Data to Value: An ‘Evaluation-First’ Methodology for Natural Language Projects

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Abstract. Big data, i.e. collecting, storing and processing of data at scale, has recently been possible due to the arrival of clusters of commodity computers powered by application-level distributed parallel operating systems like HDFS/Hadoop/Spark, and such infrastructures have revolutionized data mining at scale. For data mining project to succeed more consistently, some methodologies were developed (e.g. CRISP-DM, SEMMA, KDD), but these do not account for (1) very large scales of processing, (2) dealing with unstructured (textual) data (i.e., natural language processing also known as text analytics), and (3) non-technical considerations (e.g. legal, ethical, project managerial aspects). To address these shortcomings, a new methodology, called “Data to Value” (D2V), is introduced, which is guided by a detailed catalog of questions in order to avoid a disconnect of big data text analytics project team with the topic when facing rather abstract box-and-arrow diagrams commonly associated with methodologies.

Keywords. Methodology; process model; supervised learning; natural language processing; data science; big data; unstructured data.

1 Introduction

Engineering has been defined as “the application of scientific, economic, social, and practical knowledge in order to design, build, and maintain structures, machines, devices, systems, materials and processes.” (Wikipedia) or the “[t]he creative application of scientific principles to design or develop structures, machines, apparatus, or manufacturing processes, or works utilizing them singly or in combination; or to construct or operate the same with full cognizance of

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their design; or to forecast their behavior under specific operating conditions; all as respects an intended function, economics of operation or safety to life and property” (American Engineers’ Council for Professional Development).

In language engineering, like in all engineering, we should adhere to a principled approach following best practices (methodology) and generate a predictable outcome, namely: (1) forecasting observed runtime, (2) forecasting memory requirements, (3) forecasting delivery time, i.e. a time at which a successful project can be concluded; and (4) forecasting output quality (e.g. F1-score). At the time of writing, there is no theory that permits us to forecast even one of these factors; in this paper, as a first step towards this end, we present a methodology that addresses the point of delivery as ‘predictable outcome”: our methodology aims to deliver projects more consistently, and with less time wasted. This is achieved by a finer-grained sequence of phases, and by additional guidance in the form of guiding questions. The unique characteristics of our methodology, named D2V (for “Data to Value” process) are: it is evaluation-first, which means that the construction of a system and proceeding between the various phases itself is driven by quantitative metrics; it is intended for projects involving unstructured data (text content), as it fills a gap in the space of existing methodologies; it is question-informed, as it benefits from a catalog of questions associated with particular process phases.

The remainder of this paper is divided as follows. Section 2 briefly reviews the related work. Section 3 introduces the D2V methodology. Section 4 provides a discussion of its advantages and limitations. Section 5 concludes with pointers for future work.

2 Related Work

According to the PMI [9], a project is completed successfully if it is completed (1) on time (2) on budget (3) to specification and (4) with customer acceptance. In the area of software engineering, the waterfall model and the agile model have been the most popular process models for constructing general software systems [12].

Working with data has a slightly different focus compared to traditional software development: systems for mining rules, classifying documents, tagging texts and extracting information are also software artifacts, but the software co-evolves with various data sets and linguistic resources that are used by it. While we are not aware of prior work on any methodologies specifically for processing large quantities of text, in the context of developing data mining projects, three popular methodologies have been developed, which shall be reviewed here.
The KDD Process grew out of the Knowledge Discovery in Databases research community, which in 1995 had its first of a series of workshops. It proposes a sequence of five to nine steps to get from raw data to knowledge: Selection, Pre-Processing, Transformation, Data Mining and Interpretation/Evaluation. Each of these steps is seen as depending on the previous steps, yet its proponents suggest a certain flexibility in applying the steps was vital, and left to the discretion of the experienced researcher. For example, at any stage could one consider going back to a any previous stage and repeat the steps from there, and multiple iterations were considered likely. The initial step is to learn the application domain. Then a target data set can be created by selecting it from all available data. Raw data then gets cleaned up and pre-processed (outlier/noise elimination), after which in a data reduction and project phase, features helpful to the end goal are computed. A function is then chosen (describing the purpose and identifying whether e.g. classification or clustering can achieve it), and a concrete method/algorithm is selected that implements the function. Then the actual data mining (implementation and execution) step happens, before the data is finally evaluated, interpreted and put to use.

The SEMMA methodology was originally developed by the private company SAS Institute, Inc. The name is an acronym, which stands “for Sample, Explore, Modify, Model, and Assess. SAS Enterprise Miner nodes “are arranged on tabs with the same names.” In SEMMA, a cycle with five process stages is applied: “Sample – This stage consists on sampling the data by extracting a portion of a large data set big enough to contain the significant information, yet small enough to manipulate quickly. This stage is pointed out as being optional. Explore – This stage consists on the exploration of the data by searching for unanticipated trends and anomalies in order to gain understanding and ideas. Modify –This stage consists on the modification of the data by creating, selecting, and transforming the variables to focus the model selection process. Model – This stage consists on modeling the data by allowing the software to search automatically for a combination of data that reliably predicts a desired outcome. Assess – This stage consists on assessing the data by evaluating the usefulness and reliability of the findings from the data mining process and estimate how well it performs.”

The CRISP-DM methodology, short for “CRoss Industry Standard Process for Data Mining”, which was developed by a consortium comprising DamilerChrysler, SPSS, NCR and OHRA, can be looked at from four different levels of abstraction: phases, generic tasks, specialized task and process instances. The reference model defines the transitions between phases, and a user guide describes how-to information in more detail. It comprises six loose
phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation and Deployment. See [7][12] for more detail on the similarities and differences between KDD, SEMMA and CRISP-DM.

Marr’s Strategy Board. [8] introduces a canvas-based approach to guide big data projects, which focuses on the business aspects; no technical guidance is provided by his model, but he does use a small number of (6) guidance questions.

Here we would like to stress the shortcomings with regards to detail about a number of areas of past work: First, working with unstructured data, textual data in particular, is not specifically accommodated by either approach, despite the fact that most non-transactional data in corporations comes in the form of reports, white papers, slide decks, emails and other text-heavy formats. Secondly, supervised learning, which is the approach of choice in scenario where quality matters, is not specifically catered for by prior work. Third, ethical questions, which are increasingly becoming more important in big data work, are not part of previously proposed processes. Fourth, the scale aspects of big data influences the process and day-to-day work. Fifth and most importantly, past work puts the evaluation phrase rather too late in the overall process: for instance, in SEMMA the Assessment phase is the fourth of five phases overall. In the author’s view, this is the single most valuable contribution of this paper, namely to strongly advocate an “evaluation first” approach.

In contrast to past work, we present a process that is sensitive to ethical concerns, accommodates big data projects using unstructured (textual) data and supervised machine learning that typically goes with it, and which requires textual annotation sub-processes.

**Evaluation design**: one of the earliest steps in a project following our methodology is to determine how the output of the system is to be evaluated. This step is a peculiarity of the D2V process, and makes it “evaluation-first”. An implementation of said evaluation’s test harness typically goes hand in hand with the design.

### 3 Data to Value (D2V)

Figure 1 shows the high-level process model behind the Data-to-Value development methodology: in the beginning, the Project Planning and Initiation stage is used to draft a project charter, and to formally launch the project. A significant part of the planning process is the specification of success, the planning of automatic or manual evaluation procedures, and the budgeting of evaluation resources.
Once a business case is made (i.e., the value of a new product, service or feature has been established, the Project Planning and Initiation (1) phase aims to author a project charter and project plan, and initiate the project formally. Before, after, or during this activity, an Ethics Review I (2) is conducted to answer the question whether the project and its output are morally objectionable. Assuming no ethical obstacles, the Requirements Elicitation (3) phase seeks to obtain more detailed formal requirements, both functional and non-functional. In the Data Acquisition (4) phase, authorization and access to any prerequisite data-sets are obtained. The Feasibility Study (5) phase, shown as a “sub-process” because it could be seen as a light-weight version of the Figure 1 as a whole, is used to re-risk the project, by conducting some preliminary experiments on a static data sample drawn from the full data-set(s) to be used by the project. Although optional, it is highly recommended for all complex projects. Very early in the process, in the Evaluation Design (6) phase, an experimental design is worked out and an evaluation protocol is committed to. In the Data Pre-Processing and Cleansing (7) phase, all data sets are brought in the right formats suitable for the project. In particular, eliminating noise elements (data irrelevant to the project, or data that may be relevant that violates formatting specifications), translating elements into a canonical form, and linking data sets together where appropriate happens here. In some projects, 80% of the project time gets spent in this phase, and it is not uncommon that this phase needs to be repeated due to the late recognition that more work is required.

Fig. 1. Data-to-Value Process Model. Note two steps contain sub-processes.
The Gold Data Annotation phase is a sub-process (shown in Figure 2 and explained below) dedicated to creating data that gets used to train classifiers if a supervised training regime is used; a second purpose is to create a ground truth for regular automatic evaluation runs.

Fig. 2. Gold Data Annotation: A Sub-Process of D2V.

The annotation of gold data requires care, patience, resources and foresight, and if all of these are committed, the medium-term payback can be huge. In contrast, if conducted sloppily or omitted, projects can fail entirely or at least significant waste is likely to occur. Figure 2 shows the process, which typically takes a few weeks or months, divided into multiple iterations. First, a small, representative sample of the data to be annotated must be extracted from the full data set. A few documents are inspected and informally annotated (Experimental Annotation of a Small Data Sample phase). Once a particular style of annotation has been decided on, the Authoring of Annotation Guidelines phase can commence. The need for written guidelines is motivated by the desire to install an objective process that relies exclusively on a document artifact, and no longer on an individual’s mental representation, which is subjective. A larger data sample is then annotated. 5-10% of it is processed by multiple annotators working on the same data points in an overlapping fashion \((k \geq 3)\) to compute Inter-Annnotator Agreement (IAA) in the Computation of Inter-Annnotator Agreement phase) in order to measure the degree to which the task has been objectively specified. IAA is very important also because it defines the up-
per bound for the machine’s performance of the task (not 100%!). The remaining 90-95 can be processed by single annotators unless the project is very well resourced and/or quality demands are highest. A gold data corpus can be created by manually adjudicating (Adjudication of Discrepancies) any discrepancies caused by disagreeing annotators; alternatively, if an odd value or \( k \) was chosen, the “truth” can be selected from parallel annotator judgments using majority voting. Insufficient IAA leads to a Revision of Annotation Guidelines followed by re-annotation. Eventually, the gold data corpus is split into three parts (Split Gold Data into Training Set, Dev-Test Set and Test Set phase), a training set (“train”, often 60% or 80% of the annotated sample), a development test set (“dev-test”, often 10%-20%) and a test set (“test”, often 10%-20%)

After that, the System Architecture Design phase produces the architecture of the software system. Then a particular paradigm is chosen in the Choice of Machine Learning Classifier/Rule Formalism phase: if the system is going to be a rule based system, the kind of rule processing technology or framework, and if machine learning is to be used, which type of model. The framing in terms of choice of classifier or rule formalism may impact the detailed architecture, so in practice, the System Architecture Design and Choice of Machine Learning Classifier/Rule Formalism phases are intertwined more often than not. Then the System Implementation phase targets the actual software development of the processing engine, which comprises most of the software but not any rules or features, which are separately devised, and often by different team members. The System Testing phase, which includes both manual tests and automated (unit) tests, is dedicated to the qualitative evaluation; in other words, either the system is working to specification or there are still known bugs.

With entering the Feature Design and Implementation phase, a series of iterations begins that ultimately only terminates for one of two reasons: either the projected time dedicated to this phase is used up, or the targeted quality level has already been reached. Sometimes we may want to stop earlier if no further progress seems possible, and additional efforts show diminishing returns. Each iteration begins with feature brainstorming sessions and includes studying

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1 The training set (optional, needed only when supervised machine learning is used) is used to induce (“learn”) models from. The dev-test partition is not looked at by humans, and only utilized for blind-run regular automatic evaluations (i.e., we look at the resulting evaluation scores, but we cannot investigate the data causing any errors). The test set is not used at all during development. Its use is confined to a single evaluation run at the end of the project, to define the definitive system quality.
data from the training set, implementation sprints, and Quantitative Evaluation I (14) steps to try out new features and their effectiveness.

Ultimately, the loop exits, and four concluding phases wrap up the project (Patenting and Publication 15) to document the work and secure the intellectual property rights to novel invented methods, authoring the Final Report Authoring 16, handing over the deliverables in the form of data, software and documentation and the Knowledge Transfer 17 phase, which verbally communicates the findings to stakeholders and ascertains a full understanding at the receiving end; finally, a successful Acceptance and Closure 18 leads to the formal project closure).

While technically, our model for conducting research projects could end (Research Project 1-18), industrial real-life systems get used in production, and modern systems require recurring activities to update statistical model after deployment. Therefore, it is advisable to have a look at what happens around the launch: before we launch the system in the Deployment 20 phase, we again conduct an Ethics Review II 19* to assess potential moral objections, this time paying attention to morally questionable system functions and emergent properties (e.g. discrimination or unfairness). Once the system is running, a Monitoring 21* phase watches the system perform its function whilst logging interesting events (system decisions, user activities). At regular intervals, a Quantitative Evaluation II 22* phase is followed by Model Re-Training 23*, depending on its findings, in order to keep statistical models “fresh”.

Note that Figure 1 shows only the process for development of a system; in real-life settings, this is interleaved with deploying and operating the result of the development process: a piece of software gets sold as a product, uploaded to the Internet as an open source offering, or deployed as a service (API) after development (Figure 3). Upon launch, the longest part of the software’s life-cycle begins: it gets used by its target audience, and it needs to be monitored (Monitoring phase) in order to fix software defects. In the case of machine learning components, ongoing quantitative evaluation is required, which either requires grading system output post-hoc, or expanding the gold data with fresh data samples to be annotated. If the Quantitative Evaluation suggest the input data has deviated substantially from data the system was trained on, Model Re-training is due. This cycle continues until the product or service reaches its end of life.
Each process phase has a set of guidance questions assigned to it (cf. Appendix A for some samples), which help to increase project consistency.

4 Discussion

The D2V methodology is quite a rich model, considering the number of distinct phases. It is not aimed to be easily memorable, but was designed to give the practitioner comprehensive guidance, which may not be required for each project: a detailed question catalog Experienced project managers will adjust the process to the complexity and nature of project; for example, bigger or more complex projects need more rigid processes and detailed formal documentation than small studies conducted by teams of two.

A poll conducted twice within seven years in-between suggests that CRISP-DM is consistently the most popular process by a large margin (Table 1); that poll did not feature any choices for unstructured or big-data specific processes at the time. Only CRISP-DM has obtained broad adoption; however, neither of the processes listed are actually potential substitutes for D2V, since none of them have specific provisions for working with textual data. Indeed, since most data falls into the unstructured category, it is surprising that no process has previously been proposed. One advantage of adopting a new methodology is that it can be done immediately, and any gains materialize immediately as well. This is in contrast to technical choices (e.g. programming languages) that often face a chicken-and-egg problem in that there is a risk of adopting a technology that does not already have a broad community.
Table 1. An Internet poll conducted by the data mining portal kdnuggets.com in the years 2007 and 2014 (total N = 200). Remarkably, relative popularity has not changed much in 7 years.

| Methodology Used by Respondents | CRISP-DM | SEMMA | KDD |
|--------------------------------|----------|-------|-----|
|                                | 42% - 43%| 8% - 13%| 7% - 8% |

Table 2 shows a summary comparison between D2V and previous methodologies. One limitation of D2V methodology is that its dedication to unstructured projects makes it less suitable for structured data mining projects, but that domain is sufficiently addressed by the CRISP-DM model. Another shortcoming of D2V, in the version presented here, and also of all other models is that they do not permit a prediction of the time spent in each phase, and of the duration of the project overall; we will re-visit this in future work.

Table 2. Evaluative Comparison between CRISP-DM, SEMMA, KDD and D2V: D2V provides more fine-grained phases and more substantial guidance with around one hundred process-supporting questions.

| Process Model | Phases structured | unstructured | rule-based approaches | learning-based guidance | "evaluation-questions first?" |
|---------------|-------------------|--------------|-----------------------|-------------------------|-----------------------------|
| CRISP-DM      | 6 yes             | no           | yes                   | (yes)                   | n/a                         |
| SEMMA         | 4-5 yes           | no           | yes                   | (yes)                   | n/a                         |
| KDD           | 5-9 yes           | no           | yes                   | (yes)                   | n/a                         |
| Marr Strat. Board | 7 yes   | no           | no                    | no                      | 6                           |
| D2V           | 30 no             | yes          | yes                   | yes                     | 96                          |

5 Summary, Conclusion & Future Work

In this paper, we have described a new process model for the systematic pursuit of big data projects, in particular dedicated to working with textual data. The proposed model, D2V, is different from previous work in that it is not concerned with data mining (as CRISP-DM, SEMMA and KDD are); instead, supervised learning of textual structures are the main focus. It can be characterized as “evaluation-first”, not just because it de-risks projects by prioritizing the scrutinizing of success criteria, but also because it includes provisions for gold
standard annotation and an overall iterative approach that terminates based on diminishing returns informed by repeat evaluations. It is informed by a catalog of guiding questions. We also discussed the advantages and shortcomings of the D2V methodology. We believe this model has merit to improve awareness of the best practices for professionals in projects using unstructured data (natural language processing of text), in particular when supervised machine learning is involved, which is increasingly common (information extraction, sentiment analysis, document topic classification). The D2V methodology can also aid the teaching of data science.

In future work, data collection exercises should be attempted to measure typical absolute and relative resources spend in each phase, in order to permit forecasting-oriented modeling towards cost and quality estimation. Another avenue for future work is the predictive modeling of quality as it relates to time and cost.

A  D2V Question Catalog (Excerpt)

This appendix lists a representative sample of questions from the D2V catalog of questions (from a total of \( N \approx 100 \) questions). The full list of question will be included in a software tool supporting the process introduced here, which is left for future work.

| No. | Sample Question                                      | Area               |
|-----|------------------------------------------------------|--------------------|
| Q9  | How correct, truthful, reliable and complete is the data in the data set? | Veracity           |
| Q10 | How quickly does the data grow (in byte/s)?         | Velocity           |
| Q37 | How structured/formalized is the data?              | Data Management    |
| Q46 | What are the hypotheses that could be tested using this Value data set? | Data Management    |
| Q51 | What workflow is this data part of (in my organization, Workflow at my customers’ sites)? | Workflow           |
| Q65 | Is it morally right to build the planned application? | Ethics             |
| Q67 | What licensing entitlements apply to the data set under Legal consideration? | Legal             |
| Q72 | Will the system to be built need to support multiple languages? | Linguistics        |
| Q74 | Whose responsibility is the ongoing re-training of any machine learning models post-deployment? | Governance         |
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