

1 Ontology of RNA Sequencing (ORNASEQ) and its application

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21 Abstract

22 **Background:** Next-generation RNA sequencing is a rapidly developing technology
23 with complex procedures encompassing different experimental modalities. As the
24 technology evolves and its use expand, so does the need to capture the data
25 provenance from these sequencing studies and the need to create new tools to
26 manage and manipulate these provenance stores.

27

28 **Results:** Here we used the Ontology for Biomedical Investigations (OBI) and many
29 other ontologies from the Open Biological and Biomedical Ontology (OBO) Foundry
30 as a framework from which to create an application ontology (ORNASEQ: Ontology
31 of RNA sequencing) to capture data provenance for next-generation RNA
32 sequencing studies. Additionally, we provide an extensive real-life sample
33 provenance data set for use in developing new provenance tools and additional
34 sequencing data models.

35

36 **Conclusions:** The Ontology of RNA Sequencing (ORNASEQ) provides core terms for
37 use in building data models to capture the provenance from next-generation RNA
38 sequencing studies. The supplied sample provenance data also exemplifies many of
39 the complexities of RNA sequencing studies and underscores the need for potent
40 workflow management systems.

41 Keywords

42 Ontology, RNAseq, PROV-XML

43

44 Background

45 Until recently the cost of performing next-generation RNA sequencing (RNAseq)
46 experiments limited the amount of data generated by a single lab and managing and
47 properly documenting a few experiments was not fundamentally challenging.
48 However, as sequencing costs have dropped, research groups are now running
49 hundreds, thousands or even tens of thousands of RNAseq experiments, creating a
50 need to systematically document experimental and informatics details and track
51 provenance of the final published or publicly released datasets. RNAseq has also
52 begun making its way into medical diagnostics, where data provenance is a
53 necessity for quality assurance and regulatory compliance. Tracking the data
54 provenance for hundreds or thousands of sequencing experiments in either a
55 research or medical setting requires data models and structures that must be put
56 into place to capture the necessary information at all stages of a sequencing
57 experiment and it's not always obvious what information is necessary. While there
58 are numerous platforms and pipelines to analyze RNAseq data, there are limited
59 data models or ontologies that could be applied to successfully capture the details of
60 an RNAseq experiment [1–6].

61

62 Within a single next-generation sequencing experiment there is a dizzying amount
63 of information that must be captured throughout the often-complex experimental
64 procedures and post-sequencing informatics analyses. The problem is further

65 complicated by the number of researchers or technicians who might be involved in a
66 single sequencing experiment whose roles are interspersed in irregular patterns;
67 complexity of biological specimens, their origin and experimental designs; and, the
68 frequent disconnect between the biologists running the experiments and the
69 bioinformaticists analyzing the data. Tracking data provenance spanning
70 experiment procedures recorded in lab notebooks belonging to multiple biologists
71 and computer log files residing in a series of cryptic directories on a file system
72 quickly becomes an intractable problem. These challenges suggest a need for a
73 comprehensive next generation sequencing provenance system. Data provenance
74 requires data models, provenance models, and supporting infrastructure. Here, we
75 focus on the first part of data models for RNA sequencing experiments and describe
76 an Ontology for RNA Sequences (ORNASEQ). In addition, we provide a large next-
77 generation sequencing use case from an active RNAseq workflow, using the PROV-
78 XML database format for the community to use as an example dataset for
79 development of provenance models and tools.

80 Ontology for RNA sequencing

81 The Ontology for RNA Sequencing (ORNASEQ) is an application ontology based
82 largely on the Ontology for Biomedical Investigations (OBI)[1], using the principles
83 of OBO Foundry[7]. Specifically, ORNASEQ contains 162 terms, 117 of the terms are
84 from 16 existing ontologies, with 28 new terms having now been added to OBI and
85 17 terms being defined directly in ORNASEQ (see Table 1). ORNASEQ is designed to
86 annotate RNA-based next-generation sequencing, although much of ORNASEQ

87 would also apply to DNA-based next-generation sequencing. The ontology was
88 designed, in part, through efforts to track the data provenance of thousands of
89 RNAseq samples collected by the NIH Common Fund Single Cell Analysis Program-
90 Transcriptome (SCAP-T) program[8]. Terms included in the ontology cover pre-
91 sequencing preparations and primary post-sequencing data analysis.
92

Ontology	Number Terms
BFO: Basic Formal Ontology <i>http://purl.obolibrary.org/obo/bfo.owl</i>	10
CHEBI: Chemical Entities of Biological Interest <i>http://purl.obolibrary.org/obo/chebi.owl</i>	2
CL: Cell Ontology <i>http://purl.obolibrary.org/obo/cl.owl</i>	6
EFO: Experimental Factor Ontology <i>http://www.ebi.ac.uk/efo/efo.owl</i>	6
GENEPIO: Genomic Epidemiology Ontology <i>http://purl.obolibrary.org/obo/genepio.owl</i>	4
GO: Gene Ontology <i>http://purl.obolibrary.org/obo/go.owl</i>	5
IAO: Information Artifact Ontology <i>http://purl.obolibrary.org/obo/iao.owl</i>	14
NCBITaxon: NCBI Organismal Classification <i>http://purl.obolibrary.org/obo/ncbitaxon.owl</i>	1
NCIT: NCI Thesaurus OBO Edition <i>http://purl.obolibrary.org/obo/ncit.owl</i>	6
OBI: Ontology for Biomedical Investigations <i>http://purl.obolibrary.org/obo/obi.owl</i>	79

OBIws: OBI web service, development version <i>http://purl.obolibrary.org/obo/obi/webService.owl</i>	5
OGMS: Ontology for General Medical Science <i>http://purl.obolibrary.org/obo/ogms.owl</i>	1
OMIABIS: Ontologized MIABIS <i>http://purl.obolibrary.org/obo/omiabis.owl</i>	2
SO: Sequence Types and Features <i>http://purl.obolibrary.org/obo/so.owl</i>	1
TAXRANK: Taxonomic rank vocabulary <i>http://purl.obolibrary.org/obo/taxrank.owl</i>	2
UBERON: Uberon multi-species anatomy ontology <i>http://purl.obolibrary.org/obo/uberon.owl</i>	1

93 Table 1: The set of external ontologies included in ORNASEQ.

94

95 Pre-Sequencing Provenance

96 Knowing what happens to a data sample prior to sequencing is essential to
97 understanding the analyzed data. The provenance surrounding the preparation of
98 sequencing data can prove invaluable to diagnosing aberrant results. These
99 protocols are often revised over time and as hardware and reagents evolve and a
100 multi-year study will likely include many versions of protocols with varying degrees
101 of differential change. Even in the controlled context of medical diagnostics, changes

102 are inevitable, for example, when a reagent becomes discontinued or hardware are
103 upgraded.

104

105 When capturing experimental lab data provenance, it is difficult to know what to
106 capture and in what format (e.g. as fields in a database, as a Word or PDF document,
107 or even as a reference to an entry in an electronic notebook). As sequencing
108 preparation protocols are often distributed as PDF or Word documents, trying to
109 track changes across multiple such documents quickly becomes a tedious process
110 that is difficult to automate and nearly impossible to query for specific questions
111 (e.g., what version of sequencing chemistry was used for what samples). Conversely,
112 because the protocols involve many incremental steps and details that are inter-
113 related in a complicated manner, it is difficult to convert each protocol into a fine-
114 grained structured knowledge model suitable for standard DBMS. Similar to the
115 scheme implemented by the Genomic Standards Consortium [3], we propose
116 experimental provenance be captured in a hybrid fashion including both detailed
117 protocol files and hardcoded fields tracking fundamental datum external to the
118 protocol files. In this RNAseq data provenance schema, complete protocol
119 definitions are stored in the provenance database as files (typically PDF or Word
120 documents). Critical or commonly changed features of the protocol are additionally
121 captured in the database schema. While not optimal, this approach preserves the
122 fine detail required to replicate an experimental procedure, while allowing for
123 structured query of the main features.

124

125 Post-Sequencing Provenance

126 When RNAseq data comes off the sequencer it is typically converted into fastq files
127 by a proprietary, sequencer-specific program. A fastq file is a text file containing
128 nucleotide sequences [9]. In the case of RNAseq, fastq files contain nucleotide
129 sequences representing the RNA molecules from a biological sample. Any one RNA
130 molecule might be represented by tens to hundreds of thousands of sometimes
131 duplicate nucleotide sequences in the fastq file, with each nucleotide sequence
132 referred to as a “read” (i.e. a read out of the biological sequence). The fastq files are
133 run through what is called a “primary analysis pipeline”, which may include any
134 number of steps such as generating quality control metrics, removing contaminant
135 sequences from one or both ends of the reads, removing low quality sub-sequences
136 from reads, removing duplicate reads, and aligning reads to a pre-defined reference
137 library. Primary analysis pipelines and more generally RNA sequencing experiments
138 often culminate in the generation of gene-, transcript-, or exonic-counts of the
139 number of reads associated with each of these categories. The various steps will
140 mostly remain consistent within a research group, a project or a medical diagnostic
141 test. However, programs evolve, algorithmic bugs are fixed, and reference libraries
142 are refined. As with wet lab procedures, it is common and often necessary for
143 primary analysis pipelines to change by varying degrees over time. Since the data
144 and processes for the informatics steps are already machine readable, capturing
145 provenance for RNAseq analysis pipeline is a more obvious task than in a wet lab
146 context. However, relevant provenance information is typically realized as a set of
147 log files spread across a series of programs, each with specific directory structures.

148 Using log files to track provenance data also quickly breaks down as programs
149 change or pipelines evolve and often requires complex programming to perform
150 simple queries across data samples. As with tracking wet lab data, provenance from
151 sample processing pipelines needs to be rigorously captured and systematically
152 stored in a central database. Addressing these challenges require incorporation of a
153 well-defined and use-case oriented ontology for the provenance objects, which we
154 provide with ORNASEQ.

155 Sample Data

156 ORNASEQ is meant to provide core terms used to track the provenance of RNAseq
157 datasets. However, any particular experiment or RNAseq use case will require a
158 multitude of additional terms. Here we provide a dataset containing curated and
159 modified data provenance from 1,347 next-generation sequencing samples. The
160 dataset contains 93 data fields, using ORNASEQ terms as appropriate. Each sample
161 was processed with one of four different versions of a primary analysis pipeline and
162 there was from one to three variants (sub-versions) of each pipeline version.
163 Specifically, samples were processed either as “single-end” or “paired-end” and
164 aligned with either STAR[10] or Bowtie[11, 12], ultimately leading to nine possible
165 pipeline variants. The dataset is provided as PROV-XML (see Additional file 2), with
166 the data summarized in an Excel table (see Additional file 1). Real world use cases
167 usually include messy data. Occasionally pipelines are run incorrectly either
168 through intentional operator actions or error. It’s also quite common to have
169 missing or incomplete data provenance again through user actions (e.g. data was

170 pulled from a source that lacked sufficient provenance), programming errors,
171 computer issues, etc. The dataset provided here intentionally includes both
172 incorrect and missing data.

173

174 Primary Analysis Pipeline Stages

175 The data provided describes an analysis pipeline with seven possible stages but
176 with each analysis only including five of the seven stages. Table 2 includes a subset
177 of data tracked for each pipeline stage and which stages might be used in a
178 particular pipeline version. For example, the stage HTSeq was only used in pipeline
179 version 1.0 while VERSE was only used in later pipeline versions. The stages are
180 very briefly described here and more complete descriptions can be found in the
181 PennSCAP-T Pipeline[13].

- 182 ○ BLAST - a subset of samples was aligned to the Blast NR database,
183 using BLAST as a quality control check.
- 184 ○ FastQC – FastQC is used as an additional quality control check.
- 185 ○ TRIM – contaminant sequences were removed from reads.
- 186 ○ BOWTIE – Bowtie was used to align reads to a reference genome.
- 187 ○ STAR – STAR was used to align reads to a reference genome.
- 188 ○ HTseq – HTSeq was used to assign aligned reads to genes.
- 189 ○ VERSE – VERSE was used to assign aligned reads to genes.

190

191 In the accompanying dataset, samples were aligned with either Bowtie or STAR but
192 not both. Similarly, alignments were processed by either HTSeq or VERSE, but not

193 both. The Excel table highlights which provenance terms are consistent within a
194 pipeline version. For example “BLAST.blastn.version” has pipeline version-specific
195 values. Provenance terms that might contain incorrect values are also denoted. For
196 example, the value for “STAR.star.version” in Pipeline version 2.0.1 might be
197 missing.
198

STAGE	PARAMETER	VALUE			
BLAST	blastn version	2.2.25	2.2.30	2.2.30	2.2.30
	parseBlast.py version	1.1	1.5	1.5	1.8
FASTQC	fastqc version	0.10.1	0.11.2	0.11.2	0.11.2
TRIM	trimReads.py version	0.6	0.6	0.6	0.7.2
	removeN	1	1	1	1
	minLen	30	20	20	20
	phredThresh	-	53	53	53
	numAT	30	26	26	26
BOWTIE	bowtie version	0.12.7	1.1.1		2.2.9
	minins	250	150		150
	maxins	450	600		600
STAR	star version	2.3.0.1	2.4.0h1	2.4.0j	2.5.1b
	samtools version	1.1	1.1	1.2	1.2
HTSEQ	htseq version	0.5.4p5			
VERSE	verse version		v0.1.4	v0.1.4	v0.1.5
Pipeline Version		1.0	2.0	2.0.1	2.1
Number Samples		208	413	216	510

199 Table 2: Subset of pipeline-specific parameters included in sample dataset, across
200 pipeline stages and pipeline versions.

201 **Conclusion**

202 Next generation sequencing (NGS) is a complex technology with multiple varied
203 steps. Capturing the provenance of NGS data requires complex systems and multi-
204 user collaborations. The schemas and ontology we define here offer a basic
205 framework that can be tuned and expended by researchers to the particulars of
206 individual studies, while providing basic commonalities across studies.

207

208 The dataset provided illustrates some of the complexities of the data provenance
209 from downstream processing of NGS data. These complexities will grow as the field
210 evolves. For example, there are now hundreds of variants of basic sequencing
211 protocol that are specific to particular biology applications (e.g., ATAC-seq; [14];
212 Drop-Seq;[15, 16]). Each of these involve variations in experimental and informatics
213 processes. It will become necessary to build workflow management systems and
214 smart clustering algorithms of the provenance[17] to help segment incomplete and
215 erroneous data. We propose that our large real-life dataset example will prove
216 useful in designing future new workflow systems and provenance models.

217 List of Abbreviations

218 **OBI:** Ontology for Biomedical Investigations

219 **ORNASEQ:** Ontology of RNA Sequencing

220 **OBO:** Open Biological and Biomedical Ontology

221 **RNAseq:** next-generation RNA sequencing

222 **SCAP-T:** NIH Common Fund Single Cell Analysis Program-Transcriptome

223 **NGS:** Next generation sequencing

224 Declarations

225 Ethics approval and consent to participate

226 not applicable

227 Consent for publication

228 not applicable

229 Availability of data and material

230 The ontology presented in the current study is available from GitHub,

231 <http://doi.org/10.5281/zenodo.1311869>. The sample dataset presented in the

232 current study is available as additional article files.

233 Competing interests

234 The authors declare that they have no competing interests.

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238 Authors' contributions

239 SF and JK contributed to the design of this study and preparation of the manuscript.

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288

289 Additional Files

290 [Additional file 1](#)

291 **Format:** Excel Workbook from Excel for Mac version 16 (.xlsx)

292 **Title:** A Large Curated RNAseq Metadata Dataset

293 **Description:** This file contains a curated dataset consisting of metadata collected
294 from 1347 next-generation sequencing samples. The file also contains a set of terms
295 that can be used to separate the data samples between nine primary analysis
296 pipelines.

297 [Additional file 2](#)

298 **Format:** XML file (.xml)

299 **Title:** PROV-XML Instantiation of a RNAseq Metadata Dataset

300 **Description:** This is an XML file that contains a PROV-XML representation of the
301 data included in “Additional file 1.xlsx”; that is, an example dataset containing
302 metadata from 1347 RNAseq data samples that were processed with one of nine
303 primary analysis pipelines.