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Structure

Introduction	Algorithms	Methodology	Results	Conclusion
Context The Problem Goal	Multiple Linear Regression Decision Tree Random Forest Support Vector Regression	Evaluation Metrics Scaling Feature Extraction Training flow Model Deployment	Tp _H L Tp _L H IINT Sim. v Inf. time	Best & Worst Algorithm Future Works









Context















Algorithms

Methodology

Results

Conclusion

The Problem



- More corner cases must be considered during the electrical characterization
- Machine learning can assist digital design in many levels









Results Introduction Algorithms Methodology Conclusion Goal Regression Task! **CMOS INVERTER** SUPERVISED ALGORITHMS **TARGETS CIRCUIT** Vdd **PREDICTION MACHINE LEARNING** $Tp_{l}H$ **MODELS** Vin Vout SIMULATION DATA

Multiple Linear Regression

Support Vector Regression

Decision Trees

Random Forest









(temperature, voltage,

process variability...)







 $Tp_{\mu}L$

Energy



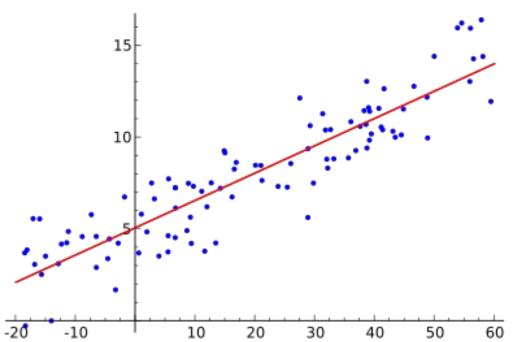






Conclusion

Multiple Linear Regression (MLR)



$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

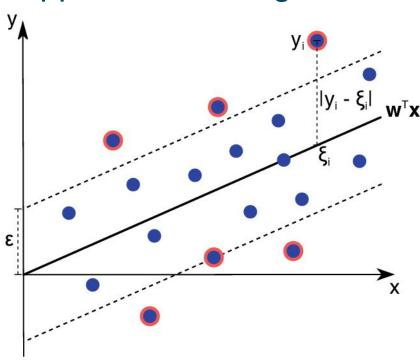








Support Vector Regression



$$\hat{y} = w^T x + b$$





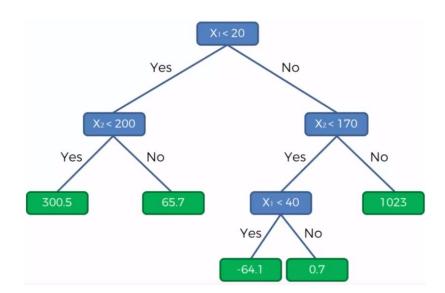




Algorithms

Decision Tree

Introduction



Methodology

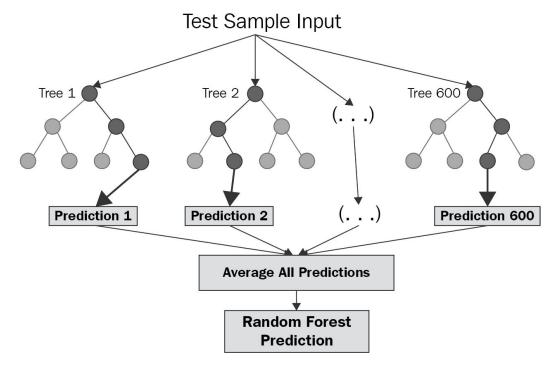








Random Forest





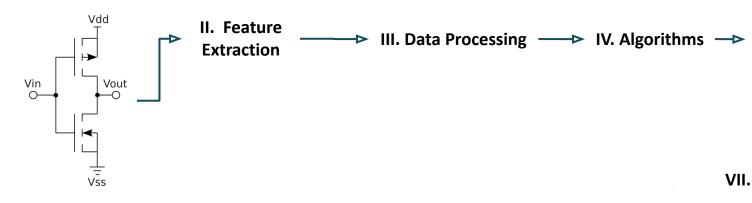


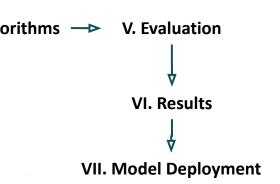




Training Flow - Overview

I. Simulation











Feature Extraction

1000 Monte Carlo transient simulations of 20ns with step of 0.1ns in HSPICE

<u>Features</u>

NMOS Vth0

PMOS Vth0 (threshold voltage)

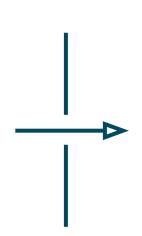
Temperature (-25, 0, 50, 75, 100°C)

Voltage (0.6, 0.7, 0.8, 0.9V)

Width PMOS (70, 140, 280, 350, 420nm)

Width NMOS (70, 140nm)

Length (20, 32, 40nm)



Targets

High-Low Propagation (Tp_L) Low-High Propagation (TP, H) Energy









Conclusion

Data processing (Scaling)

$$x' = rac{x - \min(x)}{\max(x) - \min(x)}$$
 MIN-MAX Scaler









Algorithms (Cross Validation)

Values & Best Hyperparameters

DT - Max Depth: 1, 5, 10, 25, 50 RF - Max Depth: 1, 5, 10, 25, 50

RF - **N Estimators**: 5, 25, 50, 100, 150

	DT - Max Depth	RF - Max Depth	RF - N Estimators
Tp _H L	5	5	25
Tp _L H	10	10	150
Energy	10	10	150

50% Training Set

25% Validation Set

> 25% Test Set









Algorithms

Methodology

$$\sqrt{\frac{1}{m} \sum_{i=1}^{m} (h(x^{(i)}) - y^{(i)})^2}$$

Root Mean Square Error (RMSE)

$$R^{2} = 1 - \frac{\sum_{i} (y_{i} - \hat{y}_{i})^{2}}{\sum_{i} (y_{i} - \overline{y}_{i})^{2}}$$

Coefficient of Determination (R²)



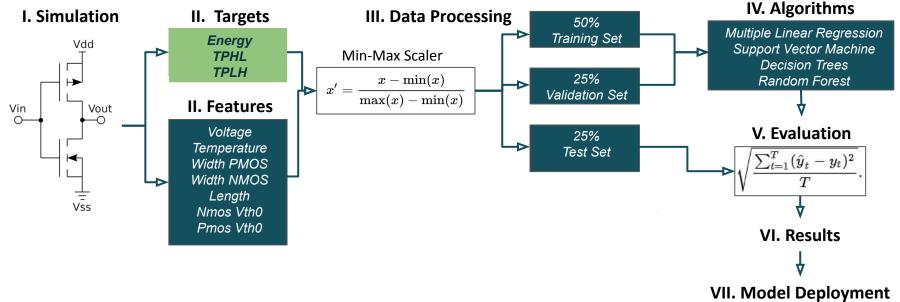


Conclusion





Training Flow



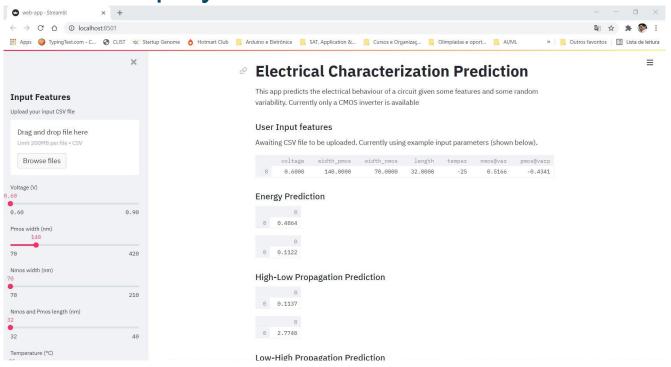








Model Deployment







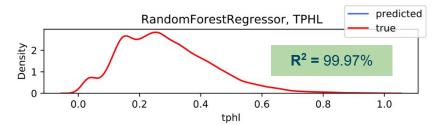


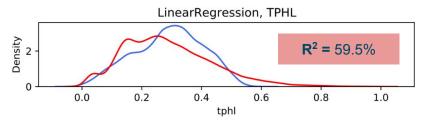


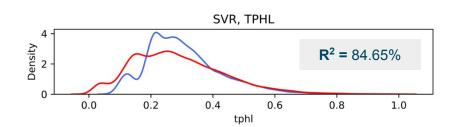


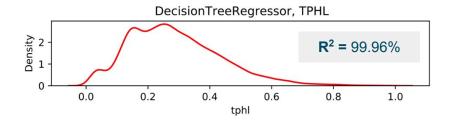
Algorithms Introduction Methodology **Results** Conclusion

Tp_HL Prediction









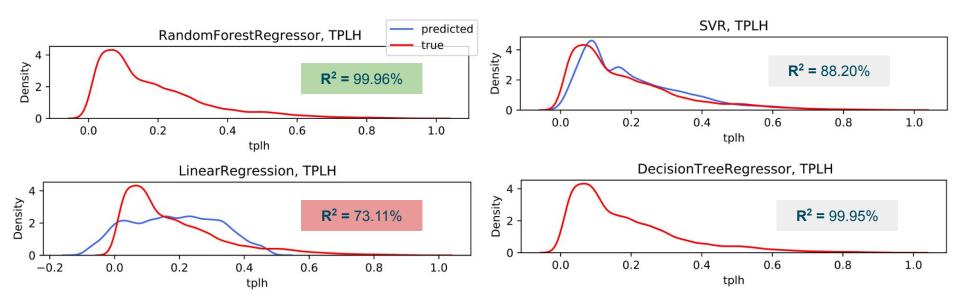








Tp, H Prediction





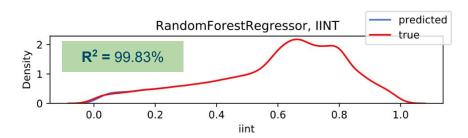


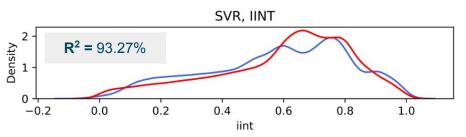


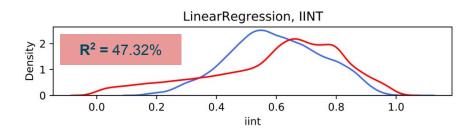


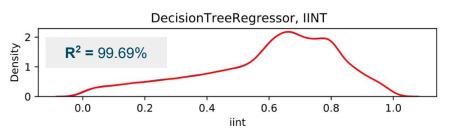
Introduction Algorithms Methodology Conclusion **Results**

Energy Prediction

















Single Hspice electrical simulation = 0.069 s

$$DT = 0.0006 s (115 \times)$$

$$RF = 0.0432 s (1.59 \times)$$







Algorithms

Introduction

Results

Conclusion

Best Algorithm

Random Forest

Worst Algorithm

Multiple Linear Regression









Methodology

Possible Applications

Foundries can adopt ML to cell characterization and make available the machine learning model trained, protecting the private data of the device models.

Future Works

Basic gates from a standard cell library

Investigate Neural Networks architectures

Evaluate the dependencies between the ML models and the technology node, considering FinFET devices







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Exploring Machine Learning for Electrical Behavior **Prediction:**

The CMOS Inverter Case Study

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Appendix

Pearson Correlation Coefficients

