

Autotuning: D-Optimal Designs

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1 Autotuning with D-Optimal Designs and Analysis of Variance

1. Use `optFederov` to find 24 experiments for the full model:

$$Y = y_component_number + 1/y_component_number + \\ vector_length + lws_y + 1/lws_y + \\ load_overlap + temporary_size + \\ elements_number + 1/elements_number + \\ threads_number + 1/threads_number$$

2. Use `aov` to fit the full model, spending the 24 evaluations:

$$time_per_pixel = y_component_number + 1/y_component_number + \\ vector_length + lws_y + 1/lws_y + \\ load_overlap + temporary_size + \\ elements_number + 1/elements_number + \\ threads_number + 1/threads_number$$

3. Identify the most significant factors from the ANOVA summary. In this case, they are *vector_length* and *lws_y*.
4. Use the fitted model to predict the best *time_per_pixel* value in the entire dataset
5. Prune the dataset using the predicted best values for *vector_length* and *lws_y*
6. Use `optFederov` to find 24 experiments for the pruned model. If there are less than or exactly 24 candidates, use the full candidate set.

$$Y = y_component_number + 1/y_component_number + \\ load_overlap + temporary_size + \\ elements_number + 1/elements_number + \\ threads_number + 1/threads_number$$

7. Use **aov** to fit the pruned model, spending the 24 evaluations:

$$time_per_pixel = y_component_number + 1/y_component_number + \\ load_overlap + temporary_size + \\ elements_number + 1/elements_number + \\ threads_number + 1/threads_number$$

8. Identify the most significant factors from the ANOVA summary. In this case, they are *y_component_number* and *threads_number*.
9. Use the fitted model to predict the best *time_per_pixel* value in the entire dataset
10. Prune the dataset using the predicted best values for *y_component_number* and *threads_number*
11. Use **optFederov** to find 24 experiments for the pruned model. If there are less than or exactly 24 candidates, use the full candidate set.

$$Y = load_overlap + temporary_size + \\ elements_number + 1/elements_number$$

12. Use **aov** to fit the pruned model, spending the 24 evaluations:

$$time_per_pixel = load_overlap + temporary_size + \\ elements_number + 1/elements_number$$

13. Identify the most significant factors from the ANOVA summary. In this case, it is *elements_number*
14. Use the fitted model to predict the best *time_per_pixel* value in the entire dataset
15. Prune the dataset using the predicted best values for *elements_number*
16. Use **optFederov** to find 24 experiments for the pruned model. If there are less than or exactly 24 candidates, use the full candidate set.

$$Y = load_overlap + temporary_size$$

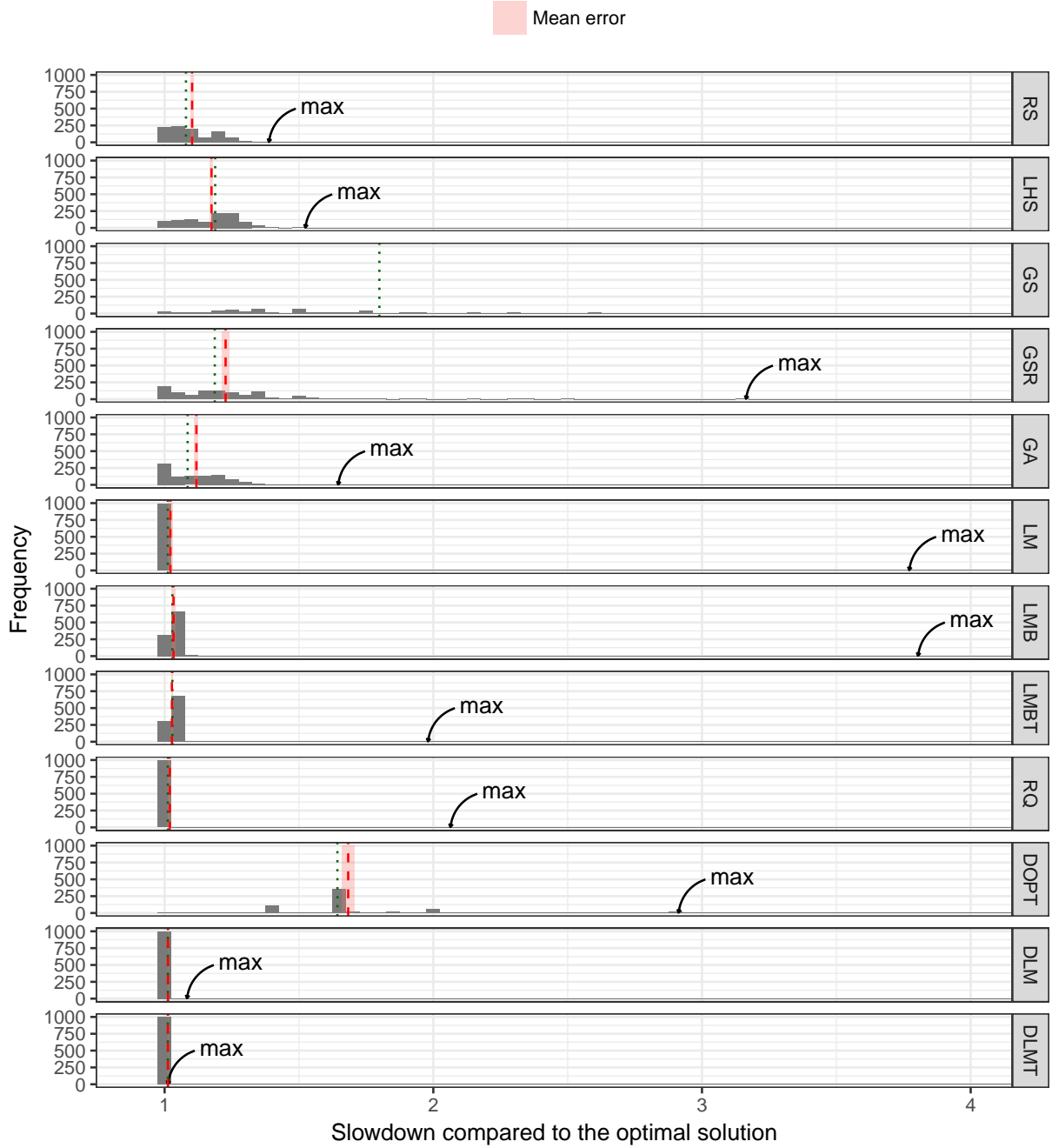
17. Use **aov** to fit the pruned model, spending the 24 evaluations:

$$time_per_pixel = load_overlap + temporary_size$$

18. Use the fitted model to predict the best *time_per_pixel* value in the entire dataset
19. Compare the predicted *time_per_pixel* with the global optimum

2 Results

2.1 Comparing Strategies



2.2 Checking Accuracy

To verify the “accuracy” of the selected metrics, I adapted the experiment scripts to check for each removed model variable in the actual **aoV** summary. Those initial choices seem to match in most cases with the variables identified as most relevant by the **aoV** summary, as shown below.

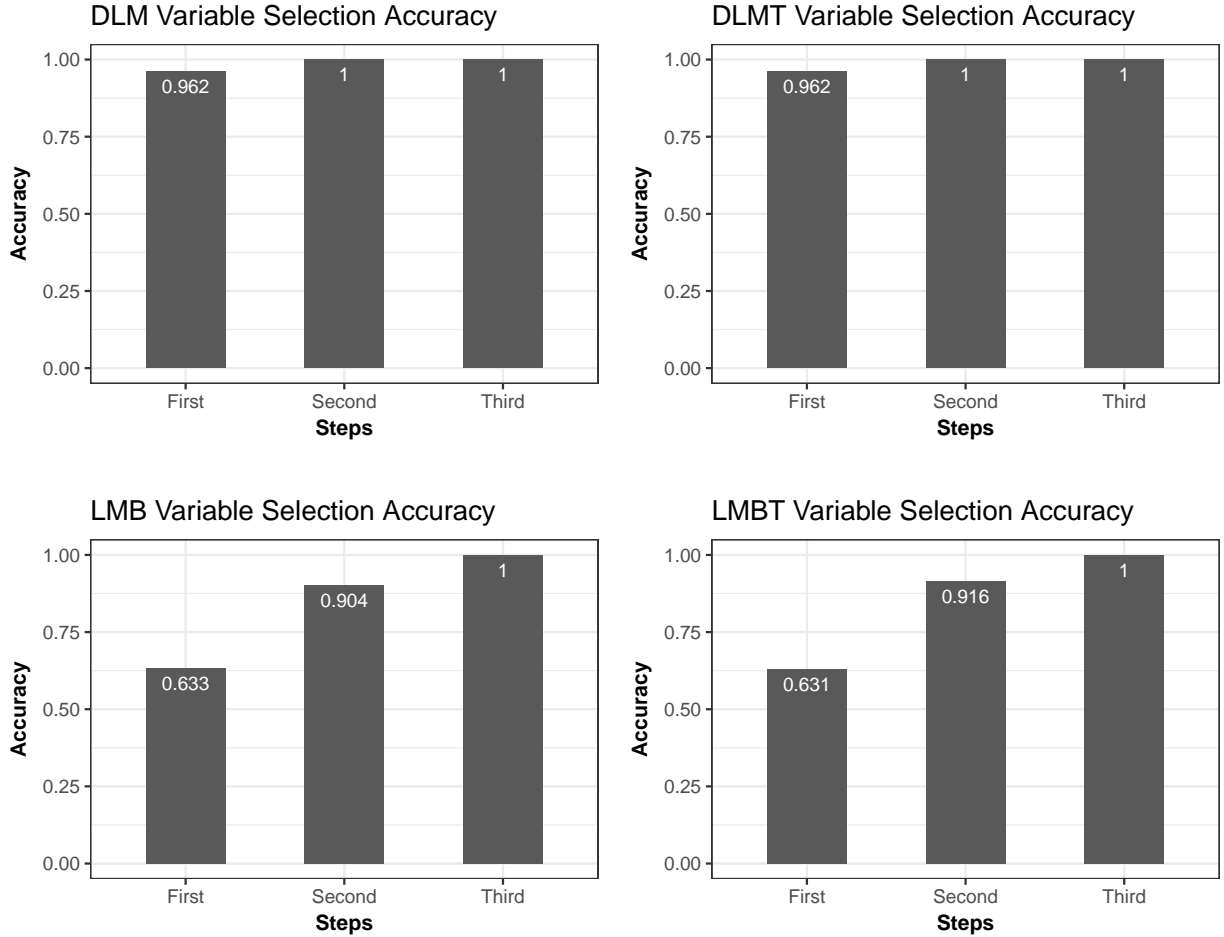
As described previously, at each step a group of variables is removed from the model based on their “score”, that is, the “ $\text{Pr}(> F)$ ” value in the **aoV** summary. I selected at most two variables at each of the three steps, based on preliminary visual analysis of the **aoV** summaries.

To measure how accurate those initial selections were I checked at each step if the n selected variables were in the n most relevant variables in that step’s **aoV** summary. If that was the case I

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Mean Pt.	Max Pt.
RS	1.00	1.03	1.08	1.10	1.18	1.39	120.00	125.00
LHS	1.00	1.09	1.19	1.17	1.24	1.52	98.92	125.00
GS	1.00	1.35	1.80	6.46	6.31	124.76	22.17	106.00
GSR	1.00	1.07	1.19	1.23	1.33	3.16	120.00	120.00
GA	1.00	1.02	1.09	1.12	1.19	1.65	120.00	120.00
LM	1.01	1.01	1.01	1.02	1.01	3.77	119.00	119.00
LMB	1.01	1.01	1.03	1.03	1.03	3.80	104.81	106.00
LMBT	1.01	1.01	1.03	1.03	1.03	1.98	104.89	106.00
RQ	1.01	1.01	1.01	1.02	1.01	2.06	119.00	119.00
DOPT	1.38	1.64	1.64	1.68	1.64	2.91	120.00	120.00
DLM	1.01	1.01	1.01	1.01	1.01	1.08	54.85	56.00
DLMT	1.01	1.01	1.01	1.01	1.01	1.01	54.84	56.00

Table 1: Summary statistics

incremented a step-specific counter. The counters were updated for 1000 iterations and then divided by 1000. This value represents the accuracy of the static selection in comparison with the values that would be selected if each individual **ao**v summary was analysed.



2.3 Comparing Models

