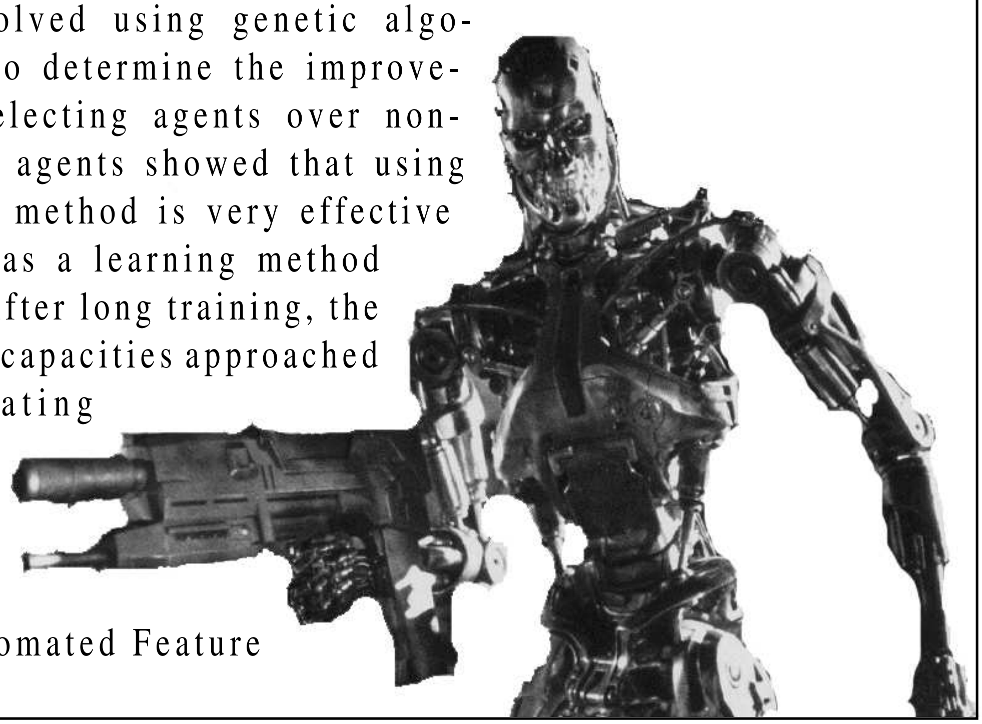
Automated Feature Selection to Maximize Learning in Artificial Intelligence

Joseph P. Turian

ABSTRACT

Traditional artificial intelligence computer programs reach a plateau beyond which learning stops. Game-playing artificial intelligence agents play at a level anywhere from beginner to expert but are never optimal, that is, they do not always make the best choice. The purpose of this project was to improve computer learning techniques so that plateau learning ability is increased. Automated Feature Selection (AFS), a new general technique, was created and implemented in two algorithms, Randomly Generating Operations (RGO) and Incremental Addition (IA). A key component of these algorithms is that neural network units which represent features are added into the training process. Feature selection (learning capacity maximization by using features in analysis) was entirely automated. Human interaction was not required once the program was started and hand-crafted features were not adopted. The agent was an independent entity that used learning methods which can be applied to any similar learning system. In RGO, features were randomly added to the neural networks. In IA, features were randomly added to the neural networks, and the most fit neural networks were evolved using genetic algorithms. Tests run to determine the improvement of feature selecting agents over non-featuring selecting agents showed that using RGO as a learning method is very effective and that using IA as a learning method may be effective. After long training, the programs' learning capacities approached optimality, indicating that intelligence maximization with minimal domain knowledge may be possible using Automated Feature Selection.



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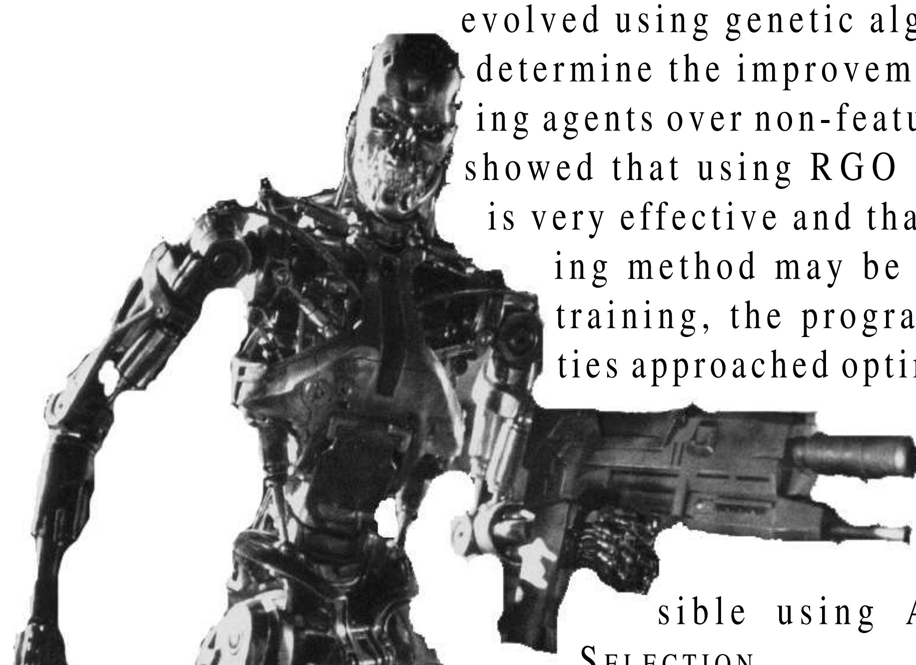

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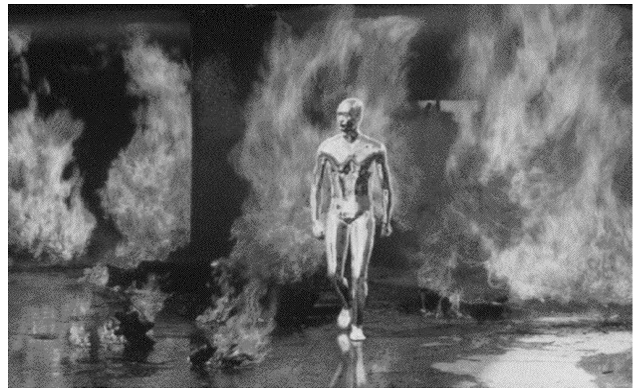

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