Proposal for Bachelorthesis

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Goal of this Bachelorthesis is to extend EmbeddedMontiArcDL (EMADL) with the special neural net architecture of generative adversiarial networks (GANs). In this proposal we will shortly introduce the already existing tools MontiCore [7], EmbeddedMontiArc [4] and EmbeddedMontiArcDL [8]. Finally we will talk about GANs and their challenges when integrating them to EMADL.

MontiCore is a language workbench which is capable of generating generators for domain specific languages (DSL). When fed with a context free grammar of a DSL and additional parameters MontiCore generates tools like a language parser and components for an abstract syntax tree. These tools can then be used to build a generator which is able to translate code of a DSL to a corresponding implementation in an existing coding language leaving the user with an executable application.

EmbeddedMontiArc is a DSL for easily creating component and connector (C&C) architectures. C&C Architectures consist of many componets responsible for different tasks and calculations. The single components have clearly defined inputs of other components and clearly defined outputs to other components via the given connectors. These architecture is designed for the purpose of being easily testable and allowing reusability of components making it expecially attractive to security-relevant cyber-physical systems. A possible application of C&C architectures is software for selfdriving cars.

Deep Learning has recently seen ever growing influence in many different applications and research fields. Thus it is an important challenge being able to build deep learning systems that are easy to understand, easy to test and easy to reuse for effective software engineering. EMADL tries to face this challenge by extending EmbeddedMontiArc with tools to implement deep learning algorithms. Hereby the focus is on being independent of an actual deep learning library thus offering many different backends for the actual implementation of the algorithms. In the currenty version of EMADL feed forward networks, convolutional neural nets, recurrent neural nets and reinforcement learning algorithms are already available.

GANs have a special architecture for generating artifical data similar to a given data-distribution. The architecture consists of one neural net for generating the artificial data and one neural net trying to discriminate the generated data and the data of the real data-distribution. The two networks play a minmax game both being trained to fool the other neural net. The idea is that eventually the generator learns to generate data similar to the data-distribution making it impossible for the discriminator to tell apart the faked data and the real data. The challenge of implementing GANs to EmbeddedMontiArcDL is that two independent networks need to be trained together. To face this challenge we will try to make use of the concepts already established in the reinforcement learning part of EMADL.

After EMADL has been extended by GANs succesfully, we want to evaluate our result by implementing some toy-examples like a mnist generator for handwritten digits. Ultimatly we want to implement the given GAN in [5] for improved road marking recognition in unconstrained datasets and for data augmentation with GANs.

The following papers will be usefull.

References

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