CARNEGIE MELLON UNIVERSITY

School of Architecture
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Thesis

Submitted in Partial Fulfillment of the requirements for the degree of

Master of Science in Computational Design

TITLE:

Design Games and Machine Learning
A Method for the Application of Machine Learning in Design Environments

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Abstract

Design problems are part of a category of problems that are considered "wicked" (Rittell et al. 1973), such that success, and the metrics to determine success, are either undefined or mutable. Machine learning techniques have been applied to an increasing variety of problems, of increasing complexity that were once considered infeasible for artificial intelligence solutions of any kind (Sliver et al. 2016). However applications of these techniques require a well-defined space. We propose a solution to resolve this seeming incompatibility by creating a shared, abstract, environment that is computable but also provides enough user-freedom to exercise a design problem through the exploration of solutions. We use a game-like environment to model not only complex simulations of systems, but also allow both human and AI actors to "play" in a shared space to explore design alternatives. To address the *openness* of the design problem, we *close* the problem for the AI by providing user-controlled weights on game performance metrics. Thus allowing the AI system to optimize in favorable ways with respect to the bespoke demands and goals of the designer.

Definitions

Technical Terminology

Terms defined here follow that of the prevailing or accepted definitions within their respective fields of study. Some however are relatively new and sources are provided where there are multiple possible definitions by different groups in contemporaneous literature.

AI - Artificial Intelligence
Artificial Intelligence(AI) refers to classical and learning techniques (defined under Machine Learning) following the definition: "The branch of computer science that is concerned with the automation of intelligent behavior" (Luger and Stubblefield, 1993). The usage of AI in this document is exclusively about weak or narrow AI.

ML - Machine Learning
Machine Learning (ML) is a system of algorithms that inductively self-alter parameters to maximize performance over some task given some set of experiences. (Mitchell, 2006). Machine Learning is a strict subset of Artificial Intelligence (AI).

Metric Space
A Metric Space is a set where all members's distances are defined. In this context we will talk about this as computing differences in game-states, scores, actions, or any other value. AI, or any other form of computation, requires a defined metric space (where the distance

function is often, but not always, a Mahalanobis distance) to compute and optimize for some evaluable criteria, and can only do so if that space can be computable values in some contiguous range.

Online Learning

       Online learning refers to how training data is processed relative to a learning system or algorithm. Online techniques are generally memory-less; using a single batch or sample at a time, adjust weights by some process to reduce error, then discard the sample. These techniques are used either where training data is too large or temporally generated at runtime (direct observation or input). Of the set of all Learning algorithms, Online learning does not describe all non-Offline Learning algorithms. There are others like Incremental or Progressive Learning, where data may accumulate, and only be partially discarded or undergo separate clustering to determine outliers. There is not yet a singular term that is externally defined that encapsulates all non-Offline techniques. We label non-Offline as "Continuous Learning" (See Continuous Learning System).

Incremental Learning

       "Incremental learning is a machine learning paradigm where the learning process takes place whenever new example(s) emerge and adjusts what has been learned according to the new example(s). The most prominent difference of incremental learning from traditional machine learning is that it does not assume the availability of a sufficient training set before the learning process, but the training examples appear over time."(Geng & Smith-Miles 2015)

ANN - Artificial Neural Networks

       Artificial Neural Networks are composed of layers filled with neurons. Each neuron is connected to each of the neurons of the next layer. Each neural connection is also Weighted. This Weight is the parameter that is changed through training/"learning". Each neuron takes each input signal, modified by the weight, sums them together, and computes the output using an Activation Function. This function is simply a means to push incoming signals up or down by some factor to determine how much incoming signal will cause this neuron to "activate" and pass the output signal on (and by what intensity).

MLP - Multilayer Perceptron

       A MLP is the most common type of ANN architecture and follows the typical rules of layers being fully connected to the next layer in the network, but not internally, or cyclically like in recurrent networks, or partially connected like convolutional networks. A MLP is said to be a "Universal function approximator" as it takes any number of parameters (input layer) and can be trained to produce the outputs (Hagan & Demuth 1999). The training is most commonly a form of Back-Propagation, where the ideal outcome is differenced against the actual output, this difference is the error and this error propagates back through the network, adjusted the weights of each connection by some factor to reduce the error. In typical Supervised Learning back propagation this is performed with a large dataset, and the network fits the input-output pairs within some degree of error. Eliminating error is problematic because this will lead to overfitting.

If the training data does not exemplify all possible real-world cases (which for our problem, is certainly true) then the MLP will misclassify the real data as it is too strictly formed to the training data. This error in a way becomes a form of tolerance.

Learning Paradigms, Reinforcement Learning

There are different Learning Paradigms in Machine Learning. Supervised Learning requires ideal pairings of input and target output data. These are assumed-true or canonical cases. Unsupervised Learning acts very differently as these algorithms look at data in aggregate and produce higher level observations on the data, without any instruction of the significance or parameters of separation. Reinforcement Learning is between these, and refers generally to a learning system that is reducing error or maximizing reward. (Sutton & Barto 2012) With Reinforcement Learning, a goal is known but the cases are unknown until the system can play.

Q-Learner

Q-Learning is a Reinforcement Learning strategy that takes an input State and Action pair, and produces a guess (Q score) as to what the outcome will be (the output signal, score, or change in score, etc.). The Q-function could be a table lookup, like in a simple path-finder problem, where the distance to the goal is known, or computable immediately. In cases where there does not exist a function or table of all possible state-action pairs, the Q-function can be modeled using a ANN, specifically a Multi-layer Perceptron (MLP).

CWA - Closed-world assumption

Closed-world assumption (CWA) is defined as a model where anything that is not known to be true or can be proven true from existing axioms is assumed to be false. This sets the notion that if something is unknown it is false.

OWA - Open-world assumption

Open-world assumption(OWA) describes the case where if something not known to be true or provably true, it is unknown, not false. Thus unknown remains unknown until proven otherwise, unlike CWA.

Definitions

The terms defined in this section are definitions that are either provided to clarify ambiguities in multiple existing definitions of the term or to clarify the particular usage of a term as it is used relative to this document as an italicized term. These will be used heavily in the discussion of the hypothesis and its formulation.

Game

A *game* is defined as a rule-based, constrained, abstract environment that models a *problem* where *players* interact with this environment in a knowable way. *Games* have a set of

criteria that can evaluate game-states for satisfaction of various win-conditions. This set can be empty. In other words, *games* can have ends, win/lose conditions, or not. Some of these may produce comparable values from game-states. This value can be a score.

Player/User/Designer

Player or *user* is the actor interacting with the *game*. *Designer* is the actor in the context of a *design problem*. Assume rational actions on the part of these actors and assume some genuine intent to use the *game* to learn and produce favorable results to the user or solve problems. These three may at times be synonymous.

Problem and Solution

A *problem* is a set of constraints, or criteria, that requires some level of resolution or can be "satisficed" (Simon 1947). This state will be known as a *solution*. A *problem's* set of *solutions* (*solution* space) can be of any magnitude. The countability of the quantity of *solutions*, whether they are enumerable (determinate), or innumerable (indeterminate), is dependent on the *problem* type. *Problem* constraints can be absolutes or merely "satisfizable" criteria where there is an accepted threshold for satisfaction, or where any range of values is accepted. The *problem* may provide criteria that can evaluate a *solution* for fitness (how well criteria is satisfied), therefore allowing the possibility of *solutions* to be comparable. In the case where *solutions* are comparable, there are "better" or "worse" *solutions* but they are all members of the *solution* space. While a provided *solution* might "solve" the *problem*, this is not necessarily the final.

Design

Design is an activity of the "discovery and elaboration of alternatives" (Simon 1972), meaning solutions have to be found and often exist in a space that is unbounded, and therefore not fully enumerable (see *Design Problem*). *Design* can take place through a number of disciplines or activities.

Design Problem

Following the definition of *problem*, a *design problem* is a *problem* is solved through the "discovery and elaboration of alternatives" (Simon 1972). *Design problems* are also a subset of Wicked Problems (Rittell et al. 1973). Following that definition a few properties of note:
- The *Solution-space* is not enumerable (Rittell et al, 164).
- *Solutions* are "good or bad" but not "true or false" (Rittell et al, 163).
- There is no immediate test to evaluate a *Solution* (Rittell et al, 163).

Recall our definition of *problem*: where there may be criteria that can evaluate *solutions* for fitness to the *problem's* specification. *Design problems* do not have this as part of their formulation. The criteria of evaluation may be partially or entirely absent. When a *designer* evaluates the "good"-ness of "bad"-ness of a *solution*, they apply criteria that is not explicitly part of the *problem*. Or following the "Wicked" property, the formulation of the *problem* itself is incomplete (Rittell et al, 161).

Furthermore the set of *solutions* to a *design problem* is innumerable as a property of this definition.

Open/Closed/Closable

Open is everything that is not *closed*.

Closed describes *problems* and g*ames* following the closed-world assumption definition. A *game* has axioms in the form of rules; a *problem* has constraints. An *open problem* is therefore "wicked", because there are unknown constraints. A *closed problem* can unambiguously evaluate a *solution* for truth, whereas an *open problem* can not evaluate truth (or fitness) in all cases.   The same follows for *games*.

Closable describes an *open problem* or *game* that can be provided truths that could not otherwise be derived, producing a new closed-world. All unknown conditions must be addressed to provide a definitive truth value. *Solutions* to a *closable problem* therefore can be definitively evaluated.

Continuous Learning System

A *continuous learning system* is a learning system that can actively train over new cases presented to it, for example, from direct observations, Strictly speaking, a *continuous learning system* is any learning system that is not strictly Offline Learning (see Technical Terminology). A *continuous learning system* therefore can train on data that is not yet available or not yet determined. Essentially it is a learning system that is constantly training on new data, regardless the source.

Introduction

The primary objective of the thesis is to demonstrate a viable application of machine learning techniques to the design process. The theoretical discussion will show how this applies to all similar class of problems, opening the door to other disciplines and contexts of application. The prototype will examine the specific efficacy of an example implementation of such a system in an applied setting through a software artifact.

There are technical and theoretical constraints to both the theory and the application. Identifying particular techniques, and in what paradigms they exist within machine learning, is critical to understanding the bounds of the AI system in how would be implemented. The system developed employs several multilayer perceptrons implemented as Q-Learners learning actively from direct observations from the game world and actions of itself and the human user. A brief overview of the domain and contemporary research will be discussed in the Background section, with further implementation details of the prototype's AI system in the Prototype chapter.

Design problems present a particularly difficult context for AI. The characteristics of such problems: the problem formulation is incomplete and dynamic, understanding the problem only through exploring solutions, an innumerable solution-space, conflicting parameters or

constraints to satisfy (Rittel et al. 1973; Gross 1985), are well discussed in literature. These characteristics present a unique challenge for AI. This goes beyond issues of data availability or choosing the right algorithm.

Design problems present an issue of evaluation. The criteria to evaluate solutions is either unknown, or ambiguous, as a property of being "wicked"(Rittell et al 1973). To address unknown criteria, we provide a way to make this known by involving the designer directly. The designer must have a way to explicitly provide this criteria in order to for the AI to evaluate game states. To adapt to changing evaluations of solutions, the AI system must be able to learn continuously over new cases. While a learning system can fit a particular model of provided data, if the evaluative criteria of how a state is scored changes, that data no longer truly represents the current world. Thus we implement a *continuous learning system* that is constantly training on new observations, regardless the world-state.

We achieve this in the prototype with a game interface that lets the player weight in-game metrics that are used to produce a score. In essence, the player is determining the policy that is applied to score the game states. The AI system is implemented as several Q-Learning multilayer perceptrons that employ incremental learning to continuously train over new observations. Not only to provide more cases, but to adapt to changing score-weighting on the part of the player. The player may freely decide to change the criteria applied to determine the score, thus the learning system must be able to observe this change to re-fit and model it.

The design game itself models an Urban Planning/Design problem as a city-building simulation game. The idea of design problem being represented by a game and explored through play has its own advantages (Habraken & Gross 1988). The design game developed follows the language from the existing genre of City-building games, most deriving origins from the canonical SimCity (Wright & Bremer 1989). It models the problem by providing the necessary tools to manipulate only certain attributes of the City, specifically zoning. The City itself grows and decays based on its own internal rule systems and logics that attempt to model real-world behaviours and patterns.

This type of game lends itself to a discrete event simulation, where the evaluative criteria of the AI is also discrete with time. Though this nature is not implicit to how other design games can or should be constructed to represent other specific design problems in a way conducive to machine learning systems. Other disciplines may benefit from entirely different representations and may also be better solved by alternative implementations of an AI system. The thesis only is directed to outline what applies in principle to all cases, and demonstrates this with a specific case through a software prototype.

Background

Artificial Neural Networks are an old technique revisited with proliferation of large and widely available data, with deeper networks leveraging increasingly parallelized hardware (GPUs). All Machine Learning techniques are only as strong as the data it has to generalize over. Too few samples and the network will approximate only against what is observed and will

fail on data that is outside of the sampled domain (Du & Swamy, 2014). While most of the research focuses on in the actual network architecture and internals, most of the practical challenges of NN implementations is the acquisition and pre-processing input data and deriving significance from output signals (classifiers, confidences, etc.).

The premise of a NN is simple, only made complex by the ability for the network to scale in breadth and depth. NN's, specifically anything with multiple layers, like a Multilayer Perceptron (MLP) will approximate any function (Hagan & Demuth 1999). This is achieved only with training. Supervised learning is the simplest, where known samples (training data with known/expected output) are provided, where the input data is computed by the NN and the expected output is differenced against the actual output. This error is the propagated backwards through the neural network. Each neural connection has a weight associated with it, that is tuned by some factor based on the error to more closely approximate what the value at that neuron should have been to reduce the error(Du & Swamy, 2014).

Reinforcement learning is another learning paradigm where training does not have an expected output, given some input. Instead output is scored, or given a reward signal of some magnitude. Different strategies to produce a reinforcement learner exist with neural networks and other learning techniques. A Q-learner (Watkins 1992) is a particular reinforcement learning strategy where there exists some Q-function that takes two arguments: a state (world), and action. The Q-function maps the state-action pair to an expected score output. That is to say, the Q-function's goal is to predict the reward of some action taken in in some world-state. Recall that a MLP is a universal function approximator, the Q-function therefore can be implemented as neural network trained to best approximate a predictor of score changes based on an observation of the current world state and possible action space.

Contemporaneos ML research, as it pertains to deep neural networks, is either a detector tasked with classification problems, or an agent in an environment working to some goal. Much of the behaviour oriented research often uses games as an environment to explore and exploit. This serves many purposes when exploring and comparing AI systems and even human performance in controlled scientific manner.

Games provide a unambiguous representation of a problem, in some abstract space. That lends itself well to being computationally represented as input vectors. Games provide a fixed ruleset which constrain the exploration space. In chess, the board is bounded, and there are a fixed number of pieces. The number of possible of sequences of moves is large but not unbounded. The same is true for Go but the possible board states are magnitudes greater than Chess. We see that even very abstract spaces can still present complexities in decision making that simply can not be brute-forced (an exhaustive search to find the global optimal), or even searched heuristically, relying on implausible hardware or time. The work of Silver et al. begins to suggest that classical techniques are ill suited to complex and vast solution spaces. Abstract does not mean simple.

Games used as a context for AI research, both classical and using more recent deep learning techniques, is typically implemented as a Reinforcement Learning problem. Games provide not only clean input signals (fixed world, board positions, possible actions), but equally clean output signals (reward/score). Most games are designed around this very framework:

players try to maximize their chance of winning. Reinforcement learning is predicated on the same premise. This makes the problem of solving a game well suited to this paradigm.

Thus in evaluating possible implementations we choose a similar model. While ours is not as "deep" as the networks detailed in the AlphaGo (Silver et al. 2016) paper nor some of the state-of-the-art classifiers (He et al. 2016), but rather we choose a more simplified approach to reduce the complexity of the total problem to avoid the "curse of dimensionality" (Domingo 2012; Du & Swamy, 2014).

Following the principles detailed in literature, as the complexity of the problem increases so does the ability for the learning system to converge. That is to say we can more easily find optimums of smaller problems. Availability and quality of data is also fundamental to any learning system. Our problem relies on learning on-the-fly as there is no database of players playing a game created strictly for the purpose of this experiment. The AlphaGo project (Silver et al. 2016) has very well documented games and communities that, over time, established well-formatted databases of game-histories on which to train. Notably AlphaGo also employed some online learning by playing others, and itself. This began to suggest that if a learning system is to learn in a new space, we can not rely on a vast collection of well labeled data, as it is likely there will never be such a database.

Hypothesis

A *continuous learning system* can solve a *design problem* modeled as a *closable game* where the parameters are computable.

Argument

To understand the formulation of the hypothesis we will deconstruct the argument and provide evidence for the conclusions drawn. Note: this relies heavily on the definitions provided in the Definitions section that preface the introduction.

Games present a well-defined space to explore a *problem*. *Games* have rules which bound the space of exploration, which in turn make it tractable. Most *games* have a method to determine a winner, which presents a solution-state. *Games* that do not have explicit win-conditions may still have a score. These are *closed games*: *games* that have fixed definitions of winning or scores. *Open games* therefore are *games* without those properties. *Open games* still have the same constrained environment with rules, but no determined win-state nor objective metric to label a score. *Players* in this case determine for themselves what winning is, not the *game*.

Design is not a *game*, but it can be "gamified". If a *game* is a model of a *problem*, it follows *design problems* can be modelled by a *Design Game*. The nature of the *problem* confines the nature of the *game*. We can not, for example, present a *Design Game* where there is a static win-condition because *design* does not have a static solution. However there is no

limit to different games[1] to model the same *design problem*. Thus we see that a *closed game* can only model *closed problems*; and *open problems* can only be modelled by *open games*.

Any AI requires a defined metric space in order to compute distances as a way to search that space, optimizing accordingly. A learning system achieves this through the use of observed cases to tune a function to approximate what could be the optimal solution in a given space. If the space is undefined or changes with time, the outcomes of a classical AI algorithm could not compare measures from what iteration to the next as the distances would become undefined. Where there exists unknown states in some world, this is known as an OWA. For a learning system, an undefined space (OWA) is equally problematic as it is for classical AI. However if the space is defined (CWA) in some discrete-time, then it is probable that some learning system could adapt parameters to any new observations. This requires that the system is learning over new observations in any new defined space as they are created. A strictly Offline training process can not capture these observations. Therefore a *continuous learning system* is used.[2]

A *game* that can not be scored can not be exploited by a learning algorithm designed to optimize said score. An undefined score is an undefined metric space producing an *open* world. This is the central challenge of the thesis: If a *design problem* is *open*, which can only sufficiently modelled by an *open game*, then how can any AI implementation be introduced, if all techniques require a *closed* world?

The solution is to have it both ways. The learning system must only exist in a *closed* world, while the game, as defined by its ruleset, must remain an *open* world. Note that the *player* is absent from this description. If we include the *player*, then we can say an *open game*, scored by the *player*, produces a *closed* world for the learning system. Any *open* world that can be provided external definition to produce a *closed* world we define as being *Closable*.

For *games*, if an *open game* is provided means of scoring game-states, the *game* becomes *closed*. For *design*, the solution is to derive this external input from the designer. We equate this to the self-evaluative process of a *player* in an *open game*. If we then provide a way for the *game* to access this evaluative process, unique to some *player* and time, then we have a *game* that can score any solution unique to the goals of the *player*, which is then said to be *closable*.

Thus a player (designer) playing a closable game, modelled from a design problem, can provide sufficient truths to the world definition of the game such that a learning system can adapt and optimize to maximize score output. This in essence is the system that can be said to present solutions to a design problem.

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[1] This too is its own design problem.

[2] Offline training assumes a fixed space, where observations are unambiguous with time and therefore observations all exist within a singular closed world. A continuous learning system requires too that observations are made within a closed world, but does not require that these worlds are the same. This however introduces challenges of balancing persistence of observation with learning convergence in changing world-states, a subject worthy of further research.

Prototype

The Game

Description

        The game is modelled as a city-planning game, similar in genre to SimCity and other themed city-builders. There is the notion of time and dynamic interaction and growth of elements in the city, people, and buildings. These systems can not be directly controlled by the player but influenced by a smaller subset of actions. The player's actions in this game are limited to Zoning. Zoning entails painting a tile with a zone property which allows for certain types of buildings to grow on that tile. This indirect control of the world-state only lets the user promote or inhibit certain conditions, but can not force growth of buildings on zones that are not suitable. This action intends to parallel that of the human actor, designer, in the real world. This level of manipulation of the game-state and metrics that are eventually scored creates a level of difficulty for the User and AI alike. Actions do not have direct or known consequences, and actions are context-dependent; these issues must be learned by both actors.

Intent

        The intent of this Game is to provide a design tool, one that combines the process of exploration and evaluation into one interface. Additionally, it is embedded with a learning system interacting with the same Game to assist or offer alternatives to achieve the design goals of the user.

        The representation of the urban-planning problem is its own challenge. This simulation is by no means a full model of urban systems. However, simulations can never fully represent a complete reality. To use a simulation effectively, one must experiment and compare simulation against simulation, not against reality. This tool, like any other, is a best-guess as to what should happen based on a given design agenda with the provided data. Any form of representation is inherent with information loss. Moving from the abstract space to a reality will require additional information, that could expose missing assumptions not captured in the abstraction. Just as a drawing is an intent to achieve something, the reality will always differ.

        The integration of an AI, specifically one that learns directly from actions in the Game, was an attempt to model how a naive user might approach the same problem. While the effects of both a human and AI user learning and playing in the same space are hard to objectively

extract conclusions from, the hope was that the learning of both could be enhanced by this interaction.


Use Case

The Designer would use this Game for a number of purposes, but primarily as a learning and experimental tool. This walk-through demonstrate the core functionality of the Game:

Walkthrough

The Designer loads a map of landcover data of a relevant area of inquiry, and initializes the Game. After the Game World is loaded, the Designer can adjust the weights of all of the City-Data parameters to indicate what the priorities are, or should be, for the Designer and the AI to work with and evaluate against. These can be changed at anytime. Then the Designer may choose to alter the configuration of the AI system's hyperparameters and model-specific parameters. At this point once the AI and score-weights are configured, the Designer can then choose to participate in the Game through a number of modes. The Designer can play the Game without AI intervention, with AI "hints", or with the AI making moves in the Game too. Along with each of these modes the Designer may configure the AI to interpret Player-moves as training cases with some weighting of success or importance.

The Game itself can then be played and turns take place either through time or through moves made in the World. Throughout the Game, each turn generates and records the City-data and scores as computed with the Designer's weighting taken into account. This way the Designer and AI can see how the score may rise and fall with moves or the consequence of moves they make.
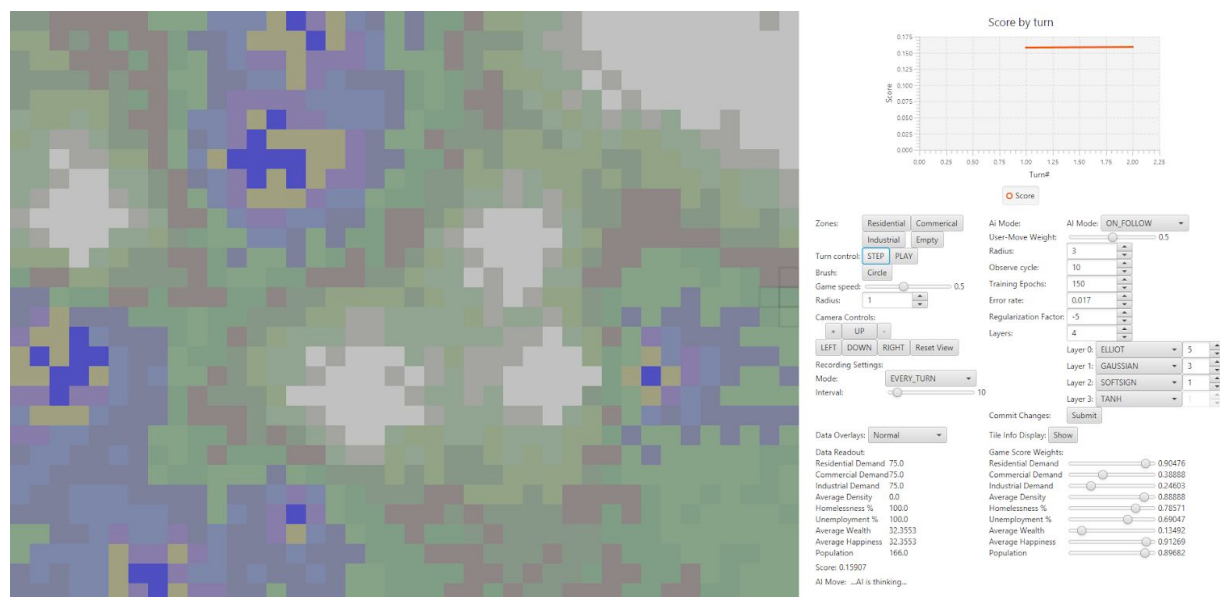
The initial state with randomly generated world.

Object Model

World

　　The `World` object serves as the `Model` implementation. `World` is composed of a collection of `Tiles` which is the representation of the land area and a `City` which contains internal attributes and metrics about non-spatial data. Actions initially pass through this object which further cascades the action, or other computation to its delegates. The `World` object controls the life-cycle of the `Tile` array and `City` object.

City

　　The `City` serves largely as a collection of `Persons`, governs the life-cycle of `Persons`, and packages relevant metrics of city properties which might be transmitted to the `View` or `AI` system. The `City` object can be queried for the `CityData` object which is used to produce the score when used with a `WeightVector` from the `View`.

Tile

　　`Tiles` model the land/terrain of the game-map, which has various properties determined by its type: material value, base land value. Some terrains are not able to be occupied by zones. `TileTypes` also have maximum allowable densities also related to this notion of terrain. The other value attributes also affect the growth of different `ZoneTypes` on those tiles.

Zone

　　`Zones` are the object that Players can directly manipulate, which determine what occurs on a `Tile` in the `World`. `Zones` have four types: `Residential`, `Commercial`, `Industry`, and `Empty` (only type that does not permit `Buildings`). `Zones` contain the `Building` object, and control its lifecycle. `Zones` and their types compute a growth-value, which is determined each turn based on initial `Tile` conditions and other dynamically produced values, like pollution or augmented land values as the result of other favorable zones developing nearby.

Building

　　`Buildings` are entities that have a `Density`, and occupants. This object has two primary abstract subtypes: `PlaceOfWork` or `Home`. An occupant in a `PlaceOfWork` is employed by that building, whereas occupying a `Home` gives that person a residence. These are important properties to maximize (should the player value person-related metrics). `Buildings` modify the `Wealth` and `Happiness` of their occupants depending on the type.

Person

`Persons` are objects that are controlled by the `City`, but can be associated with at most two `Building` objects in the `City`. This is a tricky design issue because the `Person` is now coupled to two larger classes, and could be simultaneously referenced in three separate collections. Enforcing that the `City` is the primary object of a `Person` object's life-cycle, it follows the `City` is the ultimate determinate of when and how `Person` objects are removed, and propagate removals from other `Building` collections to ensure the `Person` is fully dereferenced. When a `Building` is removed or degrades however it is responsible for altering the attributes of the occupants affected. The person still lives in the `City`, but may be removed from a `Building` for different reasons specific to the `Building`.

Persons contain notions of `Happiness`, `Wealth`, and track its state and maintains pointers to `Buildings` - for employment and housing. `Persons` also have age which strictly increases with each turn.

Rules and Behaviours

World

The `World` initialization has a couple methods method for producing simple notions of terrain for the game-map. The first initialization method can interpret Geotiff images from NLCD 2011 LandCover classifications. Beginning with sampling the image at the same resolution as the world `Tile` array, the pixel at that location is correlated to the nearest matching classification to the NLCD 2011 LandCover legend. This then determines a fixed set of `TileTypes` that the `Tile` could be. Next, if the user chooses, the `Tiles` that are shown as having existing development can be initially zoned and grown to reflect the land-cover data. This allows users to load an existing city from land-cover data, either with the `City` or with just the terrain types. This process is subject to error, reading an image, incorrect format, path, or other user supplied parameters. So as a default behaviour the world can also be generated as gradient of terrains between randomly generate mountain peaks and waterbodies.
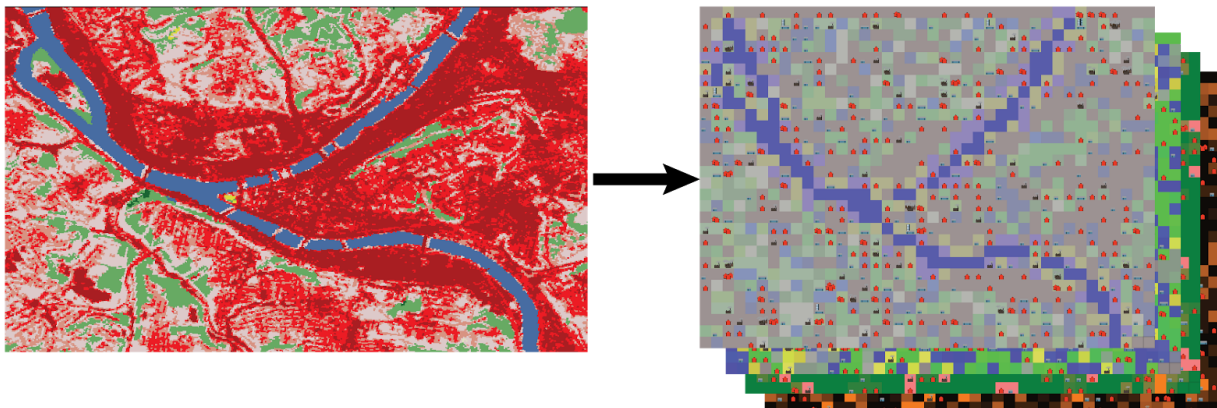
Land cover data on the left for Pittsburgh, PA and the World representation in the Game

Tiles

After initialization, most behaviour is delegated. The `Tile` largely serves as a collection of attributes and pointer to its constituent `Zone`. The type of the `Tile` is used when computing the growth-value of different `ZoneTypes` on such a `Tile`. The `TileType` contains the intrinsic parameters of the `Tile`, like material value, base land value, and density parameters. The growth of `Industrial` zones are heavily affected by the Tile's material value, whereas `Residential` zones are affected by land values.

Additionally there are accumulated values on top of the intrinsic parameters. The `Tile` can become polluted, or accumulate or lose land value over time. Every `Zone`, and the `Buildings` constructed on them have effects that are applied to their `Tile` and neighboring `Tiles`. These attributes are proportional to the `Density` of the source `Building`, and diminish over the range of their application. If a large `Factory` moved in next door to `Residential Buildings`, the pollution will quickly diminish the land values of neighboring tiles, and the residents will move out.
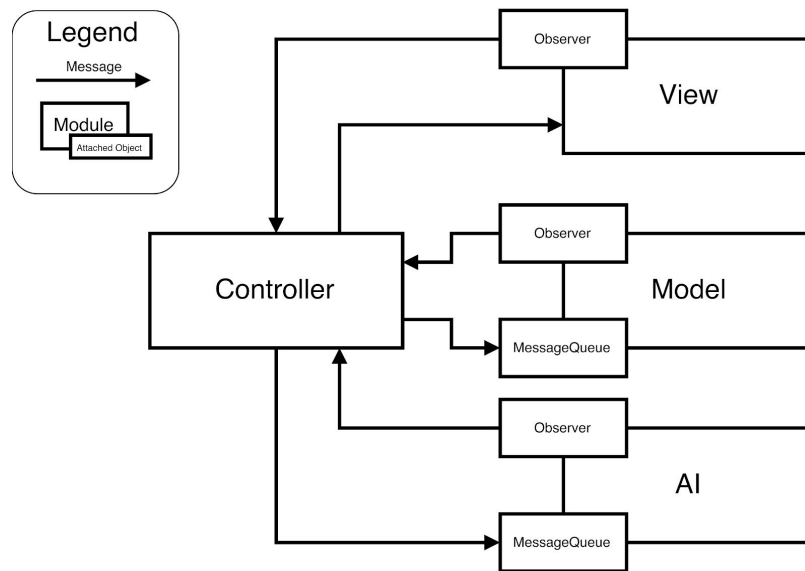
Zones

`Zones` compute and maintain a growth-value. This growth-value determines the `Density` level, and therefore effective occupancy of the buildings on this tile. A `Zone` will not advance to the next stage until it can afford to grow based on this value. The growth value is calculated as a result of the `Zonetype` and the base and accumulated tile properties (like pollution and land values). Different `Zonetypes'` growth-value are affected differently by different tile properties. `Residential` suffers greatly from pollution on its `Tile`. `Commercial` is more tolerant but still suffers from slowed growth when exposed to pollution levels.

Buildings

`Building` behaviour is dictated by its hosting `Zone` which controls its lifecycle. The computation of the `Density` change as the result of a change to growth-value on the `Zone` is delegated to the `Building` of the `Zone`. `Buildings` do manipulate the attributes of its occupants. The amount they increase these factors is based on distance between `PlaceOfWork` and `Home` (commute), as well as the `Density` (productivity or growth-state) of the `Building`.

Citizens

`Persons` at every turn in the game have a few simple behaviours: they attempt to find a job vacancy if they are unemployed, they attempt to find a home if they are homeless. If they have a home, their happiness increases. If they are employed, their wealth increases. If these two factors are satisfied, they have a chance of spawning additional `Persons` to the `City`. When their age exceeds some maximum, they are removed from the `City` to model a simple notion of lifespan. If their happiness and/or their wealth decreases beyond a certain amount, they are removed from the `City` to suggest emigration of citizens that are displeased with their situation in the `City`. This leads to interesting effects of decay if a city grows beyond its means or does not balance the demands of its citizens well.

Legend

Message

Module
Attached Object

Observer

View

Controller

Observer

Model

MessageQueue

Observer

AI

MessageQueue

Software Architecture and Concurrency

Architecture

      This game utilizes a Model-View-Controller architecture with an additional AI module each of which are on separate threads and are linked by observer patterns as a way to send messages to work-queues on each other's threads. With this pattern everything is communicating with or to the Controller, which will also pass messages, or execute other communications to other modules based on data it is notified to. The controller also contains the main game loop, turn-cycles which is messaged to the Model and AI modules.

      The AI module is much different in implementation than the View, but the coupling to the controller is very similar.

Design issues

      Responsibility for manipulating the `Person` object's properties given its two-way association with `Buildings` and the `City` was important to ensure was handled carefully. Either object could propagate an event that causes the `Person` to be removed from itself, or both the `City` and `Building`. Because `Zones` can be routinely wiped out, making sure that `Persons` that once occupied a now null `Building` are not still indicated as occupying that building. Second, `Persons` may leave a `City` through death or discontent. This behaviour is controlled and evaluated by the `City`. Thus propagating the removal of a `Person` through `Buildings` they once occupied must be ensured. Otherwise the `Buildings` will remain occupied by `Persons` not under the control of the City. This is the danger and tradeoff of having this 2-way coupling and behaviours. However we can reason about this behaviour as it relates to the domain-model.

      Architecture erosion was imperative to limit to fight coupling between modules that were not the Controller. As variety of functionality in various modules were developed, hooks to pass data or query another module for data began to bloat the interface.   Implementing an observer

design pattern for passing data between the modules early on helped avoid this issue. It was found to be advantageous to create custom struct-like objects to be generalized data packets that had subtypes that determined their purpose or ultimate destinations. This allows the Controller to pass messages by checking high-level types of the data and then routing it to the intended recipient.

This decoupling and event-based notification ensured that an action from the View would not execute a world update action on the View thread. This helped keep the GUI alive during model updates or AI training cycles. While the time-steps of each turn were discrete and locking enforced a procedure for each turn with the Model and AI, it still allowed for asynchronicity of AI and Player actions as they arrive on the Controller's notifications.

Concurrency model

Each module, Model, View, Controller, and AI are each on their own threads. The GUI utilizes the JavaFX gui-framework, which requires its own special thread singleton that it controls for rendering purposes. However, if there are asynchronous instructions to be passed to it, there are Runnable tasks that can be added from other modules so that the JavaFX view thread can execute them when it schedules the task. The Controller is the coupling node between AI, Model, and View, and as such observes all three, and can pass messages to each of their queues to be processed on their own control threads.

The Model and AI since they are parsing or modifying a large grid or array of Tile values, this becomes an embarrassingly parallel cellular automata problem to some degree. To take advantage of concurrent actions over an array of tiles, we subdivide the problem and fork off these tasks to workers that can scale based on the size of the world. The Model executes updates each turn, on each tile, which update their constituent values. However this is not a perfect cellular automata problem as Tiles may have Buildings that emit effects to their neighboring Tiles as well. This creates race conditions of concurrent non-atomic modifications, even to primitive values. Simple synchronization is enforced over these statements, which sacrifice some of the performance gains of the mass parallelization for correctness. The performance of this is still much greater than the sequential method and can handle larger world sizes without quadratically increasing in computation-time.

Meanwhile, the AI can be training on its own thread, and the View running undisturbed. This opens the possibility that the game and Player can act faster before the observed world-state according to the AI can be acted on. If a player action or AI action (in a non-paused Controller state) notifies the Controller's observer after the turn has passed, it is possible that the action may occur based on an observation of a now old-state. Even human Players' observation-act time is non-zero. This is accepted behaviour with all games with accelerated time-based turns, and a Paused turn-mode is provided to those that would like to act more deliberately per turn. This concurrency model, using work-queues to process these messages, ensures that the model will apply the actions of the AI and/or Player in sequence of when the messages were received.

AI interface and module design

The design of the interface of the AI module, as a high-level boundary between all of the neural network internals, but the game logic was difficult to decouple. This is particularly challenging because there needs to be a way that the Model information becomes an input vector, and an Action can be formulated from an output vector. The specific logic and interpretation of Model data to normalized floating point numbers was easy to separate, but the formulation of an Action requires knowledge of Zoning, and world positions. As a way to follow the initial model of the AI being "another player" it makes sense to have the AI emit Action objects (as `ViewData`) to the Controller, just like how the Player does via the GUI.

The characterization of the AI system as "another player" makes sense to characterize its output, but its input is notably different as well as its interaction with the Controller. Given alternative implementations, this could be furthered decoupled.

With the strategy to create multiple subnetworks, the opportunity to create an inheritance model for the basic network internals and configurations, and a pseudo-composite pattern for the networks, arose. A complete composite pattern does not work in this case because the nature and behaviour of the sub-nets were not the same and had specific purposes. This specificity is an unfortunate tradeoff to how the AI system was internally designed. However trading off cleaner design of a more generically applicable implementation gave us increased performance as the networks were specifically oriented to the particular sub-problems. However wherever possible, common functionality or parameters were abstracted to increase reusability and maintainability which proved of great utility when implementing the user-configured set of hyperparameters for the neural networks. `AiConfigData` is the data-packet that used to cascade hyperparameter changes to the initialization of all the constituent neural networks.

A number of interfaces characterize the behaviours of the various MLPs used in the AI module. These all cascade down through the highest level object that governs the life-cycle of all the other sub-networks, the Merge Network. With this design, we also have the opportunity to cascade hyperparameter changes relatively easily by isolating all of the neural network and training data objects to an abstract class for all of the networks regardless their specific purpose. All subnets inherit from the abstract network class, extending and implementing more specific interfaces, like the Mapper behaviours. All of which is described in the AI System chapter.

Data Layers

A lot of information is present in each `Tile` that is imperative for the player to be able to understand. To provide a more visual and easily interpreted report of this information, data-layers views were implemented.

These data-layers provide switchable view-modes to see the `World` and all of the `Tiles` colored according to some attribute including: density-level, land value, pollution, material value, and AI-Policy map.

The AI-Policy map is a view of the `World` as the AI-system "sees" it. This view runs a query through the AI module, given the current World, and the current Zone selection (a partially

formulated Action). The user can select different `ZoneTypes` in the control panel, and see where the AI system scores `Tile` locations higher to place such a `ZoneType` (at that particular time). The highest scoring tile is shown in cyan, and the rest form a gradient from pink to dark gray.
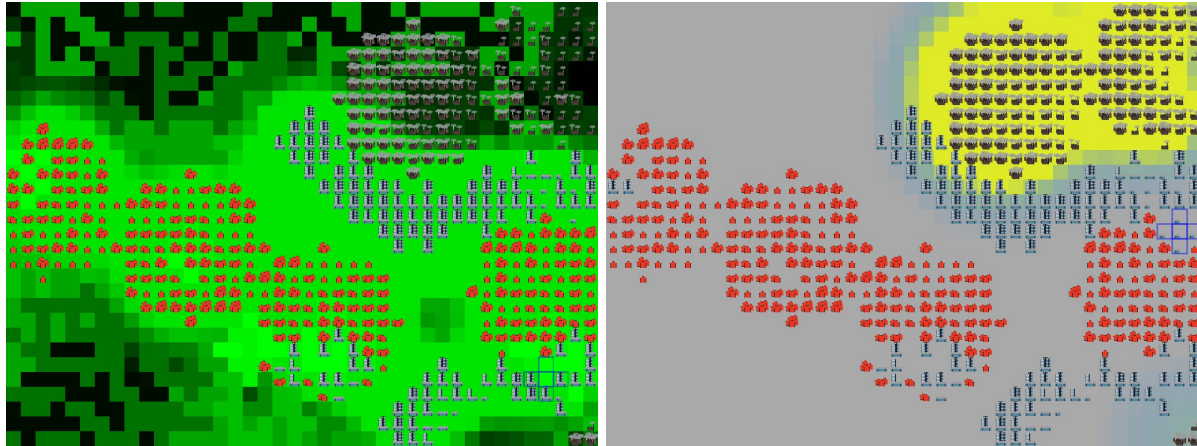
Land-value shown Left; Pollution shown Right.

Policy-map Left; Material-value Right.
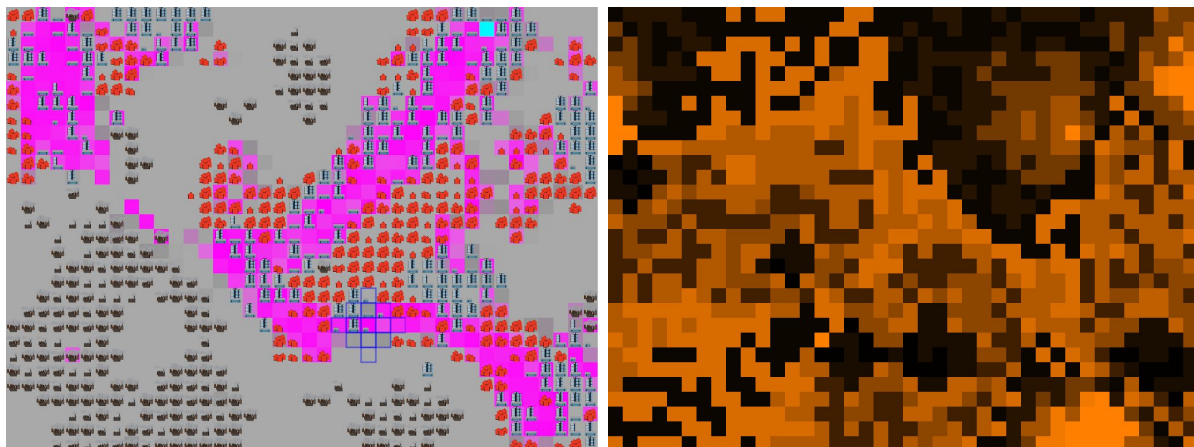
AI Modes

We discussed the Game as its own standalone tool for solving design problems, just as any other software or media serve as ways to represent and solve the problem, and for the designer to learn, react and iterate through those tools. In an attempt to cast this as a multifunctional tool to adapt to the various needs and desires of the user, several modes are implemented to allow various interactions between the user and the AI, all at the discretion of the user.

On - The AI system is actively learning, and acting in the game space.

Assist - The AI system is actively learning, and will compute best-moves to make in each observe-act cycle. However the move is not committed to the Model, but only highlights the tiles in the suggested Zoning color, and reports to the interface the text-based specification of the move. The user is free to follow this suggestion, or ignore it.

Off - Of course the user may want to play the game without any interaction or performance reduction with an active AI system computing on each turn.

Follow - Follow mode is a modifier to the On and Assist modes where the AI will learn directly from User-moves (and its own). The difference here is that the User can score their own moves arbitrarily and independently of the Game scoring logic and user-determined weighting. Essentially this provides a more direct way to influence the behaviour of the AI system.
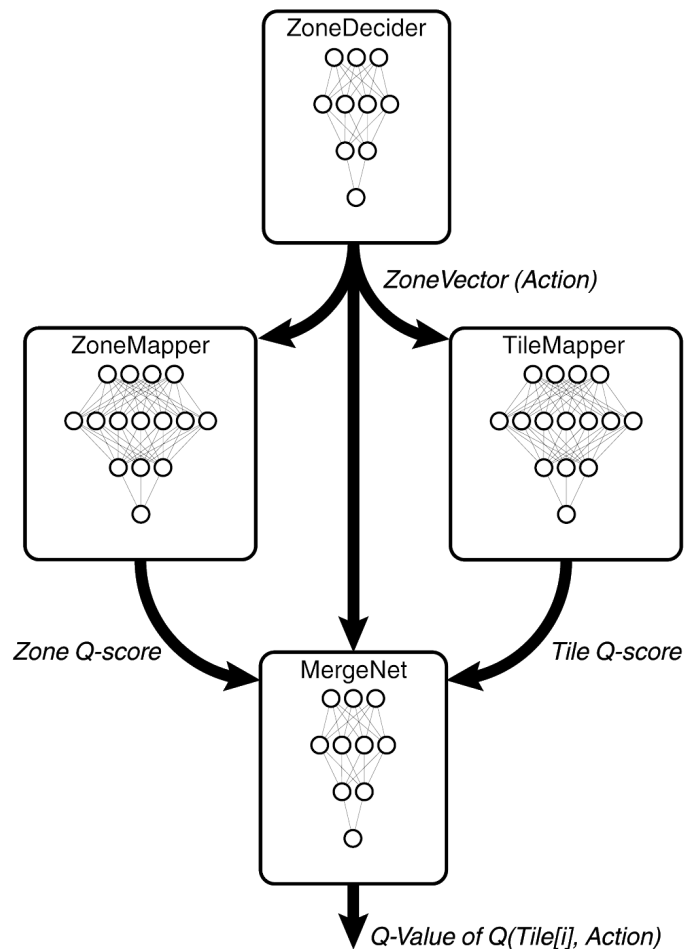
AI system

AI System Description

The AI System is composed of several Q-Learner MLP's each structured around a particular subproblem within the game logic. This is all wrapped inside a larger interface discussed in the Architecture. As each turn cycles, the state and recent action is passed to this interface where either the AI system uses it as a case, stores the world-state, or ignores it all and simply takes note of the passage of the turn.

Subnetworks

The purpose of subdividing the neural networks was to divide the magnitude of complexity of from a singular network, to provide a simpler representation of the world-state to each network, and have a focused purpose to the Q-Value's effect on the ultimate action to be taken. Subdividing the problem also radically reduces the search space and complexity, making the possibility of convergence plausible in the scope of a turn.

To guide the subdivision, we supposed a process a designer's decision making might take. First, one decides with what zone they should add to the city, based on city data metrics they observe on the feedback panel. Then they might select a location for the new zoning, looking at local tile data and current zoning conditions as they are. This is certainly not the only way to approach the

ZoneDecider

ZoneVector (Action)

ZoneMapper   TileMapper

Zone Q-score   MergeNet   *Tile Q-score*

Q-Value of Q(Tile[i], Action)

problem, and specifically allocating networks to each of these in a particular order and purpose forces this to be the applied method. However a singular deep generic network would have the complexity of all possible actions to consider and score, convergence and learning therefore suffer greatly in performance.

This subdivision is able to allow each Q-learner to attribute a Q-value to each set of possible actions for its scope. The `ZoneDecider` picks of 4 possible actions, which one is best, determining the `ZoneType` for the ultimate action. The Mapper-type MLPs walk the entire world array of Tiles, observing their attributes, and neighboring tile attributes, as the input layer, and scoring that Tile with a Q-value based on how it would affect the global score if the `ZoneType` selected by the `ZoneDecider` were to be placed in that location. The Merge Network takes the Mappers array of data, and further filters their output to come to a singular value for each Tile. The Tile with the highest value becomes the target of the action.

ZoneDecider

The `ZoneDecider` interprets a state vector produced by `CityData`. This is the same `CityData` that is weighted and scored by the user. Essentially the goal is to look at the state of the city (not any one, or collection of, Tiles) and determine the best `ZoneType` of the next action to add to the city, regardless of its placement.

The action-space given a single state representation is only the length of the vector of possible `ZoneTypes` to choose from. In the game's current implementation, this is 4 (`Residential, Commercial, Industrial, Empty`). Q-values are produced for the given state with the 4 possible action choices, the highest output (greatest increase in score as a result of such an action) is chosen.

This choice is then propagated to other `Mapper` networks in the AI system as the assumed `ZoneType` of the action to "apply" to each tile in the world-state. The Mapper-type MLP's run the action against every tile input and the tile with the highest Q-score becomes the target of the action.

ZoneMapper

The `ZoneMapper` is the first of two Mapper-type neural nets. These are Q-learner MLP's that apply an action, to every sub-state (or tile) in the World. Each Tile is Q-scored provided the action of the `ZoneType` from `ZoneDecider`. The only thing that differs is the input layer vector, and how it is derived.

The `ZoneMapper` represents each tile as a Zone-Vector a vector of 4 binary values, where only one is "on" or 1, determined by the `ZoneType`. This is the same vector-representation of the action, as a zone-vector.
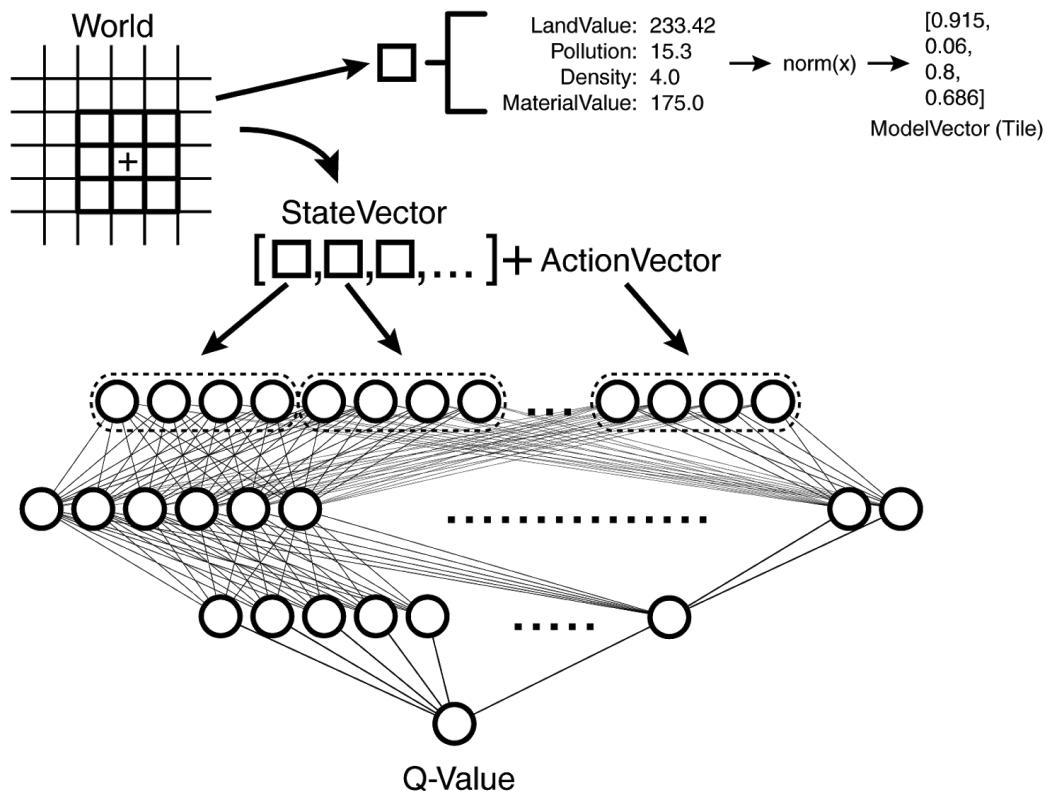
TileMapper

  The `TileMapper` is the same Mapper type as the `ZoneMapper` with a different input vector, and derivation of input values.

  A `Tile` is represented by a few key attributes. These attributes include: achieved `Density`, land value, material value, and pollution.

Merge network

  This MLP merges values of each `Mapper` for each `Tile` value. This network does the least work and computation, but can drastically change placement strategies for the application of a move on the world-state. It too is a `Mapper`, and produces a map of Q-values. The input-layer is simply the Q-score of the tile from the `TileMapper`, the Q-score from the `ZoneMapper`, and the action-vector. From this the output Q-score may balance the influence of one `Mapper` type against the other, depending on the `Zone` chosen by `ZoneDecider`, or may gradually change policy over the course of the game, shifting to favor to current `Zone` distributions over `Tile`-attributes.

Hyperparameters & AI Parameters

  There are a number of customizable hyperparameters that can be set upon initialization of any ANN. Notably the number of neurons on each layer, number of layers, activation

functions of those layers, target error rate, and max training cycles (in cases where error did not converge to meet error target).

However with this particular application of this AI system in this particular game environment, there are a few other considerations and parameters. These are context-specific parameters. While they are used to alter the actual network sizes, or how the AI interact with the game specifically, they are unique to this implementation. The "Hyperparameters" are the common structural parameters of any ANN. They are described in this context as they appear in the game and may affect the AI system and performance within the game.

Game AI Parameters

Observe Radius

This would determine the manhattan-neighborhood of tiles to "observe" in the input layers of the Mapper subnetworks. This parameter would scale the size of the input layer of the Mapper networks, quadratically. The radius could provide opportunities for the Mapper networks to make more informed observations about local surroundings and provide that many more opportunities to learn higher level patterns. However the tradeoff is performance. Because it scales the input layer, the layers beneath need to scale to avoid significant information loss. The balance of this is arbitrary and could be machine-dependent, or designer's time-dependent.

Observe Cycle

This parameter determines the number of turns to pass between Actions and Observations of score-change. This is critical in a sequential simulation environment. Because when an action is applied in this game environment, the resultant effects occur and continue to occur over a span of turns, the true reward-signal that could be derived may not show in a score-change for some time. This could also change over the course of the development of a City. Zoning an empty tile may quickly grow, but rezoning a polluted tile could take longer for the pollution to dissipate and land values to recover and then grow normally. Again, this is purely an issue of time. The computation-time of training on the observation is the same regardless how many turns one waits. However the observations that can be deduced from the observation is highly dependent on how long you wait to capture that change.

User-Move Weight

This relates specifically to the Follow modes. Should the aI system be thus configured, user's moves automatically get pushed to the AI interface with that score (regardless of what the move is and what the score may actually be). This lets the user influence the training of the system to try to encourage a particular behaviour. However, because this is just another training case, highly scored or otherwise, it is not a user-mimicry feature. Though it is possible with enough reinforcement that behaviour may replicate patterns the user is intending to create.

Hyperparameters

Layers

A Layer is a collection of neurons, that often have the same activation function, and are not connected to each other but only to neurons in other layers. In practice this is a parameter that trades off performance with the capacity for modeling more complex functions or behaviours. It is also shown that a single layer perceptron can also not model anything that is nonlinearly separable (Minsky & Papert 1988). However, more layers increases the number of steps involved in backpropagation, thus slowing the training process.

Neuron Densities

This parameter adjusts the number of neurons on a given layer as a factor of the Input Layer size. This is derived from general rules of thumb, which are highly debated. Generally speaking the layer following the input should increase in size, especially if it is known the problem is not linearly separable. There are some proposals about how to achieve this if the network is to precisely model some input data (Elisseeff, & Paugam-Moisy 1997). However this same approach acknowledges overfitting training data is not ideal for a network applied to cases outside of this set.

Activation Functions

These functions can radically determine the rate of learning and modulate potential saturation of nodes. There are also a number of follies, possibilities and tradeoffs. Most important to note is the domain of the input and output. The steepness of the curve can determine how quickly nodes activate, but could also easily saturate if the curves are very steep. If curves are steep, the ability to discriminate between values over a range becomes more difficult. Additionally, the computational complexity of the derivative calculation can drastically affect performance on training or backpropagation.

Learning Rate

This parameter is automatically calculated and regulated by the Encog (Heaton 2015) library's special propagation algorithm. Though it is worth mentioning this hyperparameter as it is central to weight-adjustment calculations during propagation. Essentially it is a number between 0 and 1 (often very small) that multiplies the computed difference of the current weight against what the propagated error needs to fully correct. If the weights are shifted to be exactly what the error indicates for that round of propagation, then it may step too far over a weight distribution that better fits the problem globally across the network. This naturally slows the process but forces training to explore the parameter space as to not step over a more optimal distribution.

Error Rate

Error is a target parameter for the training of the networks to achieve in a fixed number of cycles. Because the training data, and learned cases themselves, might mutually conflict

especially problems like the urban planning problem. This allows the training to halt if the training can not converge to a precise model of the data. Having a little tolerance in error may help the system maintain generality. This helps avoid overfitting. However too much error could produce an even more useless weight matrix in the network as the tuning of the network does not closely model anything. It is also possible that a given network can not model the data provided and properly converge on it. However if that is the case, then the problem is in too few neurons or layers to better approximate the function.

Regularization Factor

As a way to mitigate overfitting, a smoothing factor can be introduced to reduce the change in the weight adjustment over a training cycle. Essentially this parameter is subtracted from the learned-change in the weight (which is already modified by a learning rate). Because the learning-rate multiplies the difference in actual-weight and target-weight (according to error calculated through backpropagation). This applies a constant which reduces this magnitude evenly across all weight adjustments. This slows the learning process and minimization error, but mitigates overfitting.

Max Training Epochs

As a practical concern, there are a number of cases where the configuration of the neural network may not converge under the target error rate. This could be due to a poor MLP architecture (too sparse or shallow), bad activation function combinations, too tight of an error rate, not enough data, etc. To provide an escape for the AI system, if training fails to converge after some number of cycles, it will cease. If this is too low, a network that could converge instead is forced to stop short of a proper model.

AI System Design Challenges

The AI system needs to be able to interpret a representation of the World data, and compute some result to determine an Action to be taken. The engineering behind this was an exercise in understanding how to represent values and transform them between domains. However, this more importantly was understanding how the representation, and what to represent, greatly affected the ability for the system to learn. Including some features for completeness would increase the dimensionality of the problem, and reduce the ability for the learning system to converge.

There are practical concerns about the size and shape of a giant or deep NN architecture. As the problem is complex on its face, one could either ignore a great deal of data to simplify the input, or sparsely structure the neural network, which would fail to approximate more complex functions that fit to finer-grained behaviors. The problem essentially with more parameters, despite their ability to model higher orders of complexity, may still: A) never converge; B) not be enough space-time to converge in training. Because of the embedded, real-time application of this system, and the uncertainties of learning producing meaningful optimization in some realistic number of turns, a leaner, more modular, approach was taken.

Reinforcement learning also presents some problems. Q-learners are "exploration insensitive" (Kaelbling et al. 1996), they take the optimal path first and always. Because this is a time-series set of actions on the same space, if a move was found to be optimal, and the city did not change significantly, the next turn the same move would prove to be just as optimal. To prevent stagnation, or action-cycles, a brief action history was created, effectively a short-term memory. This enforces a naive heuristic for exploration. If the same Action is found to be optimal in its short-term memory, it is forced to explore alternatives. There are still many considerations for how to tune the behaviour of the system in very-late game scenarios. One could imagine a point at which abstention is the optimal move. However, there is no definitive way to determine if the Game is at a complete "end-state" as any slight imbalance in parameters may cause the city to decay slowly over time, in which case abstention will no longer be optimal. There is also no known period of turns to wait in order to detect this change.

This brings up another issue with respect to time. Because the Q-learner system requires computing a reward, but the score changes and trends over many turns as the result of some Action, it is ambiguous to determine what the true reward signal should be for the previous state-action pair that was applied to the world-state. To address this the Observe Cycle was introduced to allow this parameter to be changed or adjusted to balance the tradeoff of delaying feedback for potentially more informative Q-value error calculation.

This quickly becomes another learning and optimization problem. There are a number of projects that are exploring the automatization of optimizing, not only hyperparameters of a learning algorithm, but dynamically choosing from a set of machine learning algorithms to optimize results (Thorton et al. 2013). While the discussion of the tradeoffs of different strategies and the particular tuning of some hyperparameters is of some interest, it is well within the horizon that these issues will reach a point of resolution and automation in the near future as a standard part of any learning system. What is manually tuned now will soon be automated. Thus providing an interface to allow these to change dynamically at runtime then sets the stage for these parameters to change through an automated system. This differs from offline-trained systems where the hyperparameters may be static once the optimal is found, trained, and then set loose on real data to classify. For a continuous learning system, the hyperparameters too (not just the weights/parameters) must also account for the changes to world-assumptions presented by the user.
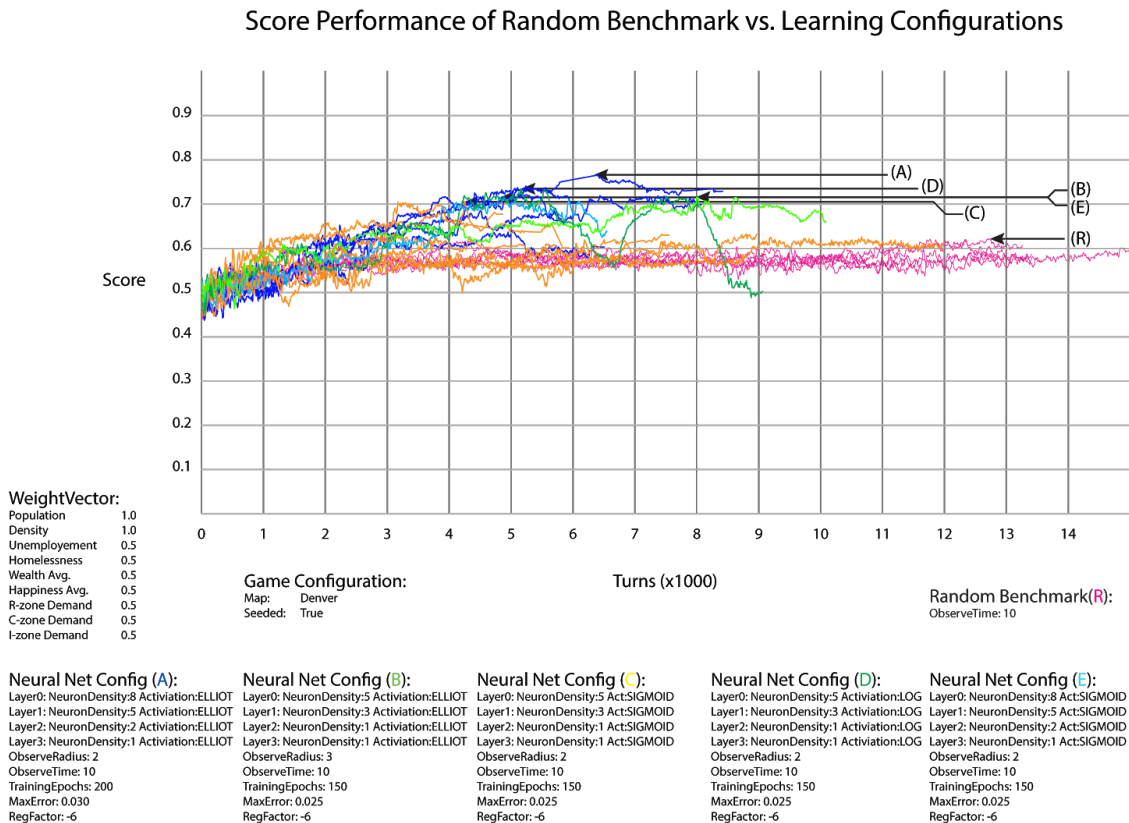
Findings & Contributions

Findings

Score optimization of Learning AI vs Random Benchmark

It is noted that with most "early game" states, any move is usually going to produce an increase in score. Testing against random, turn for turn, will always favor random in a pure

score-based observation in the early-game. However, once the network begins to "mature", acquiring a health set of observations and adjusting weights to reliably act on learned patterns, the learning system begins to outperform the Random Benchmark. Random can quickly fill a map with zoned tiles, but the subsequent actions that occur can be self-defeating, erasing previous progress arbitrarily. Thus the score seems to hit a ceiling and oscillates. With the learning system, growth is slow and deliberate.

Score Performance of Random Benchmark vs. Learning Configurations

WeightVector:

Population	1.0
Density	1.0
Unemployement	0.5
Homelessness	0.5
Wealth Avg.	0.5
Happiness Avg.	0.5
R-zone Demand	0.5
C-zone Demand	0.5
I-zone Demand	0.5

Game Configuration:
Map: Denver
Seeded: True

Random Benchmark(R):
ObserveTime: 10

Neural Net Config (A):
Layer0: NeuronDensity:8 Activiation:ELLIOT
Layer1: NeuronDensity:5 Activiation:ELLIOT
Layer2: NeuronDensity:2 Activiation:ELLIOT
Layer3: NeuronDensity:1 Activiation:ELLIOT
ObserveRadius: 2
ObserveTime: 10
TrainingEpochs: 200
MaxError: 0.030
RegFactor: -6

Neural Net Config (B):
Layer0: NeuronDensity:5 Activiation:ELLIOT
Layer1: NeuronDensity:3 Activiation:ELLIOT
Layer2: NeuronDensity:1 Activiation:ELLIOT
Layer3: NeuronDensity:1 Activiation:ELLIOT
ObserveRadius: 3
ObserveTime: 10
TrainingEpochs: 150
MaxError: 0.025
RegFactor: -6

Neural Net Config (C):
Layer0: NeuronDensity:5 Act:SIGMOID
Layer1: NeuronDensity:3 Act:SIGMOID
Layer2: NeuronDensity:1 Act:SIGMOID
Layer3: NeuronDensity:1 Act:SIGMOID
ObserveRadius: 2
ObserveTime: 10
TrainingEpochs: 150
MaxError: 0.025
RegFactor: -6

Neural Net Config (D):
Layer0: NeuronDensity:5 Activiation:LOG
Layer1: NeuronDensity:3 Activiation:LOG
Layer2: NeuronDensity:1 Activiation:LOG
Layer3: NeuronDensity:1 Activiation:LOG
ObserveRadius: 2
ObserveTime: 10
TrainingEpochs: 150
MaxError: 0.025
RegFactor: -6

Neural Net Config (E):
Layer0: NeuronDensity:8 Act:SIGMOID
Layer1: NeuronDensity:5 Act:SIGMOID
Layer2: NeuronDensity:2 Act:SIGMOID
Layer3: NeuronDensity:1 Act:SIGMOID
ObserveRadius: 2
ObserveTime: 10
TrainingEpochs: 150
MaxError: 0.025
RegFactor: -6

Learning rate and configurations

Configurations of the neural networks largely follows what is found in literature. If the network is too sparse, it is too simple and often can not model complex relationships. This usually results in an inability to converge under error tolerances. Activation functions too can greatly affect the learning rate if properly configured. Users do have the option of mixing types, and sometimes to useful effect. However some can drastically shift the domain of the output, causing other activation functions to "saturate". This also provides a way to slightly tune performance as some activation functions may have a complex derivative for computing error through backpropagation.

Besides the layers and neuron densities, the target error rate and max training epochs help calibrate performance and overfitting issues. By allowing a loose error rate, and/or higher

regularization factor, we can reduce overfitting and excessive training epochs trying to fit under tight error tolerances.

Most importantly, if a learning system is to act in a space that has changing evaluations over a solution-space, it follows that the learning system itself might need to be restructured to better be able to fit the new metric space that it is exploring.

In practice, there are more configurations (with the number of options and parameters provided) that resulted in terrible performance, than it did in novel idiosyncratic arrangements that out performed conventional strategies. The ability to rapidly customize configurations of these parameters largely leads to useless networks that often can not converge under typical error rates. Most reliable success was found using conventional selections of network density and depth, along with typical sigmoidal activation functions. However, it is impossible to rule out that some problem might be better modelled by some other arrangement of these parameters that have not yet been discovered. Providing the flexibility to adjust (and in the future optimize) these parameters is the only way to achieve that.
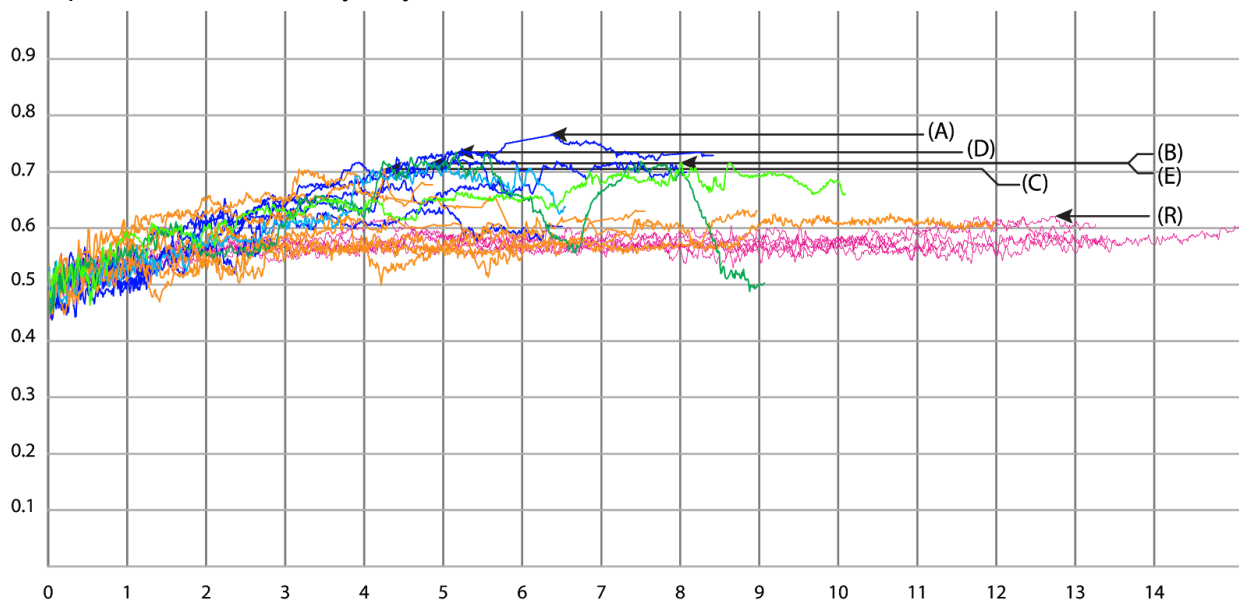
Qualitative observations

The ambition with the software artifact was to see if there was some observable high-level behaviour that was able to take into account intrinsic game rules and behaviours and how they affected the play environment. Just as a player learns to play SimCity, by trying something to achieve a goal, so too the AI system (following a reinforcement model) attempts the same thing. Specific advantages of certain Tiles or pollution tolerance of Commercial versus Residential are all programmed to create a slight asymmetrical advantage that could be observed in a City that takes advantage of these properties. However the complexity of these interactions make the observation of these behaviours particularly difficult to distinguish vs. a random or lucky guess.

The Policy-map Data layer is an attempt to provide an insight into how the AI system sees the world. The Policy map lets the user see for a given Zone, how the AI system scores each tile, and for a given AI move, how it scored the map. Using this as a way to more objectively make observations about the learning progress made on a high level is an important tool, and does shed some evidence on this progress.

Early game moves tend to value TileMapper outputs more heavily. Industry Zoning is applied to Tiles with high material values, and Residential on Tiles with high land values. Also, clustering of types becomes common. However the relationships between clusters is something that takes longer to "learn" as the negative effects of Industry near Residential occur over a number of turns.

Contribution

Feasibility and Role of AI in Design Environments

Existing tools that operate at a component level of the design process are ubiquitous. Their utility is that of anything among a set of tools. Each has a purpose and limited scope of utility. Worse existing technology integrated into design environments are just beginning to scratch the surface of Machine Learning techniques. These tools, have influenced a paradigm of design that is still in the throes of accepting a clear definition (See fluctuating definition of "Generative Design"). What plagues this methodology is the designer's task of supervising the process and taking the role of parameter-tweaker. Some of these tools, like Genetic-Algorithms, begin to automate the parameter-optimization process. We see techniques that offer advantages of over meta-heuristics like GA. However, the problem exists in how the environment presents data to a learning system, how training is performed, how data is "labelled", availability of data, etc.

We present an argument which clarifies the role of the designer, learning system and the necessary elements of a cohesive environment for both to produce meaningful results in the objective of solving design problems. Unfortunately, we recognize the overhead in the creation of bespoke environments to accomplish this. To present an avenue of future engineering work, a framework that controls the coupling of design-games and learning systems will be discussed below. Given this framework, if one can describe the problem in a way that can be presented as *closable*, where the designer can control and dictate the mechanism of evaluation in some environment, then a learning system can aid in the exploration of this space.

What designers gain from this is reduced evaluative-workload. Essentially the *closable* principle is simply a way to encode an evaluative policy into a learning system. Properties of the learning system allow it to model this space to some degree of approximation, and therefore can evaluate results and actions in this space as the designer would. Additionally, with automated self-evaluation and self-correction, the entire cycle of iterative solutions is automated and therefore can rapidly explore alternatives. Any brute-force algorithm can enumerate many

solutions. However, we have seen where these fail, the solution space of a design problem is one such space. We require a search that can apply principles to drastically reduce the space of exploration, and direct exploration in a manner that is reliably increasing in fitness. A learning system is such a mechanism to automate this search of better alternatives in a more practical (feasible) manner.

The Framework

Despite the software implemented only being a prototype of a design game with an AI module, the demonstrated value from this comes in the form of a framework that handles the coupling between a game system and an AI. Framework design is particularly problematic as every decision on what is and is not provided in the interface can drastically restrict functionality or the space of possible implementations that can utilize the framework. How much responsibility belongs to the framework and how much remains client-side while still trying to ensure that both the game and AI have necessary data is a challenge.

What we gain from the framework however is the functionality of being able to reliably couple a learning system to a game, regardless the implementation of either, and the interface to allow dynamic alteration of scoring algorithms at runtime. This means open games could be implemented modelling design problems, another client may deliver a learning system, and the play of the game can be scored and altered by the player to suit their needs and to further control the behaviour of the AI in the game.

Essentially the framework solves the *closability* problem for the AI system for any provided *open game* on the game client. Thus any *Design Game* could be implemented by domain experts that suit their needs and adapt to their process. The same holds for the AI system client-side implementations. The combinations and uses within any discipline explode from this point. The utility of such a framework could be the next step for practical machine learning applications in design practice.

Discussion

We have established the feasibility of how, and through what qualities, AI can be employed in a design environment. We did this by first classifying what about design problems in particular make them unappetizing to apply AI solutions to. Literature reveals that design problems are ill-defined, and have countless solutions, all of which may only partially satisfy the problem's criteria, and evaluating the fitness of a solution is ambiguous or otherwise undefined (Rittell et al. 1973). Given this problem, producing an environment that could represent the problem became an exploration in gamification, through which we borrowed heavily from precedent in existing game typologies (Wright & Bremmer 1989). Following contemporary research on machine learning as applied to games (Silver et al. 2016) we found relevant paradigms and strategies in machine learning techniques that fit well with our game model and learning objectives. We were able to tackle the "wickedness" of the design problem by providing a novel addition to the sandbox-game genre: a method for explicit self-scoring. This

allows the uncertainty about game-states to be known and scorable, by the policies dictated by the designer. Which in turn, the AI system could optimize within, learning from direct observation of the player's and its own actions in the game.

To some extent designers do this with their computational tools or other ML strategies, but through other means of explicitly setting the agenda and then running the system with the evaluative criteria set at compile-time. Our solution allows for the dynamic alteration of the evaluative step of the output from this learning system, at runtime, anytime. Naturally the tradeoff is the ability for the learning system to fit the changing model of the world, and how it is evaluated. The advantage is a seamless interaction of designer and AI, and the ability to rapidly iterate not only over solutions but over policies that propagate those solutions as being more favorable through new policies.

The demonstration through the software artifact has the unfortunate effect of creating a focalizer through which to see the future application of these ideas. However given the nature of the claims in the theoretical discussion, the evidence is in playing the game. In terms of the actual performance of the AI system, and solutions through autonomous or cooperative play are difficult to evaluate quantitatively. We establish it can improve on pure brute-force random, but this is a very minimal baseline. Future work may yet prove effective against more rigorous benchmarks and alternative algorithms.

There are additional matters that the argument presents but were not the direct subject of the thesis. The following section will enumerate some of the more noteworthy issues that could be, or currently are, areas of further inquiry.

The conception of materializing the design problem in a game form borrows from earlier research (Habraken & Gross 1988), and leverages ideas around "gamification" and "serious play"(Roos 1999). Leveraging the game model of thinking about a problem and solving it helps elucidate what the elements of design truly are, but in so doing does fix this in a ruleset. However, understanding design as an exploration of a constraint-space (Gross 1985) suggests that making some constraints fixed is necessary to bound exploration.

However this "representation" of a design problem presents an issue of information loss in the translation from reality to an abstraction. This is a common problem inherent to all forms of representation. We maintain plausible links, as there are feature similarities in design problems and games. There is a state manipulated and observed by an agent to achieve a goal. There are a limited set of actions that the agent can employ and constraints that can not be violated. These statements hold true for design and games. This domain similarity aids in the gamification of a design problem (Habraken & Gross 1988).

Learning systems may have issues proving reliable convergence with increasing complexities of problems. The thesis further complicates the matter by providing a means to dynamically invalidate previous training data. Since the action that causes the world-state to change is discrete and known, this could be a signal used to clean accumulated observations. However, the magnitude of the change, and relevance of past observations, is not known. Thus, there may be some benefit to introducing a clustering process over past data to allow the learning system to train on data found to still resemble current observations, thus allowing the

learning system to not abandon all progress in its continual approximation. Naturally this is a novel context and further research may suggest how to best solve such a problem.

We also make a great deal of assumptions of the user in the system. Rittell suggests that even the designer is not fully aware of the problem they are actively solving. We accommodate this through allowing real time interaction with the game policy weights and actions. It is natural that the assumptions the player holds about how her policies affect in game behaviour, and the behaviour of the AI system, may be inherently incorrect for some time. Translating "design-intent" into the policy weights, or the limited action-space of the game, injects further information loss or corruption. This is not unique to this media, but it does suggest that this process necessitates a dynamic interaction as the player comes to a more complete understanding of the effects (and causalities) in the game over time.

Following the same user-assumptions, the argument suggests that the player is achieving her goals and making them known to the AI system. We cannot of course make this guarantee. The argument is predicated on a well-meaning player/designer, but it is conceivable that the player could find an edge case of behaviours that creates high returns but the policy-weighting is used to manipulate AI behaviour, not teach it. Thus the weighting would not truly reflect designers' goals, but would be a means to an end. This is known as an "exploit": something allowed by the game mechanics and rules but results in unintended behavior. Exploits occupy an interesting space between "bug" and "feature", as it is not an error, but it is also not the programmer's intent. An analogy of this would be using a screwdriver as a hammer. It was not the intended use of the tool, but it achieves the user's goals. We acknowledge the complexities created by the design game, and the AI system, likely have this potential for exploitation.

It is an ambition of the thesis that if policy decisions lead to behaviours that might be unintuitive, this is the dynamic learning and discovery we want to promote in the AI and human designer. However this is difficult to prove and evaluate. Some of the qualitative observations revealed promising results, while many similar trials were not as compelling. A further ambition is understanding if either the human or AI actor benefit mutually in the learning process through interaction. Equally as difficult to measure, this may yet be the most important application of AI in design disciplines. The nature of the problem requires a constant learning process to understand the problem's true formulation. If a single learning agent is engaged in this process, there may be some measure of its learning convergence, or when some measurable achievement is reached. A hypothesis that can be built on this is: what then is the rate of learning of some non-singular quantity of discrete learning agents in the same space? Note we do not specify the nature of the learning agent, only that they act and learn. Understanding this with just humans is a challenge on its own, but to qualify this with AI systems suggests more difficulty in evaluation.

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