Knowledge Reuse in Genetic Programming Applied to Visual Learning

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The Common Knowledge is Out There

Idea
If the tasks are similar then also the solutions should be similar → the Common Knowledge is out there.

Why?
- better solutions,
- in less time.

ML perspective
In terms of Machine Learning, we can expect to:
- obtain better classification accuracy on testing set,
- reduce the risk of overfitting.
Std. Evolutionary Approach for Multiple Tasks

task: 1 2 3 ... k

solutions: ↓ ↓ ↓ ↓

n generations
Knowledge Reuse in GP Applied to Visual Learning
Genetic Programming (Cross-Task) Knowledge Reuse

Wojciech Jaśkowski, Krzysztof Krawiec, Bartosz Wieloch

Knowledge Reuse in GP Applied to Visual Learning
Crossbreeding Operator

Standard crossover:

```
1 \quad 2 \quad 3 \quad k
```

**task:**

```
P_1 \quad P_3 \quad P_k
```
Crossbreeding Operator

Crossbreeding:
Recognition (Classification) Task

Objective
Classification of hand-drawn letters from six classes: A, E, W, X, Y, Z

Training Data
12 examples from each class

Examples
Wojciech Jaśkowski, Krzysztof Krawiec, Bartosz Wieloch

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Objective
Classification of hand-drawn letters from six classes: A, E, W, X, Y, Z

Training Data
12 examples from each class

Examples
A
E
W
X
Y
Z
Learning Process

Original Drawing \[\rightarrow\] Set of Primitives \[\rightarrow\] Drawing \[\rightarrow\] Error Rate

transformation reconstruction comparison

0.148
Learning Process

Original Drawing \rightarrow Set of Primitives \rightarrow Drawing \rightarrow Error Rate

transformation \rightarrow reconstruction \rightarrow comparison \rightarrow (minimalized) fitness

0.148
## Learning Process

<table>
<thead>
<tr>
<th>Original Drawing</th>
<th>Set of Primitives</th>
<th>Drawing</th>
<th>Error Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Image" /></td>
<td><img src="image2" alt="Image" /></td>
<td><img src="image3" alt="Image" /></td>
<td>0.148</td>
</tr>
<tr>
<td><img src="image4" alt="Image" /></td>
<td><img src="image5" alt="Image" /></td>
<td><img src="image6" alt="Image" /></td>
<td>0.941</td>
</tr>
<tr>
<td><img src="image7" alt="Image" /></td>
<td><img src="image8" alt="Image" /></td>
<td><img src="image9" alt="Image" /></td>
<td>0.097</td>
</tr>
</tbody>
</table>
Genetic Programming (Learning) Task

**Input**

12 examples from **one class**

**Output**

A **procedure** that can reconstruct the *Set of Primitives* into the *Input Drawing*. We will call this procedure a **visual learner**.

**Input → Output**

![Diagram](image-url)
Classification System

Knowledge Reuse in GP Applied to Visual Learning
Rationale

An individual (learner) that was taught to reconstruct the letter A has no clue how to reconstruct other letters. In result, its error on A is lower than its error on other letters.
The list of GP operators

- Most of the operators process the sets of Visual Primitives.
- There are nodes that can **draw** strokes.

<table>
<thead>
<tr>
<th>Type</th>
<th>Operator</th>
</tr>
</thead>
<tbody>
<tr>
<td>ℜ</td>
<td>Ephemeral random constant</td>
</tr>
<tr>
<td>Ω</td>
<td>ImageNode – the VP representation ( P ) of the input image ( s )</td>
</tr>
<tr>
<td>( p_x, p_y, p_o ) and custom attributes added by AddAttribute</td>
<td></td>
</tr>
<tr>
<td>( R )</td>
<td>Equals, Equals5Percent, Equals10Percent, Equals20Percent, LessThan, GreaterThan</td>
</tr>
<tr>
<td>( G )</td>
<td>Sum, Mean, Product, Median, Min, Max, Range</td>
</tr>
<tr>
<td></td>
<td>(+ (\Re, \Re), -(\Re, \Re), *(\Re, \Re), /(\Re, \Re), \sin(\Re), \cos(\Re), \text{abs}(\Re), \text{sqrt}(\Re), \text{sgn}(\Re), \ln(\Re))</td>
</tr>
<tr>
<td>Ω</td>
<td>SetIntersection(Ω, Ω), SetUnion(Ω, Ω), SetMinus(Ω, Ω), SetMinusSym(Ω, Ω), SelectorMax(Ω, A), SelectorMin(Ω, A), SelectorCompare(Ω, A, R, ℜ), CreatePair(Ω, Ω), CreatePairD(Ω, Ω), ForEach(Ω, Ω), ForEachCreatePair(Ω, Ω, Ω), ForEachCreatePairD(Ω, Ω, Ω), GroupHierarchyCount(Ω, ℜ), GroupHierarchyDistance(Ω, ℜ), GroupProximity(Ω, ℜ), GroupOrientationMulti(Ω, ℜ), Ungroup(Ω), Draw(Ω)</td>
</tr>
</tbody>
</table>
Experiment

Objective

To compare GP (control, no Knowledge Reuse) experiment with GPKR-100, (with Knowledge Reuse) experiment.

GP (control):
- Crossover probability: 0.8
- Mutation probability: 0.2
- 400 generations

GPKR-100:
- Crossover probability: 0.8
- Mutation probability: 0.17
- Crossbreeding probability: 0.03
- 100 + 300 generations (primary + secondary run)
Reproductions seem to be robust despite various forms of imperfectness of the hand-drawn figures.
Results (fitness on the training set)

(Averaged over 33 evolutionary runs)
Test set = 72 shapes per class (432 shapes in total)

Test set error rates (fitness):

<table>
<thead>
<tr>
<th>Class</th>
<th>GP</th>
<th>GPKR-100</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.415</td>
<td>0.394</td>
</tr>
<tr>
<td>E</td>
<td>0.462</td>
<td><strong>0.328</strong></td>
</tr>
<tr>
<td>W</td>
<td>0.322</td>
<td>0.318</td>
</tr>
<tr>
<td>X</td>
<td>0.444</td>
<td><strong>0.354</strong></td>
</tr>
<tr>
<td>Y</td>
<td>0.381</td>
<td>0.386</td>
</tr>
<tr>
<td>Z</td>
<td>0.283</td>
<td>0.271</td>
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(Averaged over 33 evolutionary runs)
Classification accuracy:

<table>
<thead>
<tr>
<th>Recognition System</th>
<th>Accuracy</th>
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<tbody>
<tr>
<td>GP</td>
<td>91.96%</td>
</tr>
<tr>
<td>GPKR-50</td>
<td>92.65%</td>
</tr>
<tr>
<td>GPKR-100</td>
<td>93.07%</td>
</tr>
<tr>
<td>GPKR-200</td>
<td>93.82%</td>
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<tr>
<td>GPKR-300</td>
<td>93.58%</td>
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Classification on the test set

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</table>

Classification accuracy with voting (33 runs):

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<tr>
<th>Recognition System</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>GP</td>
<td>93.87%</td>
</tr>
<tr>
<td>GPKR-100</td>
<td>98.77%</td>
</tr>
<tr>
<td>GPKR-200</td>
<td>98.28%</td>
</tr>
</tbody>
</table>
Summary:

- Elegant Learning Framework that uses GP as a learning vehicle,
- Genetic Programming with Knowledge Reuse (GPKR),
- Knowledge Reuse pays off (GPKR > GP).
Example of an GP Individual

[Diagram of a GPIndividual tree structure]
## Results (fitness on the test set)

For different primary-run stop moments (50, 100, 200 and 300):

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</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.415</td>
<td>0.450</td>
<td>0.394</td>
<td>0.360</td>
<td>0.389</td>
</tr>
<tr>
<td>E</td>
<td>0.462</td>
<td><strong>0.369</strong></td>
<td><strong>0.328</strong></td>
<td><strong>0.325</strong></td>
<td><strong>0.318</strong></td>
</tr>
<tr>
<td>W</td>
<td>0.322</td>
<td>0.297</td>
<td>0.318</td>
<td>0.299</td>
<td>0.304</td>
</tr>
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<td>X</td>
<td>0.444</td>
<td><strong>0.360</strong></td>
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<td>0.381</td>
<td>0.390</td>
<td>0.386</td>
<td>0.392</td>
<td>0.375</td>
</tr>
<tr>
<td>Z</td>
<td>0.283</td>
<td>0.302</td>
<td>0.271</td>
<td>0.281</td>
<td>0.285</td>
</tr>
</tbody>
</table>
Example

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Knowledge Reuse in GP Applied to Visual Learning
CreatePairD

SelectorMin
A: 1

SelectorMax
A: 0

CreatePairD
Example
Results (fitness on the training set)

(Averaged over 33 evolutionary runs)