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Vector-based Dynamic IR-drop Prediction Using Machine Learning

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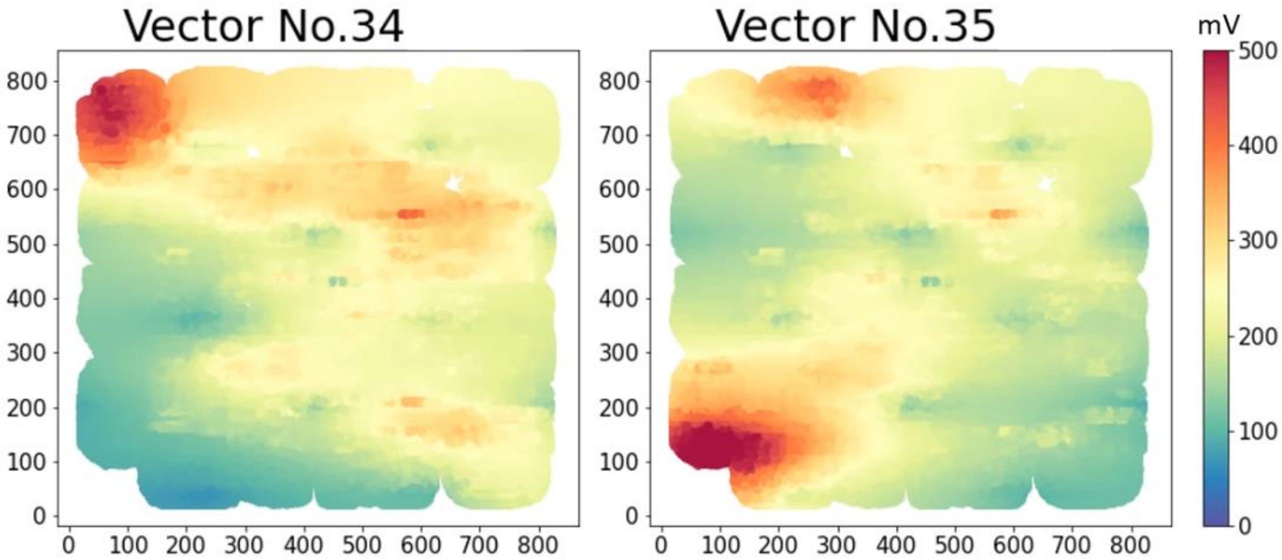
Ansys

Vector-based Dynamic IR-drop

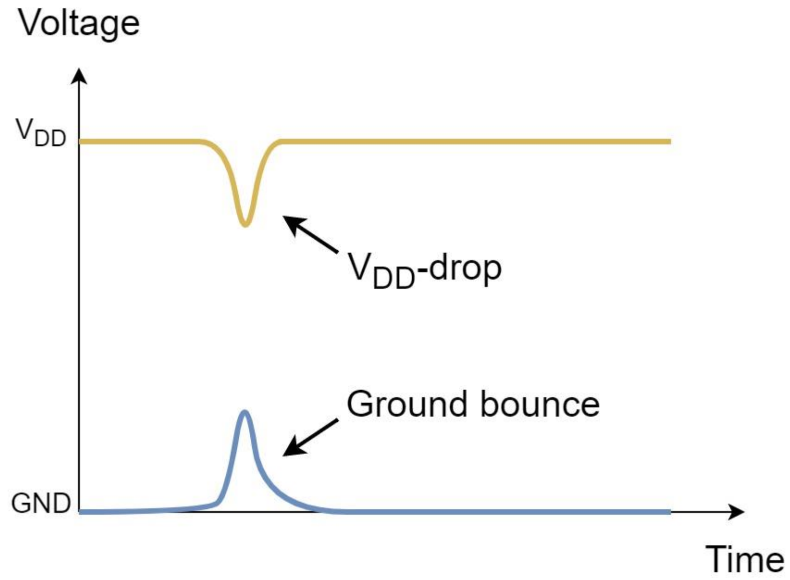
- **Different IR-drop maps for different vectors**



- **Many vectors, long analysis time**
  - B19 as example
    Around 1900 vectors, around 4000s for one vector
- **Need to speedup IR-drop analysis**

IR-drop

- **Include V_{DD}-drop and ground bounce**
- **Degrade performance and cause system failure**
- **Test issues**
  - Power is larger in test mode than in normal mode
  - Some test vectors induce large IR-drop
    - IR risky vectors
  - Overkill on good chips



Dynamic IR-drop Analysis

Vectorless [Lin 03]

- Determine transitions based on toggle probability
- Without testbench, no vector input
- Pessimistic

Vector-based

- Assign transitions recorded in waveform to cells
- Input vector
- Too many vectors
- Long runtime to perform dynamic IR-drop analysis

[Lin 03] Shen Lin, et al. "Methods for full-chip vectorless dynamic IR analysis in IC designs." U.S. Patent Application

Previous Work

- **Predict dynamic IR-drop for each cells [Fang 18]**
  - Consider floorplan (neighbor cell feature)
  - Vectorless
- **Predict average dynamic IR-drop of tile [Xie 20]**
  - Vector-based
  - Cannot predict the IR-drop value of each cell

[Fang 18] Fang, Yen-Chun, et al. "Machine-learning-based dynamic IR drop prediction for ECO." Proceedings of the International Conference on Computer-Aided Design. 2018.
[Xie 20] Xie, Zhiyao, et al. "PowerNet: Transferable dynamic IR drop estimation via maximum convolutional neural network." 2020 25th Asia and South Pacific Design Automation Conference (ASP-DAC). IEEE, 2020.

Motivations & Goals & Key results

Motivations

- Long runtime of vector-based dynamic IR-drop analysis
- No good methods to identify IR-drop risky vectors

Goals

- Predict vector-based dynamic IR-drop for all cells
- Identify IR-drop risky vectors quickly

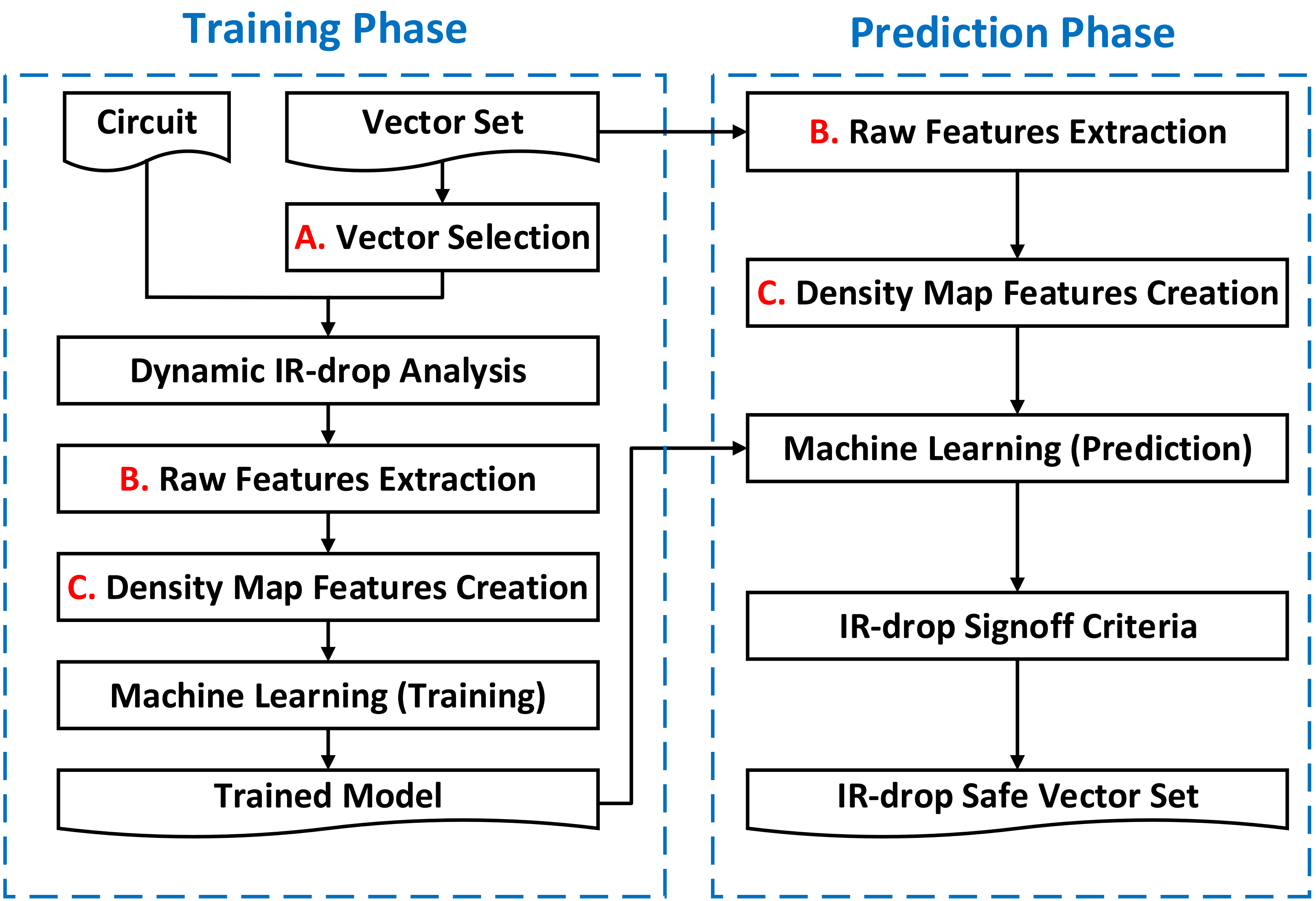
Key results

- Mean absolute error (MAE) of IR-drop predictor is less than 3% of supply voltage
- 495x speedup compared to commercial tool
- Identify 70% IR-drop risky vectors

Outline

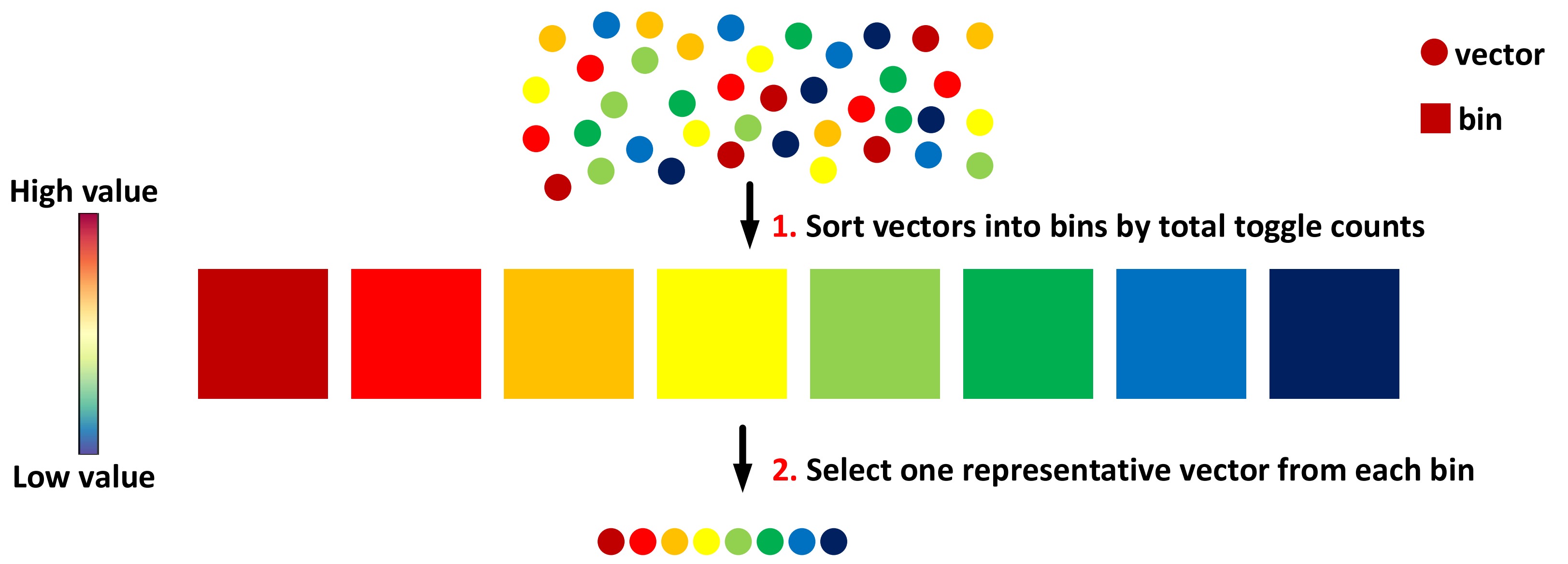
- Introduction & Background
- Proposed Technique
- Experimental Results
- Conclusion

Our Proposed Flow



A. Vector Selection

- **Need** **representative vectors** **to train model**
- **Use** **total toggle counts** **to select vectors**
  - Step 1. Sort vectors into bins by total toggle counts
  - Step 2. Select one representative vector from each bin

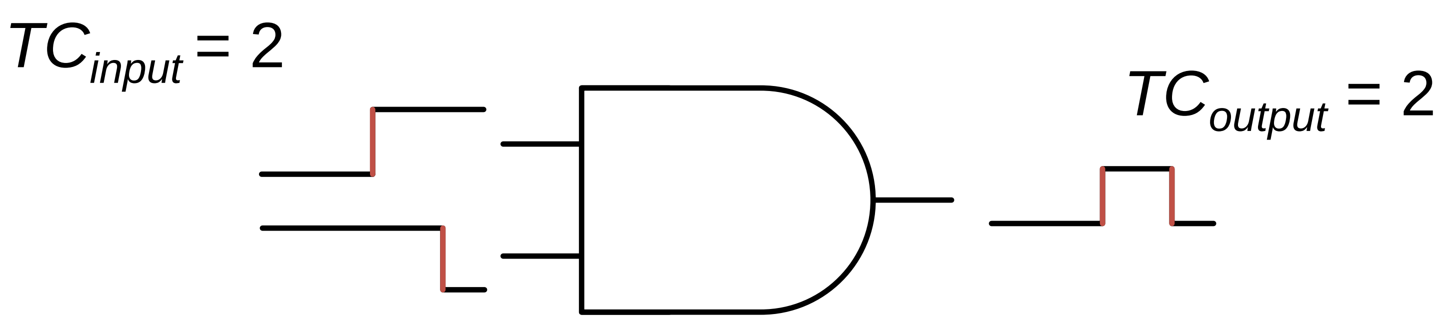


B. Raw Features Extraction

- **Vector-independent features (VI)**
  - Not change with input vector
  - e.g. shortest path resistance, physical location
- **Vector-dependent waveform features (VDW)**
  - Change with input vector
  - Extract from logic simulation waveform
- **Vector-dependent power features (VDP)**
  - Change with input vector
  - Perform power analysis

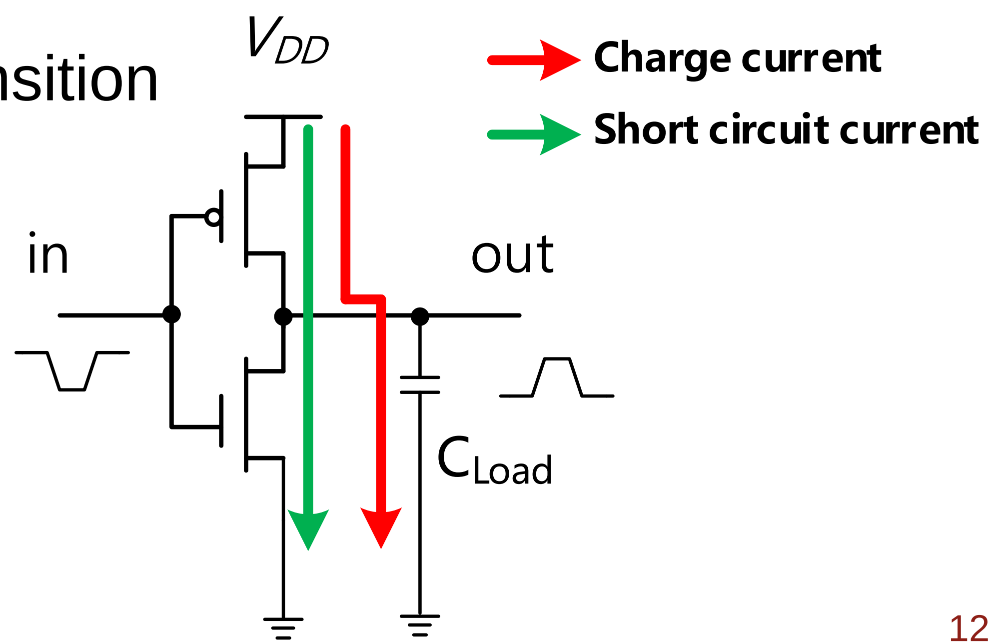
Vector-Dependent Waveform Features

- **Toggle count of input, TC_{input}**
- **Toggle count of output, TC_{output}**
- **Toggle count of internal connection, $TC_{internal}$**
- **Minimum arrival time, $T_{arrival}$**
  - Time of first signal transition at output



Vector-Dependent Power Features

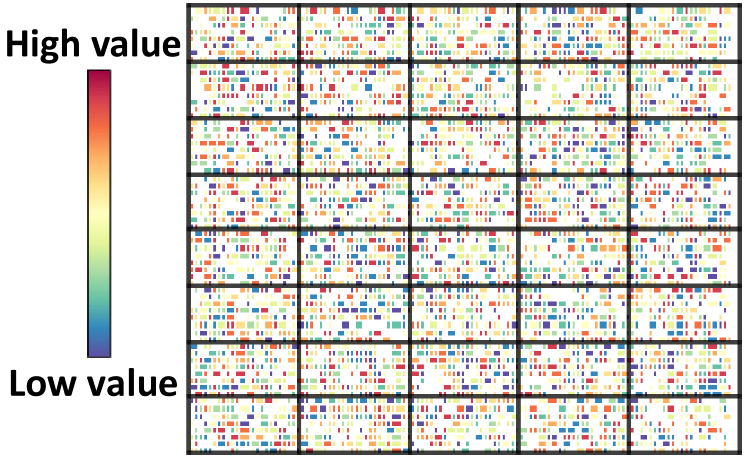
- **Internal power**
  - Power dissipated within the cell
- **Switching power**
  - Power dissipated by charging of load capacitance
- **Transition time**
  - Duration of output transition
- **Peak current**

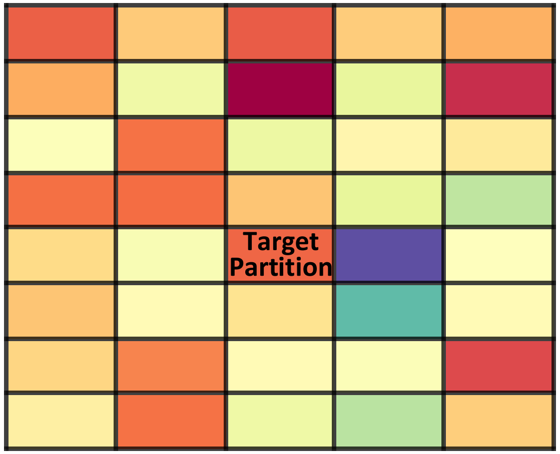


C. Density Map Features Creation I

- **Use density map features**
  - IR-drop is a local effect
  - Provide local information around a target cell
- **Creation**
  - Use raw features, Toggle count of input as example

1. Divide circuit into partitions **2. Sum up the TC_{input} of cells in each partition**



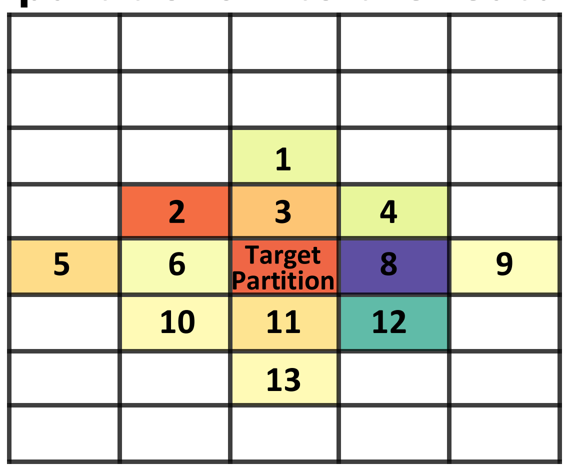


C. Density Map Features Creation II

Constant feature dimension

- Not change with circuit size
- Each selected raw feature creates 13 density map features

3. Add neighbor partitions into the feature set of target cell



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Setup

Profile of circuit designs

Circuit Design	# cells	# vectors	Mean IR-drop (mV)	Max IR-drop (mV)	Runtime of IR-drop analysis (s)
MEMC	223,829	187	248.67	402.72	7,224
b19	347,049	1,953	183.87	565.34	4,785
leon3mp	1,049,484	3,558	219.03	467.68	24,210

- Supply voltage: 0.95V, Cell library: NanGate 45-nm

Perform IR-drop analysis

- Redhawk-SC

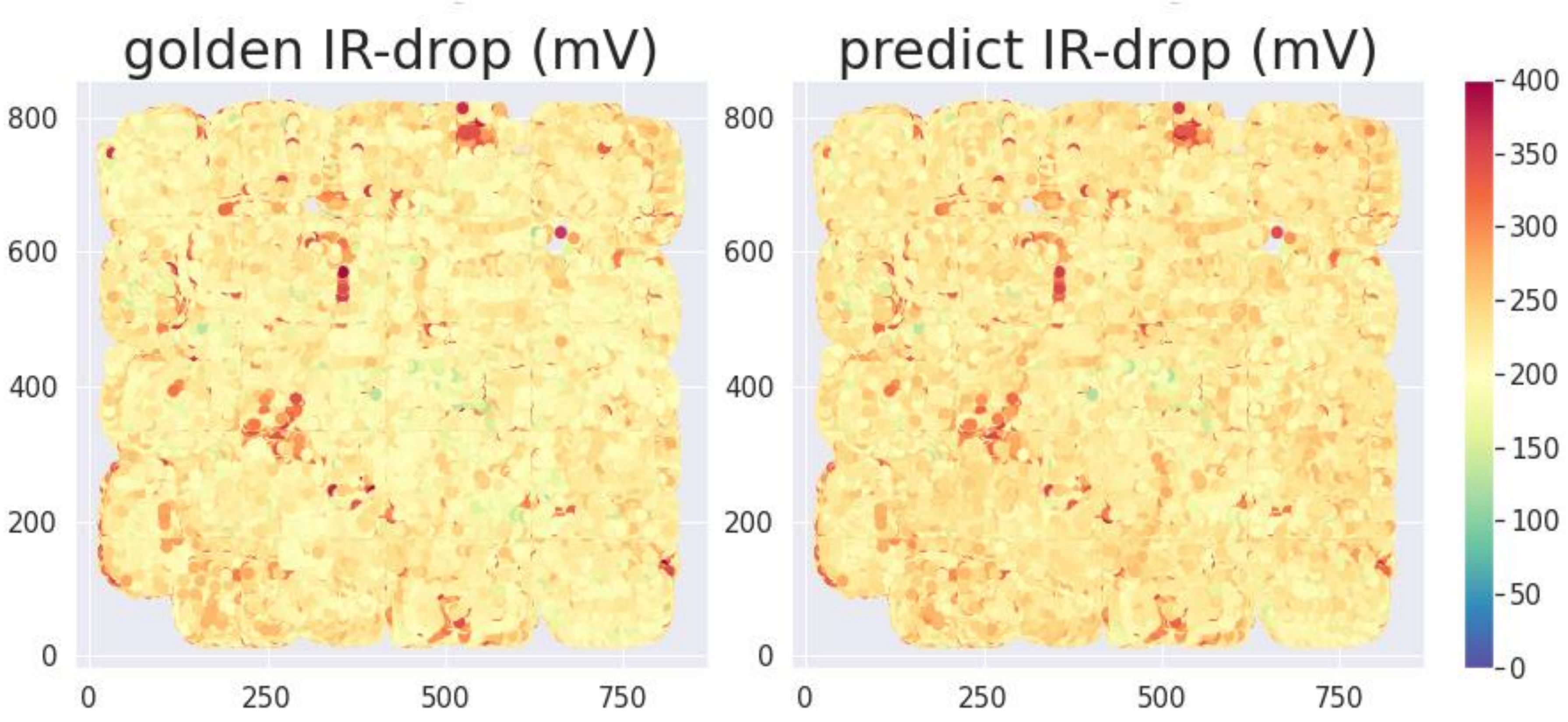
Machine learning model

- XGBoost [Chen 16]
- Use 8 raw features in density map creation

[Chen 16] Tianqi Chen, et al. “Xgboost: A scalable tree boosting system.” In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*

Golden versus Predicted IR-drop Map

- Very similar



Density Map Features Important

- **Mean absolute error (MAE)**
  - Error between predicted IR-drop and golden IR-drop
- **Correlation coefficient (CC)**
  - Measure of linear correlation between predicted IR-drop and golden IR-drop
  - Value between -1 to 1,1 implies perfect linear correlation
- **Raw+Density performs better than Raw**

Design / Metrics	MEMC		b19		leon3mp	
	Raw	Raw +Density	Raw	Raw +Density	Raw	Raw +Density
MAE(mV)	26.37	19.47	43.06	25.91	13.65	12.29
CC	0.45	0.66	0.34	0.79	0.73	0.83

Vector-Dependent Features Important

- **VI+VDW performs well as VI+VDP**

Design / Metrics	MEMC			b19			leon3mp		
	VI+ VDW	VI+ VDP	VI+ VDW+ VDP	VI+ VDW	VI+ VDP	VI+ VDW+ VDP	VI+ VDW	VI+ VDP	VI+ VDW+ VDP
MAE(mV)	19.47	15.77	15.76	25.91	30.61	30.19	12.29	14.39	13.06
CC	0.66	0.81	0.78	0.79	0.71	0.71	0.83	0.87	0.82

VI: vector-independent features
VDW: vector-dependent waveform features
VDP: vector-dependent power features

Runtime of IR-drop Predictor

- **Vector selection is important**
  - Long runtime in IR-drop analysis for training labels
- **VI+VDW has at least 495x speedup ratio**
  - Faster than VI+VDP

Stage	MEMC			b19			leon3mp		
	VI+ VDW	VI+ VDP	VI+ VDW+ VDP	VI+ VDW	VI+ VDP	VI+ VDW+ VDP	VI+ VDW	VI+ VDP	VI+ VDW+ VDP
IR-drop analysis for training labels(s)	130k			86k			435k		
Total training time(s)	132k	131k	132k	89k	89k	89k	442k	443k	443k
Total prediction time(s)	6.5	532.6	535.2	1.8	77.6	78.1	3.8	492.0	493.3
IR-drop analysis(s)	3,227			1,378			2,306		
Speedup ratio	495	6	6	778	17	17	600	4	4

IR-drop Risky Vector Identification

- **IR-drop risky vector:**
  - Average IR-drop of 5% worst cells is large than 310 mV
- **Extra modifications:**
  - One MAE as guard band
- **Identify 70% IR-drop risky vectors**

IR-drop risky vector (MEMC)

golden \ predict	Risky	Safe
Risky	10	0
Safe	27	45

IR-drop risky vector (b19)

golden \ predict	Risky	Safe
Risky	14	5
Safe	22	41

IR-drop risky vector (leon3mp)

golden \ predict	Risky	Safe
Risky	5	2
Safe	14	61

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Conclusion

- Predict vector-based IR-drop using Machine Learning with VI+VDW features
- MAE of IR-drop predictor is 3% supply voltage
- 495x speedup compared to commercial tool
- Identify 70% IR-drop risky vectors

Thank You!