中国科学技术大学
University of Science and Technology of China

The optimizationBenchmarking.org Experiment Evaluation Framework

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Outline

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  - Which setting of x_1, x_2, x_3, and x_4 can make $(x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_2 \vee \neg x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee \neg x_4)$ become true (or, at least, as *many* of its terms as possible)?

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- How can I make a good algorithm better (for my problem)?

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- Experimental analysis and comparison only practical alternative.

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- Consequence: Most optimization algorithms produce approximate solutions of different qualities at different points during their process.
- Experiments must capture solution quality and runtime data.

Structure of the Framework

谢谢！

Thank you.

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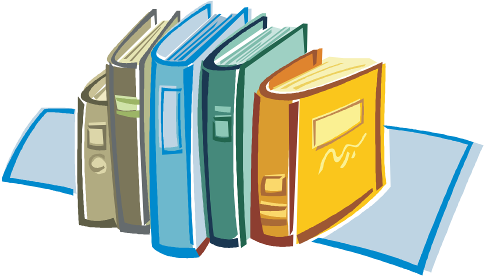
Caspar David Friedrich, "Der Wanderer über dem Nebelmeer", 1818
http://en.wikipedia.org/wiki/Wanderer_above_the_Sea_of_Fog



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