Ignoring What's Boring

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Blue Sky Goal

How much of programming can we automate?

- Lots of work done on code *generation*
- What can we do with *existing* code?
  - Abstraction
  - Simplification
  - Optimisation
  - **Understanding**
  - ...

Theory Exploration

Given definitions $d_1, d_2, ..., d_n$, what can we prove?

Example

Haskell functions `+`, `-`, `*`, `1`, `0`, `x :: Int`, `y :: Int`, `z :: Int`

Theory Exploration

Given definitions $d_1, d_2, \ldots, d_n$, what can we prove?

Example

Haskell functions `+`, `-`, `*`, `1`, `0`, `x :: Int`, `y :: Int`, `z :: Int`

$$
\begin{aligned}
0 + 0 &= 0 \\
0 + 0 + 0 &= 0 \\
0 + 0 + 0 + 0 &= 0
\end{aligned}
$$

Oops!

Ignoring What's Boring

Given prior results, *classify* new theorems as "interesting" or not:

```
interestingGiven :: Theorem -> [Theorem] -> Bool
```

Theory exploration is *function inversion*: find `t` such that

```
t `interestingGiven` prior == True
```

Ignoring What's Boring: Intuition

- "Simple" theorems are more interesting than "complicated" ones
- "Trivial" theorems are boring
- "Surprising" theorems are interesting
- "Useful" theorems are interesting
- *Analogous* theorems are interesting (theorems about `NonEmptyList` should probably look similar to existing theorems about `List`).

Function Inversion

- Classic AI/Machine Learning problem
- Two sub-problems:
  - Which function to invert (what is interesting/boring?)
  - Which search strategy?

Existing Approaches

- QuickSpec (1)
  - "Boring" := derivable from congruence closure relation
  - Search by brute-force enumeration, filtered by random counter-examples
- HipSpec
  - "Interesting" := QuickSpec find it interesting, and HIP can prove it
  - Uses QuickSpec for search
- Hipster
  - "Interesting" := requires induction to prove (configurable)
  - Uses HipSpec for search
- IsaCoSy
  - "Boring" := reducible via rewrite
  - Search by brute-force enumeration with constraints

Existing Approaches

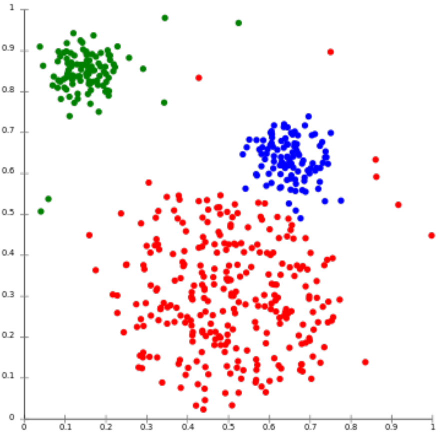
Pros:

- Exhaustive
- Repeatable
- Focuses on simplicity

Cons:

- Doesn't scale to large numbers of functions
- Hard-coded definition of "interesting", chosen for ease of inversion

Reasoning By Analogy



Source: Wikimedia

Reasoning By Analogy: Overview

- *Cluster* symbols together based on similarity of definition
  - `c1 = [+, ++, *, ..]`
  - `c2 = [[], 0, Nothing, ..]`
  - `c3 = [Just, Succ, Left, Right, ..]`
  - ...
- Existing theorems induce schemas, where symbols become cluster IDs:
  - `(+) x 0 = x` $\rightarrow$ `c1 x c2 = x`
- Instantiate schemas to make candidate formulas:
  - `(+) x [] = x`, `(++) x 0 = x`, `(*) x [] = x`, `(++) x [] = x`, ...
- Search around these to find theorems

Reasoning By Analogy: Recurrent Feature Extraction

```
all x y z = if x
               then y && z
               else False
```

Reasoning By Analogy: Recurrent Feature Extraction

```
    if
    |
+---+---+
|   |   |
x   &&  False
    |
 +--+--+
 |     |
 y     z
```

Reasoning By Analogy: Recurrent Feature Extraction

if		
x	&&	False
y	z	

Reasoning By Analogy: Recurrent Feature Extraction

cA	0	0
1	cB	cC
2	3	0

Future ML Directions

Many Machine Learning approaches seem promising to investigate

Future ML Directions: Multi-Armed Bandits

Future ML Directions: Multi-Armed Bandits

Iteratively choose which slot machine to play, from $\{S_1, .., S_n\}$

- Different machines have different payoffs
- Exploration vs exploitation
- Fundamental resource allocation problem
- Which arm to pull $:=$ which symbols to explore

Future ML Directions: Data Mining

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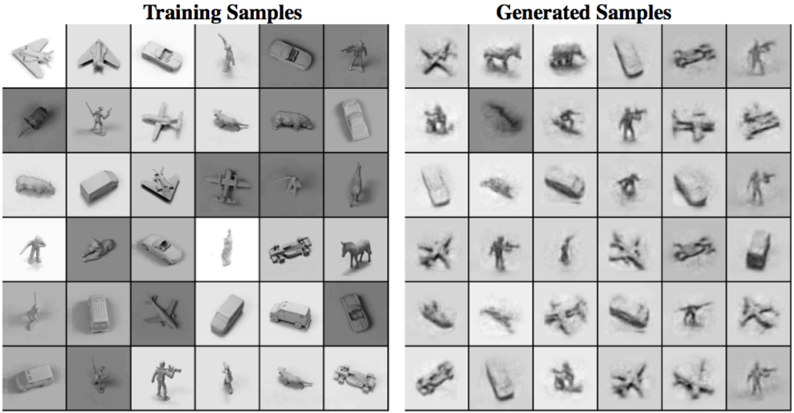
Can we analyse existing code to predict what humans find interesting?

- Haskell test suites contain equational properties
- Haskell functions are defined equationally
  - We want to provide insight *on top* of the raw definitions
- Problem: These are only *positive* examples
  - We don't know what authors *didn't* write

Future ML Directions: Generative Models

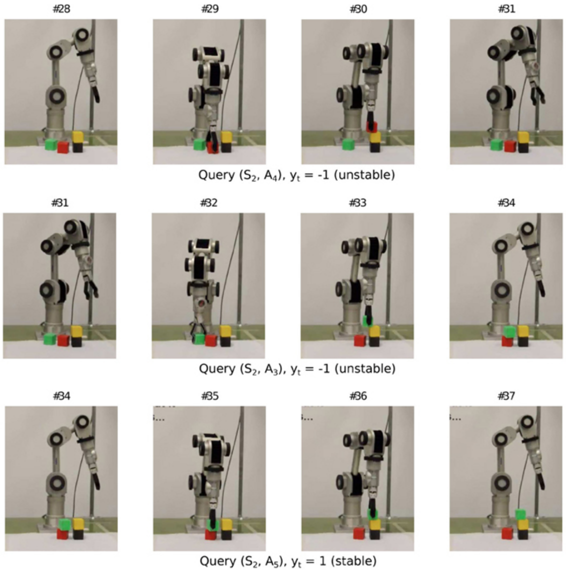


http://www.metacademy.org/roadmaps/rgrosse/deep_learning

Future ML Directions: Generative Models

- Bi-directional model of computation: learning `A -> B` gives us `B -> A`
- Learning what's interesting lets us *produce* what's interesting
- Learning similarities lets us *produce* similar definitions
- Examples: Auto-encoders, Deep Belief Networks, Baysian Networks, Probabalistic Programming

Future ML Directions: Artificial Curiosity



http://people.idsia.ch/~ngo/ijcnn2012/katana_curiosity.html

Future ML Directions: Artificial Curiosity

Information-theoretic formalisation of “interesting”. “Reward” searcher using:

- Disagreement between outcome and prediction (surprise)
- Improvement made in prediction (learning)
- Time derivatives of observation compressibility

Meta-level algorithm: biases an underlying search.

Summary

- Theory Exploration is an aid to theory/software understanding
- Existing approaches rely on brute-force
  - Natural fit for AI
- Notion of "interesting" is fuzzy
  - Natural fit for ML
- Lots of promising approaches