An Initial Look at Self-Reprogramming Artificial Intelligence

Alex Sheng
alexsheng4@gmail.com

Abstract

Rapid progress in deep learning research has greatly extended the capabilities of artificial intelligence technology. Conventional AI models are constrained to explicit human-designed algorithms, although a growing body of work in meta-learning, neural architecture search, and related approaches have explored algorithms that self-modify to some extent. In this paper, we develop and experimentally validate the first fully self-reprogramming AI system. Applying AI-based computer code generation to AI itself, we implement an algorithm with the ability to continuously modify and rewrite its own neural network source code.

1 Introduction

For decades, artificial intelligence technology has sought to emulate human cognitive capabilities within a computational substrate. Machine learning, and more recently deep learning, has enabled computers to derive programs from relevant data in order to address novel tasks for which they were not explicitly programmed.

It has long been theorized that an advanced artificial intelligence would be able to self-modify in order to continuously imbue itself with extended capabilities [9][1], eventually surpassing its pre-programmed functionalities to achieve superhuman intelligence. Meta-learning approaches have made significant progress along this avenue, from self-referential evolutionary algorithms [9][10] to RNN-based learners [8] and modern gradient-based meta-learners [4][6]. Adjacent work in neural architecture search [14][11][7] has led to the development of various algorithms for automatically optimizing the architectural parameters of neural networks.

In recent years, AI-based computer code generation has seen dramatic progress [2][13][5] stemming from breakthroughs in large-scale language processing models [12][3]. Modern language processing models trained on computer programming tasks can not only generate syntactically correct computer code, but also formulate logically correct computer programs from human-language prompts and understand pre-written programs to derive human-interpretable information.

Meta-learning and neural architecture search have seen overwhelming success across various task domains, spawning myriad approaches for algorithmically optimizing the design and learning dynamics of deep learning models. Combining these two paradigms with modern computer language processing breakthroughs, we set out to open a completely new avenue of research by applying AI self-modification principles to the limit of technological possibility.

In this paper, we develop an AI system that can rewrite its own source code, allowing it to freely modify not only its architecture and learning dynamics, but also its learning objectives, computational capacity, and data pipeline. Our self-reprogramming AI is unconstrained in its ability to modify its own programming, allowing it to freely develop beyond its original human-specified purposes and functionalities given the right circumstances.

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2 Methods

We present DeepPhoenix, the first AI system that rewrites its own source code. DeepPhoenix initializes an arbitrary language processing model and trains it on an arbitrary computer programming dataset. Within this dataset, code samples are included for creating and training neural networks. The model learns to parse and generate machine learning code, allowing it to understand and rewrite its own source code. In an iterative process, the model is trained for a period of time before it is queried to generate a new source code for itself. A new iteration of the model is initialized and trained, and the cycle continues.

With free-form source code modification, it is possible for a DeepPhoenix model to change its own data pipeline, model architecture, computational capacity, learning dynamics, and learning objectives. It is also possible for the model to extend itself with programs to accomplish auxiliary functions like accessing outside data sources, making calls to system functions, and even producing real-world effects.

In our experiments, DeepPhoenix is initialized with a standard encoder-decoder transformer model based on T5. At initialization, the model begins with 2 encoder layers, 2 decoder layers, and a feedforward layer width of 1024. The architecture of the model is easily modified by DeepPhoenix’s self-reprogramming in subsequent episodes.

Each episode of the DeepPhoenix algorithm is comprised of a training stage and a reprogramming stage. DeepPhoenix can be run for an arbitrary number of episodes to continuously self-improve, although its ability to do so is conditional on having an initial dataset with relevant code samples from which it can effectively deduce knowledge to improve upon its existing source code.

During the training stage, the model is trained on a corpus of computer code. In our experiments, we test a text-to-text "code refinement" task in order to learn code modification. Given an initial source code snippet, the model is trained to generate a modified version of that code snippet. The specific modification applied is arbitrary, but the newly generated or "refined" code should be syntactically and logically correct. The text-to-text transformer model outputs probability distributions over tokens, allowing for effective modeling of non-deterministic mappings for the code refinement process.

During the reprogramming stage, the trained model is given its own source code as input for code refinement. The model is queried to generate multiple modified versions of its current source code. Each refined source is executed to check for program validity, and the model instantiated within the refined code is quickly trained for one epoch on a small subset of the training corpus. Each model’s average loss over this "extended few-shot" training run is used as a proxy to evaluate the potential future performance of each refined source code version. A search algorithm is applied to find a high-performing modified source code which is kept as the new source code for DeepPhoenix, and the training stage is repeated with the model defined in this source.

Algorithm 1 DeepPhoenix Algorithm

Require: Default source code that defines a default model and default training algorithm
Ensure: Implements self-reprogramming artificial intelligence

```plaintext
source ← default source code;
while DeepPhoenix is running do
    if source defines a model then
        model ← model as defined in source;
    end if
    if source defines a train() function then
        train() ← train() as defined in source;
    end if
    train(model, dataset);
    for number of candidates do
        candidate ← model.generate(source)
        model, train, dataset ← as defined in candidate
        candidate.metrics = train(candidate) on a small subset of the dataset
    end for
    source ← candidate with the best metrics;
end while
```
Figure 1: Loss curves of multiple iterations of DeepPhoenix self-reprogramming models during training on text-to-text code refinement. Model 0 refers to the default model. Later model iterations tend to achieve favorable start, end, and intermediate loss values compared to earlier model iterations. The first 3 steps of each training phase are omitted to prevent scaling the graph to outlier loss values at the start of training.

3 Experiments

We carry out preliminary experiments evaluating a basic implementation of DeepPhoenix. We procedurally generate a code refinement dataset for transformer models, and use the DeepPhoenix algorithm to train language processing models on this dataset in order to rewrite their own neural network source code.

In the procedural code refinement dataset, we sample unrefined source codes for T5-based transformer models. Several model design parameters are randomly generated: number of encoder layers (between 1 and 8 inclusive), number of decoder layers (between 1 and 8), feedforward layer dimensionality (between 64 and 4096), and number of attention heads (between 1 and 16). Due to how the attention layers are designed, we also generate code to set key-value dimensionality equal to the model dimensionality divided by the number of heads in order for the attention layers to work properly. We “refine” this source code by randomly modifying one of the model design parameters. Either one among the encoder depth, decoder depth, and number of heads is incremented or decremented, or the feedforward width is randomly increased or decreased by a percentage of 1% to 50%, inclusive. The unrefined source code is used as input to the DeepPhoenix model, and the refined source is used as the corresponding output label. For the sake of simplicity, we don’t train our models on a full computer code corpus in these experiments.

In the DeepPhoenix training stage, the model is trained in a conditional generation configuration to generate refined transformer source codes given unrefined source code as input. The objective of this procedure is to teach the model to model design parameters in the source code of its own model class. This “refinement” process is more or less random, but the extended few-shot evaluation method used in the reprogramming stage of DeepPhoenix allows us to achieve performance improvements over multiple iterations of our reprogrammed DeepPhoenix model.

In these experiments, we use a simple greedy search approach to evaluate and select generated source codes that would potentially improve the code refinement model. The model is queried with its own source code as input, and randomly generates 8 refined source code candidates. The candidates are each evaluated using the extended few-shot method, training for one epoch on the first 1024 samples of the code refinement dataset. Source code candidates that produce errors are discarded entirely, and the source code candidate with the lowest average training loss in extended few-shot evaluation is kept as the new query code. If all candidates underperform the original source code, then the original source is kept. This new query code is given to the code refinement model as input to generate another
batch of source code candidates, and the process is repeated 8 times. The source code selected at the end of 8 batches of this extended few-shot greedy search is used to initialize the new code refinement model to be trained in the next iteration of the DeepPhoenix main loop. The main loop runs for 10 iterations of training and reprogramming. The resulting loss curves of our self-reprogramming models are shown in figure 1.

### Table 1: Example of an input-output pair comprised of an unrefined transformer source code and a corresponding refined source code. In the refined source, the feedforward layer dimensionality parameter is randomly increased by 30%.

| Unrefined Source (Input Text) | Refined Source (Output Text) |
|-------------------------------|------------------------------|
| config = transformers.PretrainedConfig.from_pretrained("Salesforce/codet5-small")
config.num_layers = 2
config.num_decoder_layers = 2
cfg.d_ff = 1024
model = transformers.T5ForConditionalGeneration(config) | config = transformers.PretrainedConfig.from_pretrained("Salesforce/codet5-small")
config.num_layers = 2
config.num_decoder_layers = 2
cfg.d_ff = 1331
model = transformers.T5ForConditionalGeneration(config) |

#### 4 Results

In our experiments, we successfully implement a self-reprogramming AI capable of freely modifying its own neural network design. Over several iterations of the DeepPhoenix algorithm, reprogrammed models tend to achieve increasingly favorable performance on a simple supervised text-to-text code modification task.

We propose and experimentally validate DeepPhoenix, the first fully self-reprogramming AI system. In our experiments, we successfully implement a DeepPhoenix-based AI system that learns to rewrite its own neural network source code. DeepPhoenix is unconstrained in reprogramming capabilities and can also modify various other parameters like data pipelines, computational capacity, learning dynamics, and learning objectives. With further experimentation, these results are easily extendable to models that self-modify these other parameters within a DeepPhoenix framework. We plan to promptly implement these in future work.

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