The child as scientist

Learning as “theory building”, not “data analysis”. Knowledge grows through hypothesis- and explanation-driven interpretations of sparse data, causal learning, learning theories, learning compositional abstractions, learning to learn, exploratory learning, social learning. [Carey, Karmiloff-Smith, Gopnik, Schulz, Feigenson...]
Probabilistic programs for model building ("program-learning" programs)

World state (t) \rightarrow World state (t+1) \ldots

\textit{Learning}

physics

Image (t) \rightarrow Image (t+1)

\textit{Graphics}

Learning and generalization for object concepts

“tufa”

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Learning and generalization for object concepts

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Handwritten characters

Standard machine learning: MNIST
100s (or more) examples/class

Our testbed: Omniglot
1623 simple visual concepts in 50 alphabets
20 examples/class

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The omniglot dataset

<table>
<thead>
<tr>
<th>Sanskrit</th>
<th>Tagalog</th>
<th>Hebrew</th>
</tr>
</thead>
<tbody>
<tr>
<td>कस्म गयान</td>
<td>ษ -widget</td>
<td>א ש ב ג ד א</td>
</tr>
<tr>
<td>चं जक</td>
<td>ง ฉ อ</td>
<td>ב צ ד פ</td>
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<td>टेषन</td>
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<tr>
<th>Balinese</th>
<th>Latin</th>
<th>Braille</th>
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<td>マ ハ ム</td>
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The omniglot dataset

<table>
<thead>
<tr>
<th>Angelic</th>
<th>Alphabet of the Magi</th>
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<tbody>
<tr>
<td><img src="image1" alt="Angelic symbols" /></td>
<td><img src="image2" alt="Alphabet of the Magi symbols" /></td>
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<table>
<thead>
<tr>
<th>ULOG</th>
<th>Futurama</th>
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<tbody>
<tr>
<td><img src="image3" alt="ULOG symbols" /></td>
<td><img src="image4" alt="Futurama symbols" /></td>
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One-shot learning

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A multitude of tasks

- i) 
- ii) 
- iii) 
- iv) 

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A multitude of tasks

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Bayesian Program Learning
(Lake, Salakhutdinov, Tenenbaum, NIPS 2013; in prep)

Primitives [e.g. basic movements or actions, shape elements (1D curvelets, 2D patches, 3D geons), ...]

Sub-strokes

Strokes

Character

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Bayesian Program Learning
(Lake, Salakhutdinov, Tenenbaum, NIPS 2013; in prep)

procedure \textsc{generateType}
\begin{align*}
\kappa & \leftarrow P(\kappa) \quad \text{Sample number of parts} \\
\text{for } i = 1 \ldots \kappa & \text{ do} \\
\quad z_i & \leftarrow P(z_i) \quad \text{Sample sub-parts} \\
\text{for } j = 1 \ldots n_i & \text{ do} \\
\quad x_{ij} & \leftarrow P(x_{ij}|z_{ij}) \quad \text{Transform sub-parts} \\
\text{end for} \\
\quad R_i & \leftarrow P(R_i|z_1, \ldots, z_{i-1}) \quad \text{Sample part relations} \\
\text{end for} \\
\psi & \left\{\kappa, R, z, x\right\} \\
\text{return } \textsc{generateToken}(\psi) \\
\end{align*}
end procedure

Handle to stochastic program

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Source: Lake, Brenden M., Ruslan Salakhutdinov, and Joshua B. Tenenbaum.
Learning to generate types
("generative model for generative models")

HBPL (and other models) were trained on 30 "background alphabets" that weren’t seen again.

**Number of strokes**

![Number of strokes](image)

**Learned (motor) primitives**

![Learned primitives](image)

**Relations (stroke attachment)**

- **Stroke attachment**
  - Independent (70%)
  - Stroke 1
  - Stroke 2
  - Stroke 3
  - Stroke ≥ 4

**Token-level transformations**

\[ \theta^{(m)} \leftarrow \text{GENERATE} \text{TOKEN}^{(\psi)} \]

- Gaussian noise on continuous variables
- Global object scale/translation
- Adaptive image blur
- Adaptive pixel noise

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Inferring a program from a single example

\[ P(\theta | I) \approx \sum_i w_i 1\{ \theta = \theta_i \} \]

such that

\[ w_i = P(\theta_i | I) \]

Intuition:
Fit strokes to the observed pixels as closely as possible, while also:

- minimizing the number of strokes
- choosing high-probability sub-strokes and maintaining their shape
- choosing stroke start positions that match dataset statistics and abide by stroke relations

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Classifying with probabilistic programs

Which class is image $I$ in?

$log P(I|\text{class 1}) \approx -758$

$log P(I|\text{class 2}) \approx -1880$

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One-shot classification

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Generating new examples

Machine
Generating new examples

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Turing test: Can people tell the humans from the machine?

% correctly recognized by human judges

<table>
<thead>
<tr>
<th>Judgment type</th>
<th>HBPL</th>
<th>control (affine)</th>
<th>chance</th>
</tr>
</thead>
<tbody>
<tr>
<td>two images</td>
<td>1/21</td>
<td>24/27</td>
<td></td>
</tr>
<tr>
<td>two grids of 9 images</td>
<td>2/21</td>
<td>24/25</td>
<td></td>
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</tbody>
</table>

“X/Y”: X out of Y judges who were significantly greater than chance

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Source: Lake, Brenden M., Ruslan Salakhutdinov, and Joshua B. Tenenbaum.
"Human-level concept learning through probabilistic program induction."
Generating entirely new characters

<table>
<thead>
<tr>
<th>10 Examples Given</th>
</tr>
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<tbody>
<tr>
<td>25 New Instances Generated</td>
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</table>

Machine
Explaining the dynamics of development? (w/ T. Ullman, Spelke, others)

9 months

12 months

15 months

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Explain the dynamics of development? (w/ T. Ullman, Spelke, others)

Capture different knowledge stages with a sequence of probabilistic programs?

Explain the trajectory of stages as rational statistical inference in the space of programs?

3 months
Initial Concept: Contact/No contact

5 months
Variable: Type of contact

6.5 months
Variable: Amount of contact

12.5 months
Variable: Shape of the box

9 months

15 months


Learning physics from dynamic scenes
(Ullman, Stuhlmuller, Goodman, Tenenbaum, 2014; under review)

Unobserved properties:
(c.f. parameter learning)

  e.g., mass, charge, friction, elasticity, resistance...

See the lecture video to view these video clips

New laws:
(c.f. structure learning)

  e.g., presence of forces and their shape, existence of hidden objects, kinds of substances ...
Metatheory

Objects

Inertial dynamics

F = m \times a

Theories

Different forces

Coupling

Global

Different masses

Different frictions

Events

\( F = \frac{C \times m_1 \times m_2}{r^2} \)

\( F = m \times a \)

(\text{define} \ (\text{construct-particle} \ \text{size} \ \text{position} \ \text{velocity} \ \text{mass}))

(\text{define} \ (\text{construct-barrier} \ \text{size} \ \text{elasticity} \ \text{position}))

(\text{define} \ (\text{next-position} \ \text{objects} \ \text{forces} \ \text{dt}))

(\text{define} \ (\text{attraction} \ \text{object1} \ \text{object2}))

(\text{define} \ (\text{heavy-mass} \ 9.0))

(\text{define} \ (\text{smooth-surface} \ 0.0))

(\text{define} \ \text{world-5} \ (\text{create-world} \ \text{create-forces} \ \text{create-particles} \ \text{create-friction} \ \text{create-world}))

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Comparing models and humans

Mass

Friction

Pairwise forces

Global forces

People

Model

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Learning the form of domain theories?

A really hard problem...

- What’s the right hypothesis space?
- What’s an effective algorithm for searching the space of theories, as fast and as reliably and as flexibly as we see in children’s learning?
Learning the form of domain theories?

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Hierarchical Bayesian Framework
(Kemp & Tenenbaum, *Psych Review*, 2009)

F: form

S: structure

D: data

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Hypothesis space of structural forms
(Kemp & Tenenbaum, PNAS 2008)

Form

Process

Form

Process

Chain × Chain

Chain × Ring

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Discovering the structural form of a domain
(Kemp & Tenenbaum, *PNAS* 2008; *Psych Review*, 2009)

Abstract principles

Model

Data

Features

animals

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Development of structural forms as more data are observed

“blessing of abstraction”

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Conclusion

What makes us so smart?

1. **How we start:** Common-sense core theories of intuitive physics and intuitive psychology.

2. **How we grow:** Learning as theory construction, revision and refinement.

The tools of probabilistic programs and program induction are beginning to let us reverse-engineer these capacities, with languages that are:
- Probabilistic.
- Generative.
- Causally structured
- Compositionally structured: flexible, fine-grained dependencies, hierarchical, recursive, unbounded

We have to view the brain not simply as a pattern-recognition device, but as a *modeling engine*, an *explanation engine* – and we have to understand how these views work together.

Much promise but huge engineering and scientific challenges remain… full of opportunities for bidirectional interactions between cognitive science, neuroscience, developmental psychology, AI and machine learning.
Resource: Brains, Minds and Machines Summer Course
Tomaso Poggio and Gabriel Kreiman

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