscape` function. This function uses the `p_mll_npm1c` plot generated using the `plotScoreLandscape` and overlays new data points onto it. Scores for the new data must be computed with the same signatures that were used to compute the landscape. As we are using existing data, scores computed in earlier sections are re-used. The `subSamples` can be used to select a subset of samples to project. Here, we select samples with the mutations we are interested in annotating.

```
select_aml = !mutated_gene %in% 'Other'

#label samples with an mclust NPM1c classification uncertainty of > 0.3
label_samples = substr(rownames(verhaak_scores), 6, 12) #sample ID from barcodes
label_samples[m1$uncertainty < 0.3] = NA

#project mutations onto the landscape
p1 = projectScoreLandscape(
  p_mll_npm1c,
  verhaak_scores,
  rossmll_scores,
  subSamples = select_aml,
  annot = mutated_gene[select_aml],
  sampleLabels = label_samples[select_aml]
)
p1 + theme(legend.box = 'vertical')
```


Figure 6 shows that the *MLL* fusions and *MLL* PTDs exhibit variation across different axes. *MLL* PTDs have a lower score than *MLL* fusions for the *MLL* fusion signature as expected. These sets of samples do not cluster along the two axes, consistent with observations by Ross *et al.*¹⁴. Overlaying samples annotations onto the plot assists in interpreting different regions of the landscape.

Ross *PML-RARA* fusion signature vs. Verhaak signature landscape

It is evident from the previous analysis that *PML-RARA* samples differ from all other samples examined here. We repeat the analysis with the *PML-RARA* signature from Ross *et al.*¹⁴ to verify this distinction. The signature is available on the MSigDB and is named “ROSS_AML_WITH_PML_RARA_FUSION”. We download and parse the signature, score all samples against it, plot a landscape with scores from the Verhaak *et al.*¹² signature, and finally, project samples onto the plot. The signature was constructed in a similar manner to the *MLL* fusions signature, therefore, samples are scored using the same settings.

Figure 7 shows a completely different landscape from what was observed with the *MLL* fusion signature. The *PML-RARA* signature forms a clear separation between the *PML-RARA* and *NPM1c* samples such that *PML-RARA* samples are the only ones with a high score for this signature. Moreover, no association is observed between the two

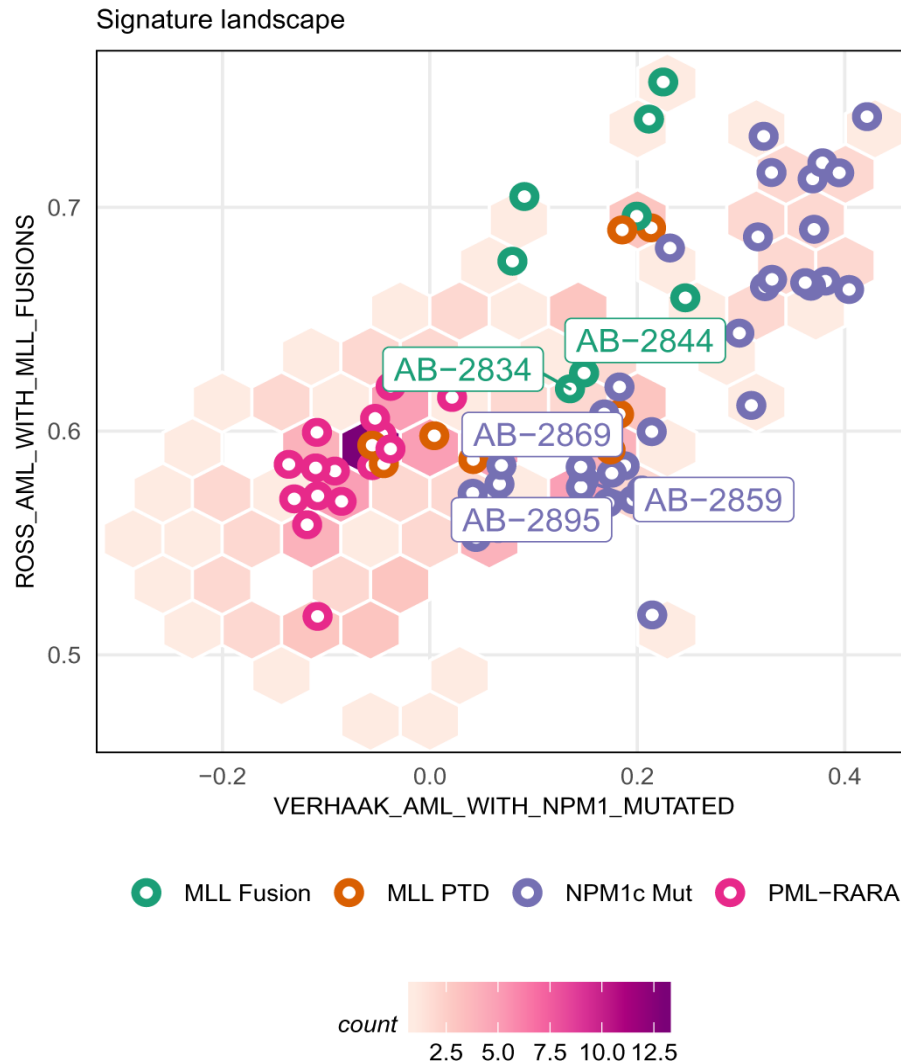


Figure 6. The landscape reveals a distinction between the *MLL* fusions and PTDs as previously reported. Different mutations occupy different regions of the landscape, possessing different types of molecular traits.

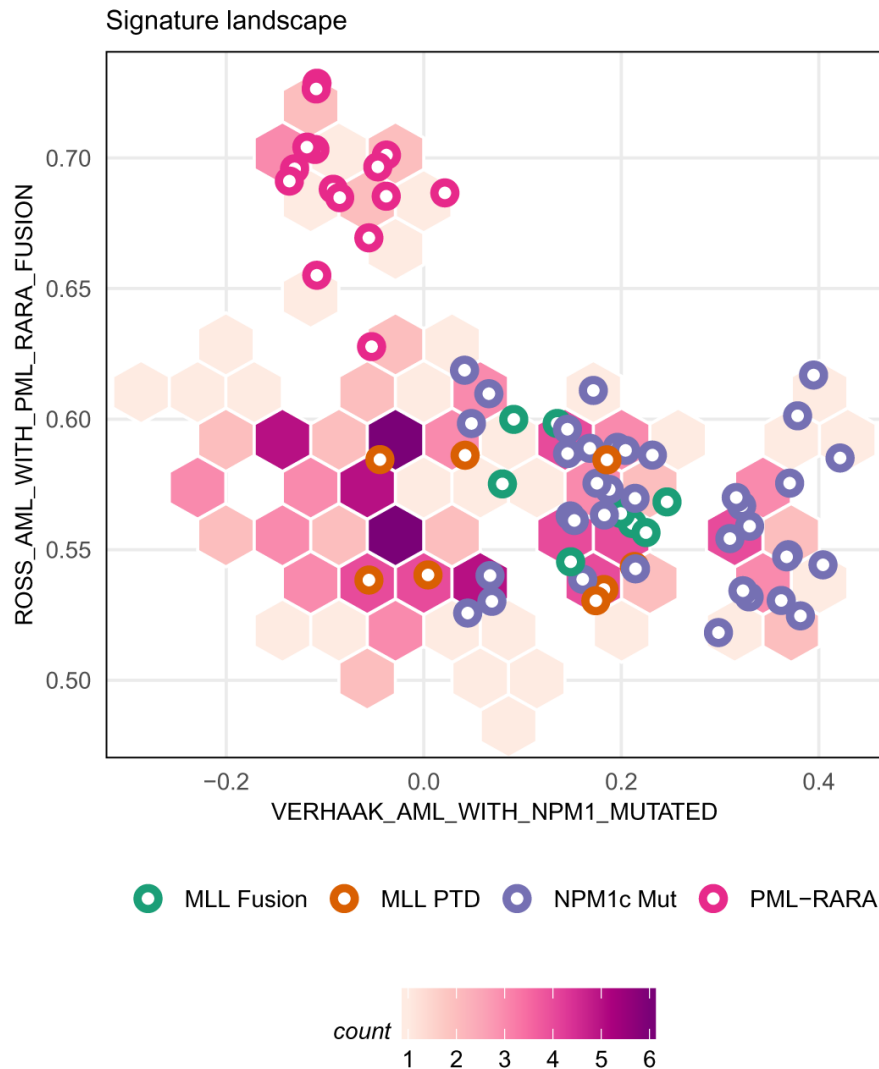


Figure 7. The PML-RARA signature is independent from the NPM1c signature in AML. The L-shaped landscape suggests the molecular mechanisms underlying these mutations are mutually exclusive.

signatures. As discussed above (Description of the biological problem) the *PML-RARA* fusion is diagnostic of a specific subtype of AML known as acute promyelocytic leukemia, with a highly distinct cell phenotype reflecting a block on differentiation at the promyelocyte stage¹⁵. The distinct features of this subtype are correspondingly reflected in the L-shaped landscape for these two signatures and the different mechanisms by which these lesions drive leukemogenesis.

Summary

The singscore package provides an easy interface to apply gene set scoring methods within the R/Bioconductor environment. The TCGAbiolinks package allows relatively easy access to large clinically relevant data sets such as TCGA, together with appropriate annotation functions for interpreting biological data. Diagnostic and plotting functions included with singscore allow the user to investigate gene sets of interest to determine their power for distinguishing differences between samples. Different gene signatures can then be combined to explore how different cellular phenotypes are associated across a large cohort of cancer samples. As demonstrated, when appropriate gene set signatures are used, metrics calculated by singscore can be used for sample classification and this may be useful for further interrogation of large transcriptomic data sets where no genomic data are available

Packages used

This workflow depends on various packages from version 3.9 of the Bioconductor project, running on R version 3.6.1 (2019-07-05) or higher. The complete list of the packages used for this workflow are shown below:

```
sessionInfo()
```

```
## R version 3.6.1 (2019-07-05)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: CentOS Linux 7 (Core)
##
## Matrix products: default
## BLAS: /stornext/System/data/apps/R/R-3.6.1/lib64/R/lib/libRblas.so
## LAPACK: /stornext/System/data/apps/R/R-3.6.1/lib64/R/lib/libRlapack.so
##
## locale:
## [1] LC_CTYPE=en_US.UTF-8 LC_NUMERIC=C
## [3] LC_TIME=en_US.UTF-8 LC_COLLATE=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
## [11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] parallel stats4 stats graphics grDevices utils datasets
## [8] methods base
##
## other attached packages:
## [1] mclust_5.4.5 dcanr_1.1.4
## [3] gridExtra_2.3 reshape2_1.4.3
## [5] singscore_1.4.0 GSEABase_1.46.0
## [7] graph_1.62.0 annotate_1.62.0
## [9] XML_3.98-1.20 org.Hs.eg.db_3.8.2
## [11] AnnotationDbi_1.46.0 plyr_1.8.4
## [13] rtracklayer_1.44.0 edgeR_3.26.5
## [15] limma_3.40.2 SummarizedExperiment_1.14.1
## [17] DelayedArray_0.10.0 BiocParallel_1.18.1
## [19] matrixStats_0.55.0 Biobase_2.44.0
## [21] GenomicRanges_1.36.1 GenomeInfoDb_1.20.0
## [23] IRanges_2.18.2 S4Vectors_0.22.1
## [25] BiocGenerics_0.30.0 TCGAbiolinks_2.12.3
## [27] ggplot2_3.2.0 SingscoreAMLMutations_1.0.1
##
## loaded via a namespace (and not attached):
## [1] backports_1.1.4 circlize_0.4.6
## [3] aroma.light_3.14.0 igraph_1.2.4.1
## [5] selectr_0.4-1 ConsensusClusterPlus_1.48.0
## [7] lazyeval_0.2.2 splines_3.6.1
## [9] usethis_1.5.1 sva_3.32.1
## [11] digest_0.6.20 foreach_1.4.4
## [13] htmltools_0.3.6 magrittr_1.5
## [15] memoise_1.1.0 BSgenome_1.52.0
## [17] cluster_2.1.0 doParallel_1.0.14
## [19] ComplexHeatmap_2.0.0 Biostrings_2.52.0
## [21] readr_1.3.1 R.utils_2.9.0
## [23] prettyunits_1.0.2 colorspace_1.4-1
## [25] blob_1.1.1 rvest_0.3.4
## [27] ggrepel_0.8.1 BiocWorkflowTools_1.10.0
## [29] xfun_0.8 dplyr_0.8.3
## [31] hexbin_1.27.3 crayon_1.3.4
```

```

## [33] RCurl_1.95-4.12          jsonlite_1.6
## [35] genefilter_1.66.0       survival_2.44-1.1
## [37] zoo_1.8-6               iterators_1.0.10
## [39] glue_1.3.1             survminer_0.4.4
## [41] registry_0.5-1         gtable_0.3.0
## [43] zlibbioc_1.30.0        XVector_0.24.0
## [45] GetoptLong_0.1.7       shape_1.4.4
## [47] scales_1.0.0           DESeq_1.36.0
## [49] rngtools_1.4           DBI_1.0.0
## [51] bibtex_0.4.2           ggthemes_4.2.0
## [53] Rcpp_1.0.2             xtable_1.8-4
## [55] progress_1.2.2        cmprsk_2.2-8
## [57] clue_0.3-57           bit_1.1-14
## [59] matlab_1.0.2          km.ci_0.5-2
## [61] httr_1.4.0            RColorBrewer_1.1-2
## [63] pkgconfig_2.0.2       R.methodsS3_1.7.1
## [65] locfit_1.5-9.1        labeling_0.3
## [67] tidyselect_0.2.5      rlang_0.4.0
## [69] munsell_0.5.0         tools_3.6.1
## [71] downloader_0.4        generics_0.0.2
## [73] RSQLite_2.1.1         broom_0.5.2
## [75] evaluate_0.14         stringr_1.4.0
## [77] yaml_2.2.0            knitr_1.23
## [79] bit64_0.9-7          fs_1.3.1
## [81] survMisc_0.5.5       purrr_0.3.2
## [83] doRNG_1.7.1          EDASeq_2.18.0
## [85] nlme_3.1-140         R.oo_1.22.0
## [87] xml2_1.2.0           biomaRt_2.40.1
## [89] compiler_3.6.1       rstudioapi_0.10
## [91] curl_3.3             png_0.1-7
## [93] ggsignif_0.5.0       tibble_2.1.3
## [95] genefilter_1.62.0    stringi_1.4.3
## [97] GenomicFeatures_1.36.3 lattice_0.20-38
## [99] Matrix_1.2-17       KMSurv_0.1-5
## [101] pillar_1.4.2         BiocManager_1.30.4
## [103] GlobalOptions_0.1.0 data.table_1.12.2
## [105] bitops_1.0-6         R6_2.4.0
## [107] latticeExtra_0.6-28 hwriter_1.3.2
## [109] bookdown_0.11       ShortRead_1.42.0
## [111] codetools_0.2-16    assertthat_0.2.1
## [113] pkgmaker_0.27       rjson_0.2.20
## [115] withr_2.1.2         GenomicAlignments_1.20.1
## [117] Rsamtools_2.0.0     GenomeInfoDbData_1.2.1
## [119] mgcv_1.8-28         hms_0.4.2
## [121] grid_3.6.1          tidyr_0.8.3
## [123] rmarkdown_1.13      git2r_0.26.1
## [125] ggpubr_0.2.1

```

Data availability

All data analyzed in the workflow is read automatically from public websites as part of the code. Mutation data for the samples in this study are available as part of the R/Bioconductor package `SingscoreAMLMutations` (v1.0.0).

Software availability

Software available from: <https://bioconductor.org/packages/release/workflows/html/SingscoreAMLMutations.html>

Source code available from: <https://github.com/DavisLaboratory/SingscoreAMLMutations/>

Archived source code at time of publication: <https://doi.org/10.5281/zenodo.3470443>

License: Artistic-2.0

Author information

DDB, JC and MJD wrote the article. DDB wrote the code for the workflow and the associated R/Bioconductor workflow package `SingscoreAMLMutations`. MF, JC, DDB and MJD conceived the idea for the workflow. YX translated the vignette for the package vignette into chinese. YX and RL reviewed the chinese translation. All authors have tested and reviewed the workflow. This work was supervised by JC and MJD.

Acknowledgments

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Open Peer Review

Current Peer Review Status:  

Version 3

Reviewer Report 06 November 2019

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Luiza Handschuh 

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All my comments were addressed by the authors. Some of the suggested improvements were introduced, other not but the authors explained they did not overlap with the objectives of the article.

I only suggest to correct a few editorial errors:

- "Normalisation" instead of "Normalisation" occurs once in the chapter "Transformation to FPKM values and normalisation";
- "those those" – repeated word in the sentence started from "Figure 2 shows that the set of down-regulated genes has more discriminant power...";
- there is no dot at the end of the last sentence of the Summary chapter. Moreover, I suggest not to use a term "wild-type NPM1c samples" formed as an equivalent of "NPM1c mutated samples", e.g. in the description of the Figure 3 and 4, as "NPM1c" means "cytoplasmic NPM1" which is typical for samples with the mutated *NPM1* gene. The term "wild-type NPM1 samples" is more appropriate.

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Genomics, transcriptomics, biology of acute myeloid leukemia

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Version 2

Reviewer Report 15 August 2019

<https://doi.org/10.5256/f1000research.22103.r52512>

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Marina Lizio 

Division of Genomic Technologies, RIKEN Center for Life Science Technologies, Yokohama, Japan

I don't have many more comments.

Figures could be improved, as noted in the first version of this peer review.

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Transcriptome analysis, Gene expression regulation

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Version 1

Reviewer Report 05 August 2019

<https://doi.org/10.5256/f1000research.21079.r51547>

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Introduction

The article presents a new package, which was developed from a previous one ('singscore') elaborated by the same authors. The package 'singscore' is a single-sample gene set scoring method which is valuable for analysis of transcriptomes of samples collected through the long time and not sequenced in the same run, experiment, platform or laboratory. Here, the authors apply the method for classification of TCGA acute myeloid (AML) samples using transcriptional 'gene signatures' identified by other authors (Verhaak and Ross) as typical for the NPM1c mutation, KMT2A (MLL) gene fusions, and PML-RARA gene fusions.

AML is a heterogeneous and multi-clonal disease. The transcriptome picture of AML is very complex and can result from different mutations, genomic rearrangements, and aberrant regulation of gene expression at different levels (see my last review paper¹). Sometimes, the gene expression profiles can overlap between samples with different genetic lesions. The examples are HOX-gene-based discriminative signatures determined by Verhaak and Ross, not limited to AML with mutated NPM1, but specific also for AML cases with 11q23 abnormalities and KMT2A (MLL) gene rearrangements. The authors are aware of

this fact and underline it in the article, too. On the other side, samples with the same mutation can present varying expression profiles because of additional features which also affect the transcriptome. Therefore, interpretation of the results must be done with caution. For me, the authors interpret the results a little bit too optimistically. The presented method is not sufficient to determine the mutation of interest, but can be used as a supplementary approach, a screening tool or (in future) a personalized medicine tool which could classify patients based on transcriptomic profiles, associated with specific treatment response.

Testing package

I have used the package in R with TCGA data and confirm the code works, it is fast and generates the same results and plots as presented in the article. Moreover, I have tested the whole procedure on my own RNA-seq dataset (not published yet but used for supplementary expression analysis of NPM1 alternative transcripts, see the article²). My dataset contains 28 AML samples, including 8 with NPM1 mutation (verified with three independent approaches). The data load was more tricky as I started from the csv table with counts and I had to convert the DESeqDataSet object into the RangedSummarizedExperiment object. The best discrimination was achieved with the Verhaak signature, but only with the down-regulated genes. All samples with NPM1 mutation were clearly separated from others, however, 2 additional samples, without NPM1 mutation, were grouped together with NPM1c. It is possible they have KMT2A (MLL) rearrangements, but I cannot verify it now. Analyzing the plots, up-regulated genes and all genes from the signature are not as efficient, separating only 2 or 3 NPM1c samples from the rest. In the article, the authors also admit that the set of down-regulated genes has more discriminant power, but they claim up-regulated genes also contribute to the discrimination.

I have no samples with PML-RARA fusion in my dataset and the status of KMT2A (MLL) gene was unknown in my patients, so I could not compare the efficiency of signatures other than NPM1c. APL with PML-RARA is the most distinctive AML subtype which is easily separated from other AML samples based on transcriptome profile, so I would expect good results. This example shows the package works well for samples with very specific gene expression profile.

Interpretation of the results

Considering the result interpretation, I have some doubts. The singscores are composed of two components, an enrichment score and a dispersion estimate of ranks. I am informed that “high expression of up-regulated genes and low expression of down-regulated genes would result in higher scores”. This is logical. I also know the maximal ranges $[-1, 1]$ for signatures involving up- and down-regulated genes). However, which value is really high? For example, is 0.2 enough (it looks like from the plots in the article and from my own data, too) or maybe I should expect much more, e.g. 0.7? Similarly, which value of dispersion should I expect? I suppose, the lowest, but which is low enough or which range is optimal? What is difficult to understand is that “despite the range of scores increasing, the discriminant power drops moderately” (for up-regulated genes from Verhaak signature, when compared to down-regulated genes). I see the same paradox in my data – the scores are higher for up-reg. genes, which are much less efficient in discrimination between NPM1c+ and NPM1c- samples. It looks like scores only do not reflect the trends observed from score vs dispersion plots.

Possible improvements

Although the package is generally useful and well described, the following improvements will make it more friendly for less advanced R users, e.g.

- Instruction how to prepare and load the data other than those deposited in the GDC database.
- Annotation of samples on the plots with unique sample IDs (when a sample is misclassified, a user does not know which one it is; it will also be helpful to localize a sample on various plots, e.g. generated with a signature of up- and down-regulated genes) – it is written in the article that the

'singscore' package supports different types of annotations ("Annotations of interest can be overlaid on each plot") but I found only color code annotation whereas I would like to have color code for mutation type and additional text labels with sample IDs on the same plot.

- A command which lists the samples typed as strong candidates for having particular mutation, ordered according to the calculated metrics.
- Generating a threshold line between samples with and without mutation.

In future, it would be also good to include other signatures, e.g. the signature of 369 genes identified by Alcalay *et al.* in 2005³, discriminating AML patients with NPMc+ from patients with NPMc-, even in cases with rare chromosomal abnormalities.

What I would expect the most from a package designed to identify mutations in transcriptomes, is a direct identification of mutations in RNAseq data. The results of mutation typing based on gene expression profile will be strongly supported when a particular mutation will be covered by RNAseq reads. From my own experience, I know it is possible (for NPM1 mutation detection, see⁴). For genes with high and middle expression level, the coverage can be even higher than that obtained from genome- or exome-level data. And in the case when DNA data are unavailable, it would be really fantastic. Because it demands completely different data processing, it may be considered for future versions of the package.

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Is the rationale for developing the new software tool clearly explained?

Yes

Is the description of the software tool technically sound?

Yes

Are sufficient details of the code, methods and analysis (if applicable) provided to allow replication of the software development and its use by others?

Yes

Is sufficient information provided to allow interpretation of the expected output datasets and any results generated using the tool?

Partly

Are the conclusions about the tool and its performance adequately supported by the findings presented in the article?

Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Genomics, transcriptomics, biology of acute myeloid leukemia.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 14 Oct 2019

Melissa Davis, University of Melbourne, Parkville, Australia

We thank the reviewer for their time and effort directed towards reviewing our manuscript and for the helpful feedback they have provided. Where appropriate we have modified our manuscript to address the reviewer's comments.

Below we include a point by point response to the reviewer's comments and where appropriate we list corresponding changes to the manuscript.

Introduction

LH: The article presents a new package, which was developed from a previous one ('singscore') elaborated by the same authors. The package 'singscore' is a single-sample gene set scoring method which is valuable for analysis of transcriptomes of samples collected through the long time and not sequenced in the same run, experiment, platform or laboratory. Here, the authors apply the method for classification of TCGA acute myeloid (AML) samples using transcriptional 'gene signatures' identified by other authors (Verhaak and Ross) as typical for the NPM1c mutation, KMT2A (MLL) gene fusions, and PML-RARA gene fusions.

DDB: *We note that the purpose of the initial manuscript may have been unclear, in part because it is listed under the F1000 Software Tool Article section. The purpose of this article is to present a workflow demonstrating the use of singscore, and it is a R/Bioconductor workflow illustrating the use of singscore, and so is not intended as a new package or tool.*

<https://www.bioconductor.org/packages/release/workflows/>

<https://www.bioconductor.org/packages/release/workflows/html/SingscoreAMLMutations.html>

Some of the review comments below assume that this manuscript presents a specific software package for detecting NPM1 mutations, so we have clarified the manuscript as outlined below in order to make the purpose and intention more clear (note that the title of the manuscript has changed from 'predicting mutations' to 'predicting mutation status' based upon feedback from reviewer 1).

This work arose from an observation in another project that the Verhaak signature scored with singscore appeared to correlate strongly with mutation status, and we thought this would be an interesting example that might also help researchers to investigate the links between genetic

lesions and corresponding transcriptional changes, an area in which the reviewer clearly has expertise.

LH: AML is a heterogeneous and multi-clonal disease. The transcriptome picture of AML is very complex and can result from different mutations, genomic rearrangements, and aberrant regulation of gene expression at different levels (see my last review paper¹). Sometimes, the gene expression profiles can overlap between samples with different genetic lesions. The examples are HOX-gene-based discriminative signatures determined by Verhaak and Ross, not limited to AML with mutated NPM1, but specific also for AML cases with 11q23 abnormalities and KMT2A (MLL) gene rearrangements. The authors are aware of this fact and underline it in the article, too. On the other side, samples with the same mutation can present varying expression profiles because of additional features which also affect the transcriptome.

LH: Therefore, interpretation of the results must be done with caution. For me, the authors interpret the results a little bit too optimistically. The presented method is not sufficient to determine the mutation of interest, but can be used as a supplementary approach, a screening tool or (in future) a personalized medicine tool which could classify patients based on transcriptomic profiles, associated with specific treatment response.

DDB: *We agree with the reviewer that gene set scoring of transcriptomic data should not be the only method used to identify patient samples carrying genetic lesions. The Bioconductor workflow we present is intended to provide an example of applying singscore to study mutation/fusion based gene sets as we believe that singscore provides a relatively flexible and intuitive approach for investigating different gene sets across large data sets. We feel that a particularly useful feature is the ability to combine different signatures/gene sets (including phenotype/cell-cycle signatures etc) to explore how these transcriptional changes are associated over different samples, demonstrated in Figures 5-7.*

We have modified the “Description of biological relevance” section to address the reviewer’s comments around the complexity of AML genomic lesions and corresponding transcriptomic changes. The review highlighted is particularly relevant for this work and accordingly we mention the complexity of AML and direct the reader towards this resource by extending the first paragraph (new text underlined):

.. A more recent study which has focused primarily on genomic data has further refined the clinically significant AML subtypes [Papaemmanuil (2016), NEJM], highlighting a number of co-occurring as well as mutually exclusive mutations. As the identification of putative driver fusions/mutations continues, work has also been directed towards how these lesions interact with each other and other features (e.g. cellular proliferation, changes due to phenotypic plasticity, or variation in post-transcriptional regulators such as microRNAs) to drive transcriptional changes as discussed in a recent review [Hanschuch (2019), J. Oncol.].

We have also added a paragraph at the end of this section which discusses some of the limitations for our approach and provides more context in which it could be applied:

While we demonstrate that singscore is capable of inferring mutation status from the transcriptional profile of AML samples, we note that it is best used to supplement alternative data which can provide a more definitive resolution of these lesions. Processing of raw RNAseq data will directly identify the presence of gene fusion products or mutations within protein-coding regions, although for many large data sets the quantified transcript abundance data are much easier to obtain without access agreements. The method can also be applied to legacy microarray data sets where genome and RNA sequencing data are unavailable. As such singscore provides a useful approach

to supplement established methods for the study of genetic lesions in cancer. By exploring associations between different genomic and phenotypically relevant signatures, it may also help to better characterise true driver mutations which exert consistent effects on the transcriptome of AML samples and other cancers.

Testing package

LH: I have used the package in R with TCGA data and confirm the code works, it is fast and generates the same results and plots as presented in the article. Moreover, I have tested the whole procedure on my own RNA-seq dataset (not published yet but used for supplementary expression analysis of NPM1 alternative transcripts, see the article²). My dataset contains 28 AML samples, including 8 with NPM1 mutation (verified with three independent approaches). The data load was more tricky as I started from the csv table with counts and I had to convert the DESeqDataSet object into the RangedSummarizedExperiment object. The best discrimination was achieved with the Verhaak signature, but only with the down-regulated genes. All samples with NPM1 mutation were clearly separated from others, however, 2 additional samples, without NPM1 mutation, were grouped together with NPM1c. It is possible they have KMT2A (MLL) rearrangements, but I cannot verify it now. Analyzing the plots, up-regulated genes and all genes from the signature are not as efficient, separating only 2 or 3 NPM1c samples from the rest. In the article, the authors also admit that the set of down-regulated genes has more discriminant power, but they claim up-regulated genes also contribute to the discrimination.

LH: I have no samples with PML-RARA fusion in my dataset and the status of KMT2A (MLL) gene was unknown in my patients, so I could not compare the efficiency of signatures other than NPM1c. APL with PML-RARA is the most distinctive AML subtype which is easily separated from other AML samples based on transcriptome profile, so I would expect good results. This example shows the package works well for samples with very specific gene expression profile.

DDB: *We thank the reviewer for the exceptional effort and time invested to test our workflow on independent data - we hope results from this analysis have been informative for identifying other features within their data. Our workflow includes guidance for users who wish to import data from other sources such as those used by the reviewer.*

Interpretation of the results

LH: Considering the result interpretation, I have some doubts. The singscores are composed of two components, an enrichment score and a dispersion estimate of ranks. I am informed that “high expression of up-regulated genes and low expression of down-regulated genes would result in higher scores”. This is logical. I also know the maximal ranges $[-1, 1]$ for signatures involving up- and down-regulated genes). However, which value is really high? For example, is 0.2 enough (it looks like from the plots in the article and from my own data, too) or maybe I should expect much more, e.g. 0.7? Similarly, which value of dispersion should I expect? I suppose, the lowest, but which is low enough or which range is optimal? What is difficult to understand is that “despite the range of scores increasing, the discriminant power drops moderately” (for up-regulated genes from Verhaak signature, when compared to down-regulated genes). I see the same paradox in my data – the scores are higher for up-reg. genes, which are much less efficient in discrimination between NPM1c+ and NPM1c- samples. It looks like scores only do not reflect the trends observed from score vs dispersion plots.

DDB: *Interpretation of singscores is intentionally left to be problem specific as it generally requires some domain-specific knowledge of the biological system and corresponding signature genes –*

ideally the computational biologist or bioinformaticians working on each project can provide some guidance.

The basic interpretation of the score is the normalised mean rank of genes within the signature relative to all other genes in the sample. At the extrema this interpretation is relatively simple - near 1, a higher value would indicate that genes in the signature are expressed at higher levels relative to other genes. For scores towards zero, however, the interpretation can be much more difficult – a score of zero (on the range [-1, 1]) could indicate the signature genes are tightly clustered around the sample-wide mean abundance, or it could indicate a highly-dispersed almost uniform distribution across the entire abundance range (with a mean near the mean of all genes). By exploring the singscores together with dispersion estimates this information is summarised, assisting in estimation of effect size variability.

Interpretation of scores depends on the context of the experiment and the typical behaviour of the gene set. A “high” score is best determined relative to other samples. This is achieved either by comparing scores from other samples in large datasets such as TCGA, or better, across a set of samples from a given experiment with known conditions. Other methods normalise the data before computing scores, and we note that a recent paper has applied z-score normalisation to results from singscore for comparison to ssGSEA [Cui et al (2019) *Oncogene*, DOI: 10.1038/s41388-019-1026-9].

All singscores for samples remain the same and do not have to be recomputed upon addition of new samples, and interpretation will improve as more samples are added to the study. For example, Gaussian mixture modelling could be used to separate the NPM1c scores based on our expectation that there are two groups. This could be switched with other unsupervised classification algorithms such as hierarchical clustering or k-means clustering. We have added an example analysis to the manuscript to demonstrate how scores can be interpreted in an unsupervised setting, under the section “Transcriptional signatures to predict mutation status/Unsupervised classification of mutations”.

There may be some cases where sample annotation is not available. In such scenarios, we are unable to build regression models to interpret scores. A higher singscore would provide stronger evidence for the signature but the magnitude is difficult to interpret without a reference. One approach to deal with this situation is to compare scores to those from other datasets where the mutations status is known. An alternative approach would be to compare scores within the dataset using unsupervised learning methods.

Here we demonstrate the use of three clustering methods (Gaussian mixture decomposition, k-means clustering, and hierarchical clustering) to stratify samples, and as we have done previously [wang et al (2012) *Journal of clinical bioinformatics*] use the adjusted Rand index (ARI) to compare classifications. As expected, supervised (GLM) classification results in the best prediction. This is followed by clustering based on the score using Gaussian mixture decomposition. Any other classification algorithm along with prior knowledge could be used to decompose scores into groups. The important characteristic of singscores is that they maintain the discriminant power of gene signatures therefore can be coupled with supervised, semi-supervised or unsupervised algorithms to perform stratification.

...

```
library(mclust)
```

```
#Gaussian mixture model
```

```
m1 = Mclust(scoredf$Score, G = 2, verbose = FALSE)
```

```
#k-means clustering
```

```
m2 = kmeans(scoredf[, 5:6], centers = 2, nstart = 100)
```



```
#hierarchical clustering
m3 = hclust(dist(scoredf[, 5:6]))

mutation_inference = cbind(
  'GLM' = prediction,
  'mclust' = m1$classification,
  'k-means' = m2$cluster,
  'hclust' = cutree(m3, k = 2)
)
apply(mutation_inference, 2, adjustedRandIndex, scoredf$NPM1c.Mut)
...

```

Possible improvements

LH: Although the package is generally useful and well described, the following improvements will make it more friendly for less advanced R users, e.g.

LH: Instruction how to prepare and load the data other than those deposited in the GDC database.

DDB: We have noted in text that the rank matrix can be computed using either a *SummarizedExperiment* object, *DGEList* object, *ExpressionSet* object, numeric matrix or a numeric data frame. As such, a numeric matrix with sample names as column names and genes as row names would suffice. Scoring should be performed on length bias corrected measurements such as *RPKM/FPKM* or *TPM* and not *CPM* or raw counts.

Transcriptional signatures to predict mutation status/Score TCGA AML samples using the Verhaak signature - extract from text: "The `rankGenes` function will compute ranks from expression data in the form of either a numeric matrix, numeric data frame, *ExpressionSet* object, *DGEList* object or a *SummarizedExperiment* object"

LH: Annotation of samples on the plots with unique sample IDs (when a sample is misclassified, a user does not know which one it is; it will also be helpful to localize a sample on various plots, e.g. generated with a signature of up- and down-regulated genes) – it is written in the article that the 'singscore' package supports different types of annotations ("Annotations of interest can be overlaid on each plot") but I found only color code annotation whereas I would like to have color code for mutation type and additional text labels with sample IDs on the same plot.

DDB: Sample labels can be added to landscape plots but were not supported in other visualisations. We have added functionality to the latest version of the singscore package (v1.5.1) to allow labelling of samples in the score vs. dispersion plots. We have modified the text to clarify, and modified Figure 6 to label samples where classification uncertainty (NMP1c vs WT) is high to demonstrate this feature. The changes below have been made to the section: "Transcriptional signatures to predict mutation status/Diagnostics of the Verhaak signature".

... Sample annotations of interest (e.g. clinical annotations) can be colour coded on each plot. ...

Figure 6:

```
...
select_aml = !mutated_gene %in% 'Other'

#label samples with an mclust NPM1c classification uncertainty of > 0.3
label_samples = substr(rownames(verhaak_scores), 6, 12) #sample ID from barcodes
label_samples[m1$uncertainty < 0.3] = NA

```

```
#project mutations onto the landscape
p1 = projectScoreLandscape(
  p_mll_npm1c,
  verhaak_scores,
  rossmll_scores,
  subSamples = select_aml,
  annot = mutated_gene[select_aml],
  sampleLabels = label_samples[select_aml]
)
p1 + theme(legend.box = 'vertical')
...
```

LH: A command which lists the samples typed as strong candidates for having particular mutation, ordered according to the calculated metrics.

DDB: As discussed in an earlier comment, we recommend such analyses to be problem specific. Generally, a higher score would indicate a stronger effect of genes in the signature relative to WT samples therefore samples with higher scores would be stronger candidates for mutations. Alternatively, the partitioning created using Gaussian mixture modelling could be used as a guide for separation and samples with a score much higher than the threshold would be the strongest candidates for the mutation.

LH: Generating a threshold line between samples with and without mutation.

DDB: See above discussion/recommendation.

LH: In future, it would be also good to include other signatures, e.g. the signature of 369 genes identified by Alcalay *et al.* in 2005³, discriminating AML patients with NPMc+ from patients with NPMc-, even in cases with rare chromosomal abnormalities.

LH: What I would expect the most from a package designed to identify mutations in transcriptomes, is a direct identification of mutations in RNAseq data. The results of mutation typing based on gene expression profile will be strongly supported when a particular mutation will be covered by RNAseq reads. From my own experience, I know it is possible (for NPM1 mutation detection, see⁴). For genes with high and middle expression level, the coverage can be even higher than that obtained from genome- or exome-level data. And in the case when DNA data are unavailable, it would be really fantastic. Because it demands completely different data processing, it may be considered for future versions of the package.

DDB: As we have outlined at the start of this review there may have been some misunderstanding around the purpose of this Workflow package/paper. We agree with the reviewer that direct detection of mutations/fusions from RNA-seq data is the best approach, and we now note this in the 'Description of biological relevance section' as stated above. The other gene signatures mentioned above could be incorporated in a workflow as singscore supports analysis and comparison of multiple gene sets.

Competing Interests: No competing interests were disclosed.

Reviewer Report 04 June 2019

<https://doi.org/10.5256/f1000research.21079.r49410>

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Marina Lizio 

Division of Genomic Technologies, RIKEN Center for Life Science Technologies, Yokohama, Japan

The authors Bhuva et al. presented the application of a previously published gene set scoring tool, singscore, to discriminate AML subsets based on gene expression signatures, using signatures derived from known specific gene mutations or fusions. The authors show that singscore can effectively separate AML samples based on such gene signatures.

Given the ability of the software to discriminate samples within heterogenous diseases, such as leukemias, its application to other cancers and diseases with similar levels of heterogeneity can be beneficial to improve patients' clinical outcomes.

The rationale behind the application of the software and its step-wise descriptions are well explained. So is the interpretation of results.

I appreciate the authors' efforts to explain all the steps and suggest alternatives, giving the software description the feel of a tutorial.

I have some small comments on some points I'd like to see addressed:

1. Title. As far as I have understood, singscore doesn't actually predict mutations. Rather, it uses gene signatures associated to certain mutations in order to identify sub-groups within a population. As it is, the title is misleading.
2. Similar rationale about the title of section "Predicting mutations using the Verhaak signature", page 16.
3. In the section "Filter out genes with low counts", page 7, the authors describe explicitly how to handle duplicated entries caused by the GDCprepare function. Here I would reorganise and shorten the paragraph by first mentioning the issue introduced by the function, then saying edgeR is applied to the data filtered of duplicate entries.
4. Figure 3. The legend below each graph is identical. I suggest to only use one legend for all three plots.
5. The authors comment on several instances about the similarities between scores for signatures of two subgroups of AML samples, NPM1c and KMT2A-/MLL-fusion, and that's due to the presence of Hox genes. I suggest to have the lists of the two gene signatures directly in the article for immediate lookup. This is not essential, as the authors already refer to the articles they take the data from, but I think it will help readers.

Minor comments:

1. Typo in the caption of figure 1 (approximately instead of approximatly).
2. Typo in figure 2 caption. I suppose "scores are plot against..." should read "scores are plotted against..."

Is the rationale for developing the new software tool clearly explained?

Yes

Is the description of the software tool technically sound?

Yes

Are sufficient details of the code, methods and analysis (if applicable) provided to allow replication of the software development and its use by others?

Yes

Is sufficient information provided to allow interpretation of the expected output datasets and any results generated using the tool?

Yes

Are the conclusions about the tool and its performance adequately supported by the findings presented in the article?

Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Transcriptome analysis, Gene expression regulation

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Author Response 16 Aug 2019

Melissa Davis, University of Melbourne, Parkville, Australia

We would like to thank Dr Marina Lizio for her very useful review, and we have addressed her comments as outlined below.

ML: I have some small comments on some points I'd like to see addressed:

1. Title. As far as I have understood, singscore doesn't actually predict mutations. Rather, it uses gene signatures associated to certain mutations in order to identify sub-groups within a population. As it is, the title is misleading.

*DDB: This is an excellent point. We have now changed the title to "Using singscore to predict mutation **status** in AML from transcriptomic signatures" in order to clarify that we are simply predicting the mutation status of samples, not actual mutations.*

2. Similar rationale about the title of section "Predicting mutations using the Verhaak signature", page 16.

*DDB: A similar change is made here, the title of this section is now: "Predicting **NPM1c** mutation **status** using the Verhaak signature".*

3. In the section "Filter out genes with low counts", page 7, the authors describe explicitly how to handle duplicated entries caused by the GDCprepare function. Here I would reorganise and

shorten the paragraph by first mentioning the issue introduced by the function, then saying edgeR is applied to the data filtered of duplicate entries.

DDB: The issue of duplicated features with the TCGAbiolinks package has been fixed in a recent update (TCGAbiolinks v2.12.2). Consequently, we will be removing the text describing the identification and removal of duplicated features. The text removed is:

Creation of a DGEList object is initially unsuccessful due to duplicated row names in the data matrix (107 features). The raw count files for individual samples do not have any duplicated features indicating this is introduced by the `GDCprepare` function. This is further supported by the fact that the counts for a single feature are the same for duplicated entries. An example of such a feature is shown below and we have verified duplicated entries of all other features to be the same.

```

```{r}
dup_features = rownames(aml_se)[duplicated(aml_se)]
```

```{r dup_entries}
library(SummarizedExperiment)

#example check on one feature ID
dup_feature = 'ENSG00000011454'
dup_data = assay(aml_se[rownames(aml_se) %in% dup_feature,])
identical(dup_data[1,], dup_data[2,])
```

```

As such, it is safe to discard duplicated entries.

We also remove the code that discards duplicate features

```

-----
aml_se = aml_se[!duplicated(rownames(aml_se)), ]
-----

```

4. Figure 3. The legend below each graph is identical. I suggest to only use one legend for all three plots.

DDB: We appreciate this point, however each plot in this figure is generated by a function in the package which includes the legend. For a normal use case, users would be generating a single plot to diagnose a single sample, which is why we include a legend for the plot. In this workflow, we simply combine the three plots into a single figure. Removing legends from the default plots would overcomplicate the code of this diagnostic procedure in the workflow which is why we decided to leave the legends as they are. If users were interested in manipulating figures in their application, they could add extra options to the ggplot2 object (as we show with adding a new title and modifying the legend to be a single column).

5. The authors comment on several instances about the similarities between scores for signatures of two subgroups of AML samples, NPM1c and KMT2A-/MLL-fusion, and that's due to the presence of Hox genes. I suggest to have the lists of the two gene signatures directly in the article

for immediate lookup. This is not essential, as the authors already refer to the articles they take the data from, but I think it will help readers.

DDB: The signatures we downloaded from MSigDB have Entrez IDs for genes. The NPM1c and MLL signatures contain 491 unique genes. The reason we did not have the lists in the article was that we would be presenting 491 numbers that would have been difficult to interpret without mapping. Additionally, our intention is for readers to execute the workflow while reading this article. In this scenario, the `genelds()` function could be used to list the gene identifiers forming the signatures once they have been downloaded and parsed into R. Identifiers could be mapped to symbols using the `mapIds()` function in the AnnotationDbi package and an annotation such those provided by the `org.Hs.eg.db` R/Bioconductor package. We hope that the ease with which these data can be accessed in the application will make the lists accessible for readers.

ML: Minor comments:

1. Typo in the caption of figure 1 (approximately instead of approximately).

DDB: Thanks for helping us identify this, we have fixed it now.

2. Typo in figure 2 caption. I suppose "scores are plot against..." should read "scores are plotted against..."

DDB: This has also been changed.

Many thanks for the useful and constructive review.

Best wishes,

Mr Dharmesh Bhuvu
Bioinformatics Division
The Walter and Eliza Hall Institute

Dr Melissa Davis
Bioinformatics Division
The Walter and Eliza Hall Institute

Competing Interests: No competing interests were disclosed.

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Author/s:

Bhuva, DD; Foroutan, M; Xie, Y; Lyu, R; Cursons, J; Davis, MJ

Title:

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Date:

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