Data Readiness Levels

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Abstract

Application of models to data is fraught. Data-generating collaborators often only have a very basic understanding of the complications of collating, processing and curating data. Challenges include: poor data collection practices, missing values, inconvenient storage mechanisms, intellectual property, security and privacy. All these aspects obstruct the sharing and interconnection of data, and the eventual interpretation of data through machine learning or other approaches. In project reporting, a major challenge is in encapsulating these problems and enabling goals to be built around the processing of data. Project overruns can occur due to failure to account for the amount of time required to curate and collate. But to understand these failures we need to have a common language for assessing the readiness of a particular data set. This position paper proposes the use of data readiness levels: it gives a rough outline of three stages of data preparedness and speculates on how formalisation of these levels into a common language for data readiness could facilitate project management.

1 Introduction

The universal formula of machine learning is

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data + \text{model} \rightarrow \text{prediction}
\]

with a high quality of prediction being dependent on both good models and high quality data. Much of the focus on machine learning in the academic world of machine learning is on the quality of the model. This focus arises because data is normally from benchmarks or publicly available data sets, so performance in a task is improved by exercising control over model.

The greater interconnectedness of modern society and apparent ease with which we digitise or record data places us in a particular position. We need to develop a lot more control over the quality of our data. Whether it be in the manner in which we choose to collect, or how we choose to annotate. Currently the academic or empirical study of modeling (e.g. support vector machines, neural networks, Gaussian processes) is prominent in the education of the graduates we produce, but approaches for understanding the quality of data are less widely used.

2 Data Readiness Levels

In this position paper we introduce the idea of data readiness levels. Data readiness levels are designed to deal with a challenge for human cognitive information processing. It’s difficult for us to reason about concepts when we haven’t developed a language to describe them. The idea of data readiness levels is to correct this issue and make it easier for us to reason about the state of our data.

The challenges of data quality arise before modeling even starts. Both questions and data are badly characterized. This is particularly true in the era of Big Data, where one gains the impression that the depth of data-discussion in many decision making forums is of the form “We have a Big Data problem, do you have
a Big Data solution?”, “Yes, I have a Big Data solution.” Of course in practice it also turns out to be a solution that requires Big Money to pay for because no one bothered to scope the nature of the problem, the data, or the solution.

Data scientists and statisticians are often treated like magicians who are expected to wave a model across a disparate and carelessly collated set of data and with a cry of ‘sortitouticus’ a magical conclusion is drawn. It is apt to think of it as ocean of data, to paraphrase “water, water everywhere and not a drop to drink”, we have “data, data everywhere and not a set to process”. Just as extracting drinkable water from the real ocean requires the expensive process of desalination, extracting usable data from the data-ocean requires a significant amount of processing.

For any data analyst, when embarking on a project, a particular challenge is assessing the quality of the available data, how much processing is required? This difficulty can be compounded when project partners do not themselves have a deep understanding of the process of data analysis. If partners are not data-savvy they may not understand just how much good practice needs to be placed in the curation of data to ensure that conclusions are robust and representative. Just as water quality should be measured before consumption, so should data quality.

When scoping a project, in most proposal documents, very scant attention is paid to these obstacles, meaning in practice the process of improving data quality is under appreciated and under resourced.

One difficulty is that the concept of “data”, for many people, is somehow abstract and diffuse. This seems to mean that it is challenging for us to reason about. Psychologists refer to the idea of vivid information as information that is weighted more heavily in reasoning than non-vivid or palid information. In this sense data seems to be rendered vivid to be properly accounted for in planning. This may relate to availability heuristics[1].

This abstract nature is also true of other terms, for example for many people the idea of “technology” is also similarly diffuse, it is palid information (although I’ve never heard anyone remark “we have a big technology problem, we need a big technology solution”). Perhaps to deal with this challenge, in large scale projects, when deploying technology, we are nowadays guided to consider its readiness stage. Technology readiness levels arose in NASA [2]. The readiness of the technology is made manifest through a set of numbers which describe its characteristics[3] is it lab tested only? Is it ready for commercialization? Is it merely conceptual? No doubt there are pros and cons of such readiness levels, but one of the pros is that the manifestation of the technological readiness pipeline ensures that some thought is given to that process. The technology is rendered more vivid even through a shared characterization.

It would therefore seem very useful to have a scale to make data readiness manifest. This idea would allow analysts to encourage better consideration of the data collection/production and consolidation, with a set of simple questions, “And what will the data readiness level be at that point?”. Or “How will that have progressed the data readiness?”. Or to make statements, “we’ll be unable to deliver on that integration unless the data readiness level is at least B3.”

This paper aims to trigger a discussion in statistics and data science communities by proposing an initial set of descriptors for data readiness.

The initial proposal is that data readiness should be split into three bands. Each band being represented by a letter, A, B and C. These bands reflect stages of data readiness which would each likely have some sub-levels, so the best data would be A1 and the worst data might be C4. The aim here is to avoid being fine-grained too early. We therefore begin the discussion by focussing on three bands of data readiness.

1See appendix for examples of technology readiness level descriptions.
2The nanotechnology community has also looked at data readiness levels in this discussion document from the nanotechnology community in 2013. However, their scope doesn’t seem to be general enough to deal with the challenges of data processing in domains beyond nanotechnology.
2.1 Band C

Band C is about the accessibility of a data set. The lowest sub-level of Band C (let’s label it as C4) would represent a belief that the data may exist, but its existence isn’t even verified. Signs that data is C4 might include statements like “The sales department should have a record of that.” Or “The data should be available because we stipulated it in the software requirements.” We might think of it as hearsay data. Data that you’ve heard about so you say it’s there. Problems with hearsay data might include

- whether it really is being recorded
- the format in which it’s being recorded (e.g. handwritten log book, stored in PDF format or old machine formats)
- privacy or legal constraints on the accessibility of the recorded data, have ethical constraints been alleviated?
- limitations on access due to topology (e.g. the data’s distributed across a number of devices)

So when we are first told a data set exists, when we have hearsay data, then it is at band C4. For data to arrive at C1, then it would have all these considerations dealt with.

When data arrives at C1 it’s ready to be loaded into analysis software, or it can be made available for others to access (e.g. via a data repository such as OpenML [3]). It is machine readable and ethical procedures for data handling have been addressed. Bringing data to C1 is often a significant effort itself involving many lines of bespoke software and human understanding of systems, ethics and the law.

Some parts of Band C are sometimes referred to as “data munging” or “data wrangling”, but those aren’t the only components of this band, there are additional challenges such as ethical and legal that need to be resolved.

2.2 Band B

Band B is about the faithfulness and representation of the data. Now that it’s loaded into the software, is what is recorded matching what is purported to be recorded? How are missing values handled, what is their encoding? What is the noise characterization (for sensors) or for manual data are there data entry errors? Are any scientific units correctly formulated?

Tukey’s approach of “Exploratory Data Analysis” also fits within Band B. Visualizations of the data should be carried out to help render the data vivid and to ensure decision makers, who may not be data aware, can become involved in the analysis process. Decision makers (e.g. project managers, or the client) should also begin to get a sense of the limitations of their data set through appropriate visualisation.

As part of Band B the characteristics of the collection process should also be verified, was data collection randomized, is it biased in any particular way?

Other things to watch for at this stage include:

1. If the data has been agglomerated at some point (for example, for privacy) how were missing values dealt with before agglomeration? If they weren’t dealt with then that entire section of the data may be invalidated
2. If the data has been through a spreadsheet software, can you confirm that no common spreadsheet analysis errors were made? For example, was a column or columns accidentally perturbed (e.g. through a sort operation that missed one or more columns)? Or was a gene name accidentally converted to a date?

By the end of Band B, when data is B1, a broad idea of limitations in the data should be present in the expert’s mind. Data at C4 was hearsay data, someone heard the data existed and they said what they thought it might be good for. At B1 the analyst knows how faithful the data is to that description. This
is the significant challenge for a data scientist. What people believe they have in their data versus what’s actually there. Only at the end of Stage B would the analyst begin to have an intuition about what my really be possible with the data set. Getting to this point is often the most expensive part of the project, but we do not yet have good methods to guage progress, or share the status of a particular data set.

2.3 Band A

Band A is about data in context. It is at Band A that we consider the appropriateness of a given data set to answer a particular question or to be subject to a particular analysis.

The context must be defined. For example OpenML [3] defines tasks associated with data sets. A data set can only be considered in Band A once a task is defined. A task could be “Use the data to predict a user preference” or “Use this data to prove the efficacy of a drug” or “Use this data verify the functioning of our rocket engine”.

Once data has been considered alongside a task and any remedial steps have been taken, then the data is in A1 condition. It is ready to be deployed in the context given and it can be used to make predictions with the data.

Because A1 is about data in context, it is possible for a data set to be A1 for one question (e.g. predicting customer churn) but only B1 for a different question (e.g. predicting customer susceptibility to a particular special offer). So the definition of the context or task is an important pre-requisite for this band.

To bring a data set up to A1, there may be a need for significant annotation of the data by human expert. There may be a realisation that new data needs to be actively collected to get the answers required. In that sense, Band A has some characteristics of a classical statistical analysis where the question would normally precede the data collection. It is in Band A where you should be carefully thinking about the statistical design because it is only when you have the question you wish to answer that you can really unpick how your data may be biased or what information is missing.

3 The Analysis Pipeline

A common mistake in data analysis is to not acknowledge the different processes above. They have different pre-requisites and require different skill sets to carry out. However, this path cannot be completely disconnected. Anyone performing an analysis at Band A also needs to be intimately familiar with the collection process so that any biases in data collection can be understood. Sharing information about decisions taken at Bands B and C will also be critical to achieving a good result.

What happens if we bring two data sets together to form a new data set? Some assessment of data readiness would still need to be performed on the new data set, even if the two other data sets had already been assessed. Why? Well, one example is that there may be ethical issues with combining data sets. For example, medical data can be easily deanonymized if it is combined with other related data sets. That would mean that some assessment would need to be made at Band C to see if it is ethically responsible to combine the two data sets in the same analysis package. Further assessments would also need to be done at Band B to understand differences in collection protocols that might make the two data sets hard to combine.

3.1 Potential Results

The idea of these levels is to increase the accountability of the process and allow the nature of the data to be manifest. With data readiness levels in place you can now imagine conversations that would include statements like the following:

Be careful, that department claims to have made 10,000 data sets available, but we estimate that only 25% of those data sets are available at C1 readiness.
The cost of bringing the data to C1 would be prohibitive for this study alone, but the company-
wide data audit is targeting this data to be C1 by Q3 2017 which means we can go ahead and
recruit the statisticians we need.

The project failed because we over recruited statistical expertise and then deployed them on
bringing the data set to C1 readiness, a job that would have been better done by building up our
software engineering resource.

What’s the data readiness level? My team will be ineffectual until it’s B1 and at the moment I
see no provision in the plan for resource to bring it there.

We estimate that it’s a $100,000 dollar cost to bring that data to B1, but we can amortize that
cost across four further studies that also need this data.

I gave them the data readiness levels to go through and they realized they hadn’t yet got the
necessary ethics approval for sharing the zip codes. We’ll revisit when they’ve got through that
and can assure us they can share a C1 set.

While their knowledge of the latest methodologies wasn’t as good as I’d hoped, the candidate
had a lot of experience of bringing data from C1 to B1, and that’s a skill set that we’re in dire
need of.

The project came in under budget because they found a team with experience of getting a closely
related data set to A1. Many of the associated challenges were the same and they could even
reuse some of that team’s statistical models.

4 Case Studies

How useful would data readiness levels be? That’s difficult to give a quantitative answer to, large scale
analysis of the scale of this problem requires meta data science, i.e. the study of data science itself through
acquiring data about data science. That would be a very worthwhile endeavour. In the absence of quanti-
tative information, we provide two anecdotal case studies below. The first is on the cahllenge of extracting
data from a popular machine learning conference proceedings.

4.1 Proceedings of Machine Learning Research

The Proceedings of Machine Learning Research\(^3\) (PMLR) were begun in 2006 (as JMLR Workshop and
Conference Proceedings) to provide a convenient way to publish machine learning conference proceedings
without the overhead of a conventional publisher.

There are now 69 volumes of proceedings published and planned. They contain over 3,198 papers. The
original website was manually curated to mimic the JMLR website, but since Volume 26 an automated
proceedings production process which relies on editors providing a zip file of PDFs and a bibtex bibliography
reference file (referred to below as ‘bib files’) specifying author names, abstracts and titles has been used.

In early 2017, as part of a rebranding process, the original website was moved to github and a new process for
receiving proceedings and publishing was set up. For the rebranding the old web-sites needed to be scraped,
converted to bib files.

A key aim in the rebranding was to make abstracts and titles easily available for analysis with an initial target
language of Python.

This entire process can be seen as taking the data readiness of website data from C4 to C1. In other words,
get to the point where the data could be loaded into an analysis software, our target here was to load it into
the pandas framework within Python.

\(^3\)http://proceedings.mlr.press
The original plan was to complete the work in some idle hours at the weekend. The actual work took much longer than projected. The major github commits of code along with a description of the effort involved are listed below.

1. An initial two day effort to create bibliography files for the first 26 volumes which were published before the publication process was first automated. Github commit: [https://github.com/mlresearch/papersite/commit/daa51a0da8](https://github.com/mlresearch/papersite/commit/daa51a0da8)

2. A three day effort to convert the proceedings to a new format website. Much of this work was on the website presentation, but part was on data curation. Github commit: [https://github.com/mlresearch/papersite/commit/81d7a0](https://github.com/mlresearch/papersite/commit/81d7a0)

3. A three evening effort to tidy the resulting data so it could load into Python pandas via web download.
   Github commit: [https://github.com/mlresearch/papersite/commit/81d7a0556948281d11d8f0652ecdca64005c3418](https://github.com/mlresearch/papersite/commit/81d7a0556948281d11d8f0652ecdca64005c3418)

The result is now available via github as a short jupyter notebook: [https://github.com/sods/ods/blob/master/notebooks/pods](https://github.com/sods/ods/blob/master/notebooks/pods)

Data loading is now possible with a single library call.

```python
import pods
data = pods.datasets.pmlr()
```

where the pods library is available from [https://github.com/sods/ods/](https://github.com/sods/ods/)

This data has therefore successfully transferred from the start of C (e.g. C4, “Hearsay data”) to the end of C (e.g. C1, data loaded into analysis software).

The data set only contains 3,198 data points, it was all available in electronic form. There were no issues around privacy or intellectual property but work still took approximately six working days. Much of that work was laborious, but it still involved well qualified understanding of computer software, e.g. regular expressions, scripting languages, libraries for downloading from the internet, github etc.. Alongside that work a new format web page was also provided ([http://proceedings.mlr.press](http://proceedings.mlr.press)). Indeed that could be argued as a consequence of the data tidy up. Naturally the hope is that future volumes will be more cleanly added to this data set.

### 4.2 Data Wrangling Snafus

Some snafus that occurred in the data wrangling of the Proceedings of Machine Learning Research.

Each bibliography file is provided by the editors of the relevant volume. Because they each used different approaches to generate the bib files, there were different issues with each bib file.

- Many of these bib files will have been produced from conference management software (e.g. CMT or Easychair). That means the original information source is often likely to be author provided. Many authors seemed to paste their abstracts from the PDFs of their papers into this software. This meant that abstracts contained ligatures. A ligature is a single typeset unit such as ‘fi’, which comes about when the previous letter runs into the second, the German ‘Sz’, ß, is an example of a ligature that in the end became a letter. Unfortunately the ligatures did not paste as unicode, but as escaped characters which the python yaml library was unable to read when presented as data.

- Papers are mostly written in Latex, so many of the abstracts contain Latex commands. But these commands in the abstracts or title are interpreted as escaped characters in yaml files. Additional ‘escaping’ was needed for these commands.

- Author names containing accents were oftentimes corrupted, perhaps due to differences in representation in the original files.

Each of the snafus above can be resolved by robust coding, but there is normally a trade off between producing the data (just getting it done quick) and producing the most robust code (ensuring the result is high quality and reusable). The right operating point for the trade off is driven by the scale of the data set. It also requires experience to judge and is dependent on the coding skills of the data engineer.
This is the work at the pit face of data mining, it’s difficult to estimate the time it will take, and yet it is normally a critical dependency in any machine learning project. For each of these snafus, better planning at early stage analysis could have saved time in manual correction of the data later. But doing such planning well requires experience and an understanding of best practice. We are not associating enough value with this experience, and therefore we continue to be tripped by snafus when preparing data.

4.2.1 How Data Readiness Levels could have helped

This is one of the first projects I undertook after conceiving of data readiness levels, but in reflection I think I still did not take enough of the ideas seriously enough. Because I underestimated the time to be spent on manual curation after the initial scrape of the data, I did not put enough effort into robust code for dealing with ligatures and other unusual character codes.

There were several moments where, in retrospect, I should have refactored my processing code. But since I was driven by the desire to complete the project, particularly given I’d severely underestimated how long it would take, I chose to push forward. One interesting question is how ideas from software engineering, such as agile development philosophies, could have helped in making myself more aware of these errors.

4.3 Disease Monitoring in Uganda

The second case study refers to work in collaboration with the University of Makerere and UN Global Pulse in Kampala, Uganda in the prediction of disease outbreak [4]. Specifically, our original interest was understanding the spatial correlations of malarial disease in Uganda, and their interactions with other measures such as NDVI, rainfall, altitude etc. Our effort was a countrywide effort, but simultaneous to our work was an international effort in the Malaria Atlas Project [4].

We constructed spatial models based on Gaussian processes that were designed to detect and use the correlations between the different covariates. The work was done through two PhD students’ thesis, Martin from Kampala, and Ricardo from the UK. The work in Kampala mainly drove the data collection and collation. In particular, interpretation of satellite images as NDVI, alignment of the rainfall and altitude maps. The data collation in itself took probably around 70-80% of the work on the project. Martin working on it full time, and Ricardo assisting and working on both modeling and data munging. Ricardo visited Uganda twice, initially for a scoping visit and later for a longer collaboration visit in the processing of the data during his PhD. These visits were to the University of Makerere where Martin was working.

The malaria incidence data was drawn from Health Management Information System (HMIS) data. For privacy purposes, original data was not available to us, but rather it had been aggregated across certain regions.

One key challenge in the data munching is that the administrative areas (in Uganda known as districts) change. One administrative area can divide into two. When this happens the history of the two districts needs to be divided across the two areas. This presented a missing data problem that Ricardo also spent a deal of time addressing during his thesis.

By the time of submission of the thesis, Ricardo had recovered a negative result, he couldn’t show spatial correlation among the districts. This was disappointing as it had been one of the main motivations of that thesis work. Nevertheless, even without the spatial correlation there was interest in deploying the system by the Ugandan ministry of health for disease outbreak prediction.

Ricardo’s expertise was such that he was able to then spend 3 months in Africa, this time at UN Global Pulse, where Martin and his supervisor were now working, rather than Makerere. This was to help with the implementation of early warning systems based on the model. These early warning systems did not require the spatial correlation that hadn’t worked during the thesis.

4http://www.map.ox.ac.uk/
During the period at the UN, Ricardo and Martin were able to work directly with disaggregated data. The UN had permission to see the raw health center results, whereas the University of Makerere did not. As a result, they found that aggregation we had previously been working on had been performed across data containing missing values. Ricardo and Martin reworked the model to deal with missing values and recovered the expected spatial correlation.

In other words, due to a data processing error at Band B, a negative result was obtained at Band A. A lack of documentation, or a lack of asking the right questions, led to an oversight on this error.

The models are now deployed for disease outbreak prediction across Uganda, where they are combined with knowledge of population movement from mobile phone data to trigger interventions.

The lessons learned were the following.

1. In data where we had direct access the amount of work required to align, and the number of design decisions we made in the summarization dominated the project.
2. There was still data that fell out of our control due to confidentiality reasons. Despite the work we’d done on our own data, which would have allowed us to infer that other design decisions would have been made by those that were aggregating the data, we failed to ask the right questions of the data providers. Indeed, those data providers may not have even known the answers. There was no substitute for directly looking at the data.
3. Although we began the project with one set of goals in mind: understanding the correlation between different factors in malaria, our outcome: disease prediction for early intervention, was quite different. Happenstance outcomes need to be accommodated in project goals. They arise particularly around Band B of the process.

4.3.1 How Data Readiness Levels could have helped

Being aware of data readiness levels would have done three things. Firstly, we would have estimated better how much time that Martin would require in data munging from satellite images etc. Secondly, we would have questioned the process by which the HMIS data was being presented to us, and what stage of readiness it was at, and how it got there. These are broadly questions that sit in Band C and B. Thirdly, awareness of the transition from Band B to Band A (data moving to its context) would have made us realize that the question may well evolve and be more responsive to that outcome. In the end this move was driven by the shift in collaboration from Makerere to the UN.

Ricardo has continued to work in this area, and one focus of his new UCSF Global Health research group has been to clean up existing data and make it available as geospatial layers for other groups to use.

5 Conclusion

Machine learning researchers probably didn’t enter the field to do project management, but it may be that many failings on large data projects are associated with a failure to provision resource for the challenges involved in preparing our data, rather than a failing in the algorithmics of the system. Costs of data curation are often underestimated and those who do the work in Band C and Band B are very often undervalued.

Data readiness levels highlight the different skill sets required in each stage of analysis, from software engineer, to data-munger, to data scientist to machine learning scientist.

Some consensus about such levels would help organizations (and their managers, financial controllers) quantify the value associated with data and allocate resource correctly to developing data sets that are robust and representative. A well conducted data analysis will lead to a good customer experience, but by the same token badly waste resources and give a poor customer experience.
This paper has outlined the basis for a partial solution to these problems, but to deploy in practice we would need consensus around data readiness levels and how they should be deployed. The emerging field of data science is the ideal domain to explore the utility of these ideas, evolve their specification and begin to properly account for the value of well curated data.

For convenient reference below we show examples of technology readiness levels from the Department of Defense (sourced from Wikipedia). For Data Readiness we are proposing to start with the three bands described above. Technology readiness relies entirely on a numbered system.

[1] T. Gilovich, D. Griffin, and D. Kahneman, Eds., *Heuristics and biases: The psychology of intuitive judgment*. Cambridge University Press, 2002.

[2] J. Banke, “Technology readiness levels demystified,” NASA, 2010.

[3] J. Vanschoren, J. N. Rijn, and B. Bischl, “Taking machine learning research online with OpenML,” in *Proceedings of the 4th international workshop on big data, streams and heterogeneous source mining: Algorithms, systems, programming models and applications*, 2015, vol. 41, pp. 1–4.

[4] R. Andrade-Pachecho, M. Mubangizi, J. Quinn, and N. Lawrence, “Monitoring short term changes of infectious diseases in uganda with gaussian processes,” in *Advanced analysis and learning on temporal data: First ecml pkdd workshop, aaltid 2015, porto, portugal, september 11, 2015, revised selected papers*, A. Douzal-Chouakria, J. A. Vilar, and P.-F. Marteau, Eds. Cham: Springer International Publishing, 2016, pp. 95–110.

### A Exemplar Technology Readiness Levels

1. Basic principles observed and reported
   Lowest level of technology readiness. Scientific research begins to be translated into applied research and development (R&D). Examples might include paper studies of a technology’s basic properties.

2. Technology concept and/or application formulated
   Invention begins. Once basic principles are observed, practical applications can be invented. Applications are speculative, and there may be no proof or detailed analysis to support the assumptions. Examples are limited to analytic studies.

3. Analytical and experimental critical function and/or characteristic proof of concept
   Active R&D is initiated. This includes analytical studies and laboratory studies to physically validate the analytical predictions of separate elements of the technology. Examples include components that are not yet integrated or representative.

4. Component and/or breadboard validation in laboratory environment
   Basic technological components are integrated to establish that they will work together. This is relatively “low fidelity” compared with the eventual system. Examples include integration of “ad hoc” hardware in the laboratory.

5. Component and/or breadboard validation in relevant environment
   Fidelity of breadboard technology increases significantly. The basic technological components are integrated with reasonably realistic supporting elements so they can be tested in a simulated environment. Examples include “high-fidelity” laboratory integration of components.

6. System/subsystem model or prototype demonstration in a relevant environment
   Representative model or prototype system, which is well beyond that of TRL 5, is tested in a relevant environment. Represents a major step up in a technology’s demonstrated readiness. Examples include testing a prototype in a high-fidelity laboratory environment or in a simulated operational environment.
7. System prototype demonstration in an operational environment.

Prototype near or at planned operational system. Represents a major step up from TRL 6 by requiring demonstration of an actual system prototype in an operational environment (e.g., in an aircraft, in a vehicle, or in space).

8. Actual system completed and qualified through test and demonstration.

Technology has been proven to work in its final form and under expected conditions. In almost all cases, this TRL represents the end of true system development. Examples include developmental test and evaluation (DT&E) of the system in its intended weapon system to determine if it meets design specifications.

9. Actual system proven through successful mission operations.

Actual application of the technology in its final form and under mission conditions, such as those encountered in operational test and evaluation (OT&E). Examples include using the system under operational mission conditions.