

SMAT : An Input Adaptive Auto-Tuner for Sparse Matrix-Vector Multiplication

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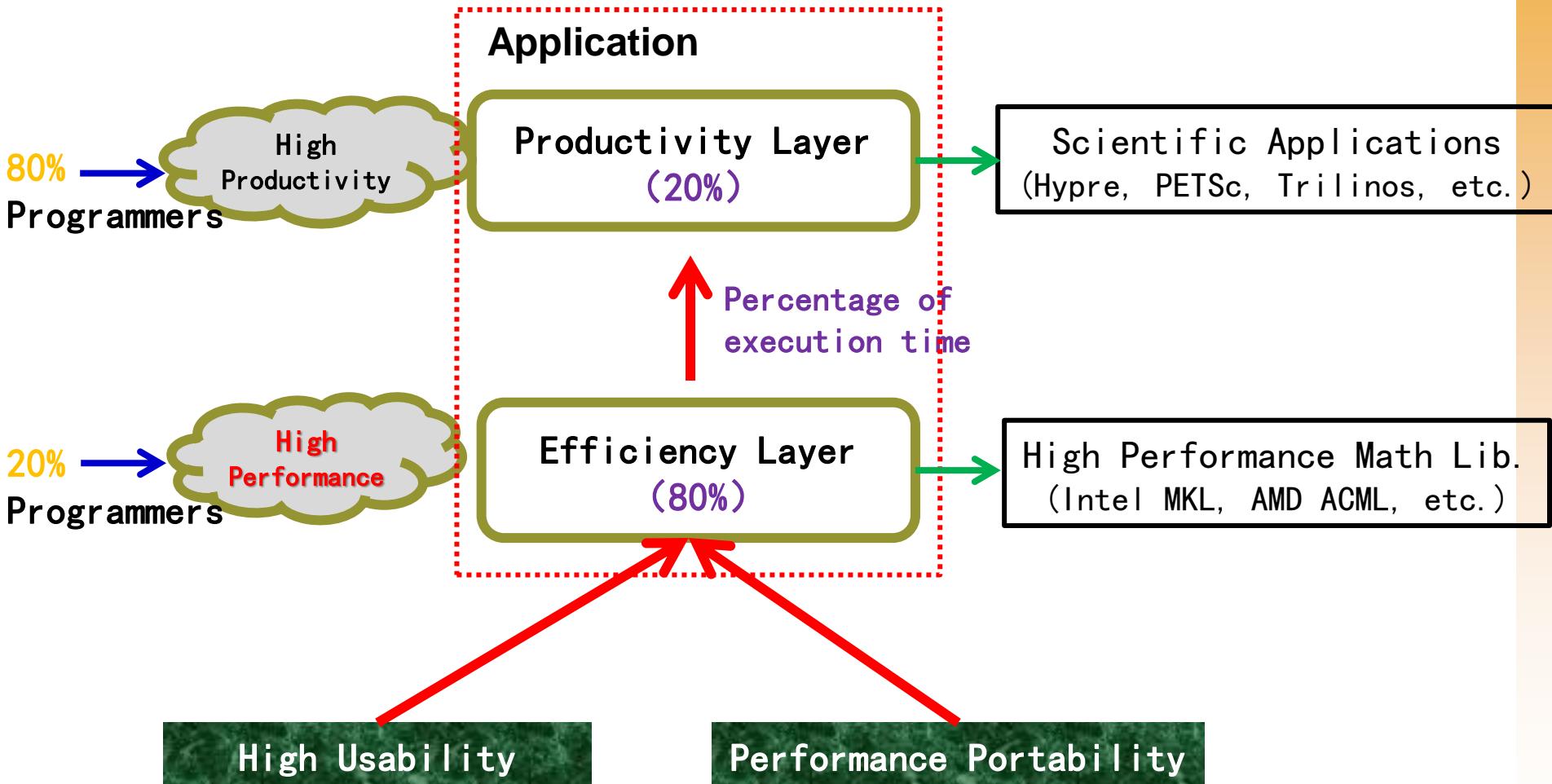
SMAT Design and Implementation

4

Experimental Results

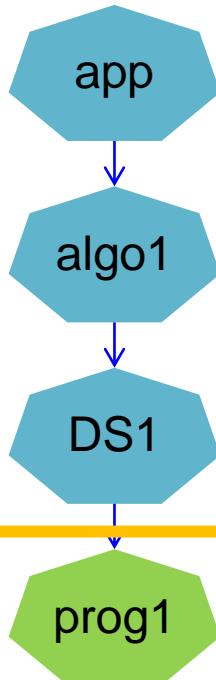
High Performance Computational Software Development-1

“2-8” Principle

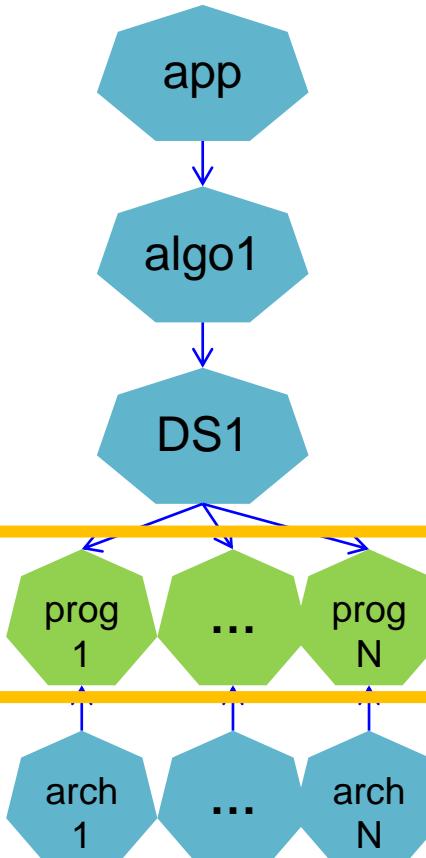


High Performance Computational Software Development-2

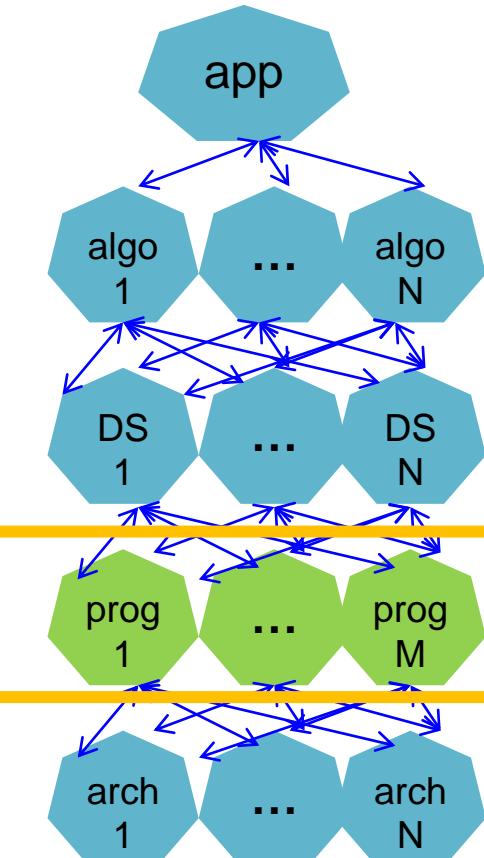
Hand-tuning



Autotuning



Co-Autotuning



Yesterday

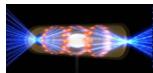
Today

Tomorrow

Killer Applications

Computational Science

ITER



Climate



Oil



Exascale

Data Science



Social network



National Security



System Biology

Big Data



Sparse Linear System

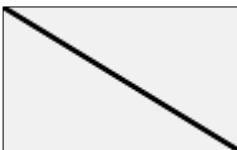
Sparse Matrices



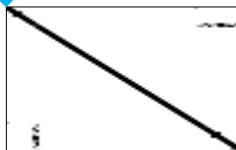
Protein



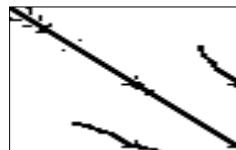
FEM /
Spheres



FEM /
Cantilever



Wind
Tunnel



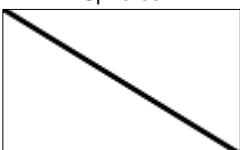
FEM /
Harbor



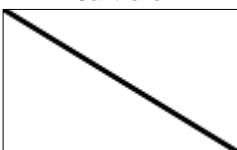
QCD



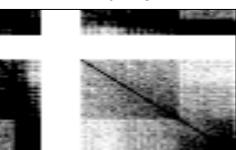
FEM /
Ship



Economics



Epidemiology



FEM /
Accelerator



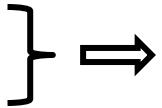
Circuit



webbase

Sparse Matrix

- Diverse Application Background
- Different Solving Methods

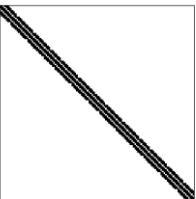


Diff. Nonzero
Distribution Structure

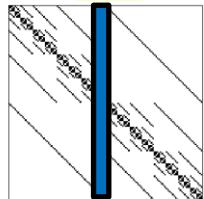


Kinds of Sparse Matrices

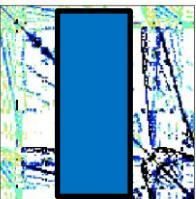
- Diagonal Matrix
- “Slim” Matrix
- “Fat” Matrix
- Power-Law Matrix
- Matrix with Dense Blocks
- ...



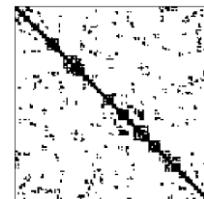
Diagonal
“pcrystk02”



“Slim”
“Bfly”



“Fat”
“crankseg_2”



Power-Law
“roadNet-CA”

number of nonzeros per row

222

Storage Formats

$$A = \begin{bmatrix} 1 & 5 & 0 & 0 \\ 0 & 2 & 6 & 0 \end{bmatrix}$$

SpMV: solve $Y = AX + Y$, where A is a sparse matrix, X and Y are dense vectors.

SpMV: solve $Y = AX + Y$, where A is a sparse matrix, X and Y are dense vectors.

```
[1 5 2 6 8 3 7 9 4] { sum = x[indices[i]] - data[i];
y[i] = sum;
}
```

(a) CSR SpMV

```
row [0 0 1 1 2 2 2 3 3]
col [0 1 1 2 0 2 3 1 3]
data [1 5 2 6 8 3 7 9 4]
```

```
for (i = 0; i < num_nonzeros; i++)
{
    y[rows[i]] = data[i] * x[cols[i]];
}
```

(b) COO SpMV

```
offsets [-2 0 1]
data [* 1 5
      * 2 6
      8 3 7
      9 4 *]
```

```
for (i = 0; i < num_diags; i++){
    k = offsets[i]; //diagonal offset
    lstart = max(0, -k);
    jstart = max(0, k);
    N = min(num_rows - lstart, num_cols - lstart);
    for (n = 0; n < N; n++){
        y[lstart+n] = data[lstart+i*stride+n] *
        x[jstart + n];
    }
}
```

(c) DIA SpMV

```
Indices [0 1 *
         1 2 *
         0 1 2
         1 3 *]
data [1 5 *
      2 6 *
      8 3 7
      9 4 *]
```

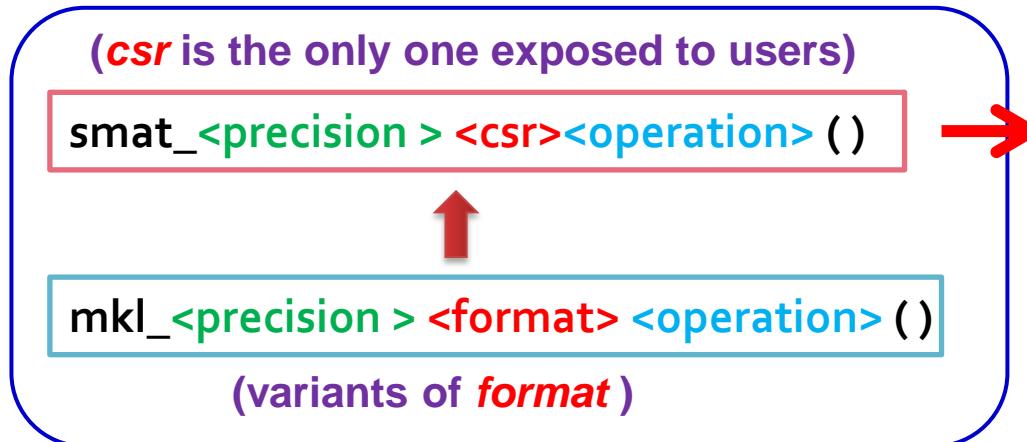
```
for(n = 0; n < max_ncols; n++)
{
    for(i = 0; i < num_rows; i++)
        y[i] =
            data[n*num_rows+i] *
            x[indices[n*num_rows+i]];
}
```

(d) ELL SpMV

Motivation

- ◆ Sparse solvers mainly use ONE storage format CSR
 - Hypre (LLNL), PETSc (ANL), Trilinos (SNL)

Low Performance



High Performance
High Productivity

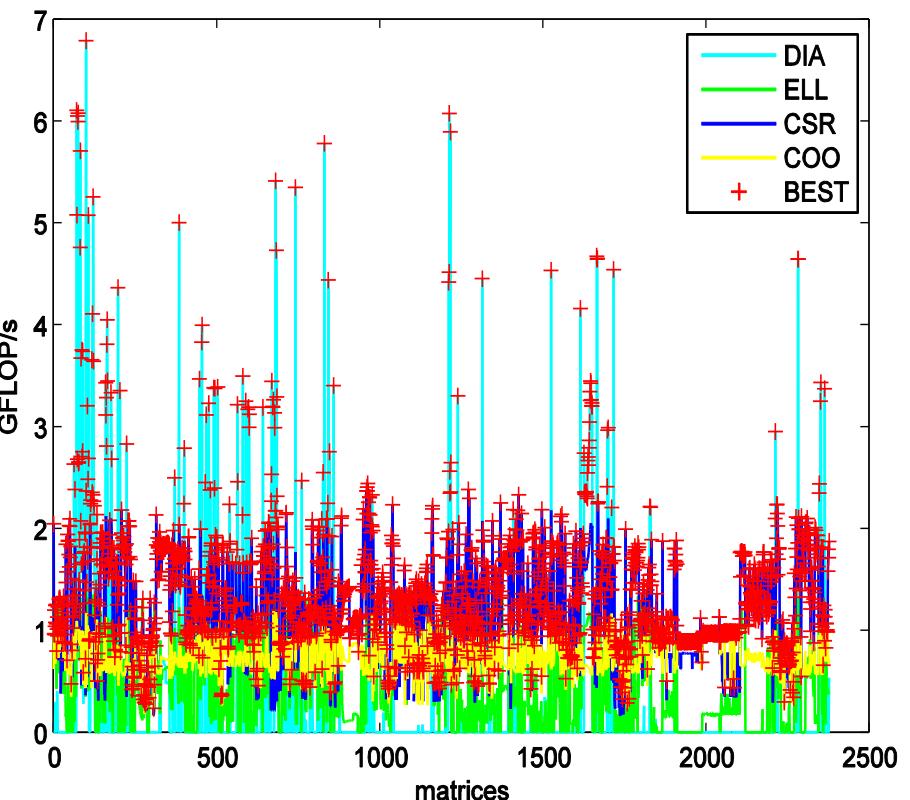
- ◆ Libraries provide complicated interfaces to users
 - MKL (Intel), OSKI (UCB), SpBLAS (UTK)

Low Productivity

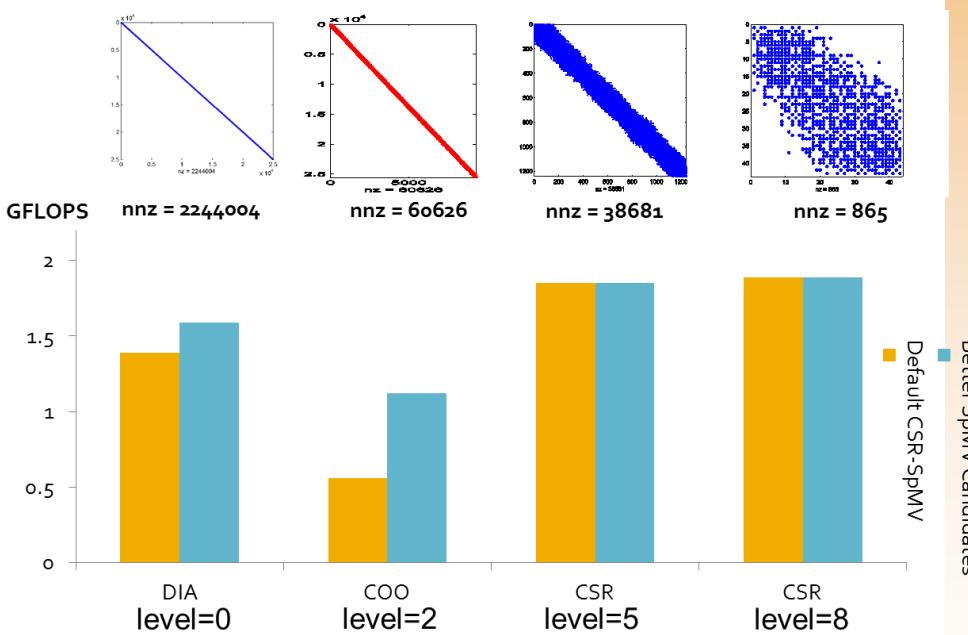
Motivation cont.

Observation 1: The optimal formats are diverse for sparse matrices from different application areas.

Observation 2: Different formats are needed in different stages of one application during runtime.



Algebraic Multigrid (AMG) Solver



Performance Gap: 10x!

Application-Architecture Aware Auto-tuner Design

◆ Offline

- Extract application
- Determine feature
- Build feature database (including the optimal implementation)
- Summarize the rules
- Choose the optimal implementation based on architecture characteristics

Sparse App.

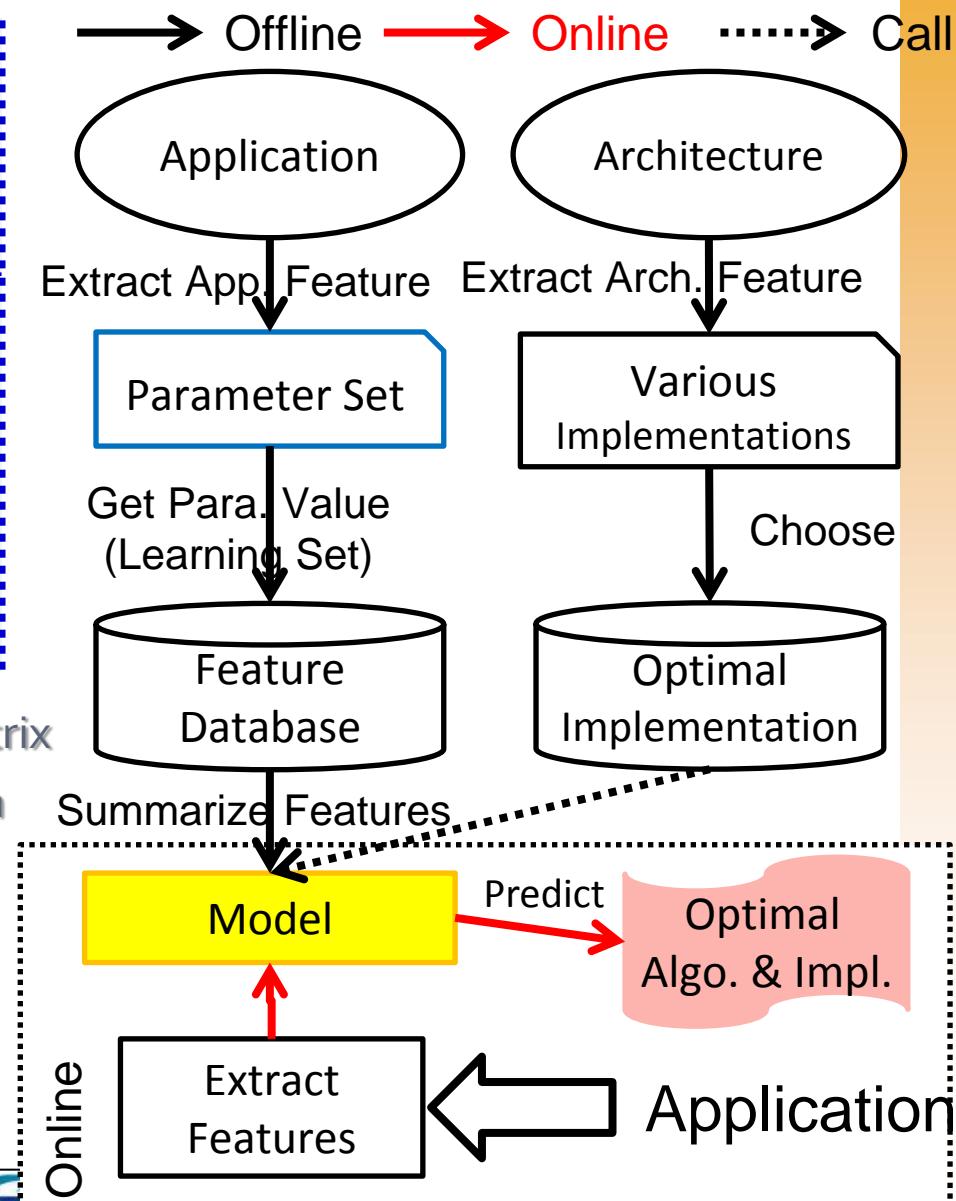
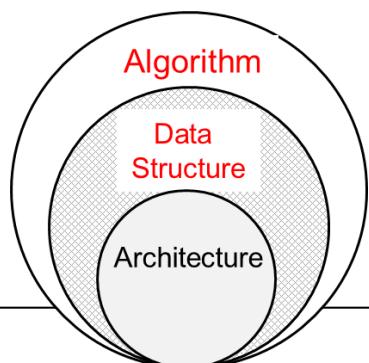
- Matrix Dimension
- Diagonal Situation
- Nonzero Distribution
- Nonzero Fill Ratio

Graph App.

- Dimension
- Degree Distribution
- Diameter
- Un-/directed
- Power-Law
- Connectivity

◆ Online

- Extract parameter values of the input matrix
- Predict the optimal algo. & impl. based on model



SMAT Framework

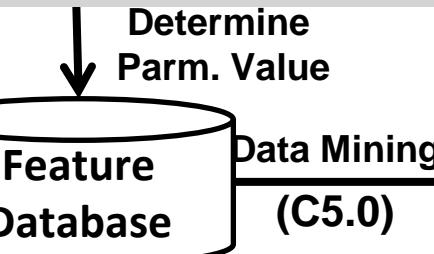
Example

- TLB size
- Cache size
- Reg. Size
- Prefetch
- SIMDization
- Branch
- Multi-thread

Arch.
Parm.

Kernel
Opt.

Offline

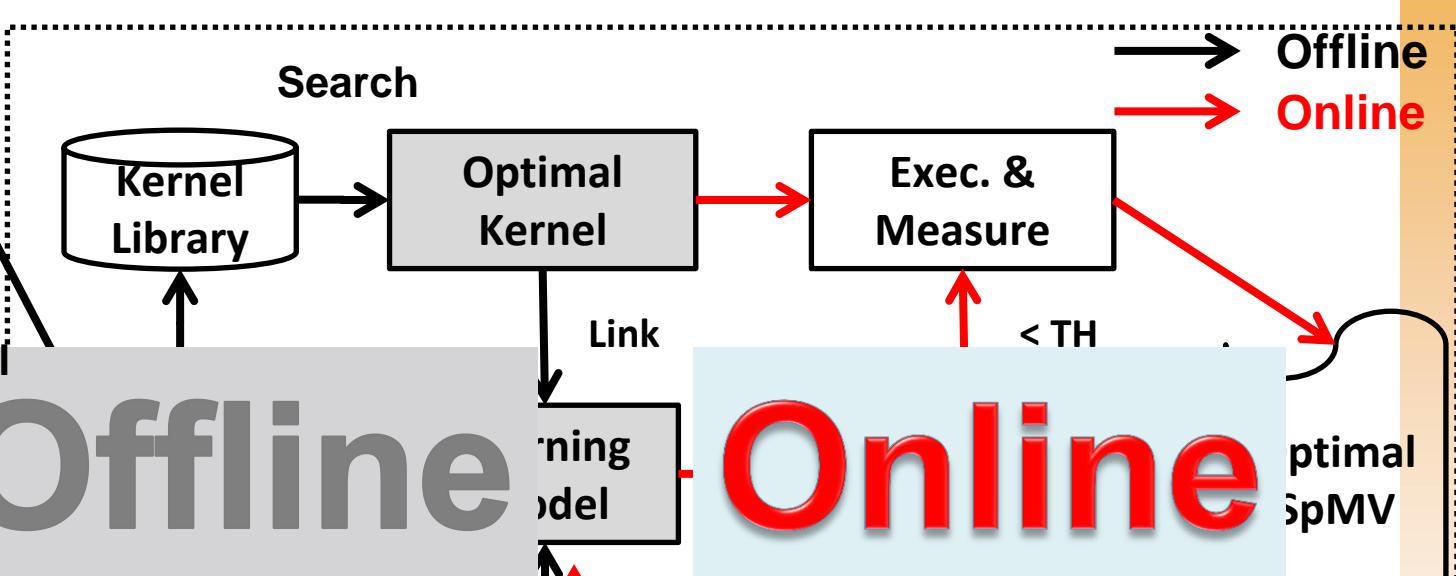


Example

- Matrix Dim.
- Diagonal Situation
- Nonzero Ratio
- Nonzero Dist.
- Power-Law

Spl
Behavior

App.
Parm.



SMAT API

Intel MKL

```
mkl_xcsrgemv  
mkl_xdiagemv  
mkl_xbsrgemv  
mkl_xcscmv  
mkl_xcoogemv  
mkl_xskymv
```

SMAT

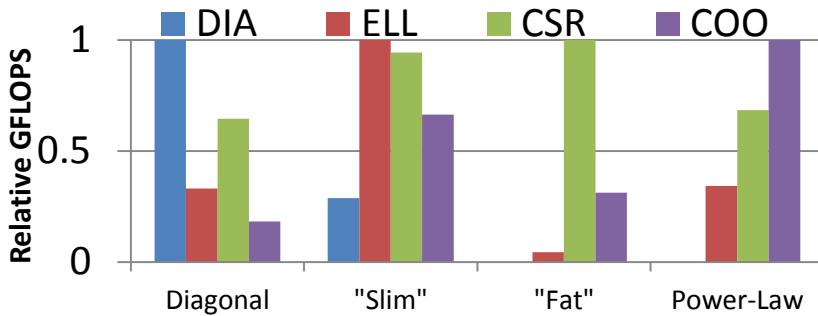


SMAT_xCSR_SpMV



So Easy!

Matrix Feature Parameters



Generally:

- ◆ Diagonal Matrix \leftrightarrow DIA Format
- ◆ “Slim” Matrix \leftrightarrow ELL Format
- ◆ “Fat” Matrix \leftrightarrow CSR Format
- ◆ Power-Law Matrix \leftrightarrow COO Format

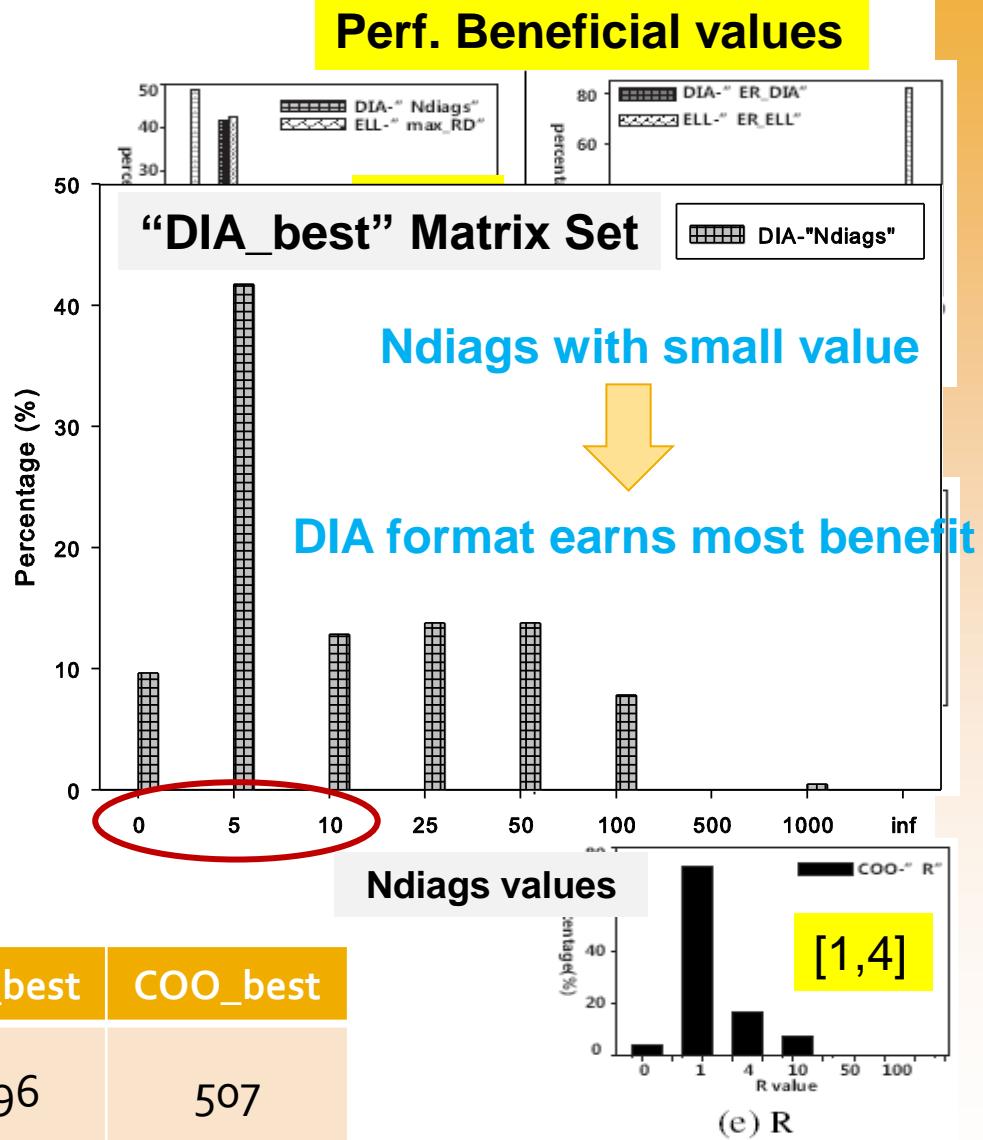
Parameter		Meaning	Formula	DIA	ELL	CSR	COO
Matrix Dimension	M	the number of rows	-	✓	✓	✓	✓
	N	the number of columns	-	✓	✓	✓	✓
Diagonal Situation	Ndiags	the number of diagonals	-	↓			
	NTdiags_ratio	the ratio of “true” diagonals to total diagonals	$NTdiags_ratio = \frac{\text{number of “true diagonals”}}{Ndiags}$	↑			
Nonzero Distribution	NNZ	the number of nonzeros	-	✓	✓	✓	✓
	aver_RD	the number of nonzeros per row	$aver_RD = \frac{NNZ}{M}$	✓	✓	✓	✓
	max_RD	the maximum number of nonzeros per row	$max_RD = \max_1^M \{ \text{number of nonzeros per row} \}$	↓			
	var_RD	the variation of the number of nonzeros per row	$var_RD = \frac{\sum_1^M row_degree - aver_RD ^2}{M}$			↓	
Nonzero Ratio	ER_DIA	the ratio of nonzeros in DIA data structure	$ER_DIA = \frac{NNZ}{Ndiags \times M}$	↑			
	ER_ELL	the ratio of nonzeros in ELL data structure	$ER_ELL = \frac{NNZ}{max_RD \times M}$		↑		
Power-Law	R	a factor of power-law distribution	$P(k) \sim k^{-R}$				[1, 4]

“✓” shows the parameter is useful for all formats.

“↑/↓” indicates the larger (smaller) the parameter value is, the format shows more benefit.

Feature Extraction Process

- ◆ Divide the matrix set based on the optimal storage format, and measure SpMV performance on them
- ◆ Draw the value distribution graph to each parameter, and find the regulations.

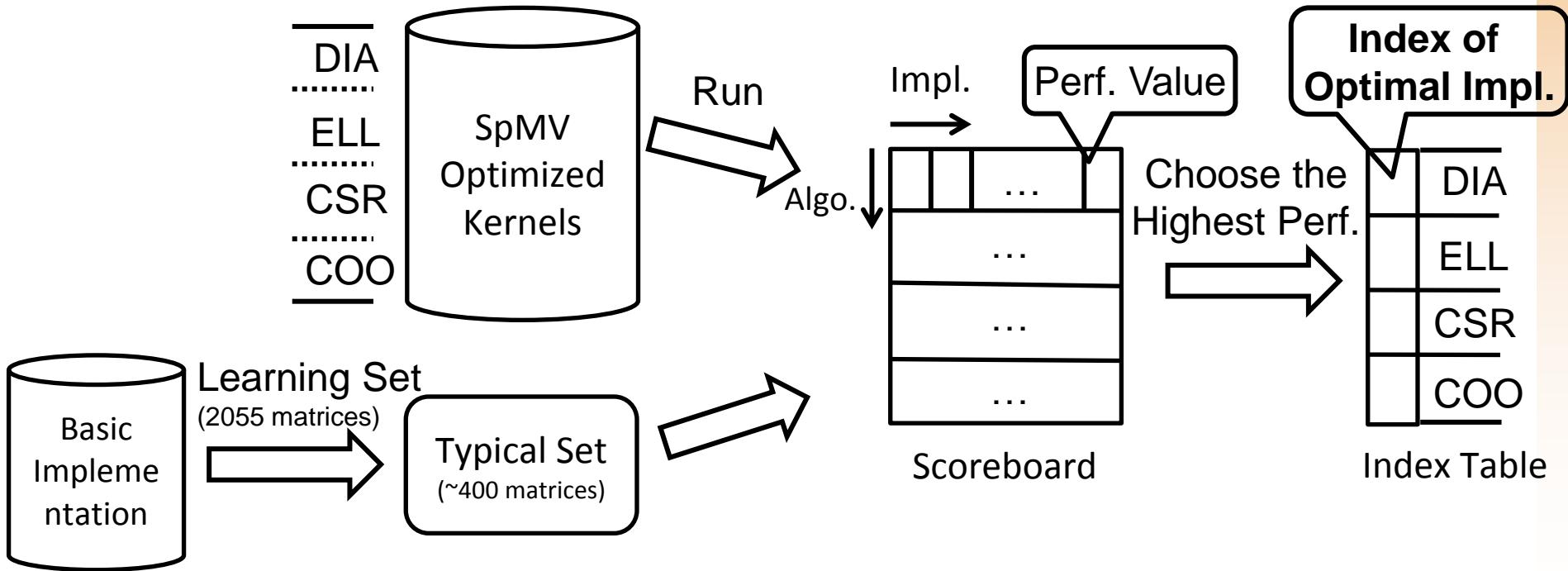
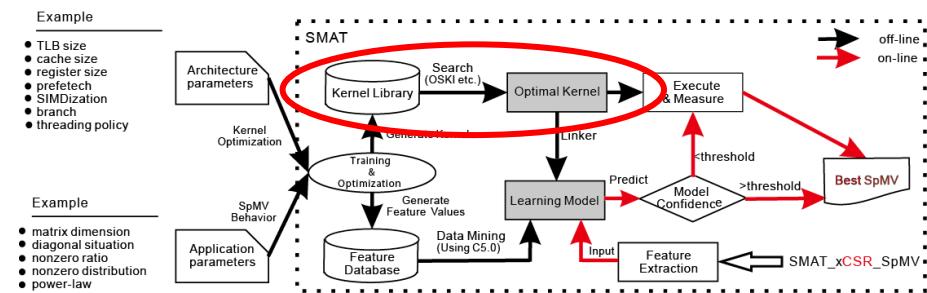


Matrix Partition	DIA_best	ELL_best	CSR_best	COO_best
Size of Sub-set	206	169	1496	507

SMAT—Choosing Optimal Implementation

◆ Scoreboard Strategy

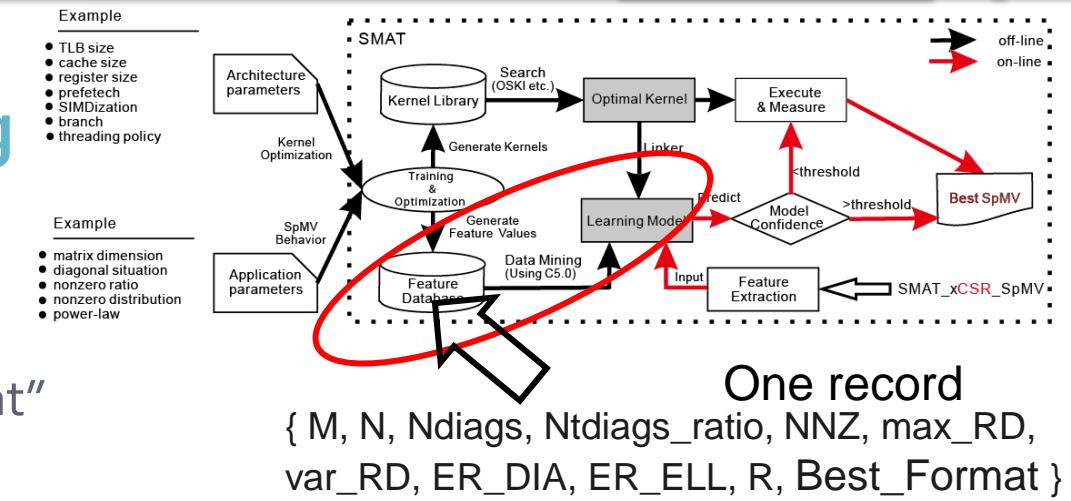
- Choose typical matrix set to test each algo. and impl.
- Record the performance value on scoreboard
- The optimal impl. for each algo. are recorded in index table



SMAT—Data Mining

◆ Belong to data mining problems

- Classification problem
- Target Attribute: “Best_format”



$$f(\overrightarrow{x_1}, \overrightarrow{x_2}, \dots, \overrightarrow{x_n}, \overrightarrow{TH}) \rightarrow C_n(DIA, ELL, CSR, COO)$$

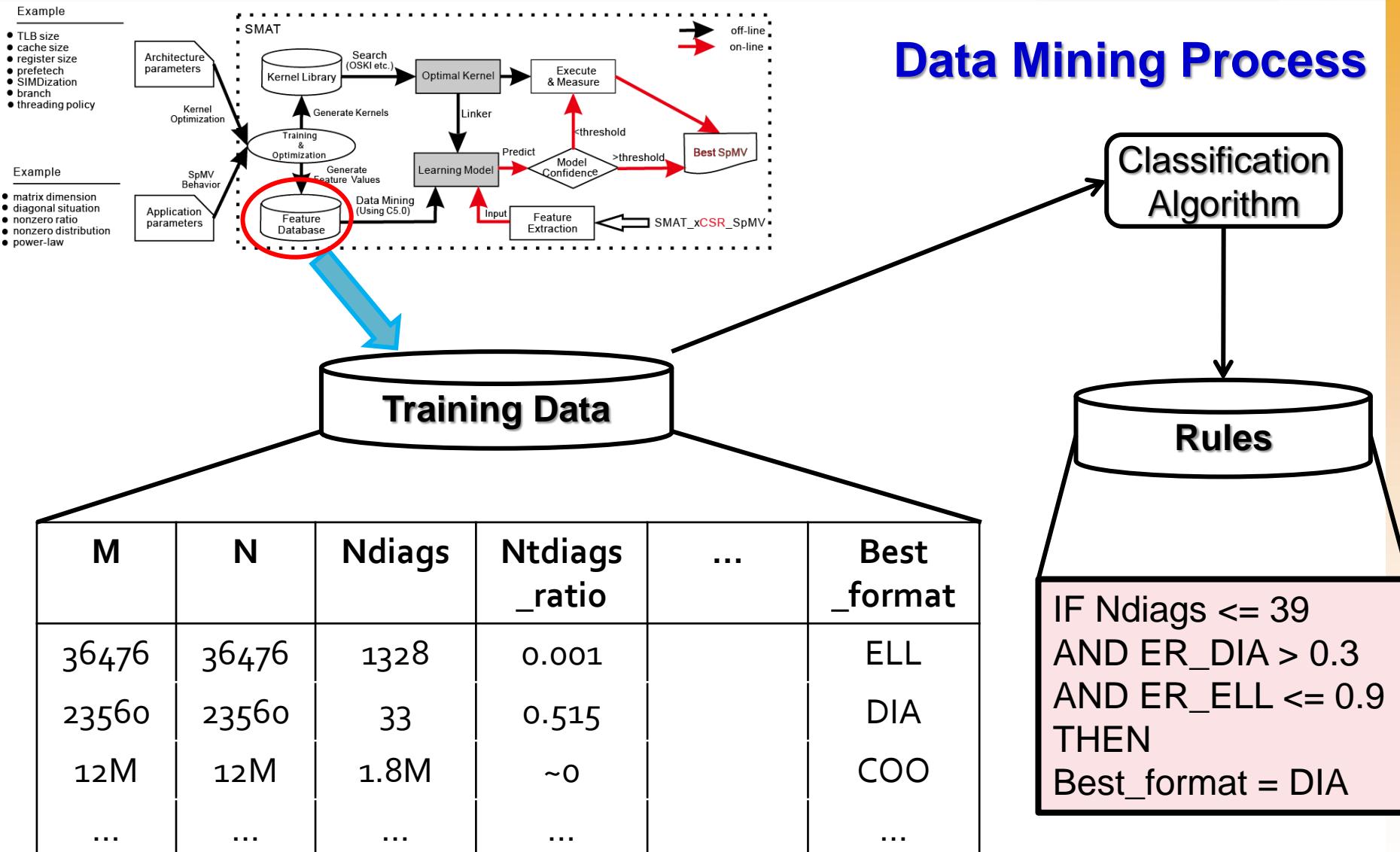
$\overrightarrow{x_i}$: value of each record, \overrightarrow{TH} : threshold of each parameter,
 $C_n(DIA, ELL, CSR, COO)$: one of the four formats.

◆ Build model

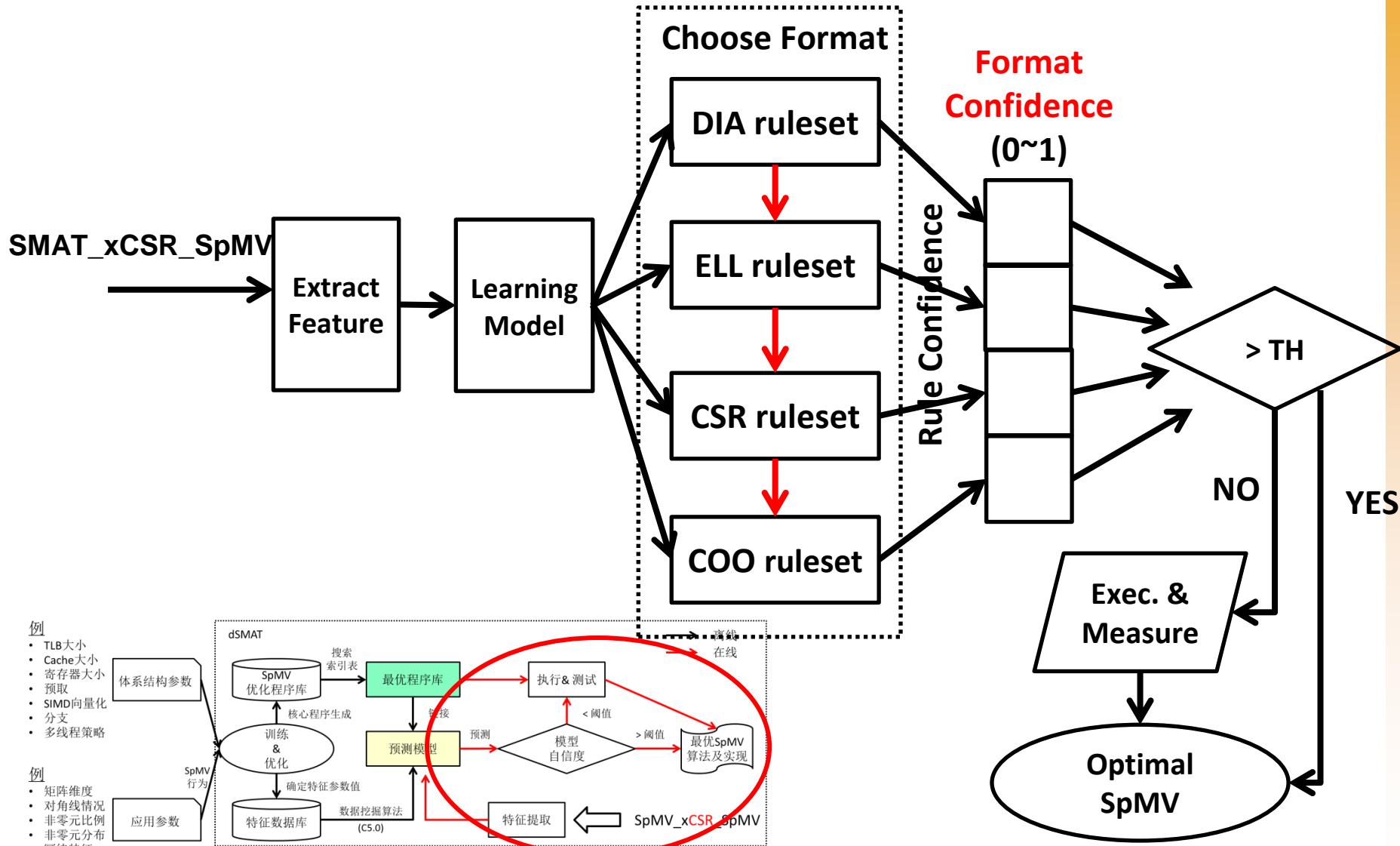
- Use ruleset to represent model
- Add rule confidence

SMAT—Data Mining

Data Mining Process



SMAT -- Online Procedure



例

- TLB 大小
- Cache 大小
- 寄存器大小
- 预取
- SIMD 向量化
- 分支
- 多线程策略

例

- 矩阵维度
- 对角线情况
- 非零元比例
- 非零元分布
- 帕累托特征

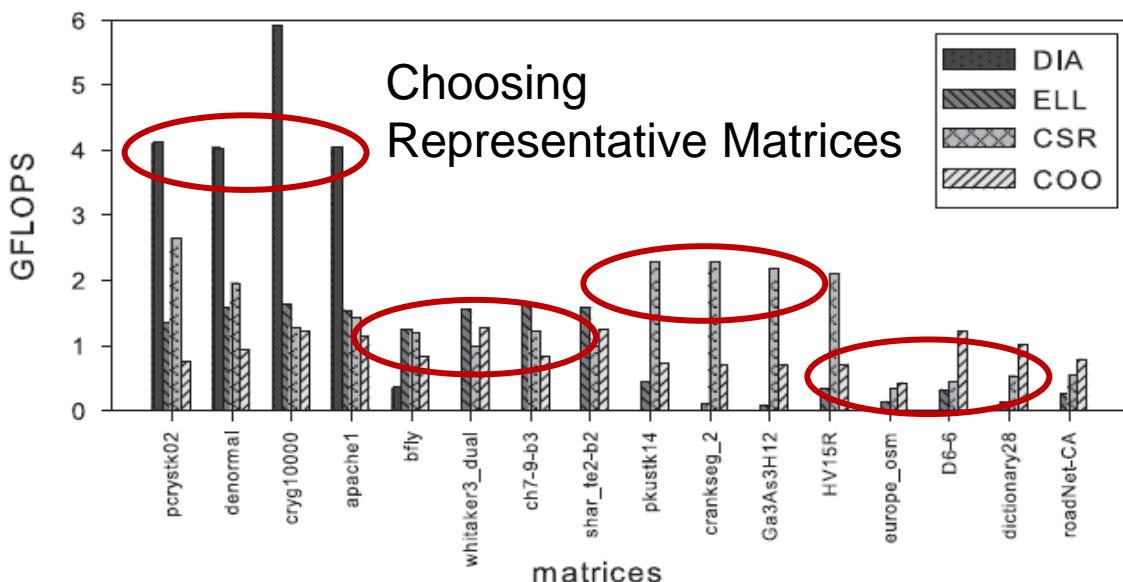
Platform and Matrix Set

◆ Platforms:

- Intel Xeon X5680
- AMD Opteron 6168

◆ Matrix set: The University of Florida Sparse Matrix Collection

- Learning Set: 2055
- Testing Set: 331, represented by 16 matrices



Representative Matrices

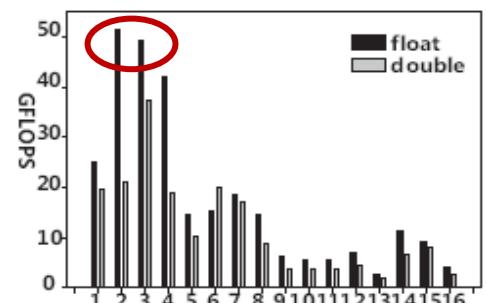
No.	Graph	Name	Dimensions	Nonzeros (NNZ / M)	Application area	
1		pcrystk02	14Kx14K	491K (35)	duplicate materials problem	
2		de	10Kx10K	~1M (5)	example	
3		cryg10000	10Kx10K	~1M (5)	materials problem	
4		apache1	81Kx81K	311K (4)	structural problem	
5		bfly	49Kx49K	98K (2)	undirected graph sequence	
6		whitak	106Kx18K	~1M (4)	3D problem	
7		_dual	ch7-9-b3	106Kx18K	combinatorial problem	
8			shar_te2-b2	200Kx17K	601K (3)	combinatorial problem
9			pkuslk14	152Kx152K	15M (98)	structural problem
10			crankseq	~1M (97)	structural problem	
11			Ga3As3H12	61Kx61K	~1M (97)	theoretical/quantum chemistry
12			HV15R	2Mx2M	283M (140)	computational fluid dynamics
13			europe_osm	51Mx51M	108M (2)	undirected graph
14			D6-5	2Mx2M	~1M (4)	problem
15			dictionary28	53Kx53K	178K (3)	undirected graph
16			roadNet-CA	2Mx2M	6M (3)	undirected graph

Performance

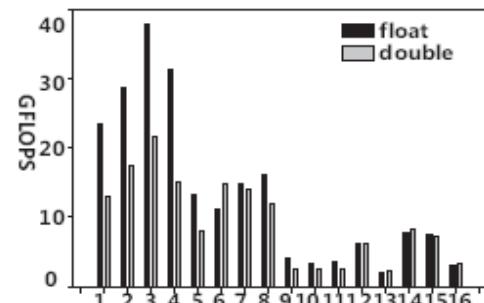
- ◆ SMAT Auto-tuning
- ◆ Optimized SpMV kernels

- Assembling opt.
 - Loop unrolling
 - SIMDization
- Multi-threading on task level
 - Allocate a sub-block to each thread
 - Independently choose the optimal algo. & impl. on each sub-block

Performance

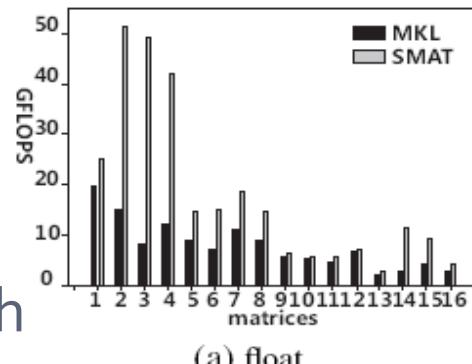


(a) Intel

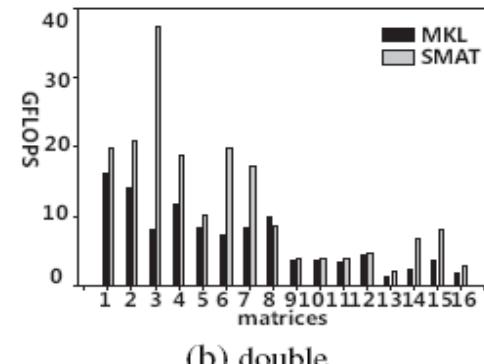


(b) AMD

Compared with MKL



(a) float



(b) double

~3X Speedup on average

Analysis on Accuracy and Overhead

◆ Analyze the prediction procedure and accuracy on 16 representative matrices

◆ Overhead

- When the model predicts right, small overhead (about 2 CSR-SpMV)
- Wrong predict, execute & measure module used, the overhead is more than 10 CSR-SpMV (OSKI:40+; cISpMV: ~10)
- When a matrix is used hundreds of times in an iterative method, the overhead can be overlapped.

Matrix Number	Matrix Name	Model Prediction Format	Execution	SMAT Prediction Format	Actual Best Format	Model Accuracy	SMAT Overhead (times of CSR-SpMV)
1	pcrystk02	DIA	-	DIA	DIA	R	2.28
2	denormal	DIA	-	DIA	DIA	R	2.09
3	cryg10000	DIA	-	DIA	DIA	R	2.11
4	apache1	DIA	-	DIA	DIA	R	1.94
5	bfly	ELL	-	ELL	ELL	R	1.18
6	whitaker3_dual	ELL	-	ELL	ELL	R	4.89
7	ch7-9-b3	ELL	-	ELL	ELL	R	2.25
8	shar_te2-b2	ELL	-	ELL	ELL	R	2.24
9	pkustk14	<i>confidence < TH</i>	CSR+COO	CSR	CSR	W	16.39
10	crankseg_2	<i>confidence < TH</i>	CSR+COO	CSR	CSR	W	16.28
11	Ga3As3H12	<i>confidence < TH</i>	CSR+COO	CSR	CSR	W	16.2
12	HV15R	<i>confidence < TH</i>	CSR+COO	CSR	CSR	W	15.43
13	europe_osm	COO	-	COO	COO	R	2.3
14	D6-6	COO	-	COO	COO	R	5.79
15	dictionary28	COO	-	COO	COO	R	2.05
16	roadNet-CA	COO	-	COO	COO	R	2.38

"R" and "W" represent Right and Wrong prediction respectively.

Application Usability— Applied to Numerical Solver

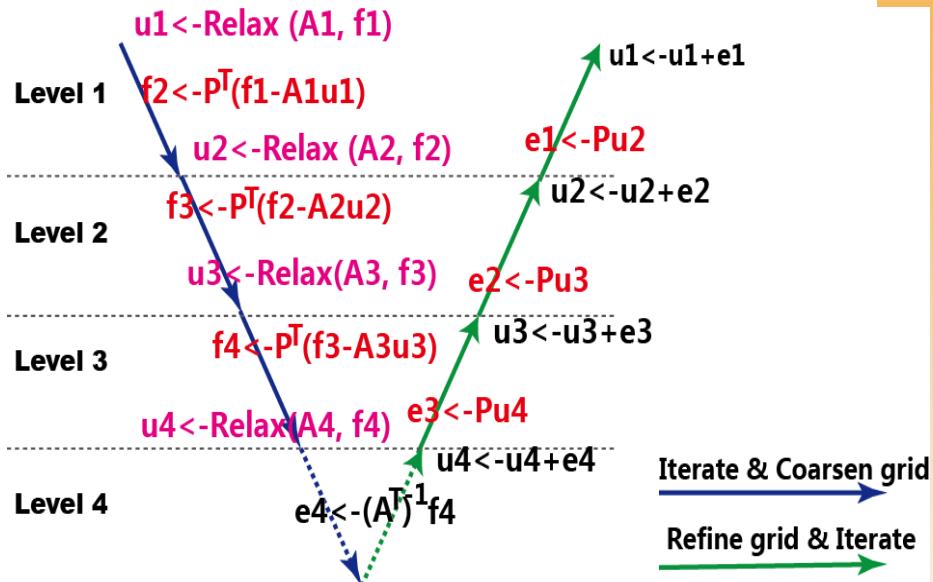
◆ Algebraic Multi-grid Algorithm

- An iterative algo. to solve linear equations $Au=f$, where A is sparse matrix, u, f are dense vectors
- As a pre-conditioner applied in applications such as laser fusion and climate modeling

◆ SpMV the critical operation of AMG, takes 90% execution time.

Coarsen	Rows	Hypre AMG	SMAT AMG	Speedup
cljp_7pt_50	125k	3034	2487	1.22
rugeL_9pt_500	250k	388	300	1.29

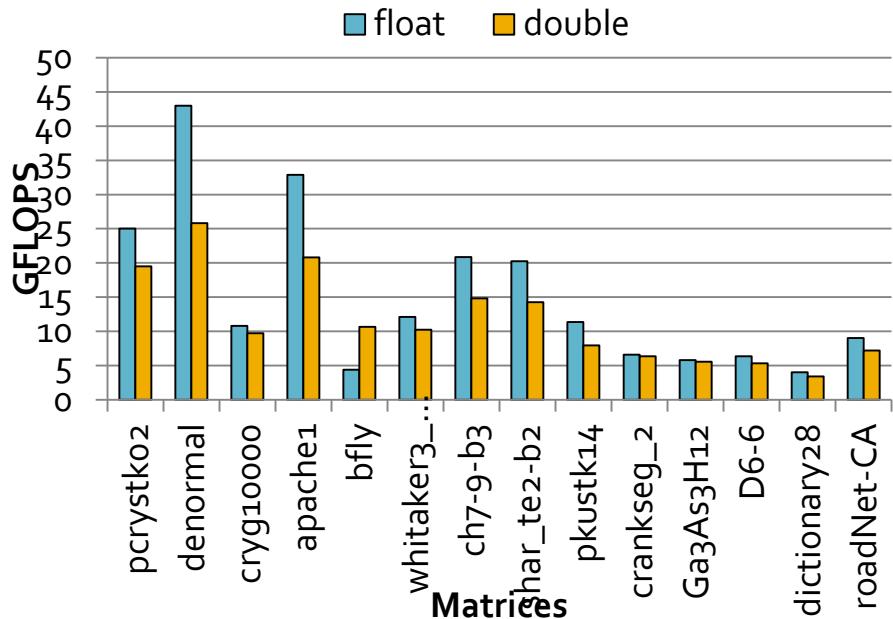
AMG Execution Process



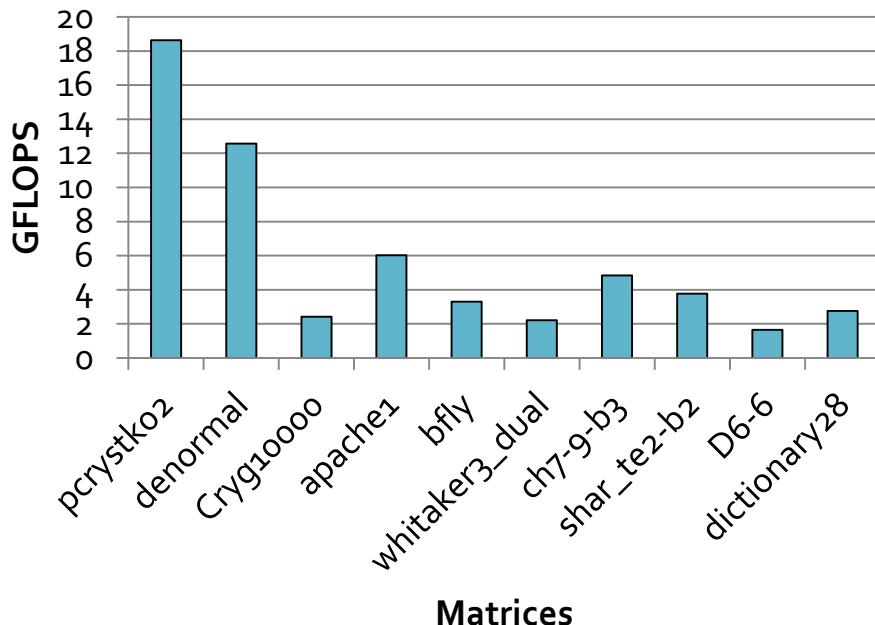
- Relax is relaxation algorithm, such as Jacobi、G-S iterative methods
- A, P are sparse matrices
- U, f, e are dense vectors

SMAT Many-core

Performance



NVIDIA K20



Xeon Phi

Accuracy

- For 289 testing matrices: 89% (single), 95% (double)

SMAT Summary

◆ Develop auto-tuning method

- Design application-architecture aware SpMV auto-tuner.
- Develop auto-tuning method to algorithm level

◆ Introduce data mining to auto-tuning method

- Reinforce its usability and extensibility

◆ API Easy-to-use

- Unify the interface

◆ Increase SpMV performance using SMAT

◆ Apply SMAT to AMG, and extend it to many-core architecture

High Performance Computational Software Development

Hand-tuning Autotuning Co-Autotuning

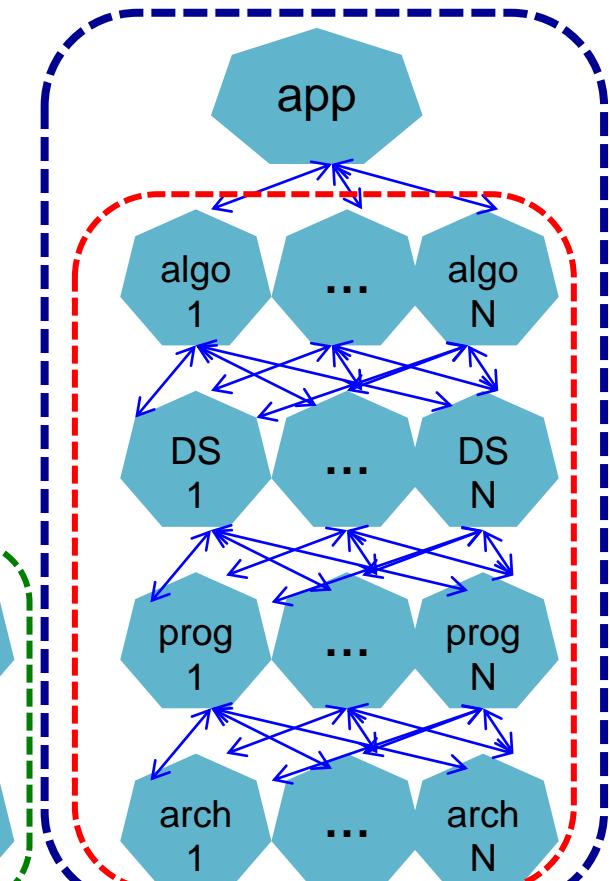
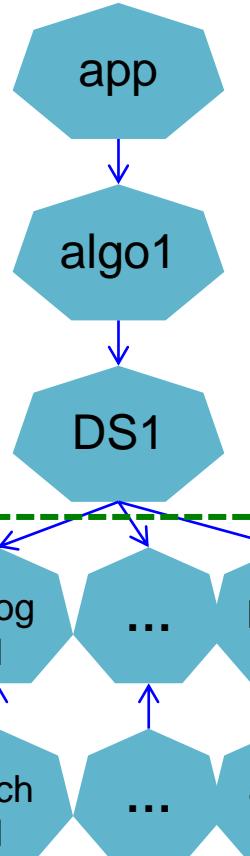
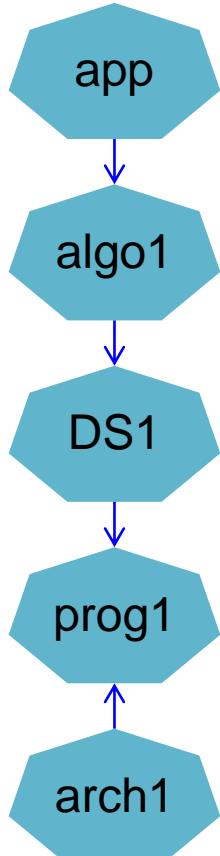
Application

Algorithm

Data Structure

Program

Architecture



Yesterday

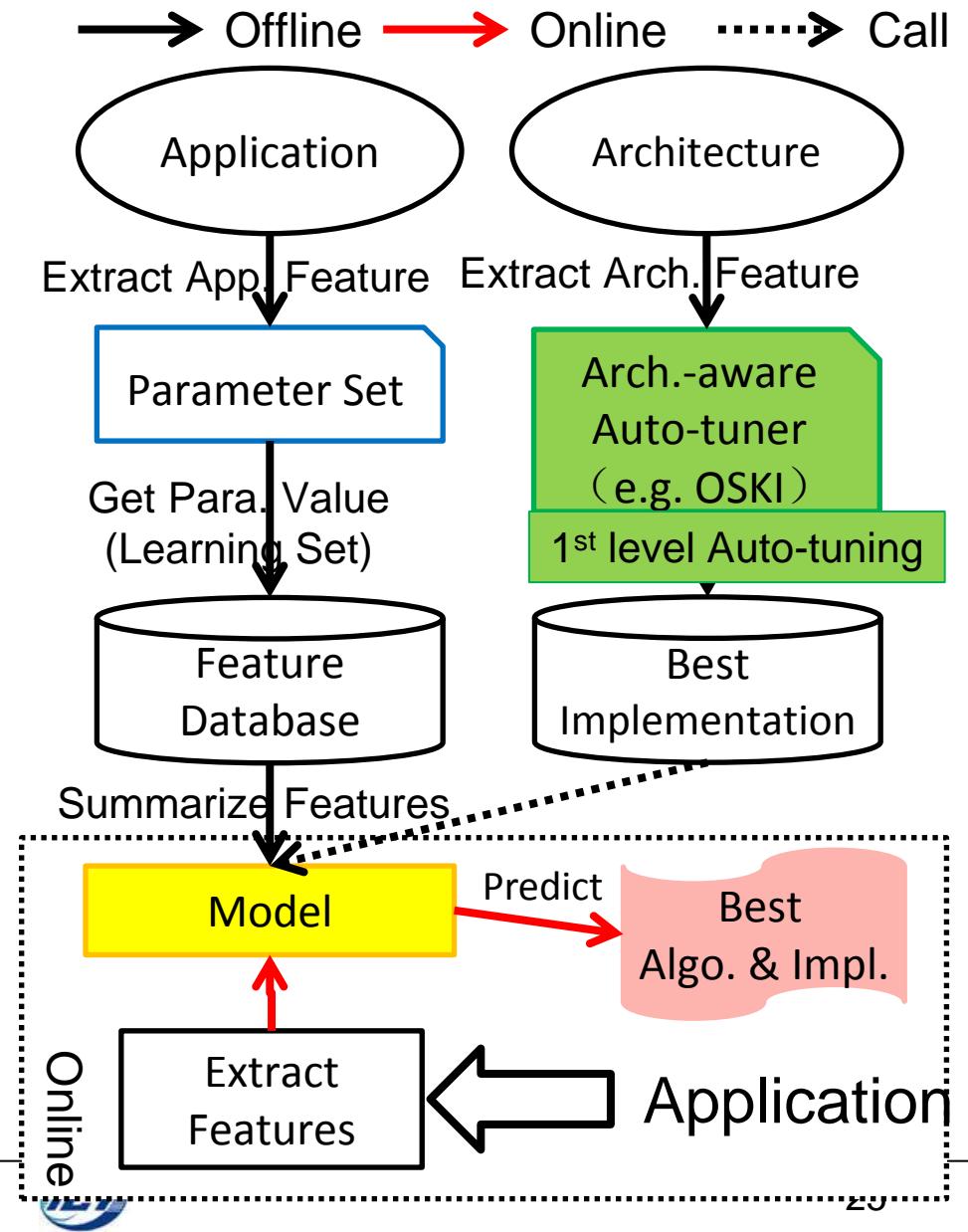
Today

Tomorrow

Future Work

◆ Extend storage formats

◆ Combine other auto-tuners



Thank You !

Question?

SMAT: An Input Adaptive Auto-Tuner
for Sparse Matrix-Vector Multiplication.

Jiajia Li, Guangming Tan, Mingyu Chen, Ninghui Sun

