Detect tissue heterogeneity in gene expression data with BioQC

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Abstract

Background: Gene expression data can be compromised by cells originating from other tissues than the target tissue of profiling. Failures in detecting such tissue heterogeneity have profound implications on data interpretation and reproducibility. A computational tool explicitly addressing the issue is warranted.

Results: We introduce BioQC, a R/Bioconductor software package to detect tissue heterogeneity in gene expression data. To this end BioQC implements a computationally efficient Wilcoxon-Mann-Whitney test and provides more than 150 signatures of tissue-enriched genes derived from large-scale transcriptomics studies. Simulation experiments show that BioQC is both fast and sensitive in detecting tissue heterogeneity. In a case study with whole-organ profiling data, BioQC predicted contamination events that are confirmed by quantitative RT-PCR. Applied to transcriptomics data of the Genotype-Tissue Expression (GTEx) project, BioQC reveals clustering of samples and suggests that some samples likely suffer from tissue heterogeneity.

Conclusions: Our experience with gene expression data indicates a prevalence of tissue heterogeneity that often goes unnoticed. BioQC addresses the issue by integrating prior knowledge with a scalable algorithm. We propose BioQC as a first-line tool to ensure quality and reproducibility of gene expression data.

Keywords: Gene expression, Quality control, Wilcoxon-Mann-Whitney test, Gene-set enrichment analysis

Background

Gene expression data has become indispensable in modern drug discovery. It reveals biological processes underlying pathogenesis and sheds light on mode-of-action and potential safety liabilities of drug candidates. However, its value in catalyzing new medicines is shadowed by limited reproducibility [1]. From the (re-)analysis of a large number of internal and external studies we observe that tissue heterogeneity, defined as unintended profiling of cells of other origins than the target tissue of profiling, is a common source of variance that exacerbates the irreproducibility.

Many factors can cause tissue heterogeneity in gene expression profiling experiments. Some are attributed to underlying physiological or pathological processes, for example infiltration of immune cells into solid organs or tumors. Some are associated with the challenge of dissecting adjacent tissues such as coronary artery and cardiac muscle. In other cases heterogeneity is due to human errors such as contamination or mislabeling. Independent of root causes, tissue heterogeneity in gene expression data should be identified as early as possible to prevent it impacting downstream analysis. No software tool, however, fulfills this purpose to our best knowledge.

Various computational approaches may address the issue and they can be broadly classified into unsupervised and supervised algorithms. Unsupervised algorithms, such as principal component analysis (PCA) and its variants, may detect tissue heterogeneity without prior knowledge [2]. Nonetheless unsupervised algorithms are only sub-optimal in this setting because (a) they cannot reveal likely sources of heterogeneity, (b) they cannot work with single sample, and (c) their application is limited to cases where few samples are heterogeneous,
since otherwise it becomes difficult to distinguish heterogeneous from homogeneous samples.

Supervised algorithms overcome these restrictions by incorporating prior information such as sets of preferentially expressed genes [3] or reference profiles of purified cells [4]. While several supervised methods are available to quantitatively estimate the composition of cell types (reviewed in [5]), their application in first-line quality control is limited because most tools rely on a substantial amount of prior information which is often not available, for instance profiles of each single cell type that may present. In addition, these tools often use complex models such as expectation-maximization or quadratic programming which demand significant computational resources and therefore are hardly scalable to large-scale datasets, for instance the Genotype-Tissue Expression (GTEx) project [6, 7] which contains more than 8500 profiles in its current (6th) version.

To allow efficient and sensitive detection of tissue heterogeneity, we introduce the software package BioQC. It takes gene expression data as input, performs statistical tests with tissue-enriched gene signatures that come with the package, and reports enrichment scores of more than 150 tissue signatures for each sample. High scores of tissues other than the target tissue of profiling indicate heterogeneity and consequently possible infiltration or contamination events.

**Implementation**

BioQC follows the supervised approach: it provides sets of genes that are preferentially expressed in one or few tissues (tissue-enriched genes hereafter), and an efficient algorithm to test enrichment of tissue-enriched genes in expression data.

**Tissue-enriched genes**

We derived 155 sets of tissue-enriched genes (tissue signatures hereafter) from four datasets: the Neurocrine Biosciences (NB) CNS dataset [8], the GNF Gene Expression Atlas [9], both based on the Affymetrix microarray technology, and sequencing-based RNA-seq Atlas [10] and Illumina BodyMap 2.0 (GEO Accession Number GSE30611 [11]). For preprocessing we normalised microarray signals with the MAST method [12] and converted sequencing read counts into the unit of *copies per million reads* [13]. Expression signals are averaged in case more than one samples are available for each tissue. Both sequencing-based datasets are merged by removing batch effects using a linear model in order to achieve a wide coverage of tissues comparable with microarray-based datasets.

**Gini index** [14] was used to identify tissue-enriched genes. Given an $m \times n$ expression matrix with $m$ genes and samples of $n$ tissues, Gini index for gene $i$ is defined as

$$G_i = \frac{1}{n} \left( n + 1 - 2 \left( \frac{\sum_{j=1}^{n} (n + 1 - i)x'_{ij}}{\sum_{j=1}^{n} x_{ij}} \right) \right),$$

where $x'_{ij}$ is the $j$th value in the non-descending ordered vector of $x_i \ (i = 1, \ldots, m, j = 1, \ldots, n)$. Gini index ranges between 0 and 1, depending on whether the gene is ubiquitously and uniformly present or absent in all tissues ($G = 0$) or is exclusively expressed in one tissue ($G = 1$) or in between ($0 < G < 1$).

We consider gene $i$ enriched in tissue $j$ if $G_i \geq 0.7$ and $x_{ij}$ ranks among the top three in $x_i$. Signatures derived from both microarray datasets are merged, while microarray-based and sequencing-based signatures are kept separate so that users can benefit from the high sensitivity offered by the sequencing technology. Users can define their own signatures using other datasets with functionalities implemented in BioQC or with other statistical methods.

**Validation of tissue-enriched genes**

We took a three-tier approach to validate the tissue signatures. First, in order to assess their robustness against batch effects, we applied surrogate variable analysis [15] to both GNF and NB datasets to detect uncaptured batch effects (not applicable to sequencing-based datasets where only one sample is available for each tissue). Based on batch-effect-corrected data, we generated a new set of signatures using the procedure described above. We applied the BioQC algorithm using both signature sets to the GTEx gene expression database [7] and found that the results are highly similar (Additional file 1: Figure S1), which suggests that the BioQC tissue signatures are robust with regard to potential batch effects in the source data.

Next, we used biological knowledge to test the validity of the tissue signatures using Roche Controlled Vocabulary (RCV hereafter), a recently developed, simplified ontology system of annotating human genes with biological processes defined by the Gene Ontology consortium [16]. We applied the BioQC algorithm, using both tissue-enriched gene sets and RCV gene sets, to the GTEx dataset, and found that for many tissues that are included in GTEx, expected tissue signatures are co-enriched with relevant biological processes. For instance, most tissue signatures associated with the nervous system are co-clustered with genes associated with neuronal biological processes (Additional file 1: Figure S2). The observation suggests that the tissue signatures are biologically relevant.

Last but not least, to test the validity of using Gini index to identify tissue signatures, we applied an independent algorithm, limma [17], to the GTEx dataset (limma was prefered to negative-binomial-model based methods such as DESeq2 and edgeR due to computational efficiency and the compatibility of results). We identified signatures of 29
tissues that are present in GTEx using very stringent filters. For those tissues that are present in the BioQC tissue signatures, we observed moderate to strong overlapping and comparable performance with BioQC on a large collection of gene expression data (manuscript in preparation). It suggests that BioQC tissue signatures are consistent with signatures generated from an independent dataset by an alternative statistical method.

**The algorithm of BioQC**

BioQC implements a computationally efficient Wilcoxon-Mann-Whitney test (Wilcoxon test hereafter) [18]. The algorithm is accelerated by (a) an approximate test procedure, (b) implementation of the core algorithm in C programming language, and (c) elimination of futile sorting operations. Improvement that we made over standard implementations is detailed in Additional file 2: Document 1.

Given a gene expression profile and a tissue signature, BioQC tests by default whether expression of genes in the signature ranks higher than expression of genes not in the signature. Users can test negative enrichment or two-sided (either positive or negative) enrichment, too.

BioQC reports an enrichment score of each tissue signature for each sample in the form of $|log_{10}p|$ (absolute log 10-transformed $p$-value of Wilcoxon test). Given expression profiles of $n$ samples as input and $s$ tissue signatures, BioQC outputs an $s \times n$ matrix with scores ranging between 0 (no enrichment) and theoretically positive infinity (strong enrichment). By examining BioQC results and comparing them with target tissues of profiling users can inspect heterogeneity and generate hypotheses about the causes.

Although this work focuses on its application to detect tissue heterogeneity, we note that BioQC can be used as a generic gene-set enrichment analysis tool (manuscript in preparation).

**Results**

We apply BioQC to simulated and real-world datasets to demonstrate its use. All computations are performed on a single thread of a 4-core laptop with 8G memory running R-3.2.0 in 64-bit Linux MINT (version 16) if not otherwise specified.

**Simulation studies**

We performed three simulation experiments to study the efficiency and sensitivity of BioQC.

**Simulations with model-generated data**

The first simulation study probes the speed of BioQC. We propose a simple model to generate random gene expression profiles of approximately 22,000 genes with each gene following the normal distribution $N(0, 1)$. We let the model generate five datasets with varying sample sizes ($n = 1, 5, 10, 50, 100$), applied BioQC and timed the runs. For benchmarking we applied the native implementation of Wilcoxon test in R (function `wilcox.test`) to the same dataset.

Both implementations delivered identical numeric results and their memory use is comparable. However, while it takes the native implementation 20 minutes to analyze 100 profiles, it takes BioQC just about one second (Fig. 1a left panel). Quantitatively BioQC accelerates the Wilcoxon test by a factor between 500 and 1000 for gene expression data (Fig. 1a right panel). The results suggest that BioQC is computationally efficient and applicable for large-scale datasets even on laptop computers.

Next, we investigated the sensitivity of BioQC towards expression changes of tissue-enriched genes. To this end, we adapted the simple model used above: while keeping random-number generators of other genes unchanged, expression levels of genes in a randomly chosen signature (ovary with 43 genes) were drawn from a series of distributions $N(\mu, 1)$ with $\mu$ varying from 0 to 3. We generated ten samples for each distribution and applied BioQC.

We observed that the average enrichment score of ovary increases steadily as $\mu$ increases (Fig. 1b left panel), and as soon as $\mu$ reaches or exceeds 1, the ovary signature ranks first among all signatures in all simulated samples (Fig. 1b right panel). Repeated experiments with other tissue signatures produced consistent and comparable results (data not shown). In other words it is sufficient for a tissue signature to rank first if average expression of its genes increases by one standard deviation. It suggests that BioQC is sensitive to even mild changes in expression of tissue-enriched genes.

We note nevertheless that the sensitivity test above suffers from the limitations that (a) the distributions of gene expression are not physiological and (b) elevated expression of tissue-enriched genes is not quantitatively associated with severity of contamination. To corroborate our findings we next performed simulations with real-world data.

**Simulation with real-world data**

We simulated tissue heterogeneity in silico with a transcriptomics study in *Canis lupus familiaris* (domestic dog) by Briggs et al. [19]. In this study the authors constructed a compendium of canine normal tissue gene expression, which includes 39 samples of 10 tissues from four dogs (four samples of liver, kidney, heart, lung, cerebrum, lymph node, spleen, jejenum, and skeletal muscle; three samples of pancreas).

Prior to simulation experiments we first applied BioQC to the dataset to test whether its results match information provided by the authors. In [19], the authors performed hierarchical clustering of both canine and
human data and reported a ‘remarkable similarity’ of normal tissue gene expression profiles between the two organisms. Indeed, BioQC confirmed the consistency in 36 (92%) cases in which canine tissues reported by the authors match the highest-ranking human tissues reported by BioQC (Table 1 in Additional file 3: Document 2). Among the three discrepant cases, one was originally labeled as prefrontal cortex but found by BioQC to resemble the spinal cord most (sample ID GSM502573), and the other two samples were labeled as lung but found most similar to monocytes (GSM502594 and GSM502596). Interestingly, the authors’ findings seem to be supportive of our observations: GSM502573 is an apparent outlier in the PCA analysis (Fig. 1a in [19]), and the authors noted that average profiles of canine lung and spleen samples, unlike other tissues, do not cluster
together with respective human tissues in hierarchical clustering and show similarity with each other (Fig. 2a in [19]).

While it remains unknown what causes the observed heterogeneity, for the purpose of simulation the three samples were excluded. We then calculated an average expression profile for each tissue using the remaining 36 samples and simulated contamination by creating weighted linear combination of expression profiles of pairs of tissues, a procedure referred to as mixing hereafter.

Mathematically, given the expression profile of tissue A (\(Y_A\)) and B (\(Y_B\)), mixing generates a new profile \(Y = \omega Y_A + (1 - \omega) Y_B\) with \(\omega \in [0,1]\). As \(\omega\) approaches 1, the new profile mimics contamination of A by B; when \(\omega\) approaches 0, it mimics contamination of B by A.

To illustrate the idea we applied BioQC to mixed profiles of heart and jejunum and visualize the results in Fig. 1c. As the weight of heart increases, enrichment score of small intestine decreases while that of cardiac muscle increases. With as little as 10% contamination by heart in jejunum, enrichment score of cardiac muscle is above 3.0 (corresponding to \(p < 10^{-3}\) of Wilcoxon test) and ranks 4th out of 155 tissue signatures. With 25% contamination, enrichment score of cardiac muscle exceeds 7.0 and ranks second. These results suggest that BioQC is very sensitive towards heart contamination in jejunum.

Intriguingly, we observe an asymmetry in the sensitivity: it takes about 20-30% jejunum contamination in the heart sample to make the enrichment score exceed 3.0 or rank among the top ten. The asymmetry is likely caused by the relatively high expression of heart-enriched genes compared with small-intestine-specific

![Fig. 2 BioQC detects pancreas contamination of mouse kidney samples](image)

**Fig. 2** BioQC detects pancreas contamination of mouse kidney samples. **a** Enrichment scores (ES) of kidney and pancreas signatures. **b** Normalised microarray signals of pancreas-enriched genes (zero mean and one standard deviation per gene). **c** Expression of amylase and elastase detected by qRT-PCR, with indices of contaminated samples labeled. AU: Arbitrary Unit
genes in the respective tissue (Figure 4 in Additional file 3: Document 2). Despite of the asymmetry, we observe a strong leap of small-intestine signature’s rank as its proportion further increases. In practice when one of several heart samples is contaminated by jejenum, an aberrant higher rank of the jejenum signature can be a warning sign of tissue heterogeneity to the software user.

Following this example, we mixed all pairs of canine tissues and found that on average BioQC is able to detect heterogeneity with 20% or more contamination (enrichment score $\geq 3.0$ or rank $\leq 10$, Figure 3 in Additional file 3: Document 2). Tissues like liver and heart with highly expressed enriched genes can be more easily detected as sources of contamination with the proportion as low as 12%.

In summary, simulation studies with model-generated and real-world data demonstrate that BioQC is scalable and sensitive in detecting tissue heterogeneity. Since the simple statistical models that we used may not fully cover the complexity of tissue heterogeneity, we now turn to test BioQC with further real-world gene expression datasets.

**Case study with whole-organ profiling data**

We applied BioQC to a dataset generated in a Roche research program. In this study twenty-five mouse whole-kidney samples were taken after diverse treatment regimen including operation and medication (details in Additional file 4: Document 3). Genome-wide gene expression profiling was performed with Affymetrix Mouse Genome 430 2.0 microarray.

Results of BioQC are visualized in Fig. 2a. As expected, kidney-enriched genes ranked first among all tissue signatures in all samples. In three samples (index 23, 24 and 25), however, the pancreas signature scored much higher than in other samples. As we examined genes in the signature, we observed substantial expression of many genes including insulin (INS), glucagon (GCG), and pancreatic carboxypeptidase A1 (CPA1) in the three samples (Fig. 2b). This made us suspect that these samples might be contaminated by traces of pancreas.

To validate the hypothesis, we quantified expression of amylase (AMY1A) and elastase (CELA1), both highly expressed in pancreas and absent in kidney according to GTEx [7] and Human Protein Atlas [20], with quantitative RT-PCR. We could indeed detect specific and substantial expression of both genes in the samples suspected of contamination (Fig. 2c). Based on these results, we decided to exclude the three samples from downstream analysis. Exploratory analysis reveals that if the heterogeneity was overlooked and the contaminated samples were not removed, several pancreas-enriched genes would erroneously show strong differential expression in certain comparisons (Figure 4 in Additional file 3: Document 2).

In summary, the case study underlines the power of BioQC to detect tissue heterogeneity in gene expression data.

**BioQC applied to GTEx gene expression data**

Finally we assessed tissue heterogeneity in a small subset of GTEx gene expression data by applying BioQC to small-intestine samples ($n=40$). BioQC revealed three clusters of samples based on enrichment of tissue signatures (Fig. 3a). Cluster 1 is highly enriched of the small-intestine signature and almost devoid of enrichment of signatures of other tissues (Fig. 3b). Samples in cluster 2 display decreased enrichment of the small-intestine signature and increased enrichment of the lymphocyte signature (Figs. 3c and d). Surprisingly, samples in cluster 3 show enrichment of neither small-intestine nor lymphocyte signature, but increased expression of muscle-enriched genes (Fig. 3e). It is noteworthy that exploratory analysis showed no significant association between the clustering and any of the clinical parameters reported by the GTEx consortium (age, sex, death causes, etc.; $\chi^2$ test, significance threshold $\alpha = 0.05$).

Causes underlying the heterogeneity are obscure to us and may require substantial efforts to be clarified. However, one may speculate that an over-representation of intraepithelial lymphocytes or Peyer’s patch, due to either physiological or pathological courses, may contribute to the enrichment of the lymphocyte signature in samples of cluster 2. Enrichment of the muscle signature in cluster 3 may be caused by over-proportional mucosa or other cells of muscle’s origin. Despite the uncertainty of causes, gained information of sample heterogeneity can enhance the quality of downstream analysis. For example, results of BioQC can be injected into a weighted statistical model to identify genes that are preferentially present in small intestine, which may reveal specific cell-surface receptors that allow tissue-targeted drug delivery. Deprioritising samples outside of cluster 1 is likely to improve the specificity of identified targets.

In summary, BioQC reveals clustering of samples and tissue heterogeneity of different severity in a subset of GTEx data. Researchers using GTEx and similar resources are advised to perform quality control with BioQC before pursuing further analysis of data.

**Discussions and conclusions**

While the impact of some factors underlying tissue heterogeneity may be minimized by taking greater care in experiment design, tissue dissection, and sample handling, factors such as immune cell infiltration are unlikely controllable. If overlooked, tissue heterogeneity may cause gene expression studies irreproducible because the heterogeneity is unlikely to be identical in an independent experiment.
Therefore we propose applying BioQC as a first-line quality control to detect tissue heterogeneity. BioQC tests enrichment of tissue-enriched genes sample-by-sample and suggests possible sources of heterogeneity, both of which are not possible for unsupervised methods like PCA. Compared with other supervised methods, BioQC comes with the required prior information and is extremely efficient. Extrapolating from the observation that BioQC needs about one second to analyze 100 genome-wide gene expression profiles, we estimate that it would take BioQC only about six hours to analyze the entire GEO database, which collects about 2.0 million gene expression profiles as of November 2016, with one CPU-thread (excluding the time of downloading, pre-processing, etc.). In light of its favorable scalability and sensitivity, we believe BioQC is suitable for small- and large-scale gene expression studies.

We expect tissue signatures to be applicable across closely related species as it was shown elsewhere that within mammals the expression patterns of protein-coding genes are more conserved between species than between major organs [21, 22]. The human derived tissue signatures are already applied successfully to tissue expression data from multiple vertebrate model species including macaque, pig, dog, rodents, and zebrafish (data not shown). The simulation study using dog tissue expression data exemplifies such an analysis.

We have integrated BioQC in our gene expression analysis pipeline since three years to routinely detect tissue heterogeneity in internal and external studies. It has raised warning flags in many datasets independent of the target tissue of profiling, organism, experiment design, profiling platform and laboratory. While a few suspects were validated such as the ones in our case study, most findings were regrettably not followed up due to limited capacity and material unavailability. With more expression profiling data generated worldwide everyday, we wish that BioQC can help experimentalists and data analysts alike to improve the quality and reproducibility of gene expression studies.
Availability and requirements
Project name: BioQC;
Project home page: http://accio.github.io/BioQC/;
Operating systems: Unix, Linux, Mac OS and Windows;
Programming language: GNU-R and C;
Other requirements: R and Bioconductor installation;
Licence: GPL-3.

Additional files

Additional file 1: Supplementary Figures. (PDF 592 kb)
Additional file 2: Supplementary Document 1. This document can also be accessed on the BioQC website under [27] respectively. (ZIP 98 kb)
Additional file 3: Supplementary Document 2. This document can also be accessed on the BioQC website under [28] respectively. (ZIP 305 kb)
Additional file 4: Supplementary Document 3. This document can also be accessed on the BioQC website under [29] respectively. (ZIP 325 kb)

Abbreviations
GEO: The gene expression omnibus database; GTEx: The genotype-tissue expression project; PCA: Principal component analysis; RT-PCR: Reverse transcription polymerase chain reaction

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Availability of data and materials
The BioQC package is written in the programming languages R and C. It is freely available from Bioconductor [23] with the GPL-3 license. The package is tested in major operating systems including Unix, Linux, Mac OS and Windows. The source code and datasets supporting the conclusions of this article are available on the BioQC website [24]. The compendium data is downloaded from the NCBI Gene Expression Omnibus (GEO) database with the accession number GSE20113 [25]. GTEx data was downloaded from [26].

Authors’ contributions
JDZ and LB conceived the study. LB derived gene signatures from public datasets. JDZ implemented the software, performed simulation studies and wrote the manuscript. KH applied BioQC to GTEx data and contributed Fig. 3. GS contributed to the software testing and documentation and setup the website. CB and ME designed and maintain infrastructure and services of Bioinformatics which enable the development of the software. MJ, FT and SIP provided whole-organ profiling and qRT-PCR data. JDZ, KH, GS, ME and LB extensively tested the software. All authors approved the content of the manuscript.

Competing interests
JDZ, KH, GS, CB, ME, SIP and LB are previously or currently employed by F. Hoffmann-La Roche Ltd. The authors declare that they have no competing interests.

Consent for publication
Not applicable.

Ethics approval
The mouse study was approved by the local ethics committee: Paris Descartes University ethical committee (reference number P2.1PB.119.09).

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