

# A Developmentally Inspired Transfer Learning Approach for Predicting Skill Durations

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**Abstract**—As robots are increasingly integrated into daily life, one of the most important roles they will assume is that of collaboratively helping us perform physical tasks. Be it helping us put together furniture, transporting materials, or assisting with food preparation, a system’s ability to assess its (and others’) skill level regarding the performance of different tasks is essential to achieving efficient scheduling and collaboration. In this paper, we present preliminary work towards an observation-driven modeling approach allowing an agent to autonomously predict the amount of time required for different agents to complete actions. This approach utilizes insights and observations from the developmental psychology and operations research communities to accurately develop agent-personalized skill proficiency models. We demonstrate our model by evaluating its performance at estimating agent performance in a set of common assembly tasks. Our evaluation measures knowledge-transfer via novel task introduction, as well as extrapolation by predicting future performance given previous experience.

## I. INTRODUCTION

Collaborative activities are strongly present in people’s day-to-day lives. Although people commonly successfully engage in different types of collaborative activities and thus understand how to coordinate their actions to achieve a common goal, there is no consensus on how adults come to have this complex understanding [1]. An essential part of this understanding is derived from evaluating one’s own proficiency at performing different tasks — not only to reach a common goal, but to reach it as efficiently as possible.

Prior work has confirmed that adults are good at evaluating other people in a variety of social contexts. Research shows that adults achieve this by analyzing both the behavior and physical features of people they interact with [2], [3]. Investigations of mechanisms employed for self-evaluation, however, constitute an entirely different line of research.

Adults do not make perfect assessments [4] and can easily overestimate or underestimate their capabilities [5] because of potential damage to an individual’s self-esteem [6], difficulty in processing available information [7], or uncertainty related to evaluating outcomes [8]. However, they do have a clear and full understanding of the concept of ability and self-efficacy. The process through which adults achieve this understanding is being extensively studied in developmental psychology research. It is believed that young children, preschoolers and kindergartners do not have a clear notion of ability as an internal quality [9].

Changes in the way children think about ability have been observed to occur between kindergartners and 7-8 year olds, and between 7-8 and 10-12 year olds [9]. Qualitative changes begin at 7-8 years old, when children become increasingly interested in performance and ability. This is indicated by the act of making comparisons with peers, with respect to friendship formation, classroom norms, and academic achievement. The notion of ability starts becoming its own domain for children at this age, whereas younger children can sometimes mix up intelligence with conduct, likability, or social behavior [10], [11]. More importantly, children start making more accurate predictions about their own capacities. Younger children tend to suffer from positive biases or “wishful thinking” [12], overestimating their abilities in a range of domains, such as school achievement [13], [14], running [15], or peer group dominance [16]. Research has shown that at the age of 7-8 years, children begin to adjust expectations, become more accurate in their self-perceptions, and get closer to their teachers’ ratings [9], [17], [18].

The second stage of changes happens between 7-8 and 10-12 year old children. At this time, children’s reasoning skills develop further, as they start being able to differentiate between the concepts of ability and effort [9], [19], [20]. Children at this stage begin interpreting ability as a capacity rather than a set of skills and knowledge [9], [21]. Although the development of their reasoning skills helps increase self-evaluation accuracy during this stage [22], [23], some children continue their trend of becoming more pessimistic and thus sometimes underestimate their ability [14].

In this work we present a skill estimation system inspired by these developmental shifts in self-evaluation. Similar to the transition experienced between kindergartners and 7-8 year olds, where comparisons between tasks and between others become prevalent, our system utilizes transfer learning strategies that allow for the use of comparable, indirectly related experiences to improve estimation proficiency. By exploiting these experiences, our system is similarly able to converge on more accurate estimations of ability (as measured by predicting task durations).

The second developmental transition, where the notion of ability separates from the skills themselves, is represented through components of the presented model that augment heuristic-driven predictions (e.g., casual or generic estimates akin to “It should take someone about 10 minutes”) of

expected performance with evaluations of personal ability. These components model agents’ proficiencies with the tools or motor skills required for a task, allowing for an accurate personal interpretation of impersonal, or crowd-based knowledge. Our work is particularly motivated by scheduling and multi-agent planning scenarios, where providing tighter bounds for worker-subtask pairings can directly result in improved time management and more efficient planner solutions.

## II. RELATED WORK

Our work utilizes techniques drawn from the Transfer Learning (TL) and Learning from Demonstration (LfD) communities. TL is a well-studied area within both robotics and psychology, leveraging the idea that one can generalize across topics as well as within them [24]. This idea has been applied within several domains, including reinforcement learning [25], cognitive architectures [26], machine learning [27], [28], and planning [29].

Transfer Learning-based techniques have also been used for improving performance on supervised learning tasks in situations where adequate labeled data are not readily available [30]. In other work, a conceptual framework is presented to capture the process of transferring skills and knowledge from one task to another [31]. Relevant work in observation-driven skill acquisition and evaluation includes the construction of parameterized skills from experience [32], the construction of skill trees from demonstration trajectories [33], and building of hierarchical collections of skills for intrinsically motivated reinforcement learning paradigms [34].

## III. DOMAIN

In this work we address the problem of estimating agent skill proficiency, in terms of generating estimations of the amount of time required for their completion. In particular, we build models that accurately estimate the amount of time required for an agent to perform subtasks obtained from decompositions of complex tasks (Fig. 1). We chose a manufacturing domain for our evaluation, using IKEA furniture construction as a task class representative of well specified, multi-step, complex assembly work.

We model construction times for subtasks within the assembly of three different pieces of IKEA furniture: a chair, a table, and a shelving unit (Fig. 2). Instructions for these pieces were segmented into seven, seven, and nine subtasks, respectively. These tasks were chosen due to their partial overlap in terms of tools required, motor skill similarity, and for their parallels to many real-world tasks.

## IV. APPROACH

We approach the problem of skill proficiency estimation as one of agent modeling. By analyzing video recordings of humans performing assembly tasks, we were able to extract relevant features such as execution duration, tools required, and motor skills used for each subtask. Once the recordings were annotated, we were able to look for features in the data indicating potential areas for transfer learning, with the

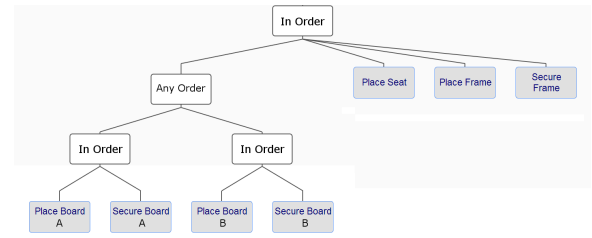


Fig. 1: The hierarchical task network used for assembling the Lätt chair, indicating the ordering constraints and goal of each step. Actions were coded in terms of the goals represented by each leaf node.



Fig. 2: Pieces of furniture that were used in assembly tasks. (Left) IKEA Lätt table and chairs. (Right) IKEA Kallax shelving unit.

goal of making previously unrelated training data applicable. An agent simulator was then built based on the human task performance data. This simulator, capable of generating agents with a multitude of proficiencies and learning curves based on the observed human data, allowed for the proposed modeling technique to be applied to a much wider and more difficult range of worker types. Finally, we evaluate our system’s performance both on its ability to estimate performance for previously untrained tasks and on its ability to extrapolate agent performance for already known tasks.

### A. Data Collection

We recorded four participants performing multiple assemblies of three different types of IKEA furniture. Participants were given instructions for each task in the form of a hierarchical task network (the “task network”), providing both goal information and ordering constraints to the worker (Fig. 1). These task networks were generated from a Semi-Markov Decision Process-compatible encoding of the instruction manuals that were provided. Each action in the task’s SMDP was annotated with metadata including any tools required (e.g., “hex wrench”, “hammer”) in addition to a keyphrase describing the motor skill required (e.g., “peg in hole”, “slide in place”, “secure 2 bolts”). Skills and subtasks were coded at a granularity such that an annotation indicating a required tool or motor skill meant that the skill or subtask was dominated by the use of that tool or motor skill.

Each participant performed between 5 and 10 assemblies of each piece of furniture in succession. For each subtask or action represented in the task network, the duration of time the worker spent was annotated from the video recording. Each demonstration resulted in an execution trace of the task that

indicates the order of subtasks completed and their durations. These execution traces, in the form of (agent name, subtask name, start time, end time)-tuples, serve as input for the model learning step.

### B. Feature Analysis and Data Synthesis

A more in-depth analysis of recorded data provided more detailed features for each subtask. The data showed a clear experience curve as participants made procedural improvements over successive demonstrations, some nearly halving their execution time over the course of their trials. As such, we investigated the magnitude of change and rate of convergence to a stable execution proficiency to model this curve for each skill. Other features we examined included the amount of variance present once a stable execution strategy was achieved, as well as the range of bias of these values as measured across agents.

Additionally, we improved prediction accuracy when accounting for differences observed between agents across subtasks that shared annotations either in terms of required tools or common motor skills. This is supported by the intuition that for any set of skills dominated by a particular action, such as the use of the hex wrench in “Secure Board A” and “Secure Frame” (Fig. 1), an agent’s performance is tied to its ability to use the tool.

Using these data, we developed generic agent templates that could generate a multitude of agents, simulating a range of proficiencies mimicking trends seen in the real-world data.

### C. Evaluation Criteria

Our approach is evaluated based on its performance in two important use cases: adaptation to new tasks and extrapolation on known tasks. These metrics are measured using the average error on a per-skill basis across tasks and agents. The model is evaluated based on its ability to predict the time taken for each execution the agent performs of each skill, incorporating effects due to procedural improvement and variance.

In the case of novel task introduction, we evaluate the model’s ability to use knowledge transfer. This is accomplished by evaluating predictions of an agent’s performance exclusively on a new, untrained task, while varying the amount of training provided to non-target tasks. Additionally, we investigate effects that arise when modulating the number of non-target tasks provided. In the case of extrapolation-based evaluation, we evaluate the model’s ability to predict future performance across all tasks, given a variable amount of training data.

## V. AGENT PROFICIENCY MODELING

Based on our analysis of the annotated video data, we predictively model an agent’s skill performance based on four types of features: a heuristic prior for a skill’s expected duration ( $E$ ), a skill’s experience curve ( $\gamma$ ), an agent’s tool proficiencies ( $\tau$ ), and an agent’s motor skill proficiencies ( $\rho$ ). The heuristic prior used for each skill represents an

expected duration (analogous to a common-knowledge estimate), based on the mean of observed execution times from the human-recorded data. This value is agent-agnostic, and does not directly represent any empirically derived knowledge from evaluated agents. A skill’s experience curve represents the efficiency gains made from procedural improvements that occur over the course of practicing a skill or task. Tool and motor skill proficiencies are indicators of an agent’s proficiency with particular tools or types of manipulation. Each feature is represented as a corrective scaling factor to be applied against the expected duration of the skill ( $E$ ), with default values of 1.0 in the case of the experience curve, and 0 in the case of tool or motor proficiencies.

We combine these features by predicting a skill’s execution duration with the following formula, given an agent  $a$ , skill  $s$ , expected duration of  $s$  from the heuristic prior  $E(s)$ , and demonstration number  $x$ :

$$\text{estimate}(a, s, x) = E(s) * \gamma(s, x) * (1 + \tau(a, s) + \rho(a, s)) \quad (1)$$

### A. Experience Curve

The experience curve of a subtask represents the effects of transitioning from a novice to an experienced practitioner. This is represented by the changes in expected duration that occur over the course of gaining familiarity with practice. These functions, also known as learning curves, have been studied extensively within operations research [35], [36], [37] as they are important in many real-world planning scenarios.

It is important to learn a subtask’s experience curve for predicting the completion duration of a skill. It is equally important to learn for the purpose of correcting experience-related effects out of observed data, allowing for the isolation of other factors that may be contributing to a subtask’s execution duration. Beneficially, doing so enables one to include early demonstrations in subtask analysis and feature extraction, as these initial samples will no longer be dominated by effects from procedural improvements. We compute this value across agents, independent of factors attributable to individual agent variation when possible, such as tool or motor skill proficiency, with the intention of isolating effects intrinsic to the particular skill or subtask’s progression as familiarity increases.

As the experience curve can be heavily influenced by agent-specific factors, we attempt to remove effects attributable to each agent’s tool and motor proficiency effects as a pre-processing step. A subtask’s experience curve is calculated by partitioning observed executions into groups by demonstration index, independent of the performing agent. For each indexed demonstration (e.g., 1st, 2nd, ...,  $n$ th), we compute the ratios of the observed durations to the expected duration (given by the baseline prior) of the subtask. With these values, we perform a power fit to obtain an estimate for how experience changes the expected duration with practice.

For a pool of agents  $A$ , skill or subtask  $s$ , heuristic function  $E(s)$  returning the expected duration of  $s$ , and function  $d(\text{agent}, \text{skill}, \text{iteration})$  returning the observed duration of a particular iteration of a skill by an agent, we compute the parameters

$(\alpha, \beta)$  of the experience curve using equations 3 and 4. We begin by constructing the set of coordinates  $(x, y) \in P$ , where  $x$  is the demonstration index (given  $X$  total demonstrations) and  $y$  is the execution duration ratio with tool and motor proficiency effects removed (eq. 2).

$$P_s = \left\{ \left( i, \frac{d(a, s, i)}{(1 + \tau(s, a) + \rho(s, a)) * E(s)} \right) \mid \forall a \in A, i \in [1, X] \right\} \quad (2)$$

$$\beta_s = \frac{|P_s| * \sum_{p \in P_s} \ln(p_x) \ln(p_y) - \sum_{p \in P_s} \ln(p_x) * \sum_{p \in P_s} \ln(p_y)}{|P_s| * \sum_{p \in P_s} \ln(p_x)^2 - (\sum_{p \in P_s} \ln(p_x))^2} \quad (3)$$

$$\alpha_s = \frac{\sum_{p \in P_s} \ln(p_y) - \beta_s * \sum_{p \in P_s} \ln(p_x)}{|P_s|} \quad (4)$$

With these parameters, we obtain the experience curve modifier value for iteration  $x$ :

$$\gamma(s, x) = e^{\alpha_s x \beta_s} \quad (5)$$

### B. Tool and Motor Proficiency

Analysis of the video data suggested a relationship between durations of subtasks with similarly annotated tool requirements or motor skill descriptions, in accordance with developmental psychology literature, suggesting that these could be substantial factors in a skill's execution duration. For some subtasks, this can be explained as the usage of a tool (e.g., how fast one can turn a screwdriver) dominating how long a subtask takes to be completed. For other subtasks, the type of motor skill involved can just as easily be a major factor, such as how well someone performs at peg-in-hole tasks or how adeptly they can manipulate a cumbersome type of object.

To measure these proficiencies, we isolate the observed execution times from any effects arising from an agent's learning curve. In practice this is imperfect, as agents may improve motor skills or tool proficiency over time concurrent with the task. In our data, these abilities were not observed to change in a perceptible way when contrasted with the procedural improvements attributed to the experience curve.

The calculation of an agent's proficiency for a given tool involves examining performance across all skills that utilize the target tool. To isolate the effects of tool use from other contributing factors, we ensure no effects from procedural improvements (as represented in an experience curve) are being mistakenly attributed to tool proficiency. Our approach accounts for this by limiting sampling whenever possible to demonstrations after the agent's performance curve has leveled off (where the magnitude of  $\frac{\partial}{\partial x} \gamma(s, x)$  is small). Unlike experience curves that are calculated cross-agent, tool and motor proficiency values are calculated strictly within-agent as a personalization feature.

Given an agent ( $a$ ), a set of skills or subtasks that agent has performed ( $s \in S$ ), their expected durations ( $E(s)$ ), and the set of demonstrations for a given skill  $s$  by agent  $a$  ( $D_{a,s}$ ), we can compute the agent's tool proficiency. First, we define a function  $r$  that returns the average ratio of observed to expected

execution durations (eq. 6) for a given agent and skill.

$$r(a, s) = \frac{1}{|D_{a,s}|} \sum_{d \in D_{a,s}} \frac{d}{E(s)} \quad (6)$$

Using this function, we can compute the weights to apply to each skill when assessing tool proficiency. In tool proficiency assessment, these weights are meant to assign more importance to skills that comprise a larger percentage of the target tool class and comprise a smaller percentage of their motor class. To do this, we assign weights inversely proportional to the distance between the mean of an individual skill's duration ratios and the mean of all skills utilizing the same tool. We also utilize the distance between a skill's duration ratio and the mean of all skills in its motor skill class. Intuitively, in measuring tool proficiency, this weighting scheme attributes more importance to the skill if it is either a poor representative of its motor skill class or if it is a good representative of its tool class.

We define  $T_s$  to be the set of all skills sharing the same required tool as skill  $s$  and  $M_s$  to be the set of all skills that share the same motor skill keywords as  $s$ . For an agent  $a$  and skill  $s$ , we compute the following weighting:

$$\omega_{a,s} = 1 - \frac{|r(a, s) - \sum_{t \in T_s} \frac{r(a, t)}{|T_s| * E(t)}|}{|r(a, s) - \sum_{t \in T_s} \frac{r(a, t)}{|T_s| * E(t)}| + |r(a, s) - \sum_{m \in M_s} \frac{r(a, m)}{|M_s| * E(m)}|} \quad (7)$$

Finally, we must compute the proportion of credit (eq.8) for any observed effect to assign to the tool proficiency (as opposed to a motor skill proficiency that may also be represented in the improvement).

This credit assignment is performed to proportionately distribute performance changes across all involved model features.

$$\psi(s) = \frac{1}{2} * \left[ \frac{|T_s \cap M_s|}{|T_s|} + 1 - \frac{|T_s \cap M_s|}{|M_s|} \right] \quad (8)$$

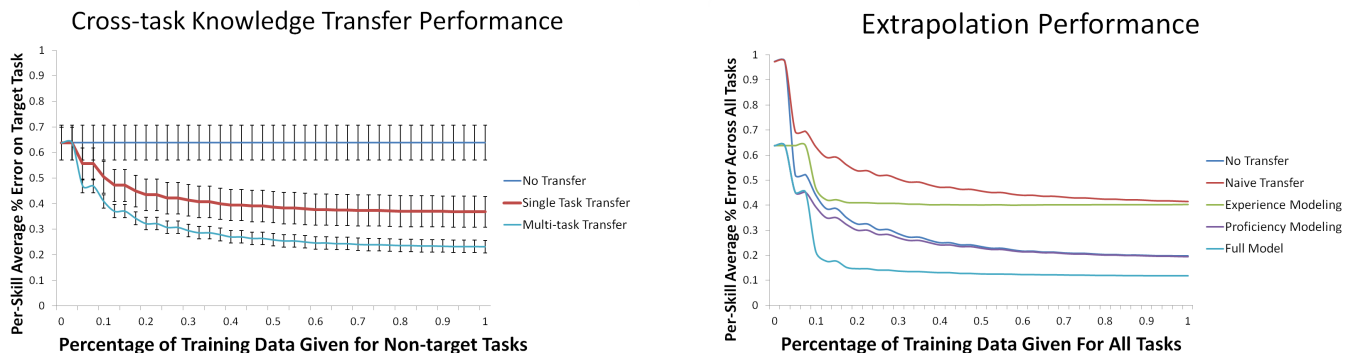
Combining these equations, we compute the tool proficiency  $\tau$  of a given agent  $a$  for a skill  $s$ :

$$\tau(a, s) = \frac{1}{\sum_{t \in T_s} \omega_{a,t}} \sum_{t \in T_s} \psi(t) * (r(a, t) - 1) * \omega_{a,t} \quad (9)$$

To calculate an agent's motor skill proficiency, we utilize the same process as for computing tool proficiency, replacing instances of  $T_s$  with  $M_s$ , and vice versa.

## VI. EVALUATION AND DISCUSSION

We evaluate our model by testing its ability to predict execution durations for specific agents on a variety of tasks in the assembly domain. Our dataset included 20 simulated agents performing 25 demonstrations of each piece of furniture. This resulted in 75 total trials per agent and a total of 1500 demonstrations. We measured model performance in two scenarios: cross-task knowledge transfer and within-task extrapolation. Performance is measured across the entire collected data set of 1500 demonstrations, measuring the



(a) Performance graph for estimating completion time of novel, untrained tasks using cross-task knowledge transfer.

(b) Predictor performance for estimating future completion time of tasks with prior experience.

Fig. 3: Evaluation results of the presented skill proficiency assessment predictor.

predictor’s ability to generate accurate estimates of future results in addition to maintaining accurate representations of its history. Error is presented as  $\frac{\text{estimated}-\text{actual}}{\text{actual}}$  for each skill execution in the data set.

### A. Cross-Task Transfer Learning

In the cross-task knowledge transfer scenario, we define the ‘target’ task to be a novel, previously unseen task. Our predictor is then trained with execution data from all tasks except the target task. Performance is thus measured as the average, per-skill duration estimation error on the target task. We repeat this process using leave-one-out validation for all tasks, reporting the average, per-skill duration estimation error across each target task (Fig. 3a). The cross-task performance indicates the ability of the predictor to perform within-agent knowledge transfer.

In the no transfer case, there was no agent- or task-specific data to use, so the heuristic prior is evaluated instead. In the single-task transfer case, the predictor was given a single task’s worth of training data to estimate performance on the target task. In the multi-task transfer case, all non-target tasks were provided as training. Intuitively, as more tasks are added to the training set, more insights are available to boost cross-task performance.

Using solely the generic heuristic prior for each skill in the target task results in a substantial performance estimation error for our generated agent pool ( $M = 0.638, \sigma = 0.136$ ). For a typical IKEA assembly task lasting 600 seconds, this means schedules based on the heuristic prior would typically be incorrect by approximately 382 seconds. Training the predictor with demonstrations of tasks sharing some tool requirements and motor skills dramatically increases performance. When trained with one other task, the prediction error reduces by over a third ( $M = .368, \sigma = 0.06$ ). Providing training data on a second task further improves prediction results, resulting in a 24% error when fully trained ( $M = 0.236, \sigma = 0.024$ ). In the 10 minute IKEA task example, this amounts to a prediction accuracy improvement of 4 minutes over a non-personalized approach.

These results are not meant to be representative of all tasks or skills, and may vary widely depending on the agents, tasks, tools, and motor skills being evaluated. However, they are encouraging and supportive of our work’s premise: that building models of agent proficiencies that leverage transfer learning can provide valuable improvements over less personalized methods in planning domains.

### B. Extrapolation-based Estimation

In the extrapolation scenario, we train our predictor on uniform amounts of execution data for each task. The model is then tested on its ability to estimate the future performance of each agent for each skill represented across each task. As in the cross-task transfer evaluation, performance is measured as the mean per-skill duration estimation error (Fig. 3b). Intuitively, this measures the predictor’s ability to estimate future performance given a limited amount of direct target task observations.

We evaluate our predictor’s ability to extrapolate on past performance by measuring performance across five methods: no transfer, naive transfer, experience modeling, proficiency modeling, and using our full model. In the no transfer case, agent performance is assumed to be the average of all demonstrations by that agent observed up to that point. The naive transfer predictor uses the average skill duration as computed across all agents as its estimate. The experience curve-based estimator fits a power curve to the unmodified observed data across all agents, using it as its predictor. Proficiency modeling utilizes the within-agent tool and motor skill proficiency estimation as a modifier on the heuristic prior. Finally, the full model combines the experience curve with tool and motor skill proficiency modeling (Eq. 1).

Our results strongly suggest that variations in agent performance rule out sole reliance on cross-agent transfer techniques for this scenario. In isolation, cross-agent methods take longer to converge and do so to less optimal solutions than their within-agent counterparts, with naive transfer and experience curve strategies peaking at approximately 41% error. Within-agent, cross-task methods do considerably better, with the

proficiency modeling and no-transfer methods converging to approximately 20% error. Our full model, combining developmentally inspired aspects of cross- and within-agent knowledge transfer, performs noticeably better, rapidly converging to approximately 13% error.

As with the cross-task results, these findings are not meant to suggest a universal performance guarantee for any particular class of task or skill. These results support the premise that transfer learning is a promising approach to skill estimation, allowing for improved accuracy in multi-agent scenarios.

## VII. CONCLUSION

In this work we present a novel approach to estimating task performance by treating task execution duration as a composition of multiple factors. We use transfer learning techniques to generalize knowledge across tasks and across agents, allowing for more accurate estimates of skill execution durations with less training data. Our approach shows promising preliminary results for planning systems, allowing for tighter duration bounds. These improvements are shown present both in cases of adapting and applying existing knowledge to novel tasks and extrapolating future performance from past experience.

## ACKNOWLEDGMENT

This work is supported by Office of Naval Research grant #N00014-12-1-0822 and NSF grants 1139078 and 1117801.

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