Modeling Personalized Difficulty of Rehabilitation Exercises Using Causal Trees

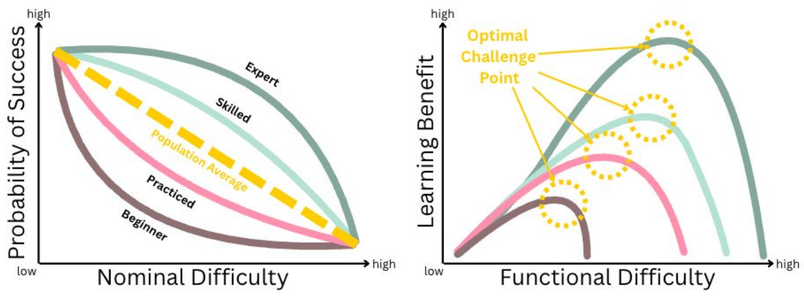
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Background

According to the Challenge Point Framework [1], optimal motor learning occurs at a specific level of task difficulty. This difficulty can be characterized in two distinct ways for a given task:

1. **Nominal Task Difficulty**, referring to the difficulty intrinsic to the task, regardless of who is performing the task.

2. **Functional Task Difficulty**, referring to the challenge a task presents to a specific individual.



Visualization adapted from the Challenge Point Framework [1]

Robots can support rehabilitation by being socially motivating and physically interactive [2,3,4,5]. To be effective, they must autonomously estimate task difficulty in the presence of measurement noise, and adapt tasks to each user's abilities, skills, and progress.

Decomposing Task Difficulty

To select optimal levels of functional task difficulty, we must quantify the difference between an **individual's performance** during rehabilitation and the **baseline performance** of the general population. We formulate this as estimating the conditional average treatment effect (CATE) for different parameterizations of the exercise x_i, using the potential outcomes framework notation [6]:

$$\tau(x) = \mathbb{E}\left[Y_i^{(1)} - Y_i^{(0)} | X = x_i\right]$$

- $\tau(x)$: individualized value of *functional difficulty*
- $Y_i^{(1)}$: performance metric for individual with limited mobility
- $Y_i^{(0)}$: average performance metric for control population (*nominal difficulty*)
- $X = x_i$: parameterization of exercise

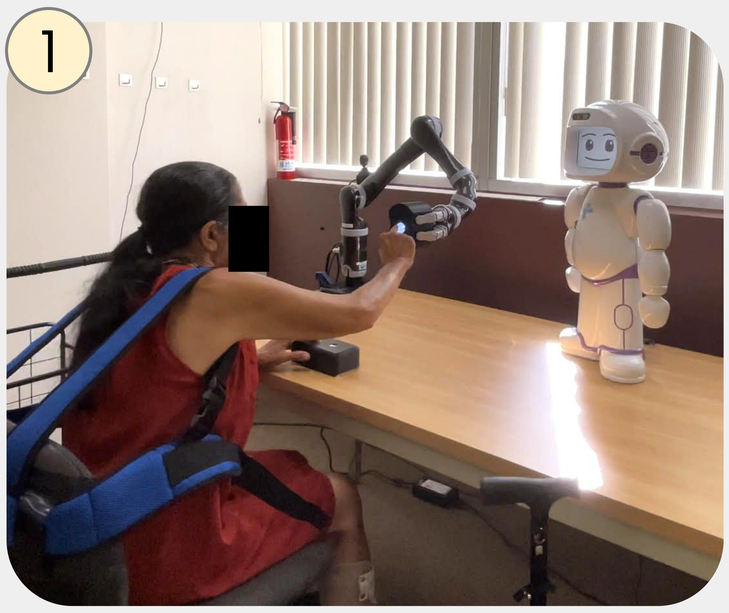
We model $\tau(x)$ by partitioning the exercise parameter space into leaves using a **causal tree** [7]. Within a particular leaf, we estimate the CATE as the difference between the average baseline performance and the average individual performance.

$$\hat{\tau}(x) = \frac{1}{|\{x_i^{(1)} \in L\}|} \sum_{x_i^{(1)} \in L} Y_i^{(1)} - \frac{1}{|\{x_i^{(0)} \in L\}|} \sum_{x_i^{(0)} \in L} Y_i^{(0)}$$

- First term: average individual performance for leaf
- Second term: average control population performance for leaf

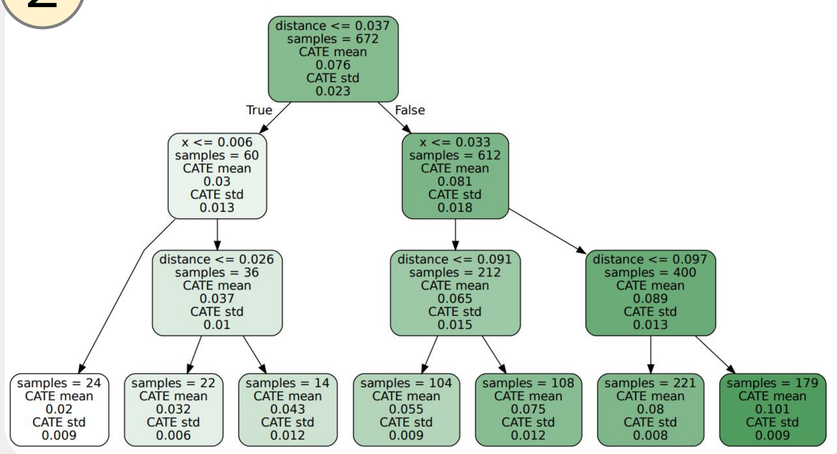
We developed a computational framework to quantify both *nominal* and *functional* task difficulty in rehabilitation tasks.

1



Collect performance data from interactions with the rehabilitation system from poststroke and neurotypical participants.

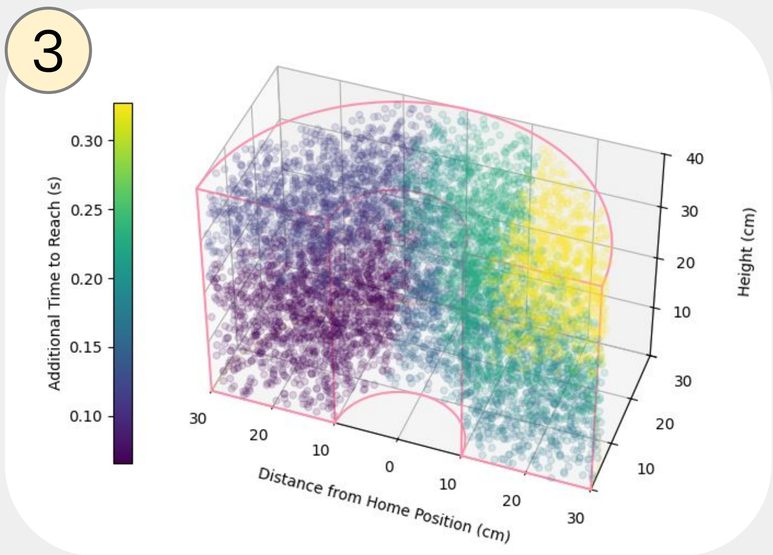
2



A causal decision tree estimating personalized functional task difficulty (darker green indicate higher functional difficulty).

Use a causal learning framework to disentangle **nominal task difficulty** from **functional task difficulty** by finding differences between an individual user's task performance from population-level task performance.

3

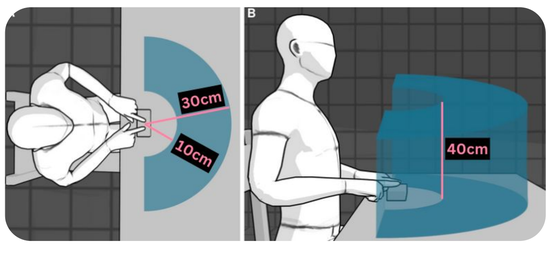


A 3D plot showing regions of higher functional difficulty (lighter colors indicate higher functional difficulty).

Visualize functional task difficulty to spatially identify challenging regions. This visualization can also summarize at-home exercises, supporting data-driven communication with physical therapists.

Results

We evaluated our approach on a reaching task where 15 poststroke participants performed 300 reaches in a region in front of them [8].



Task Parameterization (X_i): [x, y, z, x^2, distance, robot cue]

Outcome Variable (Y_i): time to reach (seconds)

Our method outperformed baseline methods that directly estimate $Y_i^{(0)}$ and $Y_i^{(1)}$ when estimating individuals' performance in the reaching task.

Model	MSE ↓ ($\pm SE$)	agg. r^2 ↑ ($\pm SE$)
Causal Forest (Ours)	**.300 ± .019**	**.826 ± .006**
XGBoost	.324 ± .021	.812 ± .006
Random Forest	.337 ± .021	.805 ± .006
Neural Network	.345 ± .022	.800 ± .006
Support Vector Machine	.488 ± .020	.718 ± .008
k-Nearest Neighbors	.380 ± .024	.780 ± .006
Decision Tree	.745 ± .045	.571 ± .011

Contributions

We created a **generalizable framework** for estimating *nominal* and *functional* difficulty of rehabilitation exercises for users interacting with robots.

We evaluated our framework using a reaching task with data collected from **15 post-stroke users** and **10 age-matched users** from the general population.

We found that causal trees outperform traditional machine learning techniques by jointly estimating nominal and functional difficulty. We showed performance gains across **individual** (MSE) and **aggregated** (r^2) evaluations.

Causal trees offer an **interpretable summary** of exercise performance that can be easily shared with physical therapists to support data-driven decision-making.

Works Cited
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