Decomposing Work

At its core, on–demand work has been enabled by decomposition of large goals into many small tasks. As such, one of the central questions in the literature is how to design these microtasks, and which kinds of tasks are amenable to decomposition. In this section, we place these questions in the context of piecework's Tayloristic evolution.

Crowd work's perspective.

Many contributions to the design and engineering of crowd work consist of creative methods for decomposing goals. Even when tasks such as writing and editing cannot be reliably performed by individual workers, researchers demonstrated that decompositions of these tasks into workflows can succeed [23, 2, 37, 32]. These decompositions typically take the form of workflows, which are algorithmic sequences of tasks that manage interdependencies [4]. Workflows often utilize a first sequence of tasks to identify an area of focus (e.g., a paragraph topic [23], an error [2], or a concept [45, 46] and a second sequence of tasks to execute work on that area. This decomposition style has been successfully applied across many areas, including food labeling [33], brainstorming [36, 44], and accessibility [26, 25, 27].

If decomposition is key to success in crowd work, the question arises: what can, and can't, be decomposed? Moreover, how thinly can work be sliced and subdivided into smaller and smaller tasks? The general trend has been that smaller is better, and the microtask paradigm has emerged as the overwhelming favorite [38, 39]. This work illustrates a broader sentiment in both the study and practice of crowd work, that microtasks should be designed resiliently against the variability of workers, preventing a single errant submission from impacting the agenda of the work as a whole [19, 28, 40]. In this sense, finer decompositions are seen as more robust — both to interruptions and errors [10] — even if they incur a fixed time cost. At the extreme, recent work has attempted demonstrated microtasks that take seconds [41, 7] or even tenths of a second [24]. However, workers perform better when similar tasks are strung together [28], or chained and arranged to maximize the attention threshold of workers [6]. Despite this, we as a community have leaned *into* the peril of low–context work, "embracing error" in crowdsourcing [24].

The general lesson has been that the more micro the task, and the more fine the decomposition, the greater the risk that workers lose context necessary to perform the work well. For example, workers edit adjacent paragraphs in inconsistent ways [2, 21], interpret tasks in different ways [20], and exhibit lower motivation [22] without sufficient context. Research has sought to ameliorate this issue by designing workflows help workers "act with global understanding when each contributor only has access to local views" [42], typically by automatically or manually generating higher-level representations for the workers to reflect on [11, 42, 21].

As the additional context necessary to complete a task diminishes, the invisible labor of *finding* tasks [31] has arisen as a major issue. Chilton et al. illustrate the task search challenges on AMT.Workers seek out good requesters [31] and then "streak" to perform many tasks of that same type [12].

Researchers have reacted by designing task recommendation systems (e.g., [13]) and others focused on minimizing the amount of time that people need to spend doing anything other than the work for which they are paid [8].

Piecework's perspective.

The research community relating to piecework and labor has been wrestling with the decomposition of work for centuries. The beginnings of systematic task decomposition stretch back as far as the 19th century, when Airy employed young boys at the Greenwich Observatory who "possessed the basic skills of mathematics, including 'Arithmetic, the use of Logarithms, and Elementary Algebra' " to compute astronomical phenomena [16].

The work that Airy solicited resonates with modern crowd work for several reasons. First, work output was quickly verifiable; Airy could assign variably skilled workers to compute values, and have other workers check their work. Second, tasks were discrete — that is, independent from one another. Finally, knowledge of the full scope of the project — indeed, knowledge of anything more than the problem set at hand — was unnecessary.

This approach found its audience in the early 20th century with the rise of Fordism and scientific management (or Taylorism). Scientific management suggested that it was possible to measure work at unprecedented resolution and precision. As Brown points out, piecework most greatly benefits the instrumented measurement of workers, but certainly in Ford and Taylor's time, highly instrumented, automatic measurement of workers was all but impossible [5]. As a result, the distillation of work into smaller units ultimately bottomed out with tasks as small as could be usefully measured [15]. [MSB: This subsection is too shallow and needs a bit more. For example, can you give examples of the last point?]

Piecework researchers enumerate a number of problems with the decomposition of work, and the conflicting pressures managers and workers put forth. Bewley in particular points out that the approach of paying workers by the piece is "... not practical for workers doing many tasks, because of the cost of establishing the rates and because piecework does not compensate workers for time spent switching tasks". Ultimately, Bewley argues that "[piecework is] infeasible, because ... total output is the joint product of varying groups of people" [3].

What's different about crowd work.

Where measurement and instrumentation were limiting factors for historical piecework, computation has changed the situation so that a dream of scientific management and Taylorism — to measure every motion at every point throughout the workday and beyond — is not only doable, but trivial [43]. Where Graves directly implicates measurement as preventing scientific management from being fully utilized, modern crowd work is measuring and modeling every click, scroll, and keyboard event [35, 34]. The result is that on–demand work can articulate and track far more carefully than piecework historically could.

A second shift is the relative ease with which the metaphorical "assembly line" can be changed. Historical manufacturing equipment was not Turing-complete, and could not quickly be assembled, edited, and redeployed.[MSB: cite for historical piecework equipment being a large time + money investment?] In contrast, today system–designers can share, modify, and instantiate environments like sites of labor in a few lines of code [29, 30]. This opportunity has spurred an entire body of work investigating the effects of ordering, pacing, interruptions, and other factors in piecework that would have been all but impossible to manipulate as few as 20 years ago [14, 6, 10, 9, 24].

Third, modern crowd work has sliced work to such small scales that the marginal activities — things like finding work and cognitive task switching — have become relatively large compared to the tasks themselves [12]. In the historical case of piecework, moving metallurgical tools, mining equipment, or other industry materials would have been prohibitively difficult and slow; workers were encouraged to specialize in a single set of tasks, allowing pieceworkers to sequence their tasks optimally on their own [17]. The result is that crowd workers are more free agents than historically was the case. However, because they spend significant time searching for tasks, the piece rate is less a good estimate of take-home earnings than before.

Implications for crowd work research.

If measurement precision limited the depth of decomposition for piecework historically, as Graves argues, then modern on–demand work stands to become far more finely-sliced and highly decomposed than ever before. Online tools make measurement and validation so easy [35] that these aspects of piecework are solved, or near enough that they no longer limit task decomposition. Now, not just tasks, but entire workers' histories [18], can be collected and analyzed in detail.

However, decomposition has hit a second bottleneck: cognition. Task switching costs and other cognitive costs make it difficult to work tasks so far decontextualized from their original intention [28]. There will of course be tasks that can be decomposed without much context, and these will form the most fine-grained of microtasks. However, other tasks cannot be freed from context — for example, logo design requires a deep understanding of the client and their goals. In part due to this limitation, 99designs workers often recycle old designs rather than make new ones for each client [1].

So, ultimately, the levels of decomposition are likely to follow the contours of context required. Low-context work will be extremely highly decomposed. High-context work will continue to be limited.

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