AutoML-zero

Genetic Programming meets Neural Networks

Luca Manzoni

The paper

Esteban Real, Chen Liang, David R. So, Quoc V. Le

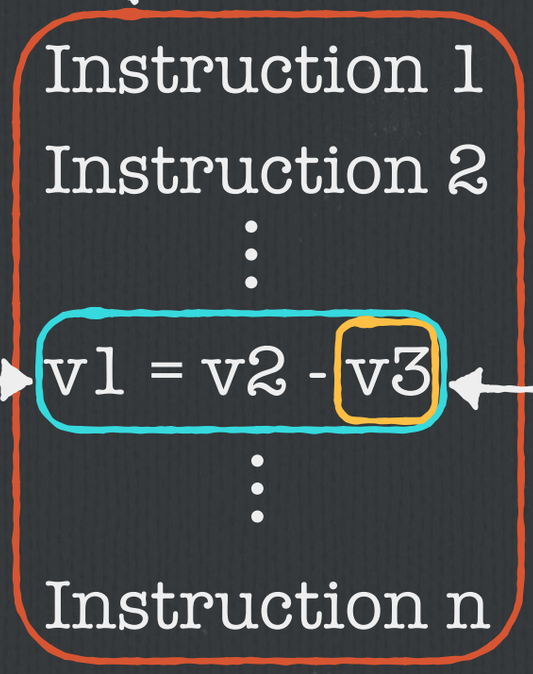
AutoML-zero: Evolving Machine Learning Algorithms From Scratch

https://arxiv.org/abs/2003.03384v1 submitted: March 6, 2020

https://github.com/google-research/google-research/tree/master/automl_zero

Code representation

Programs as linear lists of instructions

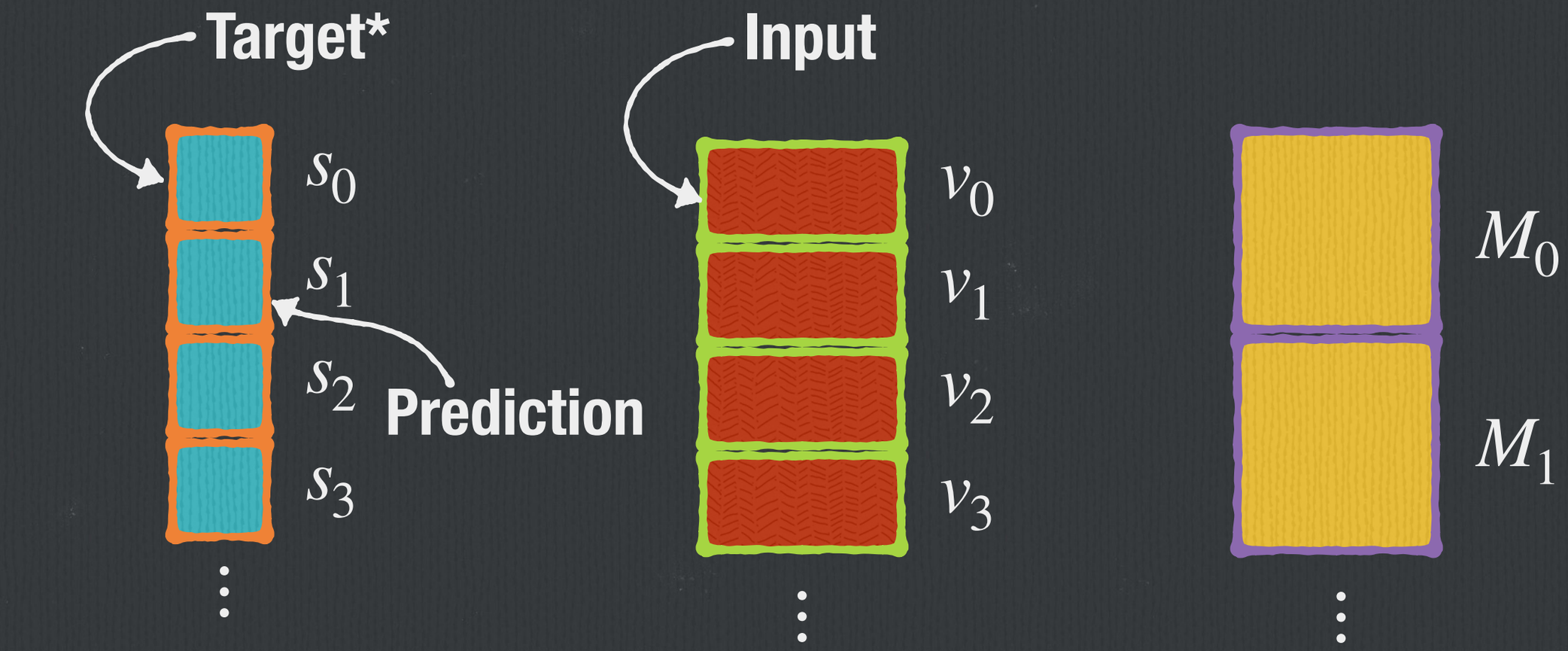


Constants or memory locations

Each instruction has one or more parameters

Instructions are selected among a list of 65

Memories



*Available only during the “Learn” phase

Which code is evolved?

- [ ] Three main blocks are evolved:
  - [ ] Setup. Run once.
  - [ ] Predict. Run to classify an input.
  - [ ] Learn. Run only after the prediction.

How are the blocks used?

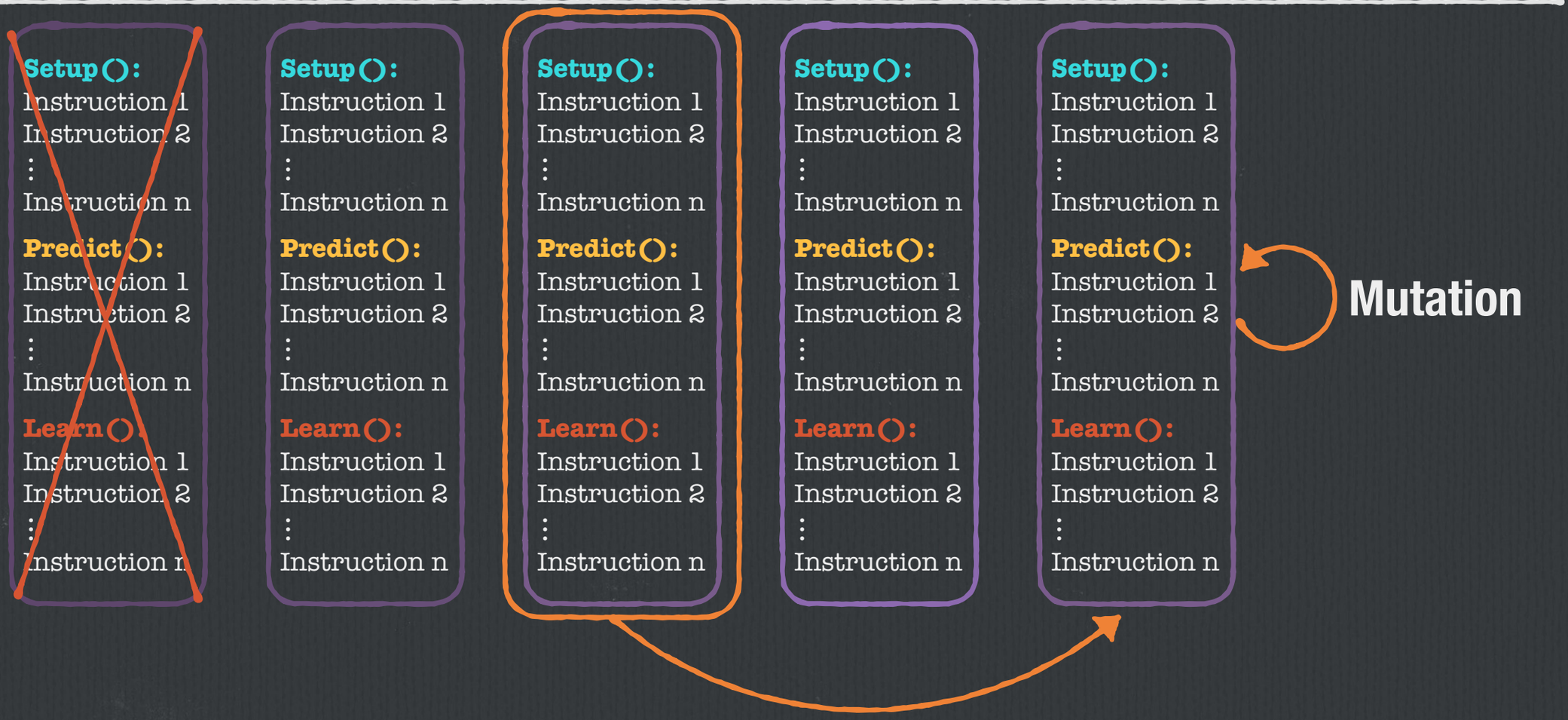
`Setup()` **Once at the beginning**

`Predict()`
`Learn()` **For each element of the training set**

`Predict()` **For each element of the validation set**

Code evolution

Best



Remove the oldest individual

Find the best individual…

… and copy it

Mutations

	Type 1	Type 2	Type 3
Setup(): s4 = 0.5 **Predict():** v1 = v0 - v9 v5 = v0 + v9 m1 = s2 * m2 **Learn():** s4 = s0 - s1 s3 = abs(s1)	**Setup():** s4 = 0.5 **Predict():** v1 = v0 - v9 v5 = v0 + v9 m1 = s2 * m2 **Learn():** s4 = s0 - s1 **s2 = sin(v1)** s3 = abs(s1)	**Setup():** s4 = 0.5 **Predict():** **s0 = mean(m1)** **s3 = cos(s7)** **m5 = m0 + m5** **Learn():** s4 = s0 - s1 s3 = abs(s1)	**Setup():** s4 = 0.5 **Predict():** v1 = **v3** - v9 v5 = v0 + v9 m1 = s2 * m2 **Learn():** s4 = s0 - s1 s3 = abs(s1)

Can random search be better?

Comparison with hand-designed reference algorithms

How frequently a randomly generated solution is better?

“Density” of acceptable algorithms

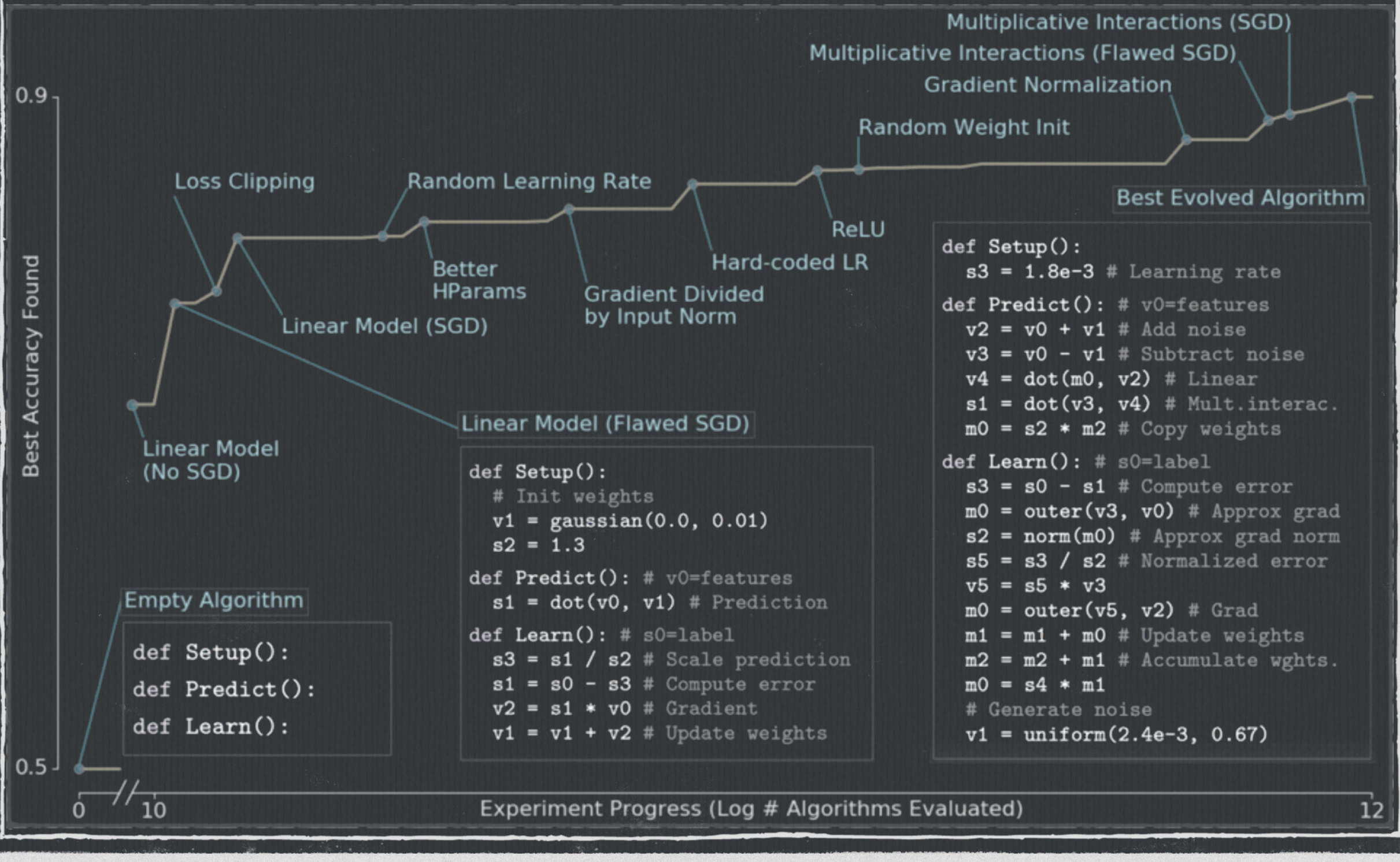
Difficulty as the logarithm of this density

Task	Difficulty
Linear regressor	7.4
Affine regressor	12.1

Experiments

- The classification tasks are extracted from MNIST e CIFAR-10
- Classification is only binary
- 8000 training and 2000 validation samples each
- During the final evaluation the constants are treated as hyperparameters and tuned

Results


Best Accuracy Found
0.9
0.5
Multiplicative Interactions (SGD)
Multiplicative Interactions (Flawed SGD)
Gradient Normalization
Random Weight Init
Best Evolved Algorithm
Loss Clipping
Random Learning Rate
ReLU
Hard-coded LR
Better HParams
Gradient Divided by Input Norm
Linear Model (SGD)
Linear Model (Flawed SGD)
Linear Model (No SGD)
Empty Algorithm
def Setup():
def Predict():
def Learn():
def Setup():
# Init weights
v1 = gaussian(0.0, 0.01)
s2 = 1.3
def Predict(): # v0=features
s1 = dot(v0, v1) # Prediction
def Learn(): # s0=label
s3 = s1 / s2 # Scale prediction
s1 = s0 - s3 # Compute error
v2 = s1 * v0 # Gradient
v1 = v1 + v2 # Update weights
def Setup():
s3 = 1.8e-3 # Learning rate
def Predict(): # v0=features
v2 = v0 + v1 # Add noise
v3 = v0 - v1 # Subtract noise
v4 = dot(m0, v2) # Linear
s1 = dot(v3, v4) # Mult.interac.
m0 = s2 * m2 # Copy weights
def Learn(): # s0=label
s3 = s0 - s1 # Compute error
m0 = outer(v3, v0) # Approx grad
s2 = norm(m0) # Approx grad norm
s5 = s3 / s2 # Normalized error
v5 = s5 * v3
m0 = outer(v5, v2) # Grad
m1 = m1 + m0 # Update weights
m2 = m2 + m1 # Accumulate wghts.
m0 = s4 * m1
# Generate noise
v1 = uniform(2.4e-3, 0.67)
0
10
Experiment Progress (Log # Algorithms Evaluated)
12

Evolved structures

- **Addition of noise to the input:**
  $a = x + u; b = x - u; u \sim U(\alpha, \beta)$

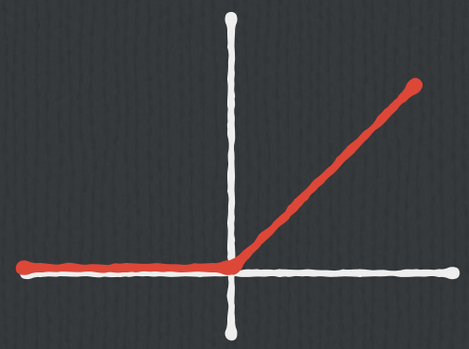
- **Multiplicative interaction:**
  $o = a^T W b$

- **Correct computation of the gradient, normalised to be a unit vector**

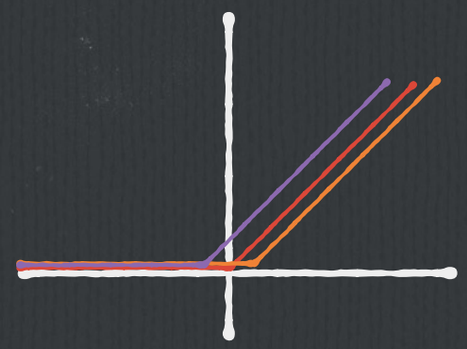
- **Weight accumulation, work similarly to weight averaging**

Limiting the number of training samples

Training on 80 example for 100 epochs made the noisy ReLU replace the ReLU



$f(x) = max(0,x)$



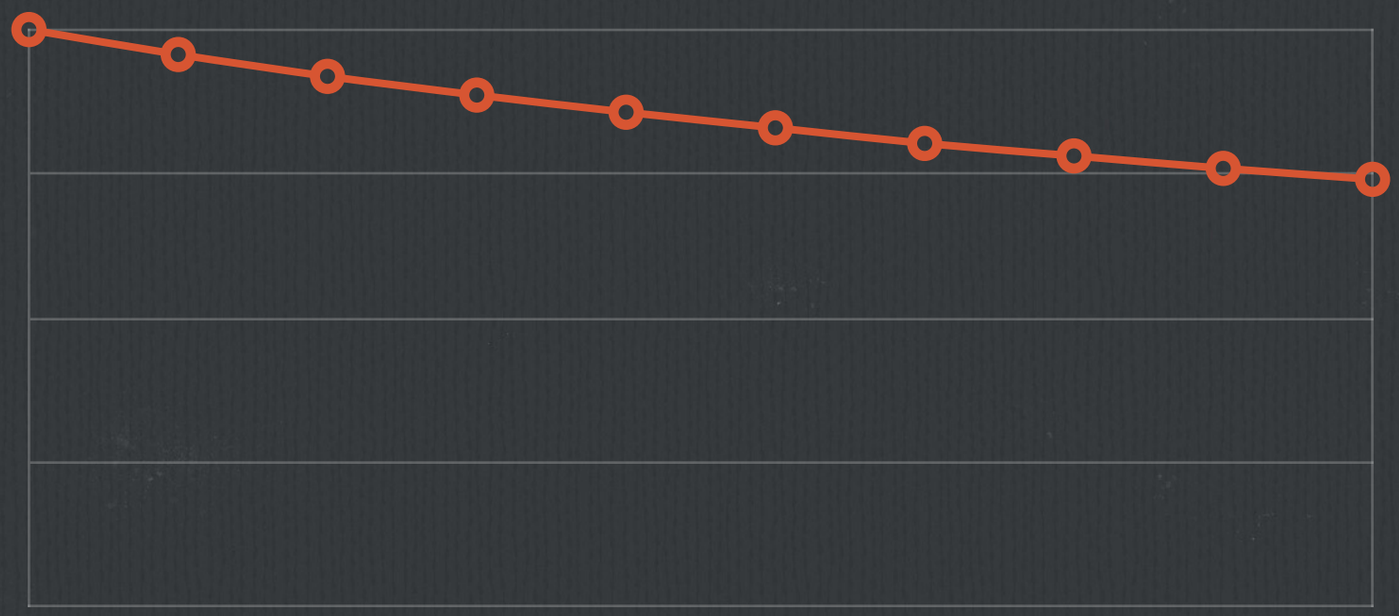
$f(x) = \max(0,x + y)$

$y \sim N(0,\sigma)$

Acts similarly to regularisations like dropout

Limiting the training time

Training on 800 example for 10 epochs made learning rate decay emerge in 30/30 cases



Setup():
s2 = 0.37

Learn():
s2 = arctan(s2)
...

Multiple classes

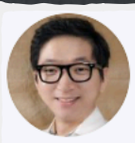
All 10 CIFAR-10 classes are used.
An unexplained behaviour appears in 24/30 cases

```
Learn():
s3 = mean(ml)
s3 = abs(ml)
s3 = sin(s3)
...
```

Average of the weights

Transformation with $x \mapsto sin(|x|)$

Value now used as learning rate



Chen Liang @crazydonkey200 · Mar 11

Hi, one of the authors here. In section 4.3, we confirmed that it helps through controlled experiments, but, to be honest, we didn't fully understand the reason. As you pointed out, it could be a hyperparameter coupling issue we discussed at the end of Supplementary section S.6.

Limitations

- ☐ “Useless code” - bloat in GP - which leads to…
- ☐ Interpretability problems
- ☐ Inability to reuse code, which leads to…
- ☐ Difficulty in evolving deep structures.

Linear GP

```
void gp(r)
  double r[8];
{  ...
   r[0] = r[5] + 71;
// r[7] = r[0] - 59;
   if (r[1] > 0)
   if (r[5] > 2)
     r[4] = r[2] * r[1];
// r[2] = r[5] + r[4];
   r[6] = r[4] * 13;
   r[1] = r[3] / 2;
// if (r[0] > r[1])
//   r[3] = r[5] * r[5];
   r[7] = r[6] - 2;
// r[5] = r[7] + 15;
   if (r[1] <= r[6])
     r[0] = sin(r[7]);
}
```

An example of Linear GP individual

Commented lines are introns,
with no effect on the output

Possible mutations:
1) macro mutations (instruction level)
2) micro mutations (inside the instruction)