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Smarter Features, Simpler Learning?

Georg Moser and Sarah Winkler

Automated Reasoning: Challenges, Applications, Directions, Exemplary Achievements
26 August 2019, Natal

Portfolio Solver for Software Verification Competition

- strategy/tool are machine learned from program characteristics

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Demyanova et al., **Empirical Software Metrics for Benchmarking of Verification Tools**, 2017.

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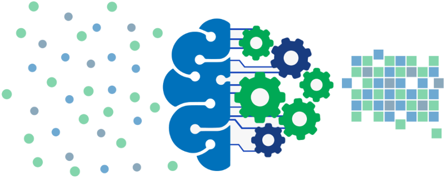
theorem proving problem →  → strategy

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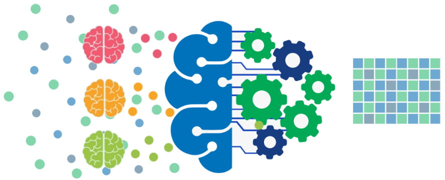

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  occurrence count for 27 roles: pointers, loop bounds, counters, ...
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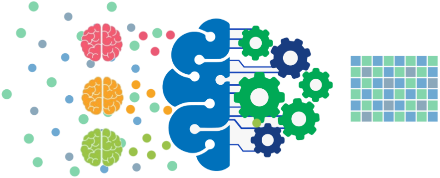

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- features: occurrence count for 3 types depending on iteration estimate
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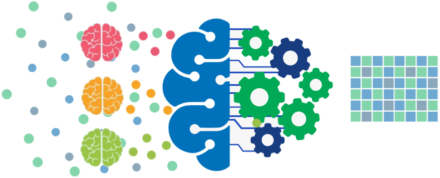
theorem proving problem →  → strategy

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basic blocks, indegree, (recursive) calls

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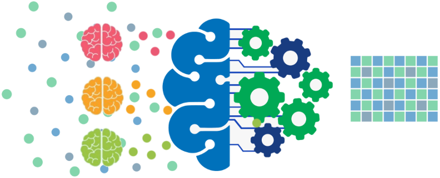

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Possible Characteristics of Rewrite Systems

- variable roles = argument positions of function symbols:

Example

$$\mathsf{add}(0, x) \to x \quad (1) \qquad \mathsf{mul}(0, y) \to 0 \quad (3)$$

$$\mathsf{add}(\mathsf{s}(x), y) \to \mathsf{s}(\mathsf{add}(x, y)) \quad (2) \qquad \mathsf{mul}(\mathsf{s}(x), y) \to \mathsf{add}(y, \mathsf{mul}(x, y)) \quad (4)$$

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- variable roles = argument positions of function symbols:
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Bellantoni and Cook, A new recursion-theoretic characterization of the polytime functions, 1992.

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- control flow = call graph analysis:

  strongly connected components, in/out degree of nodes, edges between nodes of different root symbols, ...

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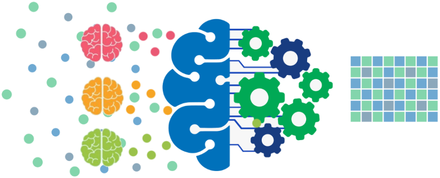
$$\begin{tikzcd}
(2) \arrow[r] \arrow[loop below] & (4) \arrow[loop below]
\end{tikzcd}$$

How about theorem proving in general?

consider machine learning of strategies applied to a given problem:

theorem proving problem →  → strategy

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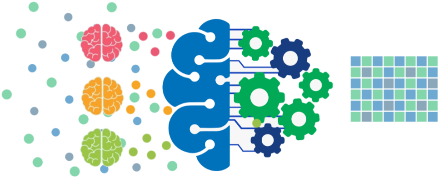
theorem proving problem →  → strategy

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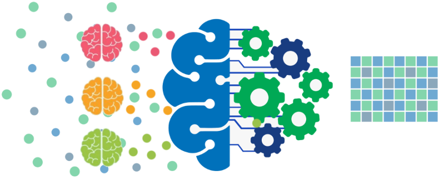
theorem proving problem →  → strategy

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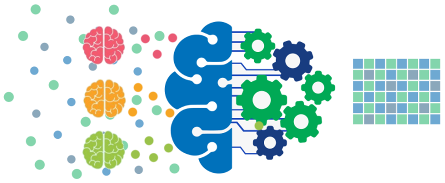
- how could such features look like?

theorem proving problem →  → strategy