A conversation around the analysis of the SiP effort estimation dataset

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Abstract

The analysis of over ten years of commercial development using Agile (10,100 unique task estimates made by 22 developers, under 20 project codes) is documented via a conversation involving the data analyst and a director of the company that created the SiP dataset.

Factors found to influence task implementation effort estimation accuracy include the person making the estimate, the project involved, and the propensity to use round numbers.

Any improvement in estimation accuracy, with practice, did not noticeably improve regression models fitted.

1 Introduction

This paper takes the form of a conversation between Stephen Cullum who started and ran the company that produced the SiP dataset (software task implementation effort estimate/actual data) and Derek Jones who analyzed 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 doing data analysis is to obtain information that is useful to those involved with the system that produced the data.

Any collection of measurements contains patterns, and some of these may be detected the statistical techniques used. Connecting patterns found by data analysis, to processes operating in the world requires understanding something about the environment and practices in which the data was generated.

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, with people who have this knowledge.

The narratives created as explanations for the patterns found in the data evolve as the conversation progresses; readers are not presented with a well-structured story fitted together after the event.

The data is available at: https://github.com/Derek-Jones/SiP_dataset

The analysis was done using R and snippets of code appear throughout the text.

1.1 Stumbling onto data

I first started talking to Stephen at a software engineering workshop[1] and it sounded like the company he had run for 16+ years had built up a very interesting software project effort estimation dataset (as a side effect of running the business). It sounded to me that this data was much larger and more detailed than anything currently available publicly, and I told Stephen I would very interested in analyzing it. Stephen promised to investigate whether an anonymized form of the data could be made available.

My professional background is compiler writing and source code analysis. Over the last seven years I have collected and analyzed 500+ software engineering datasets and made them publicly available[5].

Software in Partnership Ltd (SiP) was started in late 2002 initially providing back office insurance systems. We were an early adopter of agile methods and negotiated a green field development for a global run-off and outsourcing provider, with the remit to centralise the six separate systems they were using into one core product, providing a licence cost saving alone of 1M per year on completion.

One issue we had at that time, was that the quality of agile management tools available were somewhat lacking. The key proponents of the agile process of the time actively recommending the use of index cards and post it notes as the go to tooling (many still make that same recommendation today). We wanted something which was flexible but also allowed us to learn from our mistakes. We mimicked the planning game in a custom-built application (Clarity) that allowed each developer to pickup a Task, review the requirements and provide an initial estimate to the client. If approved the Task locked the estimate and then allowed the developer(s) to record the actual work carried out for eventual billing. Once a Task was completed, we had an Estimate vs. Actual. Actual for the developer(s) assigned the work. This approach allowed us to constantly review our estimating capability (it was a part of our Friday 'how did it go?' meetings). The history of completed Tasks also helped in our estimating process going forward, we would often be asked to do something fairly similar to something we had done previously and could use the actuals of those Tasks to guide our future planning. Our Clarity application, provides the data discussed in this conversation.

1The 56th CREST Open Workshop, http://crest.cs.ucl.ac.uk/cow/56
Prior to becoming IT Director at SiP I followed a pretty standard career development path. I had a fantastic first job working at a dispatch company in the West End, carrying out pretty much any technical work sent my way, from developing their in-house dispatch system using a form of BASIC and machine code to drilling through walls with a jackhammer to wire up the network. I subsequently joined a large insurance systems provider and spent the next five years of my career finding out how soulless software development can be when done incorrectly. I eventually jumped ship moving from the provider to consumer side of the equation, ending up running the IT function for a Lloyd’s of London syndicate. In my time here I convinced the board to bring the majority of the outsourced IT back in house and armed with a small team supported the business function through software developed and managed directly by ourselves.

1.2 The conversation

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

1.3 The SiP dataset

The SiP dataset arrives and there is lots of it, i.e., 12,299 rows; almost two orders of magnitude larger than the better estimation data sets that are publicly available.

An initial analysis needs to answer two questions:

- do I believe the data? This question is not about whether the data was fabricated, but whether the information present is likely to be a reasonably accurate representation of what it claims to be. People make mistakes, decimal points may be misplaced, times and dates entered later are misremembered, measurements are made using different units by different people (e.g., miles vs. kilometers),

- what information is present in each column and what properties does it have?

Between February 2004 and December 2014, 10,266 unique task estimates were made by 22 developers, under 20 project codes (at the time of the data snapshot, 1,848 tasks were still under development, and 166 had been cancelled). Figure 1 shows the number of estimates made by each developer, along with the number of estimates made for each project.

One method for getting a quick overview of data, is to look at it within an editor (although, if there are lots of columns, line wrap can complicate the
Figure 1: Number of estimates by each developer and for each project in the SiP dataset.

- What do the columns represent? The information present in some columns can be guessed, from the column name (but it’s always worth checking for exceptions).

The columns extracted from Clarity provide the following information:

Summary is a short text description of the action required to complete the Task, specifically designed to be meaningful to the client whenever possible.
RaisedByID the unique identifier of the individual who raised the Task. May be a client, or a member of SiP, depending on the problem being addressed.

AssignedToID the SiP staff member responsible for the completion of the work.

AuthorisedID the SiP manager with authority to sign-off a Task on behalf of the client.

StatusCode the stage of completion the Task has currently reached. A Task has specific stages to progress through, as a new stage is reached the business rules change, requiring further information; with some fields becoming locked and others unlocking.

ProjectCode the specific work stream the Task is associated with. Many are client specific though there are a few, which are used for the generic technical frameworks employed by SiP, or day to day management such as holiday booking or operational management.

ProjectBreakdownCode a further breakdown of the work stream, either to specific clients in a product with a varying client base or sub systems in products built exclusively for one client.

Category an identifier categorising a management, operational or development Task.

SubCategory a specific type of the parent category e.g., Management-Staff Recruitment or Development-Release.

HoursEstimate a decimal value representing the number of hours estimated to carry out the work.

HoursActual a decimal value representing the total number of hours it took to accomplish the Task across all SiP developers.

DeveloperID the unique identifier of the SiP developer who carried out one or more actual items of work defined in the Task.

DeveloperHoursActual a decimal value representing the number of hours a single SiP developer worked on the Task (possibly in various roles).

TaskPerformance a decimal value representing the under-run (+ value) or overrun (- value) achieved by all SiP developers for a finished Task.

DeveloperPerformance a decimal value representing the under-run (+ value) or overrun (- value), for a single SiP developer working on the finished Task.
2 An initial analysis

2.1 A general snapshot

I was expecting tasks to involve multiple developers and take a day or more to implement; incorrect assumptions on both counts.

Around 86% of tasks involve a single developer, who makes the estimate (see right plot in Figure 2). For the other 14% of tasks the estimate is made by the team.

The left plot in Figure 2 shows that task duration ranges from under an hour to hundreds of hours. I was surprised that task duration appears to be independent of team size. Note how the density plots approximately mirror each other over a similar range of estimates.

Task duration spanned two orders of magnitude (see left plot of Figure 2).

SiP recorded any and all requests made by the user base, which were reviewed after every full release. Some requests could consist of substantial amounts of work and would require a significant amount of analysis to break the Task into a number of sub-Tasks. These types of request were recorded in a placeholder Task, which ensured the idea was not forgotten and was assigned a rough estimate of the effort we believed would be involved. These placeholders were then subject to periodic review, if the client stakeholders thought the request worthwhile (perceived business benefit vs. estimated effort) then time would be spent replacing the placeholder with a range of more accurate sub Tasks (at which point the original Task would be CANCELLED). Occasionally, a Task with a rough high-level estimate, would just get green lit. In that the client agrees that this work should be done and just wants SiP to get started, no further analysis required. This was a risk for us, just as much as the client, but a long working relationship can foster this sort of trust.

The best way to understand data is to try to do something with it.

My experience is that jumping in and fitting a simple regression model is a
Figure 3: Estimated against Actual effort, in hours (left); Line showing actual hours equals estimated hours (green) and fitted regression model (red).

good place to start (my goto hammer for data analysis).
My reason for fitting a regression model is to gain understanding, prediction is not of interest (at least not yet).

2.2 The first regression model

What is the relationship between \texttt{HoursEstimate} (estimated hours, to implement the task) and \texttt{HoursActual} (actual hours taken)?

One way of discovering relationships is to plot the data.
The left plot in Figure 3 shows Estimated vs. Actual effort (in hours) using log-scaled axes.

Fitting a regression model involving two variables is straight forward:

\begin{verbatim}
hours_mod = glm(log(HoursActual) ~ log(HoursEstimate), data=Sip_uTN)
\end{verbatim}

This simple model explains over 70% of the variance present in the data; the coefficients of the relationship map to the following equation:

\begin{equation*}
\text{HoursActual} = 1.1 \times \text{HoursEstimate}^{0.87}
\end{equation*}

The numeric coefficients push in opposite directions: the 0.87 exponent shrinks the value of \texttt{HoursEstimate}, suggesting that developers are overestimating, while the multiplication by 1.1 suggests they are underestimating.

The right plot in Figure 3 shows the ideal case (green line) where actual equals estimated, and the fitted regression model (red line). The estimated hours are above actual, when estimates are below 2-hours, but below actual when estimates are above 2-hours.

Tasks estimated to take 1-hour, have an arithmetic mean for the actual time of 1.36 hours (the geometric mean is 1.1 hours); for tasks estimated to take 100-hours, the arithmetic mean of actual time is 63-hours (the geometric mean is 38 hours).

What incentives are influencing 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 doing the job. Time spent estimating will be a fraction of the likely estimation time.

A possible reason for short duration tasks 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. Stephen pointed out that short term interruptions are unpredictable and can be a significant fraction of time on short tasks.

The business context is the framework within which incentives operate. Is there an existing relationship between supplier and client, and are estimates from multiple suppliers going to be evaluated?

How changeable are clients requirements? How reliable are suppliers estimates? An existing client/supplier relationship gives both parties some idea about the answers to each others questions. As Stephen points out later in this conversation, SiP’s ongoing relationship with clients provides a foundation of confidence for everybody involved.

When an estimate is part of a bidding process, there is a strong incentive to produce a low estimate once a project is underway the client has little alternative, but to pay more (project overruns receive the media attention, and so this is the more well-known case).

When an estimate is not part of a bidding process (e.g., internal company projects, where the developer making the estimate may know the work needs to be done), one strategy is to play safe and overestimate, delivering under budget is often seen in a positive light. Underestimates receive little publicity, but are encountered in studies of company internal tasks.

\[ 2.2.1 \text{ Using more variables to improve the quality of fit} \]

The ProjectCode column identifies the project associated with the task. It is possible that the accuracy of estimates will vary between projects and this variable can be included in the model, as follows:

\[ \text{hours} \_ \text{proj} \_ \text{mod} = \text{glm} \left( \log(\text{HoursActual}) \sim \log(\text{HoursEstimate}) + \text{ProjectCode}, \text{data}=\text{Sip} \_ \text{uTN} \right) \]

The fitted equation has the form (there is a small improvement in the quality of the fitted model, as measured using AIC):

\[ \text{HoursActual} = 0.9 \times \text{HoursEstimate}^{0.86} \times \text{ProjEffect} \]

where: ProjEffect is a constant specific to each project; its value varies from 0.6 to 1.5, for this data.

The lines in the left plot of Figure 4 show the equation fitted for each ProjectCode having at least 100 estimates; the black line is the case where Estimate equals Actual. Points below the black line occur when Actual is greater than Estimate, i.e., underestimates. Projects vary in their cross-over point, from under to overestimating.
Estimate Actual

1 2 5 10 20

1
2
5
10
20

Estimate
Actual

Figure 4: Estimated against Actual effort, in hours, for tasks under ProjectCode.

There is an interaction effect between HoursEstimate and ProjEffect, and the much more complicated model taking this into account changes Figure [4] such that the lines were no longer parallel.

Each Task progressed through a number of stages, controlled by the StatusCode. The life cycle workflow followed the sequence:

CREATED -> ESTIMATED -> AUTHORISE -> CHRONICLE -> COMPLETED -> RELEASED -> FINISHED

The flow could be interrupted at any point by CANCELLED but any estimate or actuals allocated to the Task would remain for analysis. A Task would be CREATED to hold a description of what was required and who raised it. It would then be reviewed, and the SiP employee responsible for doing the work would ensure the Task was ESTIMATED. The Task would then wait for appropriate sign off. Once AUTHORISED, the Task would be in CHRONICLE mode where actuals were recorded against the Task by all SiP staff involved in the work. Once the Task owner was happy the change was implemented, the StatusCode was updated to COMPLETED. Some Tasks were effectively done at this stage, as there was no artefact to release, however if something did need to be pushed to the TEST server, or a document needed to be handed to the client, then the StatusCode would be changed to RELEASED once this was done. All Tasks should have been set to the final stage of FINISHED, once QA procedures were followed. However, for many Tasks, COMPLETED was enough, and the developers just left the Task at this status (which has proven troublesome for the analysis within this paper, as discussed below).

2.3 The practicalities of recording estimates

Would you expect all developers working on a Task to spend roughly the same amount of time on it?

In theory yes if they were truly working together, but in practice no. Sometimes someone is simply being taken advantage of, with the other developer

Stephanie

Stephen

Derek

Stephen
letting them do all the work while they coast it. Other times, one individual knows the sub system far better than the other one and essentially teaches them in chunks. One example task is 3225 where the developer who knew about the warehouse did 75% of the work and handed the easier prep work to the junior. Occasionally, they split the work rather than work together (people!), and one individual comes in much later than the other (breaking the estimate for both). Sometimes someone is just helping out when they have time, so will contribute less. In the worst case, the task is spiralling out of control, so they White Knight a developer in, who is not included in the initial estimate but may end up putting in much more effort than the task owner as they attempt to unravel any problems caused by the first party.

How were individual developer estimates evaluated when they were part of a team? Was everybody held equally responsible for accuracy?

Derek

Stephen

There had to be agreement that the estimate was achievable (before it was reported to the client), but generally the most experience developer set the pace. However, if the estimate was not hit, then the developer who owned the task was deemed to have failed (it was their task after all). This created quite an interesting dynamic as junior developers being helped by senior developers could have some spectacular overruns and feel they were led astray. However, getting estimates wrong in the beginning, when the tasks assigned were less important, helped individuals new to the team focus on getting better estimates the next time. It also taught them to rely on their own intuition and experience rather than relying on someone else. Generally though, we had a good team dynamic and any ribbing was constructive (all estimate fails [including mine] being reported at the weekly meetings) and improving estimates was encouraged, rather than being used to penalise people.

Were estimate and actual hours rounded in any way?

Derek

Stephen

The system did not round any actuals entered and despite Clarity having a timer option, we generally didn’t have a timer going (ala Toggle). Often despite working on your own work, as we were following agile, you would get a shout out and if you could help, would pop over to whomever was having trouble. Normally, this was a 5-minute interruption but sometimes it could be substantial. We often forgot to turn the timer on or off, so in the end didn’t bother with it too much as it didn’t accurately record what we were up to. The actuals were normally entered at the end of the working day (you had to have seven hours accounted for every day, otherwise all sorts of escalating alert emails went off, starting at 5pm). So, the numbers entered are pretty accurate but subject to the same sort of human rounding that the estimate value was.

3 Do people improve with practice?

Derek

In some activities, people get better with practice. There is an ongoing debate about whether the learning data is best fitted by a power law or an exponential, but in practice there is little difference in the fitted curves over the range of interest.
Does the accuracy of task estimates improve, as more are made? Every task has an associated number, $TN$, which increases over time, and individual developers may improve with practice; a model can be fitted for each developer.

Prior developer estimation experience is unknown, but is assumed to be non-zero. For the purposes of model fitting an initial experience of 100 is assumed, for estimating practice (changing this value does not have much impact), and every estimate treated as an opportunity to practice. An exponential rate of learning is assumed, so skill is expected to improve as the log of the number of learning opportunities. The following code fits a distinct model for each developer:

$$\text{df}\$TN = 100 + (1: \text{nrow(df)})$$
$$\text{ea\_mod} = \text{glm}(\log(\text{HoursActual}) \sim \log(\text{HoursEstimate}) + \text{ProjectCode} + \log(\text{TN}), \text{data=df})$$

The quality of each fitted model is better (measured by the variance explained) than the model fitted to all the data. This is to be expected since the models are tailored to the individuals making the estimates.

The fitted model coefficient for $\log(TN)$ varies between 0.4 and 2.5. This implies that with experience, some developers increasingly overestimate and some increasingly underestimate. This does not sound right, perhaps the model is too simplistic and is failing to take important factors into account.

For clarification there were no direct financial penalties incurred for the company if our developers overestimated/underestimated the effort required for a task. There were plenty of political/cultural ones though (along with financial side effects), such as being viewed as slow or incompetent. Excessive overestimates ran the risk of the client simply mothballing that part of the development or seriously curtailing the functionality, limiting the effectiveness of the product overall (and affecting income for that part of the system). However, the effect of underestimates were much more troublesome, in an agile environment where the development team sit with the users of the software, there is nowhere to hide. If you agree to deliver some functionality within a week and that overruns significantly then you need to prepare for some pretty serious conversations. As this was our first agile development with paying clients (some of us had been involved in agile projects for the companies we previously worked for; but in this instance you are immediately viewed as being ‘on the same side’. This is certainly not the case in the early stages of an agile commercial project.) the shock of developers who have accidentally underestimated (with the best of intentions), suddenly being faced with an angry client (who is not directing their anger through a hierarchy of project and business managers from previous development models but has simply rocked up at their desk) is a sight to behold.

As the development team became aware of their high visibility, there was a change in how we approached estimating. Initially (and I suspect this is true of every development team) we wanted our clients to like us and would provide some close to the wire estimates as it was the easiest way to keep them happy. We eventually realised this was a false economy, either we would end up carrying out death marches to deliver the code, becoming fatigued in the
process and having to explain to the clients finance department why the hours worked that month were far in excess of what they were expecting (and were willing to pay for) or we would fail to deliver, perhaps having to field complaints from the client, but more importantly watch the user(s) we disappointed have less faith in our ability to deliver and as a consequence engage less with us, and the product going forward. We became significantly more risk adverse. We expected unexpected issues to occur frequently and as a consequence would stand firm against client pressures to squeeze more into a release. Our clients became very unhappy during the planning stages of a release cycle, as they felt we were not really listening to what they needed to do their job. We often had a number of sessions trying to gain consensus on the bare minimum we could deliver that would provide business benefit. However, (and we were not really expecting this), they became very confident in our abilities to manage and run the project when release after release we delivered what we said we would. When we occasionally had spare capacity in the cycle and included unexpected functionality for the release [which we nicknamed ‘developers choice’ (as the developers with the free time got to choose)] the clients were genuinely very pleased, with that goodwill feeding back into the team.

Our approach simply moved client dissatisfaction from the end of a release cycle to the beginning. Hence, our approach became to under promise and over deliver. That is not to say we didn’t make some serious underestimating howlers, we did (and still do), but it became clearly preferential to be honest with the users upfront (potentially disappointing them then), to providing false hope and disappointing them later. By under promise I mean we generally added a tolerance of 5-20% (dependent on the complexity of the task) rather than simply doubling what we originally thought of. With respect to Derek’s findings above I would concur that experienced developers exposed directly to and working with a reasonable user base would tend to overestimate (to a degree) based on a clients reactions to late delivery. However, I am talking a considered overestimate to ensure the majority of tasks are delivered on time (or very close to it - no death marches). Bearing in mind the fallout of continual late delivery the instances of developers increasingly underestimating does seem anomalous.

How does the accuracy of developer estimates vary over time? Each plot in Figure 5 shows the ratio estimated/actual for successive estimates made by one developer (selected because they had made the most estimates).

One possible explanation for the fluctuating, small changes in performance is that as developer experience increases, the time taken to implement tasks decreases. If increased developer experience causes them to give lower estimates, then estimation accuracy may remain unchanged.

### 3.1 How SiP tracked work

In our day to day work clients and staff worked at the Task level. By that I mean if a Task came in 30 minutes early, they didn’t assume that those 30 minutes, would be used on another Task automatically, perhaps the developer would spend time chatting with a user, carry out housekeeping, return phone
calls or emails or any other non-chargeable Task you can think of. If it came in late, then the additional time was generally found by pushing back work outside of the release or taking the work home with you.

If the Tasks agreed for the release were completed by the deadline, then everyone was happy. This meant that under estimated work was bad but accurate and over estimates were deemed OK, i.e., we hit the target or came in earlier (and cheaper). We reported Tasks to the client not hours because that is what they cared about. This meant we thought of Tasks in terms of accurate, under and over estimates, rather than hours, minutes and seconds.

Carrying out a very crude timeline analysis of COMPLETED and FINISHED Development Tasks across all SiP staff shows some interesting behaviour.

In the heaviest development times (first 5-years) over and under estimates flip flopped, which lead to improved accuracy. After the first 5-years when the majority of development tailed off into the support phase, work volume dropped but interestingly so did the focus on accuracy, with over estimating taking precedence. I am assuming we became more aware of the political benefits of under promising, whilst over delivering.

Taking two active developers, say 13 and 26 this pattern repeats (see Figure 6).

Accuracy improves over time, especially in heavy development phases (2005-2008), but as supporting the product becomes the key activity, accuracy loses its
Figure 6: Number of accurate, over and under estimates, for each quarter; top all developers, others are specific DeveloperIDs.
prominence. Generally, accuracy and over estimating prevail but occasionally the developer has a phase of under estimating but that does seem to get corrected over time.

Interestingly, my behaviour is quite different to other staff, see Figure 6.

Very early on I seem to have decided an over estimate was preferable to an accurate one! (As well as the client good will, it provides a buffer to any of my under estimates.)

Very roughly, about 30% of our estimates are under estimates, which is consistent across all staff.

I believe there was learning going on, but not necessarily to improve estimates by reducing the risk buffer. We learnt that whilst accurate estimates are king in hard core development phases, over estimates are beneficial in support phases. Over estimates where you simply procrastinate to pad the time is unethical behaviour and simply becomes an 'accurate' estimate that is costly to the client. An over estimate whereby, if you avoid any unanticipated delays, you simply pass that gain straight back to the client (in terms of reduced cost, fresh development staff or additional Task pickup for that release) is a way to accept a margin for risk reduction but reward the client if the risk does not materialise.

4 Coworker influences

The previously fitted model treated developers as individuals, not as possible members of a team.

Teams are small (78% of multi-person teams contain two people), which means there is likely to be an impact due to individuals and perhaps a team size effect.

The following code adds team size (i.e., number of developers): some trial-and-error experimentation (i.e., 0.5 and -1.0) was used to select the exponent for team size. Adding a variable for the cumulative number of estimates made by developers on the team has a minuscule impact on the fitted model:

\[
\text{ea} \_\text{form} = \text{formula}( \text{paste("log(HoursActual) ~ log(HoursEstimate)+", ProjectCode+I(\text{size}^0.5)+", paste0(udevID\_str, collapse="+")))}
\]

\[
\text{ea} \_\text{mod} = \text{glm(ea} \_\text{form, data=unq\_sip\_exp)}
\]

The fitted equation, which explains 77% of the variance in the data, is:

\[
\text{HoursActual} = 0.15 \times \text{HoursEstimate}^{0.82} \times \text{ProjEffect} \times \text{DevEffect} \times e^{6.7 \sqrt{TS}}
\]

where: \( TS \) is a task’s team size, and \( \text{DevEffect} \) is the combined influence of all developers on the team.

Points of interest include:
• adding the square-root of team size to the model improves the quality of fit by 1% (this aspect of the model is dominated by the 86% of teams consisting of a single developer),

• estimates from some individuals were consistently much lower/higher than the average team estimate,

Derek sent Stephen a list of DeveloperIDs and the model’s prediction concerning the lower/higher than SiP developer average characteristic of their estimates.

The SiP Clarity system allowed staff to collaborate on a given task, so actuals could be recorded for each category of effort carried out by each individual working on the Task. For example, individual 1 could be enhancing the code (adding features), individual 2 could be updating the application documentation, whilst individual 3 could be responsible for manually testing the changes. A Task could hold a range of actuals, which were representative of an individual’s involvement. We could also cater for Pair Programming but there was not an explicit category for that (both developers would enter the same category Enhancement or Bug).

The system did not have this flexibility for recording the estimate. A multi-estimate mechanism, whereby everyone involved could provide their own estimate (for their involvement), before the total was supplied to the client would have been a better instrument for improving estimating skills across the team.

I decoded the serial over and under estimators (based on their DeveloperIDs). Derek identified one software developer who consistently overestimated. This uncovered nothing exceptional other than a junior developer (first software development position) who was ultra cautious. Derek also identified two SiP staff members who were serial under-estimators, their business function was client management/sales and marketing. The two roles were not subjected to weekly peer review (they were not a chargeable resource). SiP required all staff to use Clarity, but the focus on Estimates vs. Actuals was a function of the software delivery process and internal tasks were not subject to this review. This is the probable explanation as to why these individuals were so poor at estimating, they were never challenged on their estimates so there was no need to learn from the artefacts they had previously created (although self-improvement would suggest you should try).

5 Serial correlation of estimates

When estimating, are developers influenced by recently completed estimates? Possible causes of serial correlation, in task estimation times, include:

• Anchoring is the term used to describe the situation where a statement given to a person prior to asking them a question, influences the answer they give. For instance, asking: “Did you on average write more or less than N Lines of Code per work-hour in your last project”, where the value of N varied between 1 and 200, changed the mean response by 72 lines.
work on related tasks may be ordered to fill a complete day or week, or to fill in time remaining in a day or week,

- the estimates are often integers and six values account for 54% of all estimates. The correlation may be an artefact of the probability of identical values appearing in sequence.

The following list shows the 10 most frequent pairs and triples of the same sequence of estimates (prop is the proportion).

| ngrams | freq | prop  | ngrams | freq | prop  |
|--------|------|-------|--------|------|-------|
| 1      | 1    | 1     | 256    | 0.0249 | 7 7 7 | 55    | 0.00536 |
| 2      | 7    | 7     | 199    | 0.0194 | 1 1 1 | 45    | 0.00438 |
| 3      | 1    | 2     | 176    | 0.0171 | 1 2 2 | 40    | 0.00390 |
| 4      | 2    | 1     | 170    | 0.0166 | 7 7 1 | 34    | 0.00331 |
| 5      | 0.5  | 1     | 165    | 0.0161 | 0.5 1 1 | 34 0.00331 |
| 6      | 1    | 0.5   | 164    | 0.0160 | 1 2 1 | 32    | 0.00312 |
| 7      | 2    | 2     | 134    | 0.0131 | 2 2 1 | 29    | 0.00283 |
| 8      | 7    | 1     | 131    | 0.0128 | 1 1 0.5 | 27 0.00263 |
| 9      | 1    | 7     | 118    | 0.0115 | 0.5 0.5 | 26 0.00253 |
| 10     | 1    | 3     | 114    | 0.0111 | 2 1 1 | 26    | 0.00253 |

Given 1,525 estimates of 1-hour and 8,741 non-1-hour estimates, how many 1-hour estimate pairs are likely to occur? The number of pairs is 1,525+8,741, and the probability of a pair occurring is: \(\frac{1525}{1525+8741} \times \frac{1524}{1525-1} \approx 0.022\), giving \((1525 + 8741) \times 0.022 \rightarrow 226\) pairs; 12% less than the pairs of 1-hour estimates that occur.

Table I shows the expected number of pairs of the same value, for the ten most common estimate values. The number of pairs calculated is much lower than those appearing in the data.

If the correlation seen is a consequence of the sample containing a few frequently occurring values, the correlation will be present when the values are randomised. Randomising the sample, calculating the correlation, and repeating the process many times, finds that the mean correlation is almost zero (with a standard deviation close to zero).

The correlation present is not the result of the series containing a few frequent values.

|   | 1     | 2     | 7     | 0.5   | 3     |
|---|-------|-------|-------|-------|-------|
| 226.41 | 99.67 | 96.74 | 84.35 | 41.73 |

Table 1: Expected number of pairs of the same estimate value.

I have found some serial correlation, i.e., the estimate for the previous task sometimes seems to have had an impact on the next estimate.

This is interesting, I was not expecting that for the Estimates. I would have expected it for Actuals as we tended to group specific sorts of tasks together and
process them one after the other. For example, we often got various requests made throughout the week for changes to be made to metadata (say fields available in our Search Control) each of these Tasks were quick to implement (< hour) so we saved them up (generally for an easy win on Fridays). We had much less control over the estimates though, as we did not know when the clients would turn up at our desks and request something. Whoever was approached had the job of raising the task, prior to the estimate being added at the next planning session. Perhaps at the planning sessions we grouped alike tasks as well, but subconsciously as it certainly wasn’t something we did intentionally.

I later found a mistake in my analysis. In the data, tasks involving multiple developers appear multiple times, one row per developer. Filtering, so that each task is represented by one row, halves the serial correlation. The signal in the data suggesting a possible $AR(1)$ model, disappears.

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 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.

Figure 7 shows the total number of estimates (red) and actuals (blue) having a given value (lines are slightly offset so information is not obscured).

There are estimate peaks at 7, 14, 21 and 28 hours, suggesting that some developers estimated in days and then converted to hours. There are 35 hours in a week, and the 300+ estimates for this value suggest that one week is a
round-number for some task estimates. The estimate peaks at the round values 10, 15, 20 and 30 hours are smaller than the 'day' peaks, but still larger than adjacent non-round values.

Regression models built using hour round-numbers and 'day' hours (having the same range of hour values as the hour round-numbers) are very similar (see below), i.e., if developers are thinking in units of hours and days, the estimates are not significantly affected.

\[
\text{HoursActual} = \begin{cases} 
1.27 \times \text{HoursEstimate}^{0.80} & \text{round-number hours} \\
1.31 \times \text{HoursEstimate}^{0.77} & \text{'day' hours}
\end{cases}
\]

### 6.1 The impact on accuracy

It looks like low hour estimates are balanced under/over estimates, but the larger estimates are biased towards overestimating.

This makes sense as the low estimate work was generally something we were comfortable with and probably did fairly frequently (essentially plug & play code into our framework). Larger estimates were normally a big block of functionality that did not exist in our framework already and was therefore more technically complex with unknowns.

The 1-hour estimates would have been more accurate if they had been 1.4 hours (the arithmetic mean of the actuals; the median is 1-hour, i.e., there are as many overestimates as underestimates); the corresponding value for the 2-hour estimates is 3.3 hours. Let's say you were given this analysis after running the company for a year, i.e., based on a year’s data. What would you have done with it?

This is a difficult one to answer as the client, but moreover the users of the system, were fundamentally happy with how we proposed and delivered work. We released to production every 3-4 weeks, so it was unusual for a slippage on a single Task to affect them (but not unheard of). Generally, where we lost on one Task, we gained back on another or if the release deadline was approaching, and a Task looked shaky we could increase developer effort (which could be cashed in after the release). In cases where we failed to deliver on a key specific Task for that release (i.e., it was negatively affecting the business), we could always push out an emergency release. But essentially, system users were used to waiting for a Task, so if we overran an hour estimate by 100% or delivered in half the time, the user who raised the Task would not see it until the next release anyway, so we had a recovery buffer, which withered as we got closer to the release deadline.

Estimate quality affected the SiP Developers ability to decide how much we squeeze into a release, much more than the users of the system. If we got it wrong, then as professionals we suffered the consequences, rather than passing them onto our clients. By that, I mean, if my estimates were off, I would often work overtime to ensure that the Task was still delivered to the client for the release (as would the majority of our developers).
Increasing estimates from 1 to 1.4 hours (or 1.5 to keep to client hours of 1 hour 30 mins) would have had minimal impact. Going much higher, I think would have raised concerns, especially as, after a while, the users become familiar with how we estimated the simpler work. Given the information I would have fed back to the developers that unless they were really confident (i.e., lots of evidence in Clarity [where they are doing the work]) then low end Tasks would benefit by adding an extra half an hour to them. If the client queries any specific Task for the increase, then we can provide evidence as to why it is more accurate than what we were previously providing. So yes, I would have taken action on the information but would have monitored client reaction at the planning meetings quite closely. What we see as an informed decision could be seen as a way to squeeze additional money from the client, so handling this sort of change delicately is paramount.

Picking round numbers, rather than more accurate estimates, has the advantage that clients may find round numbers more believable. Client influenced estimates are a perennial problem. Getting developers out of a round number mindset is not useful if the client thinks in round numbers. There are very few estimates for 6-hours, but lots for 5 and 7 (1 day). This is obviously a rounding effect, which decreases estimate accuracy, but it might make clients happier (or less unhappy), whereby little effort is likely to be investigated in tasks thought to require a short amount of time. More time will be invested to estimate tasks likely to require many hours.

Nice insight Derek, we often think of how we affect business as they interface with us, but it is much subtler the other way around. Here is a clear indication that we became naturalised to the client’s ways of working/thinking despite working within an Agile framework (something that was alien to the client). I had never considered this before.

7 More data becomes available

Feed your supplier of data interesting information, and they are more likely to be willing to spend time tracking down more data.

The new data contains three columns: the date on which the Estimate was made, work started on the task and when the task was completed.

Figure 8 shows the number of days experiencing a given number of events (task estimate, start, completion), with fitted regression lines. The numbers for tasks estimated and started are very similar because for 90% of tasks, both events occur on the same day.

8 Time distributions

8.1 Distribution of actuals

How are the actual task hours distributed about the estimate for a task?
Figure 8: Number of days on which a given number of task estimates, starts and completions occurred, with fitted regression lines.

The left plot in Figure 9 shows actual task hours for common estimate values (given on each line, vertically above the 60).

The distribution of actual hours, for a given estimate value, changes with the magnitude of the estimate. It is possible to create a list of task characteristics that change with task duration, but without detailed information about the application and task implementation, explanations are essentially just-so stories.

8.2 Distribution of estimates

How are the estimated task hours distributed about the actual hours for a task?

Figure 9: Actual hours for specific estimate values (number on line, vertically above 60), x-axis normalised (left); Estimated hours for specific actual values (number on line, vertically above 60; right).
The right plot in Figure 9 shows estimated task hours for common actual values (given on each line, vertically above the 60).

8.3 Distribution of elapsed working days

While 51% of tasks were started and completed on the same day, some relatively low effort tasks experienced much longer elapsed times (i.e., multiple working days); 89% of tasks were estimated and started on the same day.

The left plot in Figure 10 shows the elapsed time, in working days, between a task estimate being made and work starting on the task (blue) and between work starting and completing for a task. The fitted regression models are (the Estimate/Start distribution has a long tail, and the fitted model is based on intervals of less than 100-days):

\[
\text{Tasks} = \frac{473}{\text{StartCompleteWD}}
\]

where: \(\text{Tasks}\) is the number of tasks, and \(\text{StartCompleteWD}\) the number of working days between estimating and starting; and:

\[
\text{Tasks} = \frac{173}{\text{EstimateStartWD}^{1.2}}
\]

where: \(\text{EstimateStartWD}\) is the number of working days between starting and completing the task.

9 Developers and tasks

How many tasks do developers have 'in-progress' on any given day (i.e., started, but not yet completed)?
The right plot in Figure [10] shows the number of days on which a developer (who has worked on at least 200 tasks; one line per developer) has a given number of tasks 'in-progress'. Tasks started/completed on the same day are not included in the total.

Our preference was for picking a Task and working on it until completion. However, in an agile environment, after a cycle of work (in our case the release), the client could (and sometimes would) re-specify priorities. In some cases, developing functionality could cater for 80% of a business problem. It could well be decided that this caters for a large component of the users work, so a partial release could be arranged, and the Task is put on hold while resource is used to address a more (perhaps new) pressing requirement. Clarity had no way of tracking this type of behaviour.

9.1 Corrupted tasks

I have noticed some interesting Tasks, especially for Developer 24. His workload consisted of a lot of repeatable work, and it looks like he defined certain Tasks for this and just left them open! We automated checks for ensuring staff hours totalled 7 per working day but there was nothing in place to check that the Tasks were being marked as FINISHED. In hindsight, this is something we should have put in. For the most part he treated these as normal Tasks but just never marked them as done. However, there are a few catch-all Tasks whereby the Task was defined as something common e.g., Check Log For Errors, an Estimate was set, 7 hours say BUT all effort was flagged against that Task going forward. An example is Task # 12640 where the estimate is 14-hours, but the actuals are 112.64, so 98.64 hours late! He just never bothered to close the Task and open a new one (I believe we were all guilty of this type of behaviour, occasionally, but it obviously became the de rigueur for some!). This obviously has a big effect at Est vs. Act level but at the level we worked it is just one late Task. Toward the tail end of SiP’s trading history we were mostly supporting products, so the review process of late running Tasks was lax as the clients did not care as the product worked and as long as there were no surprises on the billing, Task review was not top of their list.

10 Monthly totals

Figure [11] shows the total number of tasks completed per month, along with the number of unique developers who worked on at least one of these tasks. A change-point analysis produces three dates for the step-change in occurrences of the three quantities plotted, and the first day of 2009 was chosen as a common branch point.

The step-wise change around the start of 2009 raises the question of whether there is a step-wise change in the estimate/actual models fitted in section 2.2 which used data for all the years; might the coefficients be significantly different for the data pre/post 2009?
Figure 11: Number of tasks completed per month, number of unique developers working on these tasks and average actual hours.

The following is the equation from a fitted model, which includes a before/after 2009 variable:

\[
\text{HoursActual} = \begin{cases} 
1.04 \times \text{HoursEstimate}^{0.88} & \text{Before 2009-01-01} \\
1.1 \times \text{HoursEstimate}^{0.86} & \text{After 2009-01-01}
\end{cases}
\]

11 Model fitting algorithm

Stephen sent me plots based on counts of the number of over/under estimates made by specific developers. These made me realise that fitting a model based on equalizing the number of over/under estimates (rather than the quantity of over/under estimate) might provide some insights.

The standard regression modeling technique fits an equation, which can be used to calculate the expected mean value of the response variable (e.g., HoursActual). If we are interested in calculating the estimated median value (i.e., the estimate having an equal number of recorded tasks above and below), quantile regression (sometimes called median regression, although the technique also supports model fitting based on quantiles other than 50%) is the technique to use.

The following are the equations fitted to 75%, 50% (i.e., median) and 25% quantiles (that is, with 75% of actual hours below the estimate, 50% below and 25% below):

\[
\text{HoursActual} = \begin{cases} 
1.1 \times \text{HoursEstimate}^{1.1} & 75% \\
1.0 \times \text{HoursEstimate}^{1.0} & 50% \\
0.8 \times \text{HoursEstimate}^{0.84} & 25%
\end{cases}
\]
Figure 12 shows plots of these equations. The SipP estimates are on the 50% (green) line, with half of all task actuals greater/less than the estimate. For a given task estimate, 75% of all actuals were below the blue line (25% below the red line).

12 Discussion

This analysis is based on 10 years of data from a company operating within a particular niche of a particular ecosystem (financial services). How might companies operating today, in the same or different ecosystems, make use of the patterns uncovered by the analysis?

How might the findings be used?

We developed Clarity to aid our staff in providing accurate estimates. From a business perspective just having this information recorded made it much easier for the client to accept our estimates. Obviously, every client wants the work completed yesterday and can be very inflexible when it comes to negotiating the time available to carry out the work. Companies can be forced into agreeing impossible deadlines to get the work, knowing they will overrun, but it will probably be too late for the person who appointed them to back out without losing face (or their job), so an unholy alliance ensues, with decreasing amity as the project overruns and corners are cut to get it back on (impossible) track. We found that by having evidence of previous similar work, we could argue for more realistic timelines from the beginning. When we delivered (on time) this strengthened the overall client relationship, leading to more work, rather than SiP burning its bridges and subsequently having to find new forms of income, which is (extremely) expensive.

Your analysis confirming that this data meets sanity checks and that the SiP staff making the estimates are not fluctuating (too) wildly would be used to
confirm to the client that our approach through Clarity had merit, and the data was not simply 'made up' to influence them in directions favourable to SiP. Essentially we could provide evidence to potential clients that our estimates were trustworthy.

How accurate do estimates need to be?

That’s a really good question Derek. I think it depends on the client and the amount of goodwill you have built up. Some clients are micro managers and any form of overrun is agonised over, with lots of finger pointing and drama, which tends to taint the project and create an us-and-them culture, which is not at all beneficial. The best clients take a bigger picture approach, accepting that some tasks will overrun and some will under-run. If the aggregate is a small under/overrun, then they generally deem the project successful. Having a little wiggle room in each task provides protection against those work items in which an unknown problem is being addressed, and the likelihood of something unexpected happening is high. Having sufficient analysis of the problem at hand (which in turn creates a high number of tasks) negates the need for having unnecessarily precise estimates as things should balance out at the end of a work cycle.

Personally, I think excessively accurate estimates (where you spend a lot of time breaking things down to the nth degree are a waste of time); I prefer good estimates, not guesswork (which is why we built Clarity) but a more evidence-based approach where you can reference aspects of work you have done before. If you cannot find any previous evidence for work you are currently bidding for, then I would tread carefully as you are in unknown territory. However, aiming for accurate ‘good’ estimates should be a key goal, as it lowers risk and means you don’t have to rely on a fudge factor (i.e., the number of under-runs beats the number of overruns) to be able to successfully deliver the agreed workload. In the Lloyd’s of London marketplace 6-month overruns (seriously) are not uncommon, all because their supplier agreed to absolutely anything to get the work. In these instances, the client loses first and further down the line the supplier does as their reputation is shot, and the client moves on as the relationship is unsalvageable.

12.1 What did I learn?

Many of the patterns of behavior revealed by this analysis will be familiar to those involved in managing software development projects. People will differ in their opinion of the impact these behaviors have on the final outcome (i.e., the estimate); data analysis provides an impartial view.

- people differ in their willingness to accept risk, and their confidence in their own abilities. A consequence of this difference is making higher/lower, than average, estimates.

Developers and their managers are often aware that personal characteristics have an impact on the estimates made.
An analysis can provide information about individual patterns of behavior, relative to group average. Might this information provide useful feedback for individuals and managers? While individual measurement-based feedback has been provided in other work domains, the possibility of having and using this kind of information is new in software engineering.

- projects have characteristics that can make it harder/easier to accurate estimate task implementation time.
- round numbers play a significant role in estimation. Despite regularly using round numbers in my own estimates, I had not appreciated how pervasive they were; Figure 7 was eye-opening.

The habituated use of round numbers may hinder estimate accuracy, but is it worthwhile training developers to overcome this habit?

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.

Stephen highlights the use of project data analysis to show clients that the estimation process is reliable, but adding a source of friction to client interactions is never desirable.

- developers did not learn to make more accurate estimates.

I was expecting to find evidence of learning. It is possible learning did take place, developers learned to increase their productivity (with estimating accuracy remaining unchanged). In a competitive environment, increased productivity is a much more desirable goal, than improved estimation accuracy. In a non-competitive environment, where profitability depends on hours worked, estimation accuracy may be the learning goal, not increased productivity.

It has been a strange experience reviewing our Clarity Task data, my initial reaction was to try to defend any inaccurate estimates, with the view that perhaps we were not professional enough. On review though, the estimates were appropriate for the environment we were working in. There are some hideous underestimates but at no point did we miss a release deadline (although some functionality may have been light or delivered as an emergency release). The way we normally dealt with an underestimate was those responsible just worked overtime to commit the work (the users was therefore not directly impacted by the slippage, we may have behaved very differently if they were).

SiP continually developed the Lloyd’s of London back office system for a five-year period and continued to support and extend it for another six years after that until the technical assets of the company were sold off. The majority of products developed using Clarity are still in use today.

- Buffers to accurate estimates.

I learnt that our agile process provided a buffer to inaccurate estimates. By having a set number of deliverables agreed for a release, an organisation gains the ability to balance over and under estimates. As long as
everything promised is delivered by the deadline then the client really does not care that some estimates were off, you delivered what you promised, so all is good. Intelligent release planning (not over promising and breaking the work into enough Tasks) provides a measure of risk mitigation for ambitious estimating. An over running Task can also be recovered by the developer working on it outside of normal working hours (late nights/weekend working), which ensures it still meets the client deadline. Dependent on the relationship, this may be chargeable or the supplier may have to absorb the overrun.

- Development estimates vs. support estimates.
  A more surprising finding was how SiP provided (and the client more readily accepted) overestimates (c.f. accurate estimates) when we moved into the support phase for the products we had built (Figure 6 - upper plot, after 2008). Thinking about this, I believe one of the reasons this happened was the client was heavily involved in the first five years of the project and would actively review/discuss/direct work. A lot was on the line if the project failed. However, once the product was proven (all required business processes were delivered) and all outsourced solutions were successfully migrated, the project was deemed a success and the client became more focused on other challenges. My take away here is active client involvement (read, criticism) drives estimation accuracy. Over estimating in the support years provided two benefits for SiP, 1) an unexpected delay did not necessarily mean we delivered late, 2) by passing any gains straight back to the client, we converted cost/time savings into good will.

- The tooling can always be better.
  Our Clarity tooling has been found wanting. It was sufficient in ensuring that estimates and actuals were recorded but processes to ensure that Tasks were correctly closed off, in hindsight, should have been put into place. Also, allowing each developer to contribute their own estimate, rather than recording a single group consensus would have provided better learning opportunities.

- We became naturalised.
  The analysis has made it clear that we estimated the way the client wanted us to estimate. We very clearly acclimatised to their working patterns. We would often be some of the first in the office, and nearly always the last to leave, but providing estimates which meant the user could begin reviewing the code close to home time or first thing (when they would often be fielding their real work) made no sense to them. Providing estimates which suited the users was a natural behaviour, when working so closely with them.
• It is different at the coal-face.

Estimating at the coal-face, with all the political pressures that brings is very different from reviewing those same estimates years later. We were very lucky (in the most part) with the companies and individuals we provided solutions to. There are some clients who will demand the tightest of margins and then complain bitterly when something slips, despite being warned that there was a high probability that could happen. We learnt over time that it was better to decline work in certain instances rather than engage in projects that were destined to disappoint (both parties). Improving estimates can however be very difficult, even with empirical evidence if the client simply refuses to listen and insists on an unrealistic schedule. If you refuse the work, some other company will inevitably pick it up. It can be problematic explaining to the entity commissioning the work that their expectations are unlikely to be met.

13 Actionable point?

Most companies fail; Software in Partnership was a success. A basic tenet of engineering is: don’t fix something that is not broken.

The patterns found in the data may suggest tweaks to existing practice, and if existing patterns changes, it may indicate that something about existing practice has changed (which may an improvement, a regression, or neutral).

The primary actionable item for other companies, is to collect data about what they spend their time doing. 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 insights or suggest new ones.

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