Intelligent Computational Media

Course overview, 2019

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Structure

- First days: lectures, some light exercises (neural network principles & architectures, optimization)
- Rest of the days: most of the time for hands-on exercises and individual/group work, possibly a short lecture each day

Learning goals

- Understand how common AI algorithms & tools work
- Understand what the tools can be used for
- Get hands-on practice of designing, implementing and/or using the tools

My goal has been to create visualizations that help one form a high-level understanding without mathematical details => helps you understand the math if you want to go deeper. This is often missing from textbooks and papers, with distill.pub publications as the exception.

Co-creating with AI – competition is futile

Even though many may feel threatened about such technology we have to learn to embrace it or face obsolescense.

Gatys et al. (2015) Neural Algorithm for Artistic Style

There’s been tremendous recent progress in artistic applications of neural networks.

For example, in this seminal work by Gatys et al., a neural network is given the two images on the left, and it produces the image on the right.

A Neural Algorithm of Artistic Style

Leon A. Gatys,[1,2,3*] Alexander S. Ecker,[1,2,4,5] Matthias Bethge[1,2,4]

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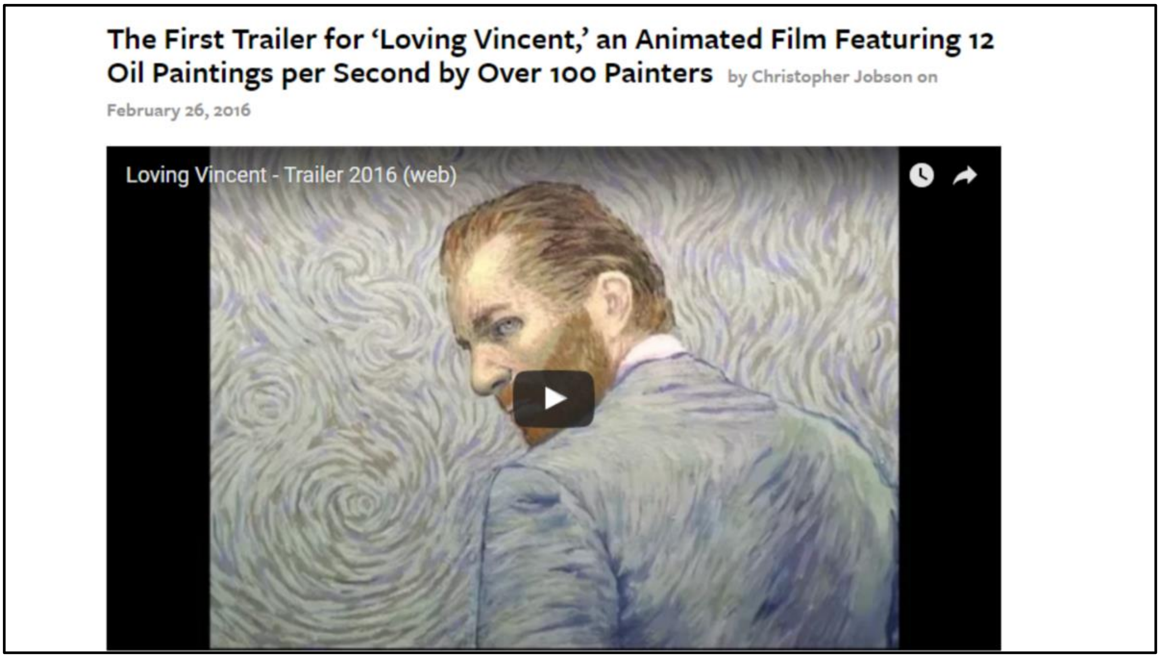
In fine art, especially painting, humans have mastered the skill to create unique visual experiences through composing a complex interplay between the content and style of an image. Thus far the algorithmic basis of this process is unknown and there exists no artificial system with similar capabilities. However, in other key areas of visual perception such as object and face recognition near-human performance was recently demonstrated by a class of biologically inspired vision models called Deep Neural Networks.[1,2] Here we introduce an artificial system based on a Deep Neural Network that creates artistic images

Here's another example. Basically, the algorithm can paint a photograph in the style of any painting.



The recently released film Loving Vincent provides a cautionary example. It's a film where artists spent thousands of hours handpainting over filmed material in the style of Van Gogh, and now an algorithm can do the same for free in a few hours.

Basically, the trailer of the film came out at the same time as the Gatys et al. paper

AI and media

- Media creation (content design, with or without human assistance)
- Media adaptation (e.g., style transfer, adapting a game to support player needs and motivations)
- Media use (testing, collaboration & competing with humans, e.g., using game playing agents)
- User modeling: biomechanical, perceptual, emotion, experience (models of users yield predictions and estimates of human behavior and experience, which enables and informs all of the above)

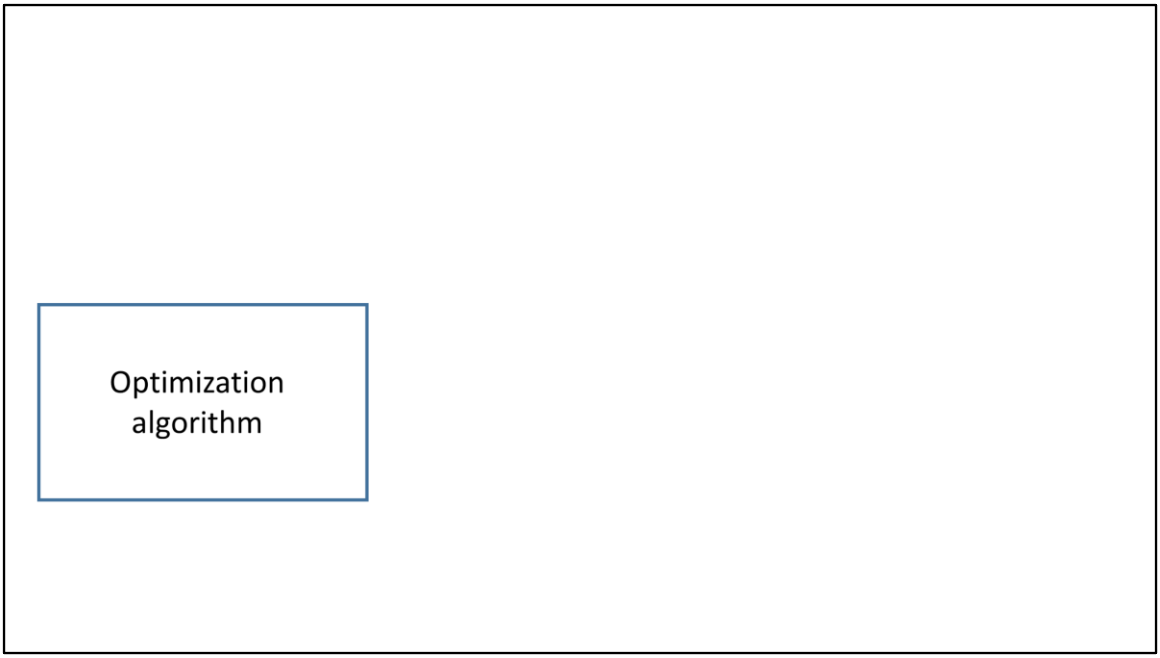
We can further continute the breakdown.
Player modeling at the heart of it!

AI players for playtesting?

Since the user modeling media testing part may feel abstract, let’s consider the example of AI players for playtesting

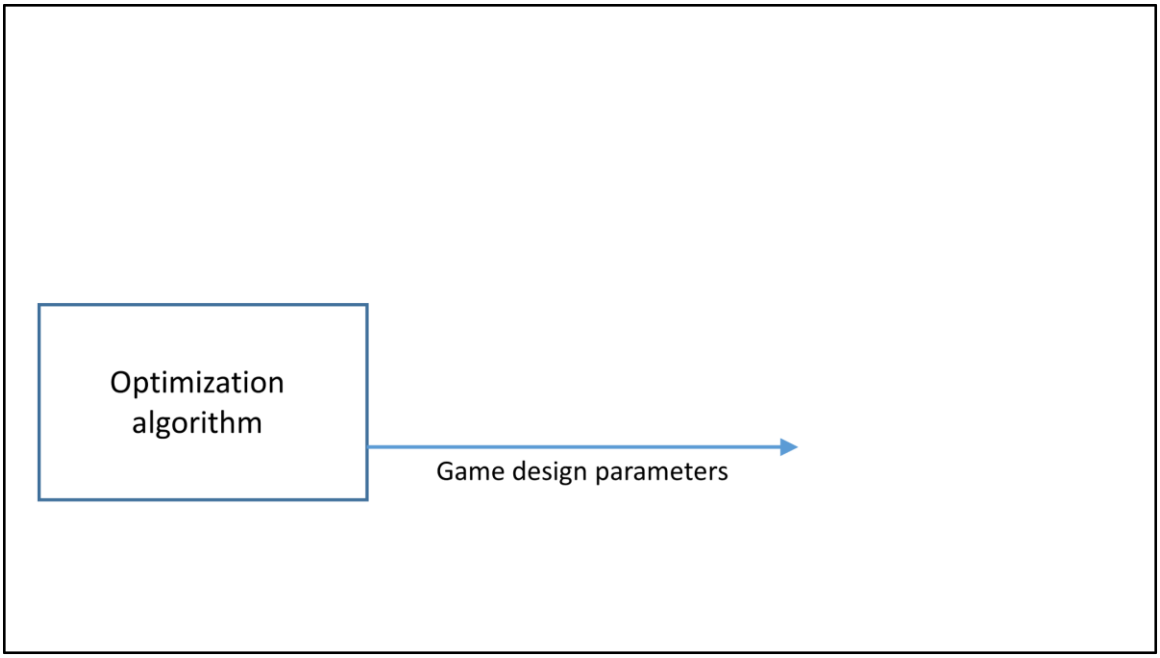
Automated game design

Although the current use is mainly in testing simple things like whether a level can be completed, AI-based player models can ultimately enable automated game design.

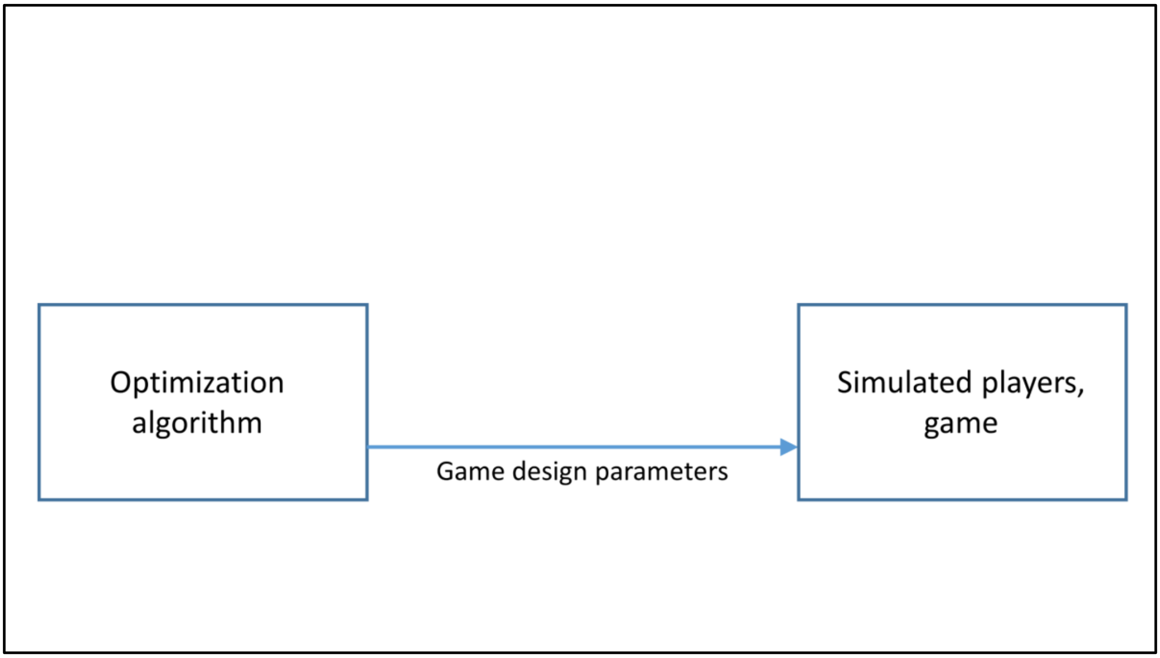


For example, suppose we have an optimization algorithm here.

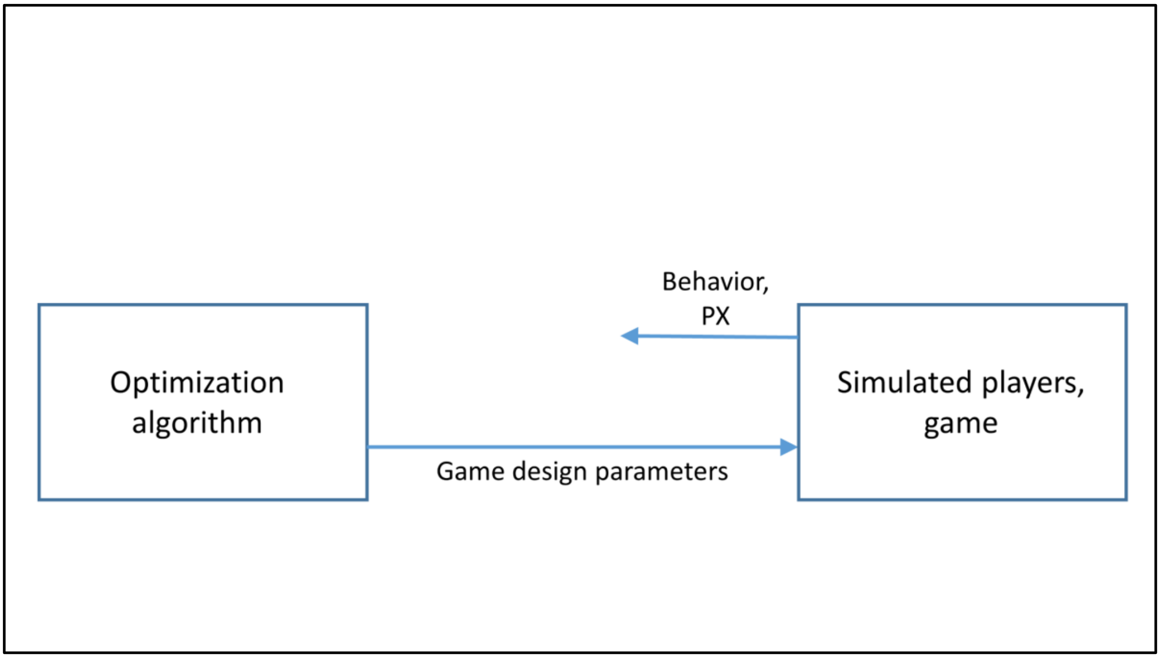
Optimization algorithms adjusts some parameters to maximize or minimize some measure of success; these are crucial to all AI and we'll talk more details later.



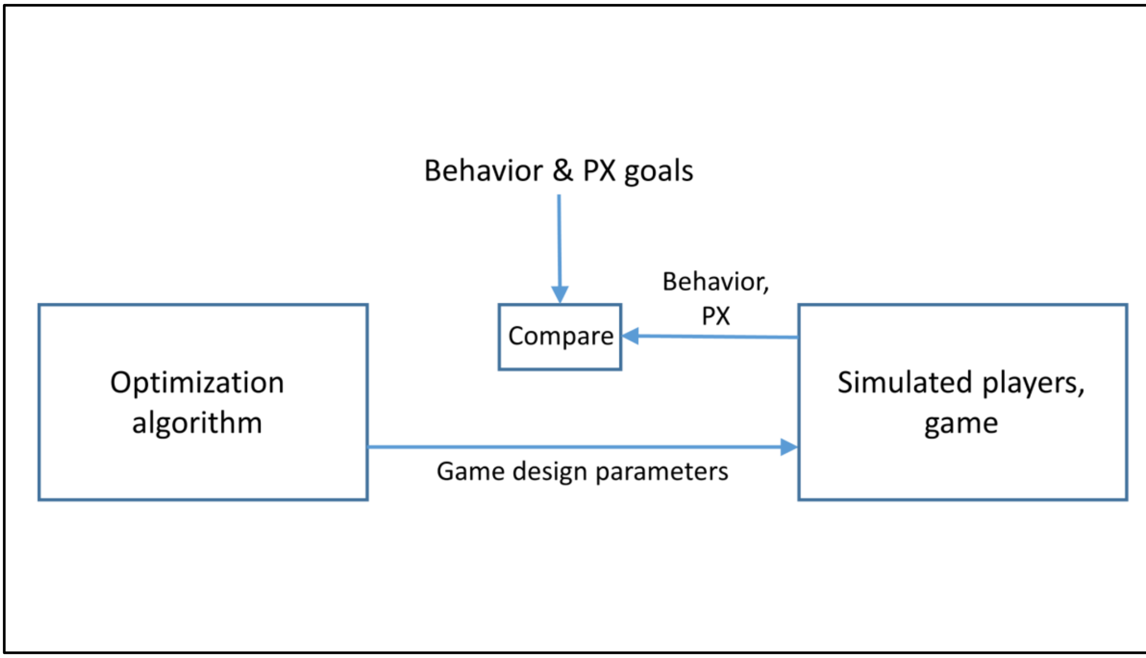
In this case, the optimizer outputs some game design parameters



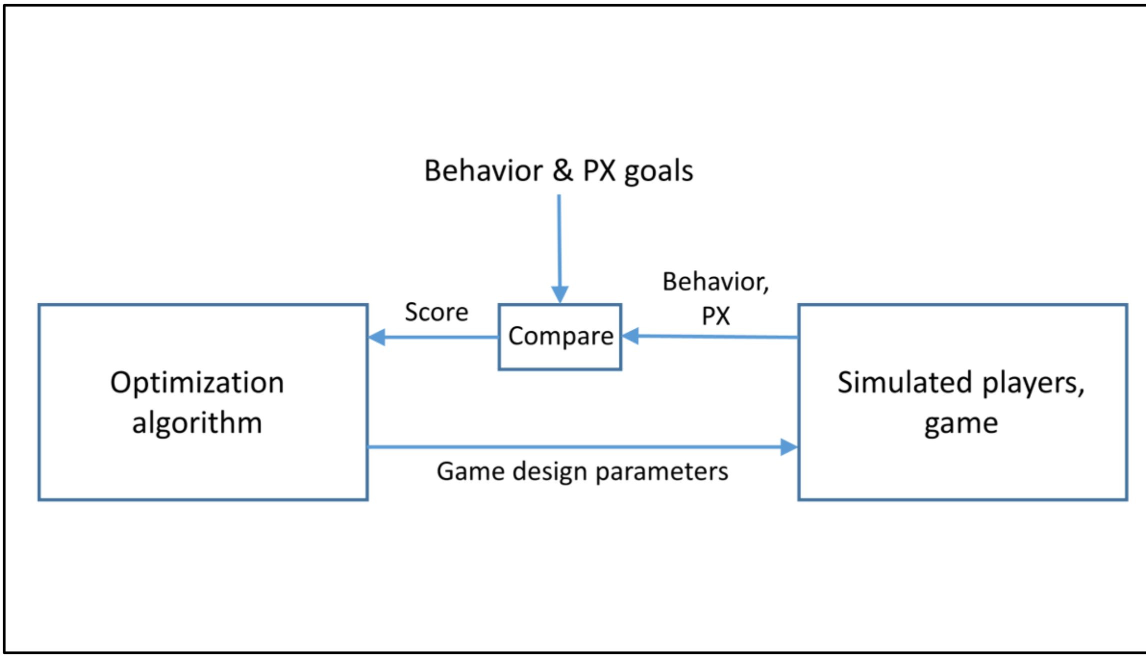
That define the game played by simulated players



The players would then generate behavioral and player experience data



This data can be compared against some targets defined by a game designer



And, this then results in a score that the optimizer tries to maximize through iterating the design parameters

An Experiment in Automatic Game Design

Julian Togelius and Jürgen Schmidhuber

***Abstract*—This paper presents a first attempt at evolving the rules for a game. In contrast to almost every other paper that applies computational intelligence techniques to games, we are not generating behaviours, strategies or environments for any particular game; we are starting without a game and generating the game itself. We explain the rationale for doing this and survey the theories of entertainment and curiosity that underly our fitness function, and present the details of a simple proof-of-concept experiment.**

Keywords: game design, evolutionary design, entertainment metrics

I. Introduction

Can computational intelligence (CI) help designing games? One is tempted to answer "Yes, obviously, the whole field of Computational Intelligence in Games (CIG) is devoted to this, isn't it?"

However, the majority of CIG research is concerned with [...] interest from game developers in learning to play the game better *per se*.

Now, there is certainly other research being carried out in the CIG field that is more directly relevant to real game development (and often dependent on research done in learning to play games, which thus becomes indirectly relevant to game development). For example, we have CI techniques proposed to generate NPC controllers that play interestingly as opposed to just well [1], [2]; CI techniques for automatically finding exploits/bugs in games [3]; CI techniques for modelling the behaviour of human players[4], [5]; CI techniques for making NPCs trainable by human players [6]; and techniques for generating the content of a game, such as tracks, levels or mazes [4], [7].

While the above techniques all represent relevant research directions for game design, they all assume that there is a game there to begin with. Before we let CI loose on

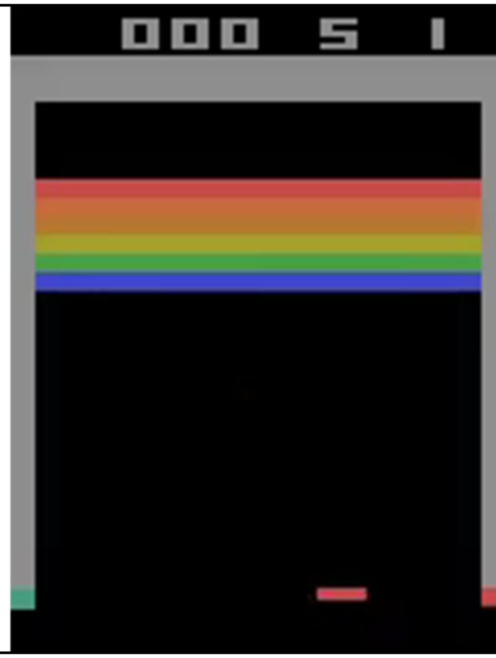
If this sounds like science fiction, I should stress that it's by no means a new idea, and various experiments already exist, such as this seminal paper from 2008

Why is it hot now?

The topic is hot now because the scope of games that can be played or solved by AI has experienced a sudden explosive growth

Mnih et al. 2015:

Human-level control of Atari games using Deep Reinforcement Learning



If you haven’t been living under a rock, you probably know that just a few years ago, Deepmind showed that it’s possible to beat humans in many classic games using deep reinforcement learning. This new and exciting thing here was that thanks to the power of deep neural networks, the AI was able to use raw pixel data as input, without any game-specific information or parameters

Reinforcement learning?

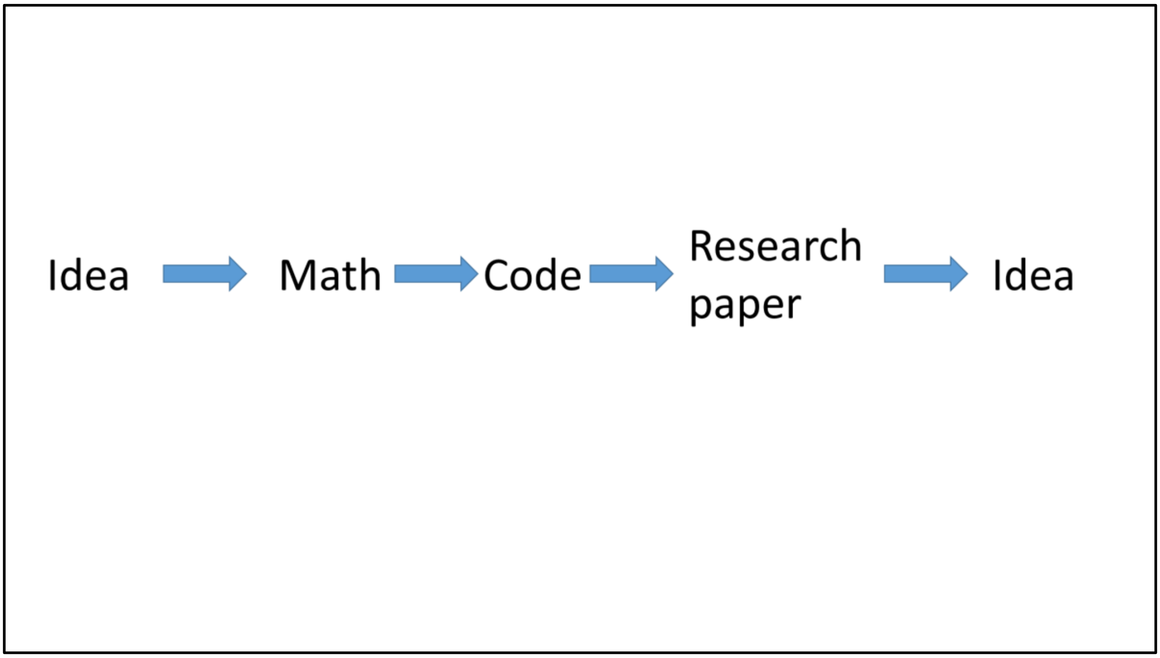
- Initially, random exploration
- Repeat actions that yield rewards

Reinforcement learning is conceptually very simple, yet powerful. Basically, the agent at first simply explores random actions. It then gradually learns to repeat actions that yield high rewards.

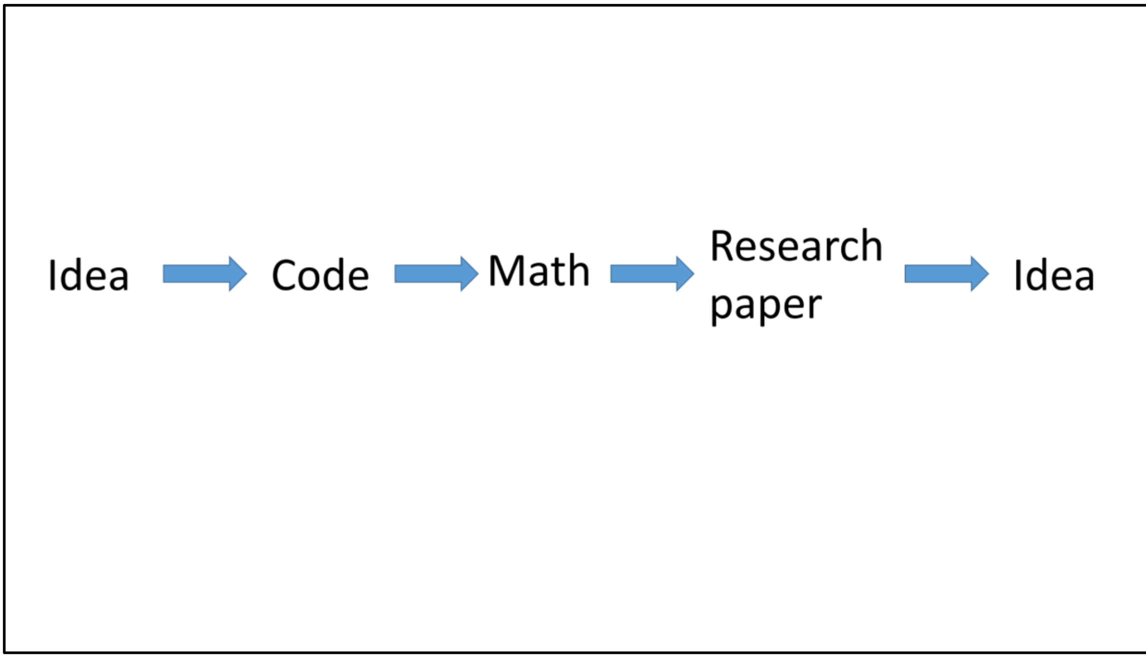
This is simply another form of mathematical optimization. Thus, in the automated design case, we have optimization inside optimization, which can be very slow, but the methods are advancing rapidly.

Pedagogical approach of the course

- The slides and talks have minimal math, focus on visualizations and hands-on practice
- But: learn to not just use, but also to create
- Everything in Github: Lecture slides, exercises, extra material



This is how science is supposed to work: you get an idea, do the math, implement, write a paper and that sparks an idea in someone else's head



However, what often happens is that you code something that is kind of intuitive and simple, but because of conventions of science, you just have to formulate the code as math. Math is precise and very compact representation, and the encoding is hard. Further, the decoding and understanding the mathematical representation can be even harder, and the spaghetti code that exploratory research experiments produce doesn’t help

Kill Math

Bret Victor / April 11, 2011

The power to understand and predict the quantities of the world should not be restricted to those with a freakish knack for manipulating abstract symbols.

When most people speak of Math, what they have in mind is more its mechanism than its essence. This "Math" consists of assigning meaning to a set of symbols, blindly shuffling around these symbols according to arcane rules, and then interpreting a meaning from the shuffled result. The process is not unlike casting lots.

This mechanism of math evolved for a reason: it was the most efficient means of modeling quantitative systems given the constraints of pencil and paper. Unfortunately, most people are not comfortable with bundling up meaning into abstract symbols and making them dance. Thus, the power of math beyond arithmetic is generally reserved for a clergy of scientists and engineers (many of whom struggle with symbolic abstractions more than they'll actually admit).

We are no longer constrained by pencil and paper. The symbolic shuffle should no longer be taken for

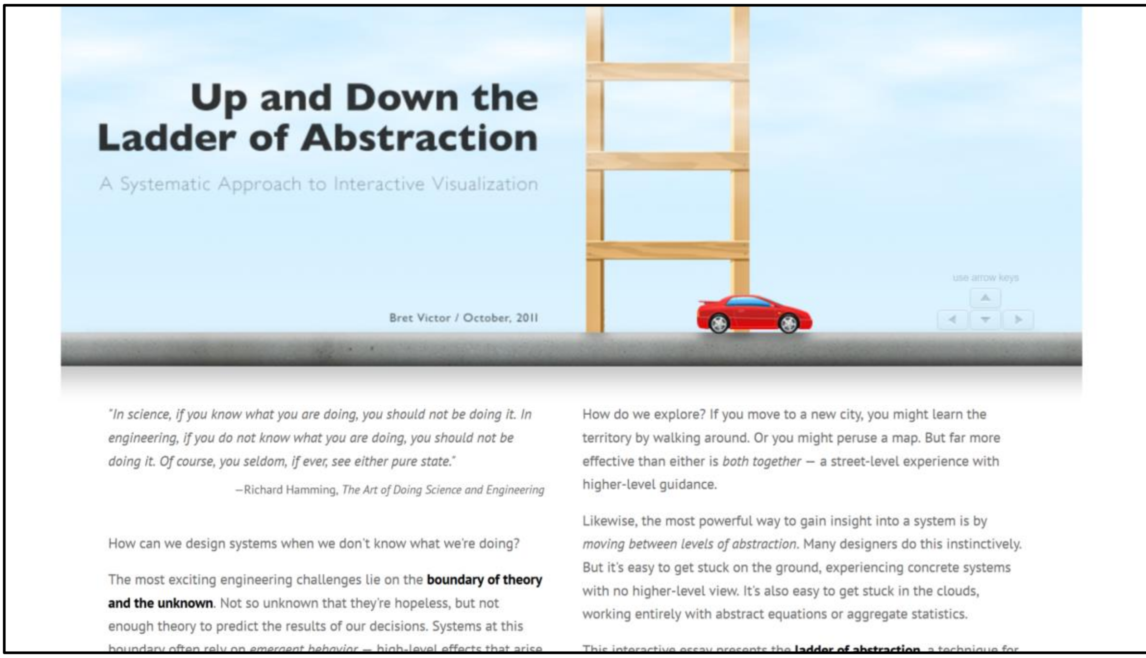
http://worrydream.com/KillMath/

I subscribe to Bret Victor's Kill Math ideology – symbolic notation is not often optimal.

Alan Kay: *Doing With Images Makes Symbols*

> Jacques Hadamard, the famous French mathematician, in the late stages of his life, decided to poll his 99 buddies, who made up together the 100 great mathematicians and physicists on the earth, and he asked them, "How do you do your thing?" They were all personal friends of his, so they wrote back depositions. Only a few, out of the hundred, claimed to use mathematical symbology at all. Quite a surprise. All of them said they did it mostly in imagery or figurative terms. An amazing 30% or so, including Einstein, were down here in the mudpies [doing]. Einstein's deposition said, "I have sensations of a kinesthetic or muscular type." Einstein could feel the abstract spaces he was dealing with, in the muscles of his arms and his fingers...
>
> The sad part of [the doing -> images -> symbols] diagram is that every child in the United States is taught math and physics through this [symbolic] channel. The channel that almost no adult creative mathematician or physicist uses to do it... They use this channel to communicate, but not to do their thing. Much of our education is founded on those principles, that just because we can talk about something, there is a naive belief that we can teach through talking and listening.

Victor motivates his manifesto by quoting the legendary Alan Kay, who tells a story of Jacques Hadamard.



Victor proposes interactive visualizations as one solution, and that is why I'm also using interactive visualizations such as Tensorflow Playground and distill.pub on this course. See, for example, http://worrydream.com/LadderOfAbstraction/

I've also produced a lot of visualizations of core algorithms such as Value Iteration and gradient-based optimization for the course. Math is useful, but I firmly believe that many of us benefit from also having non-mathematical understanding of what the math represents.

Passing the course

- Project work, either design or tech. 3-5cr depending on project.
- Example tech project: implement an AI method such as Monte Carlo Tree Search for your game, or integrate some existing tool.
- Example design project: learn to use an existing tool such as Unity Machine Learning Agents, Pix2Pix, style transfer, create some new prototype or experiment using it
- Ideally, team up and create something cool, interesting tech with interesting design!
- We will talk to everyone personally to comment/approve the project

Passing the course (3-5cr)

- Submit a report to get the credits, via MyCourses
- Deadline June 1st
- Include:
  - Names of the students in the team
  - What was each student's starting knowledge
  - What did you create: 1 page text + images, link to video if possible
  - How did it work out / what were the results
  - If purely conceptual work or essay, 5-10 pages text & images (sketches, storyboards...)
  - What each student learned