ML-Based DRV Prediction and Optimization for DTCO

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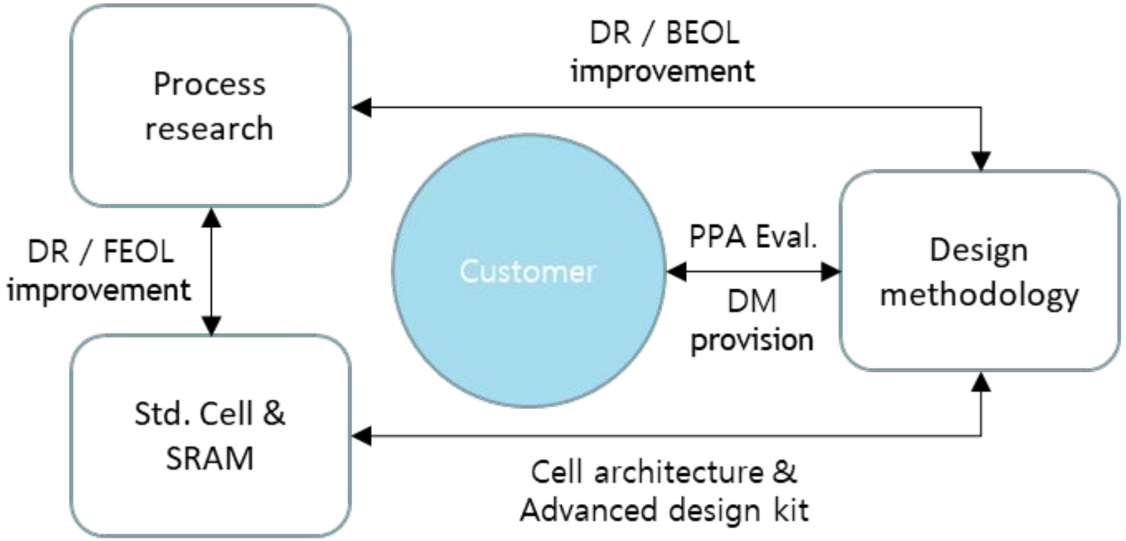
Motivation: Optimal design rule search in DTCO (1/2)

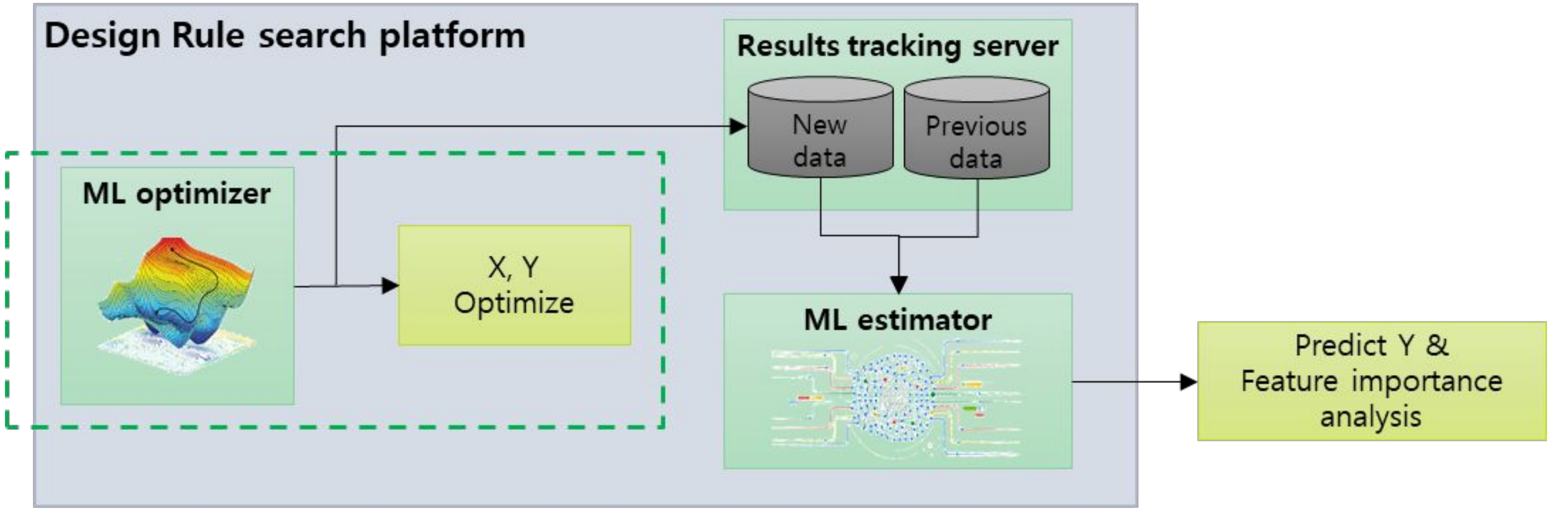
- Importance of Design-Technology Co-Optimization (DTCO) work in modern semiconductor processes
  - Due to the limitations of intrinsic scaling of the process, it has become important to consider design aspects when improving processes
  - To improve Power-Performance-Area (PPA) in the new process, the design and process should be co-optimized
- Problem: huge resources are required to optimize for the Design Rule (DR)
  - As the number of design rule parameters increases, the search space grows exponentially
  - In a tight TAT, it is difficult to find the optimal parameters based on an engineer's knowledge and experience alone



DTCO flow

Motivation: Optimal design rule search in DTCO (2/2)

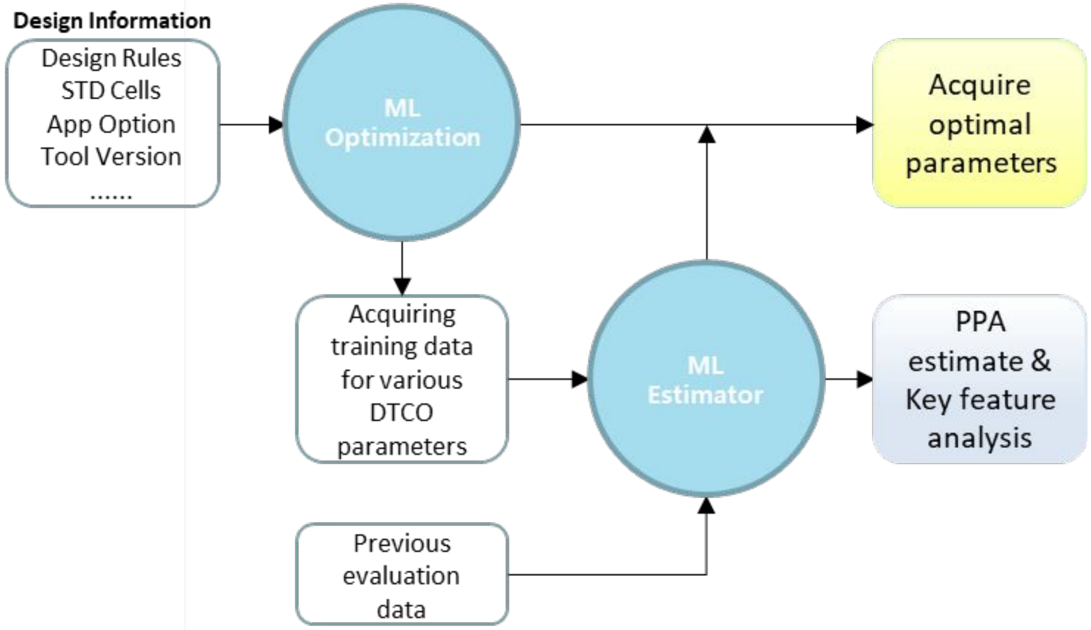
- Problem of the conventional DTCO process
  - Manual design-space exploration: Exploring entire space by changing dozens of DRs is virtually impossible
  - Quantitative data is hard to come by because engineers can only empirically determine how parameters tend to behave
- Goal: Develop a ML-based platform for finding optimized DR for PPAs
  - Develop a DR Violation (DRV) prediction surrogate model for DR analysis and guide provision
  - Can search a larger search space in less time than before



Schematic of the platform

OptiMuS: Platform proposal for ML-based DTCO

- DR optimization platform: OptiMuS (Optimizer for Multi-engineering System)
  - OptiMuS sweeps through the DR parameters to extract different P&R results
  - From these results, OptiMuS learns the correlation between DR and DRV and identifies the DR that minimizes DRV
  - Based on this correlation, create a surrogate model and search for Design Rule space
  - OptiMuS performs DRV optimization and feature importance (FI) analysis using SHAP[1], an explainable AI (xAI) technique



OptiMuS working flow

SHAP feature importance

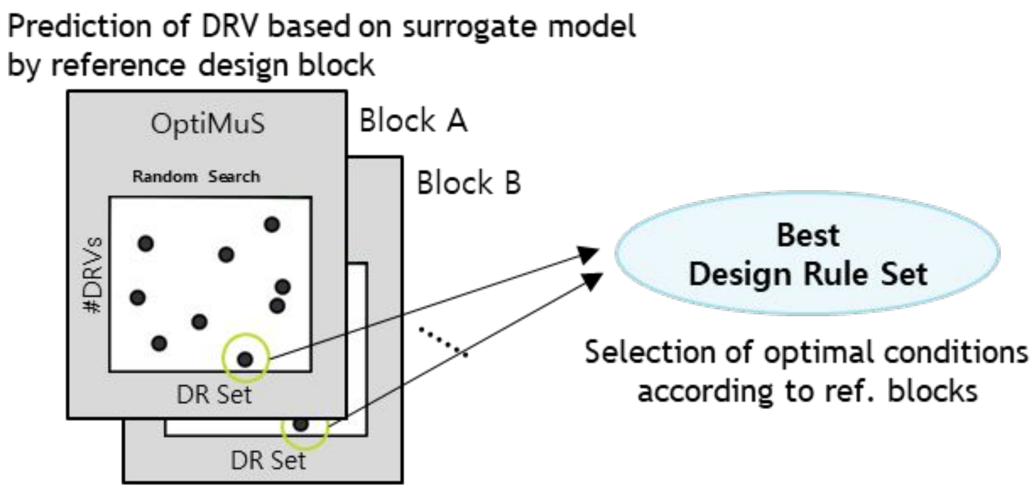
X axis : #DRV

Y axis : FI of DR to DRV

[1] Lundberg, Scott M., and Su-In Lee. "A unified approach to interpreting model predictions." Advances in neural information processing systems 30 (2017).

ML-based optimizer & estimator (1/2)

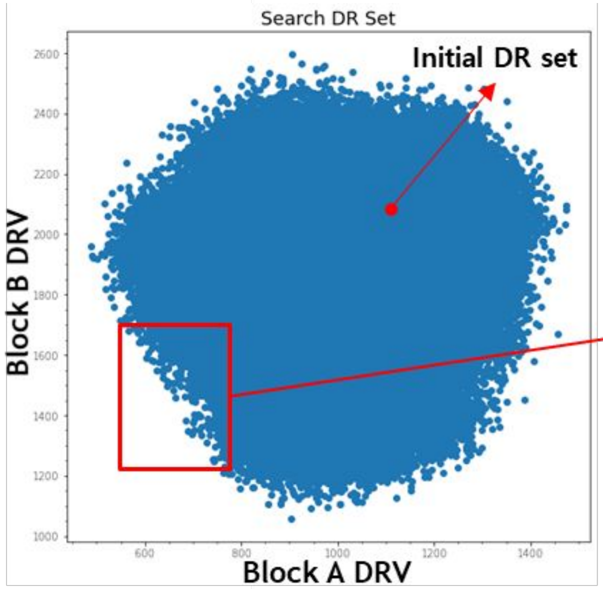
- Design space exploration at SF3 process: Industrial block design A and B
  - Parameters for optimization: DR sets (input) and #DRV (output)
  - Optimizer learns P&R samples of 200 to 300 route steps
  - Samples are used to build a surrogate DRV prediction model using tree-based regressor for each blocks



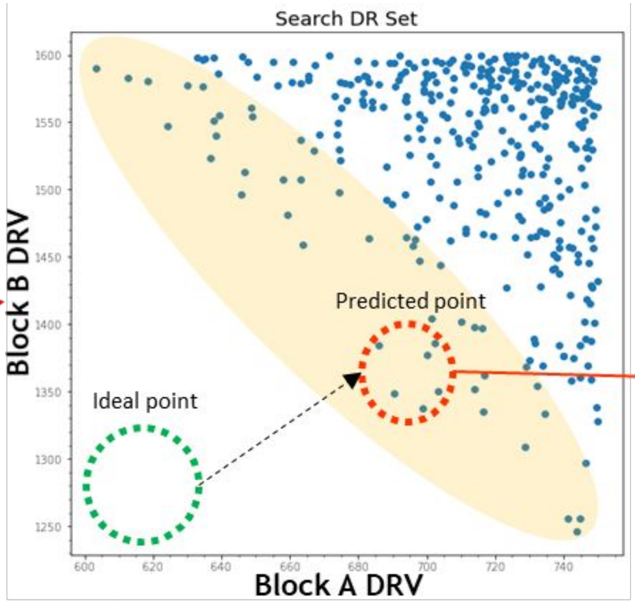
Searching best DR set

ML-based optimizer & estimator (2/2)

- Design space exploration at SF3 process: Industrial block design A and B
  - Optimal DR exploration by the surrogate model: 1 million DR sets
    - We found that for the same set of DRs, each block has a trend
    - Optimal conditions in Block A degrade the #DRV in Block B, and vice versa
    - Should consider that each block has a trade-off
  - Considering the trade-off, we chose optimal DR set candidates and checked DRV at final route opt. step
    - Were able to find an optimal set of DRs that satisfied the DRV pass condition



Result of searching 1M DR sets
by tree-based regressor



Select the best DR sets
considering trade-off of block A and B

Knob	A Block #DRV	B Block #DRV
1	**152**	210
2	**167**	246
3	230	205
4	**177**	**173**
5	**140**	**196**
6	290	275

Optimal DR set candidates
Knob 4, 5 passed #DRV condition (less than 200)

Experimental results (1/2)

- #DRV prediction model and DR/DRV tendency between block A and B
  - Accuracy of the surrogate model: For industrial block design A and B, the model showed average R^2 **score of 0.6**
  - TAT Improvement: TAT was reduced by half compared to manual work
    - Compared to manual work that took 4 weeks, OptiMuS completed DR optimization and area improvement **in 2 weeks**
  - Total average area improvement: OptiMuS achieved a total average block area improvement of **0.94%**
    - Under the same DR conditions, the area of Block A was reduced by 1.87% compared to manual work. Block B remained at its current level

	Block A	Block B
Train : Test	7:3	
#Data	238	246
R^2	0.6	

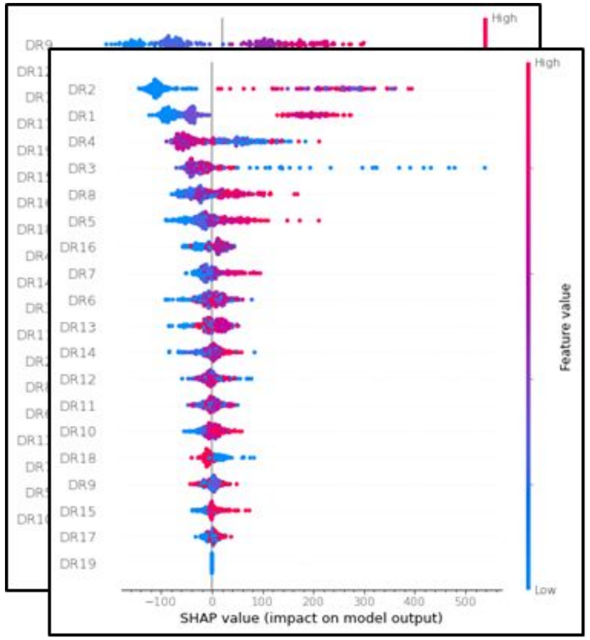
Surrogate model evaluation

	Manual	OptiMuS
#Search DR	5 or less	More than 10
Search Space	Hundreds conditions	Billions of conditions
Duration of Time	4 Weeks	2 Weeks

Optimizer summary

Experimental results (2/2)

- Feature analysis by SHAP
  - We found that 4 of top 7 features had different tendencies
  - In Block A, #DRV increased as value of DR4 increased, but in Block B, #DRV decrease as DR4 value increased
  - We were able to provide guidance to DTCO engineers through SHAP feature analysis



Feature	Block A	Block B	Importance Rank (avg.)
DR1	+	+	1
DR4	+	-	2
DR2	-	+	3
DR16	+	+	4
DR12	-	?	5
DR3	-	-	6
DR9	+	-	7

<DR / DRV tendency>
+ : DR / DRV direct proportion
- : DR / DRV inverse proportion
? : DR / DRV ambiguous proportion

DR tendency analysis by SHAP

Summary

- We propose that OptiMuS can improve block area
  - Our ML-based platform optimizes DTCO work with automated/parallelized systems and can conduct a wide range of DR multivariate analysis that engineers could not
  - On this platform, we performed a random search for a DR set using a boosting-based regression model, which allowed us to identify FIs and analyze and suggest trends for each DR
  - Using an optimized DR sets, we improved block area by 0.94% on average with an evaluation time 2.0x faster than the manual DTCO work at the SF3 process. In other words, it proved that OptiMuS can perform the engineer's DTCO work

- With this methodology, OptiMuS can positively impact DTCO in tight TATs
- We believe it can replace or contribute to tasks that engineers can't do in DTCO, and we plan to expand OptiMuS into a platform that targets power and performance