Simulation-driven gym layout optimization

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Collective behaviour course research seminar report

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This report describes our work on gym layout optimisation. We begin with a brief overview of the problem and related work, followed by a description of our model and simulation. We conclude with a discussion of our results and future work.
NOTE TO REVIEWERS: TODOs will be replaced in the final version of the report.

gym layout | crowd simulation | gym-goer behaviour | gym traffic

Introduction

In this report we describe our work on gym layout optimisation. A common occurrence in gyms during peak hours is over-crowding of popular equipment and lots of wandering around searching for a free machine. Through simulating gym-goer behavior, we aimed to identify the most effective arrangement of exercise equipment to improve the flow, accessibility, and overall customer satisfaction. Our goal is to offer practical insights for gym owners, managers, and designers seeking to optimize their facility layout for the benefit of their clients and business success.

To simplify the problem we will limit ourselves to simulating the behaviour of bodybuilders (performing resistance exercises for muscle hypertrophy). In this case, a typical workout routine partitions the body into several sets of muscles, cycling through them on a per-workout basis. To further simplify the problem, we will only simulate the *push-pull-legs* (PPL) partitioning, which is a popular choice for beginners and intermediate lifters. We will model the gym as a rectangular grid of cells with pre-set equipment locations, distributed similarly as isles in a grocery store.

Related work. The only publication related to gym layout optimization we could find was ref. [1], which assumed all gym clients had fixed-order workout routines (including ones with weight loss as a goal) and optimised a circular gym layout to minimise backward movement. Unfortunately, this does not give a good foundation for our work, as the assumptions diverge too far from what we are trying to model.

Thus we started from a crowd modelling review [2] for basic model design principles. We also found two useful articles about incremental urban layout optimisation [3, 4] for inspiration.

Methods

We used Python's *Mesa* library for simulation, analysis, and visualization of agent-based models.

Gym layout model. A gym is represented as a subclass of `mesa.Model` with two discrete rectangular grids: the agent layer (where gym-goers move around) and the equipment layer (where machines are statically placed for one simulation cycle). The agents can only move around in cells that are not occupied by a piece of equipment, but there can be multiple agents in a single cell. We do not feel that agent collision resolution is necessary for realistic modelling of gym traffic. One corner of the area serves as the locker area entrance, where agents enter and exit the gym.

For generating a concrete placement of machines, we have to assign certain cells to be equipment locations (where one machine is placed) while making sure we don't create unreachable areas. For a start, we will develop some layout templates mimicking the arrangement of isles in a grocery store, with sensible walkways in between. In this case, layout optimisation comes down to choosing the best assignment of machines to equipment locations.

Gym-goer behaviour model. A gym-goer is represented as a subclass of `mesa.Agent` with a training checklist (multiset of muscles) and its current state. The agent's goal is to exhaust the checklist as quickly as possible and exit the gym.

When an agent is created, it is assigned a workout routine (eg. push) and a workout plan (eg. chest, chest, triceps, frontal deltoids). Routines will be sampled with probabilities based on our observations of people in our local gyms. The workout plans are constructed ad hoc, in keeping with general workout programming practice.

TODO
TODO1 | TODO2

Upon entering the gym, an agent starts in state *searching*, where it looks for a free piece of equipment it can use to check any item off its checklist. In the current implementation, the agent moves around randomly until an appropriate machine appears in its field of view (as defined by a radius r where $r = 1$ means the 8 neighboring cells). In the future, we will implement more realistic searching movement, such as walking along a pre-defined exploration path around the gym (which for the right kind of layout template could be an eulerian cycle through corridors in the equipment layer), or actual pathfinding to the nearest free machine.

When a free machine is found, the agent enters state *exercising* and occupies the machine for a certain amount of time. After the time has elapsed, the agent re-enters state *searching* or exits the gym if the checklist is empty.

Layout optimisation. We have not yet decided on a specific optimisation algorithm, but here we outline some of the possibilities we are considering.

We will begin the optimisation with a random layout (or set of layouts) and apply some local optimisation. Given the right kind of layout template, we could try genetic algorithms. Alternatively, we will consider the Metropolis-Hastings algorithm which was successfully applied to urban layout optimisation [3, 4].

Objective function. The quality of a layout will be measured as a weighted sum of the following factors (determined in a simulation cycle):

- proportion of time spent exercising (vs. searching or waiting around),
- local gym crowdedness (eg. maximum number of agents in a single cell), and
- an agent's ability to finish its workout in the amount of time it has available (eg. 1 hour).

We might also consider the cost of equipment (and its installation), though this is difficult to estimate in general and might make more sense as an input to our optimiser, given by a gym designer.

Results

Up to this point, there are not many results to report on. For now we have a partially working simulation (figure 1).

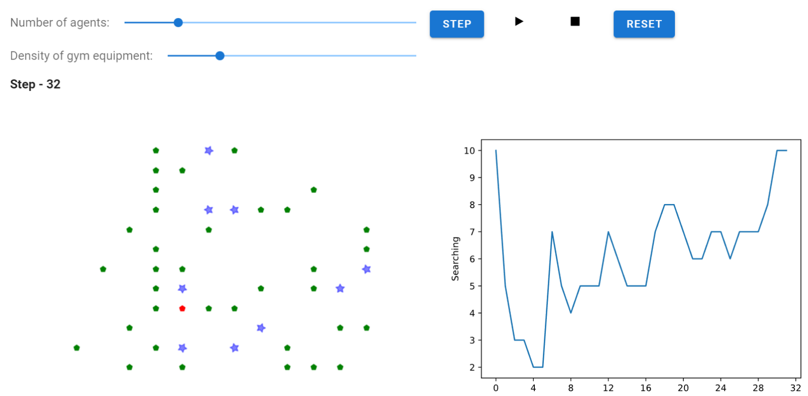

Figure 1. An example of our simulation thus far

The simulation offers the flexibility to change the number of agents and the density of equipment through a slider interface. Following the adjustment of these parameters, the simulation is rebuilt, generating a layout characterized by the chosen parameters.

The simulation interface in the bottom left section, showcases agents denoted by purple stars and gym equipment represented by green rectangles. When a piece of gym equipment is in use, its color transitions to red, providing a clear visual indication of activity.

A graph located in the bottom right section represents the number of agents that are currently searching for a machine and thus not working out.

Discussion

Given the current state of our simulation, optimal gym layouts remain to be obtained. The prerequisite for attaining this goal is the enhancement of our agents pathfinding capabilities. Consequently, there are no substantive results available for discussion at this moment.

Future work. We could make our gym layout model more realistic with the addition of shared resources (eg. free weights beside a set of benches), compound machines (eg. a cable harness with multiple weight stacks) and multi-purpose equipment (eg. a squat rack with a pull-up bar), but none of this is a priority for now. It might be far more interesting to let our optimizer come up with a layout from scratch (without hand-crafted templates), but it's likely this will make the optimizer take too long to converge to anything sensible.

We will also consider implementing more fine-grained agent behaviour, such as:

- **Parallel use of gym equipment:** A resistance exercise is usually performed as a sequence of (typically 3) *sets* where a movement is repeated some number of times, with short breaks in between. These breaks facilitate parallel use of gym equipment by two people, where one works out while the other rests. Note that this might involve time-consuming weight adjustment in between sets in case of differing strength levels, depending on the type of machine. Thus we will have to model a preference for free machines, even if it means greater travel distance for the agent.

- **Non-uniform arrival of agents:** In the current implementation, a simulation starts with all agents entering the gym simultaneously. We will implement a more realistic arrival process, where agents arrive at a time-dependent rate which peaks in the early evening.

- **Smarter exercise selection:** An agent could exhibit preferences based on its immediate workout history. For example, it could try to avoid performing two chest exercises back-to-back in a push workout, since the chest fatigue will make the second exercise less effective.

- **Larger timescale of simulation cycles:** If we simulated several days of gym traffic, we could have agents persist across workouts and thus actually cycle through their workout routines (such as push, pull, legs, or some alternative partitioning) instead of just assigning each agent a random workout upon creation.

A more detailed list of contributions is yet to be written.

CONTRIBUTIONS. Andrej Jočić wrote the simulation code. Matic Stare wrote the report. Martin Starič worked on the pathfinding algorithm.

Bibliography

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