The CESAW dataset: a conversation

Derek M. Jones  William R. Nichols
Knowledge Software  Carnegie Mellon University
derek@knosof.co.uk  wrn@andrew.cmu.edu

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Abstract

An analysis of the 61,817 tasks performed by developers working on 45 projects, implemented using Team Software Process, is documented via a conversation between a data analyst and the person who collected, compiled, and originally analyzed the data. Five projects were safety critical, containing a total of 28,899 tasks.

Projects were broken down using a Work Breakdown Structure to create a hierarchical organization, with tasks at the leaf nodes. The WBS information enables task organization within a project to be investigated, e.g., how related tasks are sequenced together.

Task data includes: kind of task, anonymous developer id, start/end time/date, as well as interruption and break times; a total of 203,621 time facts.

Task effort estimation accuracy was found to be influenced by factors such as the person making the estimate, the project involved, and the propensity to use round numbers.

1 Introduction

This paper takes the form of a conversation between William Nichols who was the technical lead member of the team who obtained and analysed the data, and Derek Jones who reanalyzed the data.

Data analysis is an iterative process; ideas may have been suggested by discussions with those involved before the data arrives, and new ideas are suggested by feedback from the ongoing analysis. Most ideas go nowhere; failure of the data to support an idea is the norm. Analysts who are not failing on a regular basis never discover anything.

The reason for analyzing data is to obtain information that is useful to those involved with the processes and systems that produced the data.

Any collection of measurement data contains patterns, and some of these may be detected by the statistical techniques used. Connecting patterns found by data analysis, to processes operating in the world requires understanding something about the environment and practices that generated the data.
Table 1: Number of rows and columns in CESAW’s largest files. 

| File                        | Rows   | Columns |
|-----------------------------|--------|---------|
| CESAW_defect_facts.csv      | 35,367 | 14      |
| CESAW_size_fact_sheet.csv   | 15,942 | 16      |
| CESAW_task_facts.csv        | 61,817 | 12      |
| CESAW_time_facts.csv        | 203,621| 15      |

All defects found during development. CESAW_size_fact_sheet.csv: All size information from the projects’ work breakdown structures. CESAW_task_facts.csv: All task information connected to the projects’ work breakdown structures. CESAW_time_facts.csv: Time log entries from projects connected to work breakdown structure.

If the person doing the data analysis is not intimately familiar with the environment and practices that generated the data, they either have to limit themselves to generalities, or work as a part of a team that includes people who have this knowledge.

As the conversation progressed, the narratives created as possible explanations for the patterns found in the data evolved; readers are presented with a semi-structured story fitted together after the event.

One purpose of this conversation is to provide an introduction to the CESAW data.

The data is available for download at: https://kilthub.cmu.edu/articles/CESAW_Project_Data_Fact_sheets/9922697

1.1 Stumbling onto data

Detailed software project data is very difficult to acquire, and I was surprised and delighted to discover that a report by Nichols, McHale, Sweeney, Snavely and Volkman included a release of a very large collection of project data. This data contained a lot more information than was discussed in the report, and Bill Nichols was very prompt in answering the questions I asked about the data, and agreed to work on publishing this conversation.

Table 1 shows the number of rows and columns contained in the largest files in the CESAW dataset.

My professional background is compiler writing and source code analysis. Over the last ten years I have collected and analyzed 600+ software engineering datasets and made them publicly available.

Although my background in Physics, I’ve been doing software development and software engineering my entire professional life. Since 2001 I’ve been tracking individual effort on project work using the Team Software Process framework and since 2006 I’ve been doing this with the Software Engineering Institute. The CESAW dataset is a small subset of my project inventory that was selected because the developers used some specific software assurance tools. The work is tracked in sufficient detail that I was able to isolate the direct effort to use...
Figure 1: Left: Number of tasks (in sorted order) recorded for each project; right: Number of people (in sorted order) who worked on each project.

those tools, the defects found by those tools, and the effort required to fix those defects. In short, the data is designed for both work tracking and process improvement. I was able to show that using source code analysis tools don’t slow down initial development because the find and fix rates are so much faster than dealing with the issues that would likely have been found in test. The challenge isn’t the math in the analytics, it is becoming familiar enough with the data to use it.

1.2 The conversation

Getting the most out of data analysis requires domain knowledge. Bill has that knowledge, but is a busy man. I find the best way to get a busy person to talk to me, is to tell them things about the data that they find interesting and useful. Derek

My top priority is to find something in the data that the domain expert finds interesting. The boring, but necessary, stuff can be done later. This approach is one reason for the disjoint organization of the paper.

2 SEMPR and the CESAW subset

The SEMPR data contains about 1,000 software project cycles from 85 companies. SEMPR (the Software Engineering Measured Process Repository) is a data warehouse populated from Process Dashboard project data files. CESAW (Composing Effective Software Assurance Workflows) was a research project that examined the cost/benefits of static analysis. The CESAW report included three companies from the SEMPR data for which we could identify the use of static analysis tools: five projects from a company working in Avionics (safety critical), 16 from a company working in business intelligence, and 15 from a company working in design automation. These companies use Team Software
Figure 2: The Work Breakdown Structure tree of the 961 wbs elements in project 615; leaf WBS elements (in black, contain a sequence of tasks), non-leaf WBS elements reference other WBS elements (in red; or terminate with no corresponding tasks), other colored edges denote year in which associated leaf tasks were first started.

Process\textsuperscript{(TSP)} for software development, and the Process Dashboard for data collection.

Figure 1 shows the number of tasks contained in each of the projects, along with the number of people involved in each project. Project implementation occurred between 2010 and 2017, see figure 19 right plot, for project durations.

The analysis in this paper involves the task related data contained in the files: CESAW\_task\_facts.csv and CESAW\_time\_facts.csv. The data in the code related files: CESAW\_defect\_facts.csv and CESAW\_size\_fact\_sheet.csv are not analyzed.

2.1 Work Breakdown Structure

All projects used the Work Breakdown Structure (WBS) to subdivide a project into ever smaller components. The smallest component, a WBS element, contains a sequence of tasks to be performed to implement that component. These components are denoted by integer values in the column wbs\_element\_key.

A Work Breakdown Structure is a hierarchical tree; figure 2 shows the WBS tree for project 615. A WBS is intended to support the evolution of a system through incremental development, with the requirement that the system be broken down into a structure that shows which capabilities will be satisfied by a specific increment. MIL-STD-881E\textsuperscript{[3]} is the US Department of Defense standard for Work Breakdown Structures.
In practice there are three major perspectives on the approach to the use of a work breakdown structure:

Deliverable-oriented: The approach defined by the PMI body of knowledge, in which decomposition is structured by the physical or functional components of the project. The major project deliverables are the first level of the WBS.

Activity-oriented: This focuses on the processes and activities in the software project. The major life cycle phases are the first level of the WBS.

Organization-oriented: This focuses, like the activity-oriented approach, on the project activities, but groups them according to project organizational structure. The subprojects or components of the project are the first level of the WBS. Subprojects can be identified according to aspects of project organization as created subsystems, geographic locations, involved departments or business units, etc. An organization-oriented WBS may be used the context of distributed development.

Figure 3, left plot, shows the duration of each project; the right plot shows the number of WBS whose implementation took a given number of elapsed working days, for all projects and project 615.

The WBS should structure the overall work, and is a basis for tracking progress to completion. In our approach, the top levels can be product based (modules) or functionally based (requirements). It doesn’t matter. The leaf elements represent the process elements of the work. There will always be some grey areas on where to place integration, test, and deployment. These are often process leafs off a higher level node. In the Dashboard, task is related to the WBS element through the Plan item. For the fact sheets I flattened the relationship, but the warehouse has more indirect links. The warehouse was optimized for adding data to a dynamic project. That sometimes makes extracting the data more work.

Tasks in the WBS are built from process workflow definitions. The phase list has a natural sequence of work order, requirements before design, before code,
before test.

The product is physically decomposed (sometimes modules, more often features or changes that cut across physical modules). The final level of decomposition is task by phased activity. This is done automatically. The work package (WBS element) is sized, and the effort is distributed across the phases using historical phase effort ratios.

Why are some leaf WBS elements not associated with tasks (in figure 2 these are the red nodes that terminate without an outgoing child link)?

First, when I built the task sheet, I only included tasks that had time logged. I took the effort by aggregating the time log entries by task then got the other task data from task tables. So no tasks only tells us that these tasks were not worked. Next, I went to the context information to look into this. Unfortunately, I cannot share that material because it cannot be anonymized. (there should be some future work joining that context data)

I see two distinct types of WBS component that these could be.
1) placeholders that were never estimated,
2) WBS components that were estimated but never started and completed.

Type 1) seem to be work that is kind of speculative, for example a placeholder for fixing issues returned from test that someone else (not in the plan) has performed. Another example included fixing security issues or defects. This is often speculative rework. The tasks did not look like software components, but placeholders to make the plan more realistic by reminding them, "hey, these were things did in the past, but they might not be needed, but we better put them in, so we don’t forget about them.

Type 2) can be different. If you look at the task sheet, some of the tasks have an end date, but no start. These were closed off without working them. If the task was not worked and never closed, it never made the task sheet. I can only make an educated guess that these were either not needed, de-prioritized and not worked, or they ran out of time and didn’t get to these before the plan was submitted. That is, cancelled tasks. There is no direct evidence for why these things happened. The data only tells us something odd happened. There may be explanations in a team meeting report.

Figure 4, left plot, shows the number of leaf WBS elements in each project (in sorted order), and the right plot shows the number of tasks in each WBS element (for all projects in both cases).

While most WBS involve a few tasks (across all projects), in some projects many WBS contain many tasks; see figure 9, right plot.

Derek: WBS 80208 has 7,143 tasks, and WBS 1 has 3,796 tasks. Might these be database extraction mistakes?

Bill: I won’t claim there are no mistakes in extraction, but these are heterogeneous projects. Some are very short while several that are multi-year efforts. I don’t see any reason to believe a priori that the structures should be all that similar.

I want to look at the structure one more time, there may be some multiple counting because of the structure.

The Misc phase is used as a catchall for tasks that pop up or don’t fit into a standard workflow category. Misc often includes orphaned entries. Req Inspec-
tion also depends upon a specific team raises some questions that would require context. Nonetheless, an inspection should normally be part of a sequence of tasks, i.e., a workflow.

As you have recognized, there is a lot of opportunity to audit the data and inconsistencies sometimes appear. It is entirely possible there is a bug in my extraction software, but I can always go to the original source to verify.

Multiple people may be on a plan item (for example, a code inspection) each would have a task. Note, WBS Element may not always be a physical product. Integration or System test may stand alone without a direct mapping to the design and code products. The integration content must be inferred from timestamps.

The leaf element usually has a process associated with. WBS item(X) Process Vector == task list. But sometimes they needed to add a task with only a single process phase. To verify I’ll have to look more carefully at that data.

This planned item was worked in two sessions, one of 81 minutes, the (other the next day) of 131 minutes. That’s a little over an hour and a little over two hours. Those are very reasonable work times. Neither work session recorded interrupt time, but for 1-2 hour sessions, that is also reasonable.

It is pretty normal that a task is worked on in short bursts over multiple days and this is a reason that date stamps are not very useful for measuring effort on small tasks. I’ve been trying to get the Agile community (using Rally, Version One, or other tools) to recognize this, to no avail.

2.2 Team Software Process

Team Software Process breaks down the creation of software into phases defined by a primary activity. This phase structure does not imply a waterfall project structure, instead it reflects the natural progression of software through a sequence of activities. After a piece of software completed a phase, any escaping
defects must be recorded. The phase, as an accounting mechanism, thus helps
to isolate rework. Table 2 shows some typical phases in a TSP project.

TSP is a superset of PSP phases. PSP focuses on the individual tasks a
developer performs to write a small piece of code. PSP has little with require-
ments, but understanding the assignment, which is roughly similar to a small
user story. PSP also doesn’t have major integration or regression/system test.
The teams define their own workflows and are free to define task categories,
but most are at least loosely based on ISO 12207 lifecycle phase definitions.
A colleague has suggested we describe these as ISO 15504 lifecycle activities
to avoid confusion with “waterfall”. Think of the activities as the steps that
single piece of software must proceed through from an idea to running code. A
DevOps pipeline helps to visualize this. Each story goes some set of activities
such as requirements analysis, design, code, various reviews or inspections, unit
test, integration, regression test, and deployment. The value of TSP is that
it captures and places into context all the development work within a project
team.

2.3 How SEMPR tracked work

The Process Dashboard was the data collection tool and developers used this
tool as a work log. But the dashboard served several purposes. It was used to
plan the project, to gather data during project execution, to monitor project
performance, and to analyze the project during cycle or project post-mortems.
The planning included building a Work Breakdown Structure, estimate WBS
elements by size or effort, define work process flows and processes, apply a
workflow to convert some WBS elements into a tasklist, record project staff and
estimate effort available per week, distribute tasks to individuals, and build a
schedule.

| Description                                      | Phase Type |
|--------------------------------------------------|------------|
| Detailed-level design                            | Creation   |
| Personal review of the detailed design            | Appraisal  |
| Unit test case development                        | Creation   |
| Peer inspection of the detailed design            | Appraisal  |
| Writing the source code                           | Creation   |
| Personal review of the source code                | Appraisal  |
| Peer inspection of the source code                | Appraisal  |
| Developer unit test execution                     | Failure    |
| Integration test                                  | Failure    |
| System test                                       | Failure    |
| User acceptance test                              | Failure    |
| Product life                                      | Failure    |

Table 2: Typical phases of a TSP project, and the types of actions that can occur that are applicable to the project team.
Each task was assigned to an individual. The teams then sequenced upcoming work to manage important coordination events and balance the workloads. The resulting straw plan demonstrated that work was at least possible. During execution, individuals work the task at the top of their list. They used an electronic stopwatch to record time, and marked the task complete when done. Any defects discovered after "done" were recorded as defects. As work deviated from the plan, tasks would be reordered or reassigned to keep the plan in balance.

At regular intervals, sometimes weekly, but at least at releases, the Process Dashboard data was exported, shipped to SEI, then imported into a Process Dashboard data warehouse (SEMPR). We extracted the data into fact sheets using R scripts and SQL code.

### 2.4 Data collected

Both the Nichols’ report and the README included with the data, provide a basic overview of the information contained in the columns of each file. Table 3 lists some of the columns and information contained in the files, while table 1 lists the number of rows and columns in the largest files.

To make full use of the information collected it needs to be mapped to developer work practices. Inside knowledge is needed.

Teams collected an enormous amount of data. We had a list of every task performed, the effort spent, where defects were injected, where they were found, how long they took to fix, and so forth. That’s a lot of data, but it doesn’t tell you the work domain, the product, the trade-offs between time and functionality, the definition of done, how the process steps were executed, the tools used, the programming languages, why the plan was changed, the basis for estimates, and so forth. This was not a problem for the teams because they knew all this. But
those of us trying to use the data have some big information gaps. We also have other project artifacts including reports, meeting minutes, and post-mortem analysis. But these were not automatically stored in the SEMPR. We cannot release those because they include a lot of identifying information.

The information in the files `CESAW_time_fact.csv` and `CESAW_defect_facts.csv` corresponds to PSP’s time recording and defect recording log, respectively. The `CESAW_task_fact.csv` file aggregates the time fact information for each task, e.g., a sum of the time deltas and range of start/end dates.

The CESAW date, like everything in SEMPR, uses the TSP framework. Some teams use the standard TSP data framework, which includes traditional PSP as a subset, but there were some variations. One team that had systems engineering responsibilities elaborated on the requirements, including personal review of requirements and high level (architecture and structural) design. Isolating Static Analysis was a little tricky because no one defined it as a separate phase. Fortunately, the defect descriptions helped to identify the source of defects, so I was able to use the defect find and fix time. Other static analysis work turned up in Integration Test and System Test. It depended on the type of tools being used and what type of issues it was designed to find.

The report lists three companies (A, B, and C), but there is no mention of the D company that appears in the data.

Company D was removed from our study because we could not reliably isolate the use of static analysis tools.

3 Initial analysis

The CESAW dataset shares some similarities to a company dataset previously analysed by Derek, the SiP dataset, and the initial analysis investigated the same relationships.

As the analysis progressed the structures present in the data began to be discovered, suggesting possible new patterns of behavior (some of which were found to be present).

To provide some focus for the initial analysis project 615 was chosen as a test bed because it was the project containing the most tasks; this project contained safety critical components.

Project 615 is an end to end development so there is a lot of requirements engineering work. Many projects do primarily code. That is, most teams are given requirements or stories and work mostly in the implementation phase. In this project we get to see more of the life cycle.

3.1 A first regression model

Before starting work on a task, the person involved makes an estimate of the expected duration (in minutes); the actual time taken is recorded on completion. What is the relationship between estimated (the `task_plan_time_minutes` column in the data) and actual time (the `task_actual_time_minutes` column)?
Figure 5: Left: Estimated task work time (in minutes) against actual task work time for the 61,817 tasks in all projects, with fitted regression model of the form Actual $\propto$ Estimated$^{0.85}$; right: Exponent of models fitted (in sorted order) to every project.

Analysis of estimates made for other projects has found that a power-law provides a good fit. Figure 5, left plot, shows estimated time against actual time to complete a task, for all 61,817 tasks, with a fitted regression model (in red); the fitted equation has the form:

$$Actual_{\text{mins}} = 1.5 \times Estimated_{\text{mins}}^{0.85}$$ (1)

This model explains 52% of the variance present in the data. The first equation fitted to the SiP data has the form: $Hours_{\text{Actual}} = 1.1 \times Hours_{\text{Estimate}}^{0.87}$, and explained 70% of the variance.

Keep in mind that this is direct effort, not wall clock or calendar time. We coached the teams to aim for consistent estimation. As long as they had a consistent distribution, accuracy could be corrected for with regression and the high and low estimates would balance out.

How do individual projects compare against the aggregate model? Figure 5, right plot, shows the fitted exponent value (in equation 1) for each project.

This regression model can be extended to include other columns in the data, e.g., organization, project, individuals, and task phase. However, there are larger project structural factors that probably ought to be investigated first. For instance, the TSP phases occur in a specified order, and the relationships between tasks performed in a sequence may need to be taken into account in a realistic model.

I’ve puzzled for a while how to use the data for observational studies of programmer/developer performance. Absent an objective measure of task size, how could we infer productivity effects for long or short work sessions, or having multiple tasks open? I’ve tried to set up structural equation models, SEM, but the structure doesn’t seem quite suit the models and data.

Hypothetically, the optimum number of open tasks should be 1, and the ideal work session without breaks would be longer than 30 minutes, but shorter
than 3 hours. There should be a start up penalty for performing work after a
long break (say several hours).

Because this is observational, these might not be available from the data,
but I can imagine starting with the estimate, then calculating the effect of the
adjustment factors.

What is productivity? When repeatedly creating the same item, such as
a widget, the number of widgets created per hour is an obvious measure of
productivity. Each task on a software development project is different, yes tasks
may have similarities, which means the effort involved is different for each of
them. Monitoring developer brain activity is another possibility, but without a
model of how the brain solves problems we can do little more than say somebody
is thinking.

While one task is ideal, in practice there will be road-blocks. So it might be
useful to be able to take on multiple tasks.

Most definitely. As with everything, it is a matter of degree and sequencing.
Which types of tasks include a lower penalty? When I ran a team, we tried
to keep an inventory of "filler tasks", that were short and independent. These
often involved small updates to documentation, reviewing, but were heavy on
team management tasks. For those that incur the highest penalty for blocks,
(we typically thought of design or debugging test cases) we made it a focus to
coordinate on the blockers.

That is, having tasks ready to go is a good idea. However, I have data that
putting people on multiple projects is catastrophic. About 20% of a persons
time is consumed just *being on a project*. A weekly staff meeting consumes about
an hour direct time, 15-30 minutes prep, and another 15-30 minutes transition.
That’s 5% of a work week. I also have evidence that direct time on project
tasks is about 15% of the work week, but at the team level, the coefficient of
variation for direct task time is about 25%. This was for teams using TSP,
who are presumably somewhat better than average with time management. (15
hours is about a 2.5 "Load factor" that some agilists like to use to convert effort
days to "ideal time")

The fitted equation for WBS Estimate/Actual, based on summing the values
for the corresponding tasks, is:

\[ WBS_{Actual}\_mins = 1.4 WBS_{Estimated}\_mins^{0.94} \] (2)

A slightly better fitting model can be obtained by including the number of
people working on the WBS, or the number of tasks in the WBS:

\[ WBS_{Actual}\_mins = 1.5 WBS_{Estimated}\_mins^{0.89} e^{0.08 People}, \text{ or} \]
\[ WBS_{Actual}\_mins = 1.7 WBS_{Estimated}\_mins^{0.85} Tasks^{0.21} \]

### 3.2 Tasks

Tasks are the basic unit of work in TSP, with a WBS containing a sequence of
more or more tasks. Figure 4, right plot, shows that 14% of WBS contain a
single task (e.g., Misc), and 53% of WBS contain five or fewer tasks. Within the
WBS of project 615, the most common task sequence is: Ident, Ident Inspect, Work, Inspect - Author, IT (forming 22% of WBS elements).

The following list shows the total number of each kind of task, by phase name, for project 615. The large role played by inspections in TSP development is reflected in the frequency of this activity.

| Task Occurrences | Task Occurrences |
|------------------|------------------|
| Inspect - Others | 2031 Documentation |
| Ident Inspect    | 1964 Design |
| Misc             | 1171 Test Devel |
| Ident            | 1153 Code |
| Work             | 1037 Planning |
| Inspect - Author | 1024 Design Review |
| Reqs Inspect     | 934 Test |
| IT               | 848 Code Review |
| Design Inspect   | 550 Postmortem |
| Code Inspect     | 547 Compile |
| HLD Inspect      | 371 Reqs Review |
| HLD              | 204 \N |
| Int Test         | 195 Strategy |

Figure 9 shows information on the number of people working on a WBS, per project, and the number of WBS per project.

### 3.3 Work structure

Previous project task data I have analysed had a flat, linear, structure; any higher level structure that existed in a project was not present in the data. I spent some time analyzing the CESAW data assuming it had a flat structure, this was a mistake that led me down various blind alleys.

The leaves of a WBS are self-contained elements of work involving a sequence of tasks. Successively higher levels in the WBS work hierarchy specify higher level requirements, which are built from one or more lower-level WBS elements; see figure 2.

A pattern for much of the work will be Create, Review/Inspect, Test. These will apply to Requirements, High level designs, Code, and other products like documents. The Phase list should include the overarching set of phases from which workflows will be derived.

A development tasks normally includes design, reviews and inspections, code, code review and code inspection, unit test.

Requirements usually include some requirement’s development, Builds *usually* are a separate WBS and may include Build and integration, and system test.

Most code activities will include maybe (design, design review, design inspection), code, code review, code inspection, and unit test.

Review is a personal review, inspection is peer review and usually becomes 2-4 tasks.
Teams have a lot of flexibility in setting up their workflows. The standard process phases help a lot to understand what is actually going on. They also have flexibility in their work habits. This one planned item was worked in two sessions, one of 81 minutes, the (other the next day) of 131 minutes. That’s a little over an hour and a little over two hours. Those are very reasonable work times. Neither work session recorded interrupt time, but for 1-2 hour sessions, that is also reasonable.

This explains one of the questions on my list, i.e., why does CESAW_Time_fact contain so many more entries than the Task facts.

The data is now even more interesting. It is possible to look at how individual tasks are split up over given intervals.

Yes, the time log is very interesting because you can see exactly when direct work was performed. I was surprised I could not get the community interested in using it because the data tells us a lot about work habits. We always coached that the sweet spot for work sessions was a 90-120 min then a break. Actual direct time is seldom more than 50% of the work week, and anything above 35% (14 hours) is good, >16 hrs/week was outstanding, 20 hrs/week was best in class. More than 50% always was a flag for bad data.

Essentially, two 2-hr work sessions a day (without interruption) resulted in first-rate effort time.

Other flags include long sessions (our rule of thumb was 180 min) without interrupt time.

This needs additional context and explanation. The phases names are not intended to capture the *activity* as much as to highlight rework. The phase types are Creation, Appraisal, Failure, Other. Creation phases (Design, Code) include only the first draft by the author. This is expected to be the creation work, everything else is correcting defects. Test is a special case that deserves additional discussion.

In test, there is the test execution time, and the defect fix/rework time. Double entry accounting includes time in test along with Defect fix times.

Defect fix time includes finding a defect (debugging, reviewing.....) fixing the defect (some code/compile) and rerunning/evaluating test results.

The difference between total test time and defect fix time approximates the time a zero defect product would require.

This is a systems engineering team performing many of the early lifecycle activities. Over the course of several projects, they changed the high level process several times, but the early phases were requirements development activities.

The sequence you show doesn’t look quite the right order, but I’m sure I have that recorded in the fact sheets. Memory fails, so I will have to look up the location. The key idea is that they had a Requirements Identification followed by a Requirements development/documentation phase.

Inspection is for code is somewhat separable because we recommend (strongly) never inspecting for more than 2 hours at a time, and proceed at a rate no more than 200 LOC/hr. Larger packages, thus would require multiple sessions.

Inspect Author is the rework the author must perform in addressing the inspection findings. This is well named for clarity, unlike how inspection recorded
for coding.

For accounting purpose phases are a logical "waterfall". The individual coding task is performed, reviewed by the author, then send for inspection. All rework/recoding is recorded as an inspection task by the author. Code splits will record only how many sessions the author required to complete the initial code draft.

This may seem plodding, but they escaped something on the order of <1 def/KLOC new and changed code. Their best work was measured in two digit defects/MLOC.

Work on some tasks was split across multiple sessions. For instance, the person involved may have taken a break, or had to pause while a dependency was resolved. When work on a task is split, there is a separate row in the time log for each work session on the task.

When tasks are split across two sessions the most commonly involved phases involve inspections; for several projects the most common phases are: Design, Inspect and Code Inspect.

How many tasks are not completed on the day on which they are started? Figure 6, left plot, shows the number of tasks whose end date was a given number of working days after the start date, for project 615 (similar results are seen for projects 614, 617 and 95); red lines are fitted power laws with exponents of -1 and -1.6. The C, in red, shows the number of tasks completed on the day they were started.

The change of slope in figure 6 happens at around 9-work days, i.e., 2 working weeks. Is 2-weeks a special duration of some kind?

It was not possible to fit a regression model connecting continuation days to: planned time, number of work sessions, or day of the week.

Bill
Our guidance was that developers should try to complete 2-4 tasks per week. By keeping tasks small, they can track work more accurately and lower work in progress (WIP). We held weekly status meetings, so we could expect some uncompleted work to show up as WIP. If WIP showed more than a half week, that indicated a problem. We would look at the open tasks to see if there was something we needed to do. If the task went beyond a couple of weeks, this was almost usually a problem. Sometimes it was just too big, or was stuck waiting. We sometimes tracked miscellaneous work in what we called a "bucket". This was something we wanted to track, but didn’t correspond to a direct deliverable, it was more a level of effort (LOE). Support tasks like maintaining the revision control system, for example, would be allocated some time in a metaphorical “bucket”, from which time would be drawn as needed. We often did this to maintain an historical record of effort, so we could plan for it in the future. This sort of bucket was more a LOE than an earned value task. But they needed to be time boxed and closed, or they would mess up tracking by increasing the noise to signal.

A person may work on more than one task per day. Figure 7, left plot, shows the number of days on which each person spent the day working on a given number of tasks, for project 615; red line is a fitted zero-truncated Negative binomial distribution.

Including the number of sessions worked for each task, num_sessions, in a regression model updates equation 1 to give the following fitted equation:

$$Actual\_mins = 3.1 \cdot Estimated\_mins^{0.55} \times \frac{num\_sessions^{0.75}}{e^{0.24 \times (day\_diff = 0)}}$$

where: $day\_diff = 0$ equals 1 when the task started and completed on the same day, and 0 otherwise.

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1Zero-truncated because zero values do not occur.
Figure 8: Left: Total number of tasks worked on during a given day of the week, for project 615; right: Autocorrelation of the tasks worked on per day, for project 615.

This model explains 71% of the variance in the data. Similar fitted equations were obtained for projects 95, 614, 617.

If completing a task requires multiple sessions, the weekends at either end of a working week are a potential delimiting barrier. Do people aim to have in-flight tasks completed by the end of the week?

Figure 8 left plot, shows the total number of tasks worked on during a given day of the week, for project 615.

Figure 8 right plot, shows the autocorrelation for the total number of tasks worked on per day, for project 615. The recurring peak at 7-day intervals show that the number of worked tasks on any day is highly correlated with the number of worked tasks on the same day of the previous and following weeks. The high auto-correlation values either side of each peak implies a strong correlation between the number of worked tasks on a given day, and the previous day of the previous/next week and the following day of the previous/next week.

The natural planning time frames were the day, the week, and the "cycle". Developers thought in terms of a work day and would make a plan of the day (PLOD) with the intention of trying to get something done. The team planned weekly, so the teams and individuals built a plan of the week (PLoW) during which they would reorder, add or remove, and if necessary re-estimate their remaining tasks.

The overall plan was broken into cycles, similar to sprints, where the high level goals were detailed out for planning. We found, empirically, that a natural timescale for a detailed plan horizon was 12 weeks, (three months or a quarter). That is, for about 12 weeks, we could manage the detailed plan to the quarterly targets. After that, plans tended to get so out of date that they needed to be refreshed with a thorough replan. Some teams did this monthly, but we tended to find quarterly was a good frequency to have the team step back to revisit goals, priorities, risks, and long term strategy.
3.4 WBS staffing

What is the process used to decide who will be involved in the implementation of a given WBS?

There is the macro dimension between teams and the micro level within teams. Real projects are messy. I wrote a short paper that listed some common staffing patterns we observed, which found various patterns in people working together. None of them are surprising, but it’s useful to understand some different work flow structures involving teams and multiple teams. Sometimes they work in parallel, sometimes in sequence by speciality, and in other cases people came on during periods of intense work.

Figure 9 left plot, shows the number of WBS elements that involve a given number of people, broken down by project (colored lines). On some projects most WBS involve one person, while on other projects a three-person WBS is the common case.

Figure 9 right plot, shows the number of WBS elements that contain a given number of tasks, broken down by project (colored lines).

That’s an interesting view, and I’d never seen it presented that way before. With Yaz Shirai, we looked at multi-project teams, and only looked at people and time. That plot shows patterns on a single project rather than multiple team projects. It’s a pity this hasn’t been studied more, there may be some insights about why they work a certain way and what is effective in different situations.

Within a project, how often do the people work together on a WBS?

Figure 10 shows, for projects 614, 615, 617 and 95, a clustering of pairs of people working together on the same WBS, based on the number of times they worked together on a WBS.
Figure 10: Clustering of pairs of people based on number of times they worked together on a WBS, for projects 614, 615, 617 and 95.
4 Staffing

Companies are often concurrently implementing multiple projects, and the implementation of a large system may be split into multiple projects.

It is unlikely that the demand for staff on a new project will occur just as a project is being completed. One way of reducing the time staff spend not earning income between projects is to have them work on multiple projects, e.g., starting work on a new project while an existing project is not yet nearing completion.

When projects are components of a larger system, it may be necessary for them to be implemented concurrently; for instance, to allow a common interface between them to evolve by agreement through implementation experience.

Figure 11 shows the date on which each person working on a project started each of their tasks, for projects 614, 615, 617, and 95; people are ordered on the y-axis by date of first task.

The values appearing in the person_key column, denoting distinct people working on a project, vary across projects, i.e., it is not possible to match up the same person working on different projects.

Yaz Shirai and I looked at some common patterns and found 6 or that were pretty common.

Some projects have cross-functional staff. The same people do all the work.
Or sometimes, only the development work is closely tracked. Both of these look like the same people from beginning to end. In other cases, specialists might come onto the team for a period of time, for example requirements or test staff. Then there were more specialized teams. The requirements, architecture, or test may be teams of specialists. The point is that teams had different ways of organizing and staffing their work and there was no one size fits all. Another pattern we saw was a team or team members dropping in during a period of high work load.

What percentage of their time do people spend working on a project? Derek

Figure 12 left plot, shows the average number of hours worked per week (i.e., total hours worked divided by number of weeks between starting work on the first and last tasked worked) by each person who worked on projects 614, 615, 617, and 95. People are sorted in hours per week order, and person numbers do not correlate across projects.

How many people are actively working on a project, over time? Derek

Figure 12 right plot, shows the number of different people starting work on a task during each week.

Reading Humphrey’s book[^5] I did not see anything about the distribution of people across projects. Is there any informal practice? Bill

There are a lot of opinions on how it should be done, but very little empirical work quantifying what people actually do. My observation is that smaller companies are more likely to be cross-functional and bigger places have more specialists. Bigger companies also had more teams, so it was easier to just move work between teams rather than add people to an existing team. We strongly encouraged keeping teams stable and had strong evidence that someone should be on only one team. The overhead for being on a team was about 20% of total time. It was tempting to “phantom staff” by spreading people. We showed from time logs that a second projects didn’t create two half-time people, but two third-time people. A third project usually meant you had someone who only

[^5]: Humphrey, W. (1989).
attended meetings for two teams or who ignored two teams.

5 Estimates and actuals

A wide range of cognitive and social factors have been found to influence human time estimates. When giving a numeric answer to a question, people sometimes choose to give a value that is close to, but less exact, than what they believe to be true; values may be rounded towards preferred values, known as round-numbers. Round-numbers are often powers of ten, divisible by two or five, and other pragmatic factors; they can act as goals and as clustering points.

Analysis of task estimation data from other projects has found that frequent use of round-number values is common, e.g., 30 and 60 minutes. The frequent appearance of round-numbers in actual task times has not been as common.

Figure 6, right plot, shows the fraction of unique estimate and actual values, for each person who worked on at least 20 tasks, for project 615.

5.1 Estimates

While this section focuses on the estimates made for project 615, similar patterns can be seen in the estimates made for other projects.

Figure 13, left plot, shows the number of times a task is estimated to require a given number of minutes, for project 615. While round-numbers such as 30 and 60 are very common, some surprising (to me) numbers are also common, e.g., 12. Many of these surprising estimate values are for inspection tasks.

Figure 13, right plot, shows Estimate against Actual for the Inspect - Others tasks of project 615: the red line is a fitted power law, and the blue line shows Actual = Estimate. The large number of estimates clustering around certain values is visible in the concentration of points forming vertical shafts.
Adding the (anonymous) identity of the person doing the inspection to the regression model (i.e., equation 3) significantly improves the fit. The fitted model shows that estimate accuracy varies by a factor of more than 10 across inspectors.

Figure 14 shows the multiplicative factor added into equation 3 for each individual who made at least five estimates on project 615. Points below the grey line indicate overestimation, compared to group average, while points above the grey line indicate underestimation. The left plot is based on the seven possible inspection tasks (denoted by distinct red plus symbols for each person), and the right plot is based on the seven possible creation tasks.

Why is there so much variation in the relative accuracy of individual estimates?

Possible reasons include: risk tolerance, implementing tasks that involve more/less uncertainty, inexperience, and factors external to the project that have a greater need of cognitive resources. Data analysis can highlight a behavior, uncovering likely causes is down to project management.

Inspection tasks have two recommended constraints.

1) the inspection rate should be less than 200 LOC/hr or about 4 pages an hour for typical documents,

2) the size of the inspection needs to be limited so that inspectors don’t spend more than an hour or 90 minutes in a sitting.

Based on size, the effort is typically: $\text{Effort}_{\text{Estimated}} = \text{Size} \times \text{Historical Rate}$

Tasks should be estimated at the leaf WBS. A WBS element has Plan items which are tasks. A process (workflow) is applied to a WBS component, and the activities are each allocated a percent of the total effort. This way, while the development of WBS component (for example a story) may take a couple of calendar weeks to complete, but would have separate tasks for design, design review, design inspect, code, code review, code inspect, (compile), and test. 2
to 4 of tasks should be completed in a week. This provides frequent feedback on progress and limits the work in progress to about half a week’s worth of effort.

Inspect - Others refers to the peer inspectors on a requirement. The owner is responsible for collating and disposing of all comments and IIRC, assigns this to *Inspect*.

The WBS in the task list should contain leaf elements. I expect this distribution to be somewhat constrained. As we go up the tree, we will likely find some distribution of number child nodes. One use might be to estimate the planning effort required to prepare a backlog. I’ve also seen instances where design re-work was required to decompose large components so that work could be partitioned and allocated. Without partitioning, a single developer could not realistically have achieved the desired schedule.

Based on size, there may be a minimum amount of planning required to get to some number of implementable pieces. There is likely a realistic limit into how many pieces a component can be subdivided. This may be useful to know. One could probably make an educated guess about the number of WBS levels required. This in turn may provide a more principled way to estimate staffing, schedule, and cost for requirements development, architecture, and design work. Benchmarks might be a reality check that the planning is adequate, or overdone.

5.2 Actual time

Methods of measuring the actual time taken to complete a task include:

- the amount of time spent working on the task. Figure 15 left plot, shows a fitted bi-exponential (red line) to the data, for project 615, with spike values (circled in grey) excluded from the fit; purple and green lines are the components of the bi-exponential,
• elapsed time between starting and ending a task, which may include intervals where work on the task is stalled, waiting for some event to occur. Figure 15, right plot, shows elapsed time for tasks completed on the day they were started, for project 615; red lines are fitted power laws (the break is at 20 minutes),

• time spent working on the task, plus time consumed by work interruptions; see figure 17.

In some cases, people may work hard to complete a task within the estimated work time, or may work more slowly to use up the available time. Parkinson’s law claims that work expands to fill the time available. Both behaviors predict a peak at the point where actual time equals estimated time.

Figure 16 for all projects shows: left plot, the number of tasks having a given actual time when a given amount of time was estimated (e.g., 30, 60 or 120 minutes); the right plot shows the number of tasks having a given estimated requiring a given amount of actual time to implement.

Both plots show that the main peak, in number of tasks, occurs when actual equals estimated time. There are also smaller peaks at round-number values less than and greater than the estimated time.

5.3 Work interruptions

Work on a task may be not be continuous, e.g., input from other activities may interrupt work, or a person may take a break. The TSP records interrupt time, and the splitting of a task across work sessions.

A continuous work session to complete a task was the exception rather than the norm. We found that working more than a couple of hours at a time tended to be hard to sustain, requiring a short break. For coding or testing a 5-10 minute break was often enough. But while debugging was almost hypnotic,
intense work such as design or inspection was so physically demanding that more than a couple of hours in a day was the max someone might be able to do. Since normal tasks might take 5-10 hours, most required several work sessions, often across multiple days. Moreover, there are a lot of other things, like team meetings, support work, filling out the time sheet, and so forth that get in the way. It was normal for only 10 to 20 hours per week to go towards tracked tasks. For this reason, wall clock, or calendar duration, had a weak correlation with direct effort. One of our productivity tricks was to have a team "quite time" or "focus time", two or three hour blocks several times a week during which there would be no interruptions.

All this is pretty straight forward to track with the Process Dashboard. During the plan of the day, you just place your top task at the top of the stack, and maybe make sure the next two or three are in sequence. The Plan of the Week should have these all ready. The active task has an on/off checkbox with a timer. We used it like a stopwatch. The task time only accumulates while the timer is on and placed this in the log.

How often is work on a task interrupted, and what is the duration of interruptions?

The CESAW data contains the total number of interrupt minutes (i.e., the `time_log_interrupt_minutes` column), but no count of the number of interruptions. The project average for percentage of work sessions interrupted is 89% (sd 6.9%).

Figure 17 left plot, shows the number of task work sessions having interruptions that consumed a given number of minutes; the red line is a fitted power law having the form: $\text{interrupt_freq} \propto \text{interval}^{-1.8}$ (round-numbers that ‘spiked’ were excluded from the fit). The right plot shows the percentage of work sessions experiencing at least one interruption, sorted by project.
Figure 18: Left: Number of tasks (in sorted order) implemented on projects 614, 615, 617 and 95, by each individual working on it; right: For all CESAW projects, the number of tasks each individual implemented against the total implementation time for those tasks, red line is a fitted power law with exponent 0.88.

The column task_actual_time_minutes in CESAW_time_fact.csv does not include interrupt time. Including interrupt time in the regression models finds that its impact, across projects, varies between 3-20%.

Work on a task may be split across multiple work sessions (see figure 6), with 45% of all tasks completed on the day they are started. A small percentage of tasks are worked on during two sessions on the same day; figure 19, right plot, shows the number session intervals having a given length (in 15-minute bins).

5.4 Impact of practice on accuracy

Through performing some activities, people get better with practice. There is an ongoing debate about whether changes in performance, through practice, are best fitted by a power law or an exponential; in practice there is little difference in the fitted curves over the range of interest.

The analysis of estimation accuracy in the SiP dataset found that developers did not improve with the number of estimates made, and it was hypothesized that developers prioritized learning to perform tasks more effectively (rather than learning to improve estimate accuracy).

Adding a variable containing the log of the relative order of when an estimate was made (for creation phases only), by each individual developer (who made more than ten estimates), to regression models similar to equation 3 failed to improve the fit (for projects 614, 615, 617 and 95).

Figure 18 left plot, shows the number of tasks performed by each person working on a project. The right plot shows for each of the 247 people working on the CESAW projects, the number of tasks implemented, and the time taken to implement those tasks (the red line is a fitted power law with exponent 0.88).

How were individual developer estimates evaluated when they were part of a team? Was everybody held equally responsible for accuracy?
Which factors and incentives influence the thinking process of the person making an estimate?

It would not be cost-effective to spend more time estimating than it is likely to take to do the job, and time spent estimating will be a fraction of the likely estimation time. One possible reason why short duration tasks tend to be underestimated is that the person making the estimate does not spend enough time studying the task to notice the potential pitfalls; intrinsic optimism holds sway.

Staff incentives are driven by the work context, and may be experienced differently by management and individuals.

Developers were expected to manage their own estimation. By and large, they were making work commitments, so it was their responsibility to make a reasonably accurate estimate. Estimation method varied by team, and we don’t always have data for a basis of estimates in the SEMPR. In some cases, they used a PSP workflow, and this automatically used PROBE High level estimates usually involved a size estimate and an historical development rate. Individuals were expected to apply their own rates for work they were assigned. Tasks were generally spread across phases using the historical percentage time in phase.

5.5 Wall clock time

What are the characteristics of daily work activities, relative to time of day?

Figure 19 left plot shows the number of tasks on which work started, within 15-minute intervals, for a normalised time of day. The time of day has been centered to allow comparison between projects (the times given in the time log columns of CESAW\_time\_fact.csv were converted from project local time to US Mountain Standard Time).
For this team, typical working hours (before COVID-19) are something like 0700 to 1700 Monday-Thursday (9-hr days w + 1hr lunchtime), and an eight-hour day every other Friday (with the other Fridays off). This is called a ‘Flex’ schedule, with every two weeks having 80 work hours. That was similar to my work schedule when I worked at the lab.

The ‘core’ hours are something like 0900-1400 so that people can come in early or late but should be covering the ‘core’ times of the day so that they are available for meetings. Personally, I used the early start as my focus time since I know there would be no meetings between 7:00 and 9:00.

The dashboard stores timestamps based on standard unix time. I imported the data on a computer using US Eastern Time. This is where things can get a little strange looking with the data. My computer system always knows what time zone I am using. When I imported a team’s data into the SEMPR, the time typically is stored in the database using the time in my time zone. Europeans will look like they are starting in the very early morning, like 3:00 AM, while US west coast teams will seem to start several hours later than an Eastern Time Zone team.

Figure 19, right plot, shows, for tasks worked on during two sessions on the same day, the number session intervals having a given length (in 15-minute bins).

6 Round numbers

When giving a numeric answer to a question, people sometimes choose to give a value that is close to, but less exact than, what they know to be true. Values may be rounded towards a preferred value, known as a round-number. Round-numbers are often powers of ten, divisible by two or five, and other pragmatic factors; they can act as goals and as clustering points.

This is why we preferred T-shirt size estimation. We trained and coached to avoid direct numeric estimates by using the T-Shirt size method, Very Small, to Very Large.

We converted the T-shirt size into cardinal numbers by calibrating with historical data. The T-shirt size tables had an average sizes for each size bin. We’ve found that size is log normally distributed, so we took advantage of that observation. We built the size tables by log transforming historical size data so that it looked roughly like a Normal (Bell) curve, then segmented it into size bins based on standard deviations from the mean. The actual (untransformed) size ratio between bins was usually about 2.5.

This is similar to how agile teams using story points a Fibonacci sequence, but the biggest difference is calibrating a parametric distribution to actual historical sizes.
6.1 The impact on accuracy

Picking round-numbers, rather than potentially more accurate values, has the advantage that managers or clients may find round-numbers more believable. Management/client influenced estimates are a perennial problem. Getting developers out of a round-number mindset may not be useful if management/clients think in round-numbers.

That’s an interesting perspective. We had a Top-Down estimate before work began, but the develops did their own bottom up estimate. Aggregating the bottom up has at least the appearance of being more precise.

Of course, round numbers can be both inaccurate (biased) and imprecise. We tried to avoid bias through calibration with actual data. A medium was a medium, and a large was a standard deviation larger. If the bins were centered and wide enough for people to distinguish, we could have imprecise (but unbiased) point estimates, but the central limit theorem drove big picture precision. This relies on some parametric assumptions that turn out to work in most cases.

BTW, we could also look at a plan to see if the estimates were balanced around medium. This was often used to check for bias during the planning.

Did people actually use the T-Shirt technique to make estimates? The task estimates have too many distinct values to be T-Shirt based, see Figure 6, right plot.

That’s certainly fair. There is no direct way to tell what they did for estimation. We trained estimation using the PSP. In that course we taught estimation by parts. Break the component into small parts, use a different size tables for each part type, then combine the results.

In my experience, estimation by parts as taught in PSP was seldom used in the field, it was too elaborate. Often they made tables using the wbs level components. Not everyone estimated size (new and changed lines of code) because the correlation of size and effort was sometimes weak. For example, the effort to make a small change to a large component didn’t predict the required effort very well. For that kind of problem, effort depended more on the complexity and number of components. Other tasks, such as running build and test depend more on defects found than changed code. So often they used historical data to build tables of direct task effort rather than make tables of the product size and run a regression. But in the end there was nothing stopping them from estimating directly, and this was probably the norm for non-development tasks.

You might see some traces of using direct estimates in Figure 5.

Looking at the left side of Figure 5 you might notice the huge variation of the actual from the estimate. As long as you mostly got things into the right bin and the high and low misses balanced out the central limit theorem drives the overall estimate toward the middle. That wide variation is really very typical in most point estimates and I don’t think it’s been handled appropriately most of the time. There are significant differences between people, but people have a high variance too. If you don’t account for both the between variance effects are impassible to see. If you don’t account for the within variance you wonder why so many people don’t seem to follow a pattern. If you don’t account for
both within and between variation, your models will be fundamentally wrong.

More practically, we were not concerned that every estimate was right, only that the highs and lows would cancel out. If we did this correctly and used relevant estimation tables, we could avoid systematic bias and the central limit theorem would be our friend.

### 7 Data quality

People make mistakes during data entry, and their memory for past events may be fuzzy. How reliable and accurate are the values contained in the CESAW dataset?

A previous analysis of the CESAW data investigated the percentage of values thought unlikely to occur in practice (this previous analysis included the data in the file `CESAW_defect_facts.csv`). The data quality analysis in this section applies to the files: `CESAW_task_facts.csv` and `CESAW_time_facts.csv`, i.e., the files analyzed.

There are a fixed number of minutes in a day, and people are unlikely to be working during all of them. While TSP practices recommend an upper limit on the amount of continuous time spent on a task, there may be deadlines that need to be met.

Figure 20, left plot, shows the number of tasks recorded as taking a given number of delta minutes, in the time log, over all projects. The descending bundle of points crosses the x-axis close to the number of minutes in a working day, i.e., 450. The numbered points, in red, are round-numbers, and are suggestive of people working for a planned amount of time. The larger round-numbers (e.g., 10, 12 and 15 hours) may be from continuous work on one task, or forgetting to press the stop button after finishing a task (and pressing it later just before going home). The even larger numbers may be due to pressing the stop button the next day.

Inaccurate data can cause analysis code to fail, in a statistical sense. For instance, the task facts file contains 638 (1%) rows where the start date is later than the end date.

The percentage of tasks that appear to be worked on continuously for long periods is sufficiently small (0.27% for 6-hours, 0.075% for 10 hours), that they can be treated as background noise.

The process used to log the SiP dataset checked that each person’s daily actual time equalled one working day.

As a coach, when I see unusually long hours, I try to verify them. You always want to try to understand if something unusual is happening, or if there was some sort of recording error. It’s not hard to image reasons for an unusually hard push, a severe bug or a push for a key delivery. These should be rare. As we get far removed from the source, we have to take some care that our analysis is robust to an occasional outlier. Since software is written by people, lots of odd or unexpected things can happen.
A large difference between the actual and estimated time for a task may be due to one of the values being incorrectly recorded, it could also be due to the implementation turning out to be much easier/harder than expected, or a poor estimation.

Figure 20, right plot, shows the number of tasks having a given actual to estimated ratio, for all projects (ratios aggregated into 100 bins); red lines are power law fits with exponents of 1.3 and -1.6.

Most task ratios are close to one, and the consistent pattern of decreasing counts suggests that the more extreme values might not be outliers.

Bill: Any ideas why some ratios are so extreme? There are not that many, so perhaps the regular pattern is a regular pattern of incorrect data entry?

I have a few guesses about the outliers, but I’d be sceptical of data entry errors. Really big errors seem likely to be caught during status reviews (unless the total is really small). Very low values are likely tasks that were stopped because they were de-prioritized and removed from active work. Just closing them would not be my choice because we tended to use the task close information for progress tracking, but each team has their own way of working. It’s surprising that some of the high ratios are as high as 100 to 1. I’d be interested in looking at task log comments to see what’s happening, for example some might be difficult to find bug. Sometimes they used a task as a catchall for miscellaneous work, or they might have put in an unrealistically small estimate for some reason. Usually I’d expect replanning if a task went way beyond plan. It’s remarkable that the shape slopes are so consistent on the log scale.
8 General discussion

Companies want to control the processes they use, which is only possible when they understand what is going on. Patterns of behavior discovered by the analysis of historical data can help refine existing understanding of development processes or suggest new ones.

This analysis has found many patterns in the CESAW data. The usefulness of this analysis of the CESAW data can only be assessed by those involved in the production of software systems.

There are two parts to this, the tracking and the post action analysis. Both are really important. The tracking helps steer projects, make interventions, adjust priorities, control the costs, hit targets. Post action analysis is how we get better for the next time.

Just getting tasks to a small size and estimating with reasonable accuracy is a huge win. The developer of the Process Dashboard presented some evidence from Monte Carlo that just balancing work frequently (as with Agile pull systems) was the single biggest source of schedule improvement. It keeps everyone busy and identifies problems early.

Another big part of the data is understanding what really works and what doesn’t. CESAW showed that static analysis was cost-effective, but really only about 1/3 as effective as a good review. But it also took only about 1/3 the time.

8.1 What did I learn?

While some of the patterns of behavior revealed by this analysis were familiar to me, and I hope also others involved in software projects, many were new to me.

• I was surprised by the short duration of many tasks. If the recording processes is easy to use and management requires detailed reporting, then here is the evidence that information on short duration tasks can be captured,

• this analysis is my first hands-on encounter with projects that use the Work Breakdown Structure. While it is possible to highlight a variety of patterns that appear in this WBS data, without prior experience of using WBS it is not possible for me to know whether these patterns have any practical significance,

• use of round-numbers, as estimation values, was so common that model fitting sometimes had to treat them as a separate cluster of values, e.g., see figure [17].

Estimates have to be sold to clients, and if the client thinks in round-numbers a non-round number estimate introduces friction to the sales process[13].
These are late estimates rather than early estimates used to bid a job. I’ve found again and again that we have to stop the developers from trying to estimate too precisely. They always want to use more bins. But our data shows that it just makes things worse. If you keep the components small, put it in the right bin most of the time (accurate, not precise), then the central limit theorem will drive the aggregate toward the middle.
References

[1] Defense, Department of. Work Breakdown Structures for Defense materiel items. Standard MIL-STD-881E, U.S. Department of Defense, Oct. 2020.

[2] T. Halkjelsvik and M. Jørgensen. Time Predictions: Understanding and Avoiding Unrealism in Project Planning and Everyday Life. Springer International Publishing AG, Apr. 2018.

[3] A. Heathcote, S. Brown, and D. J. K. Mewhort. The power law repealed: The case for an exponential law of practice. Psychonomic Bulletin & Review, 7(2):185–207, Apr. 2000.

[4] W. S. Humphrey. A Discipline for Software Engineering. Addison-Wesley Longman Publishing Co., Inc., USA, 1st edition, 1995.

[5] W. S. Humphrey. The team software process (TSP). Technical Report CMU/SEI-2000-TR-023, Software Engineering Institute, Carnegie Mellon University, Nov 2000.

[6] ISO SC7. ISO/IEC 15504:2003 Information technology -- Process assessment. International Organization for Standardization, 2003.

[7] ISO SC7. ISO/IEC/IEEE 12207:2017 Systems and software engineering -- Software life cycle processes. International Organization for Standardization, 2017.

[8] C. J. M. Jansen and M. M. W. Pollmann. On round numbers: Pragmatic aspects of numerical expressions. Journal of Quantitative Linguistics, 8(3):187–201, 2001.

[9] D. M. Jones. Code & data used in: Evidence-based software engineering: based on the publicly available data. http://www.github.com/Derek-Jones/ESEUR-code-data, 2020.

[10] D. M. Jones and S. Cullum. A conversation around the analysis of the SiP effort estimation dataset. In eprint arXiv:cs.SE/1901.01621, Jan. 2019.

[11] D. D. Loschelder, M. Friese, M. Scherer, and A. D. Galinsky. The too-much-precision effect: When and why precise anchors backfire with experts. Psychological Science, 27(12):1573–1587, Oct. 2016.

[12] W. R. Nichols, J. D. McHale, D. Sweeney, W. Snively, and A. Volkman. Composing effective software security assurance workflows. Technical Report CMU/SEI-2018-TR-004, Software Engineering Institute, Carnegie Mellon University, Oct. 2018.

[13] D. Pope and U. Simonsohn. Round numbers as goals: Evidence from baseball, SAT takers, and the lab. Psychological Science, 22(1):71–79, Jan. 2011.
[14] Project Management Institute. *A Guide to the Project Management Body of Knowledge*. Project Management Institute, Inc., fifth edition, 2013.

[15] Y. Shirai and W. Nichols. Classification of project team patterns for benchmarking. In *Proceedings of the 8th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement*, ESEM’14, page 65, Sept. 2014.

[16] Y. Shirai, W. Nichols, and M. Kasunic. Initial evaluation of data quality in a TSP software engineering project data repository. In *International Conference on Software and System Process*, ICSSP’14, pages 25–29, May 2014.

[17] J. Sonnemans. Price clustering and natural resistance points in the Dutch stock market: A natural experiment. *European Economic Review*, 50(8):1937–1950, Nov. 2006.

[18] D. Tuma. The software process dashboard guide, Dec 2014. [https://www.processdash.com/download](https://www.processdash.com/download).

[19] D. Tuma. The team process data warehouse, Dec 2014. [https://www.processdash.com/tpdw](https://www.processdash.com/tpdw).