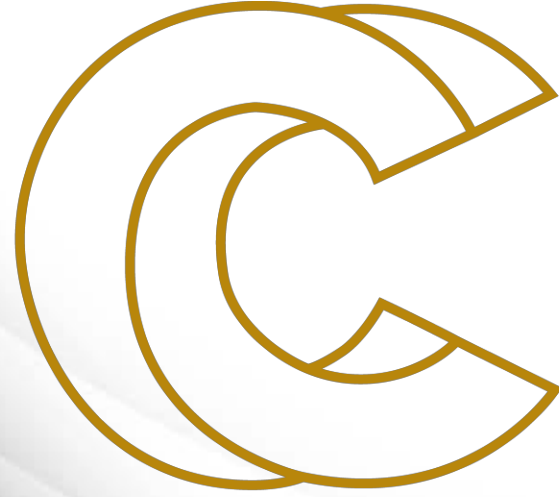




Sabancı
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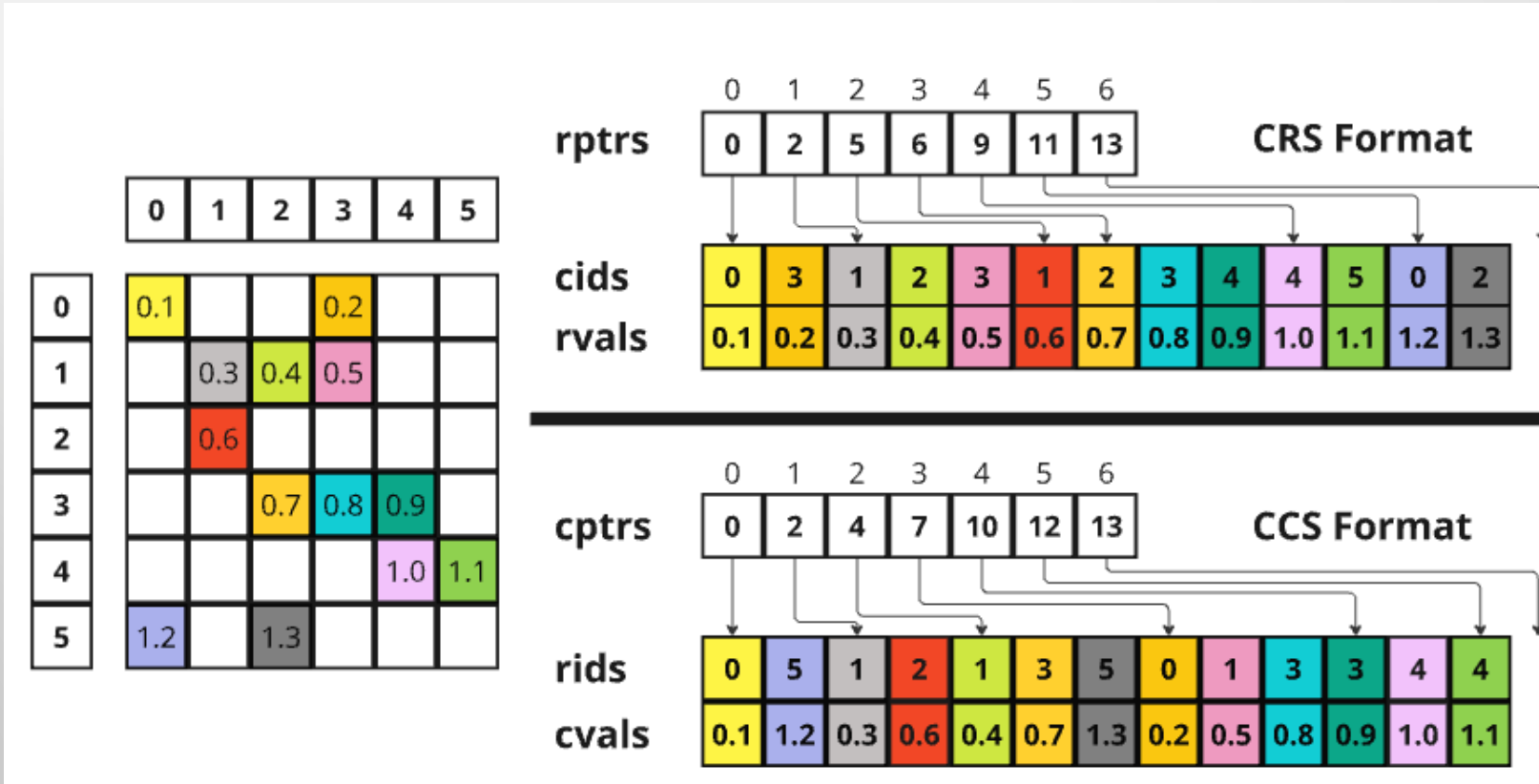


EURO²

High Performance Computing with Sparse Data
Graphs, Matrices and Tensors

Kamer Kaya, Sabancı University

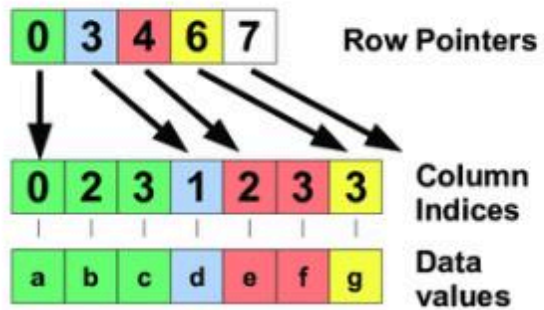
Sparse Matrix Data Structures



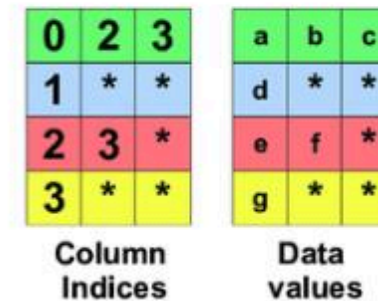
Sparse Matrix Data Structures

	0	1	2	3
0	a		b	c
1		d		
2			e	f
3				g

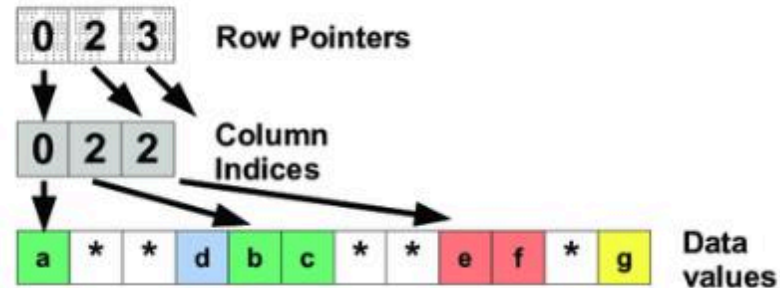
Compressed Sparse Row (CSR)



ELLPACK (ELL)

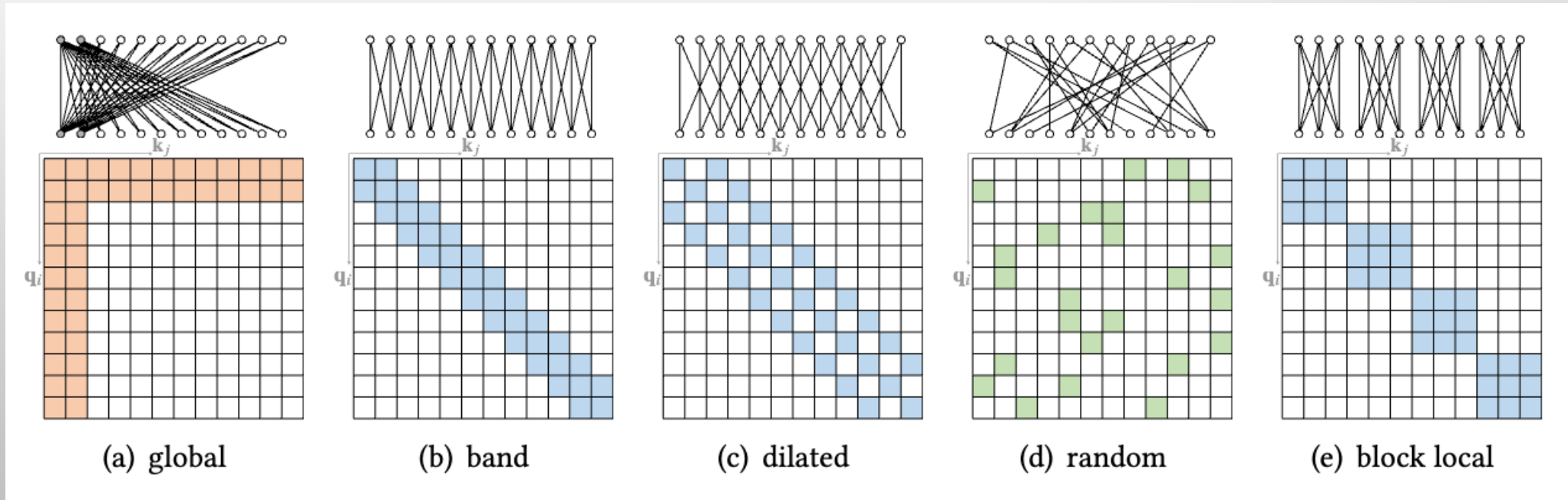


Blocked Compressed Sparse Row (BSR) – 2x2 blocks

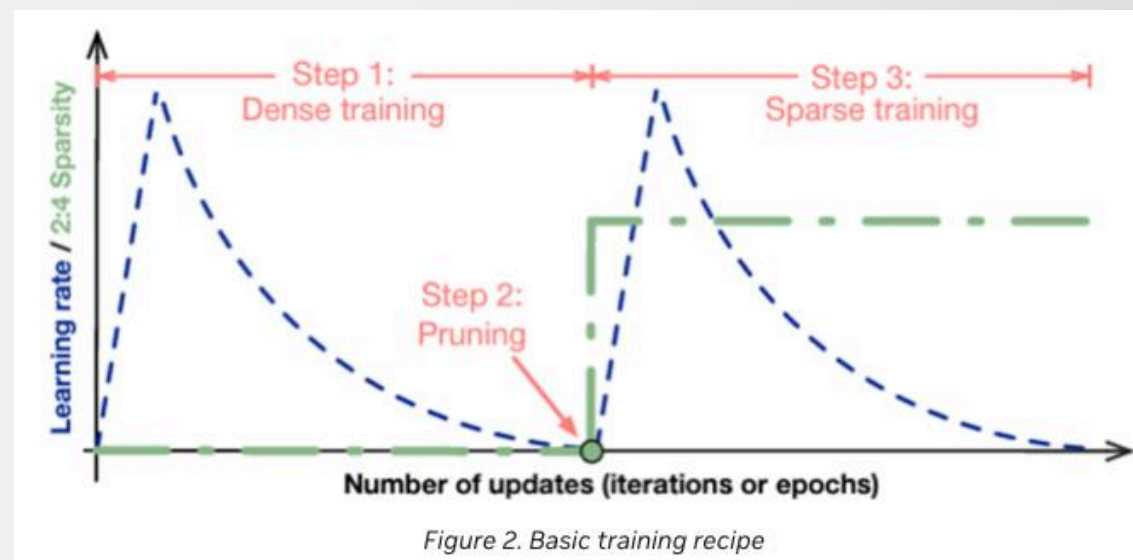
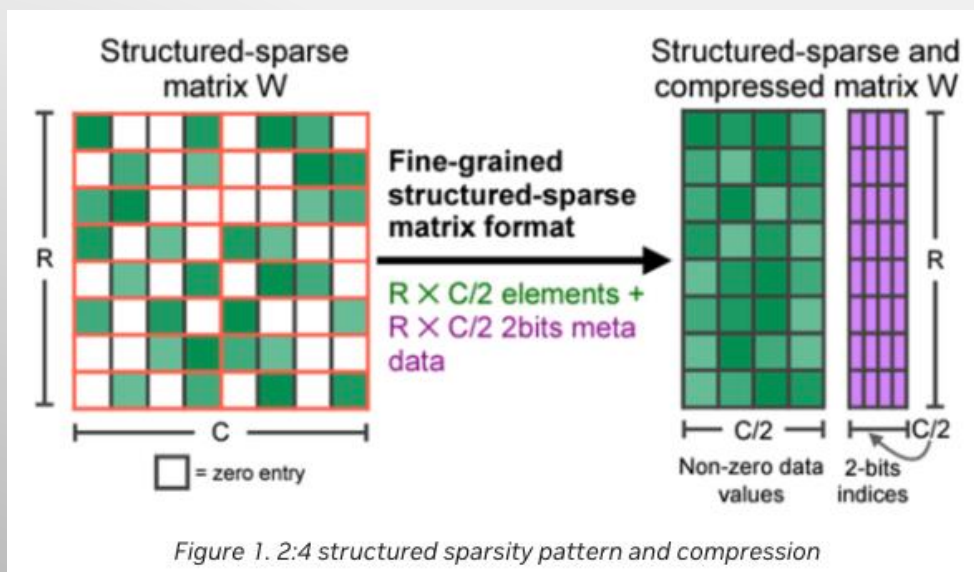


J. C. Pichel and B. Pateiro-López, "Sparse Matrix Classification on Imbalanced Datasets Using Convolutional Neural Networks," in *IEEE Access*, vol. 7, pp. 82377-82389, 2019, doi: 10.1109/ACCESS.2019.2924060

Sparse Matrices – Sparse Attention



Sparse Matrices – Sparse Attention



```
// Perform Sparse Matrix-Vector Multiplication (SpMV)
// A is stored in CSR format (values, row_ptr, col_idx)
// x is the input dense vector
// y is the output dense vector
void spmv_csr(const std::vector<double>& values, const std::vector<int>& row_ptr,
             const std::vector<int>& col_idx, const std::vector<double>& x,
             std::vector<double>& y) {
    // Check dimensions
    assert(row_ptr.size() > 1 && "row_ptr must have at least two elements.");
    assert(x.size() > 0 && "Input vector x must not be empty.");

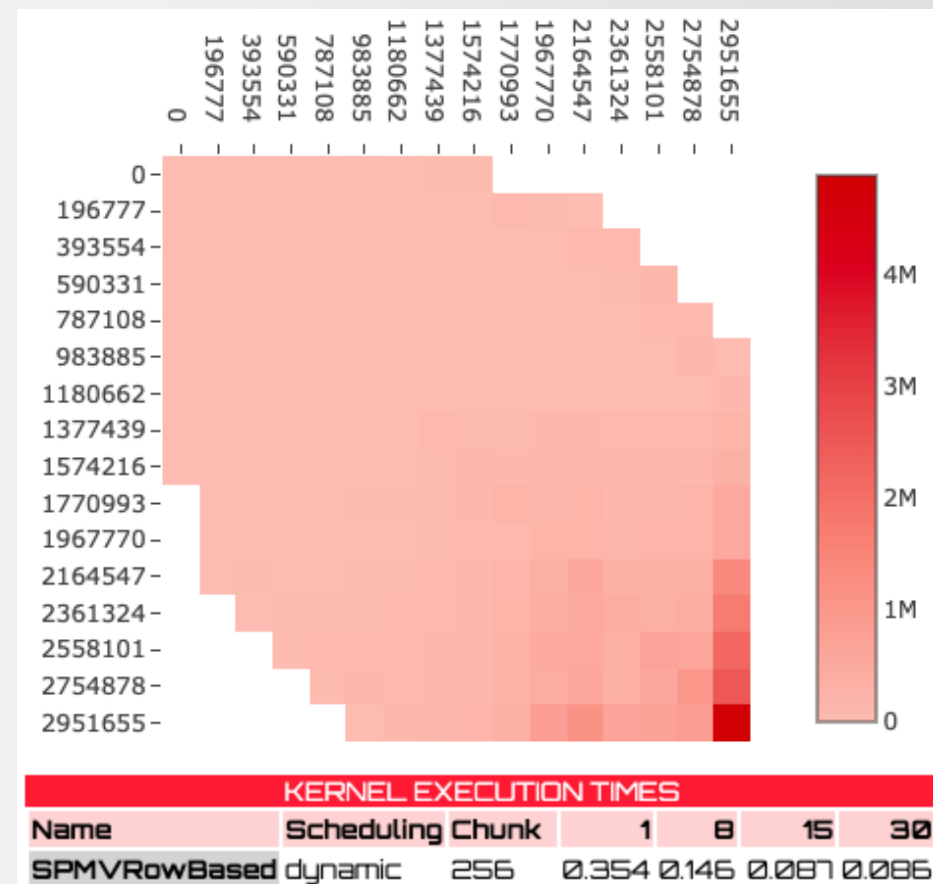
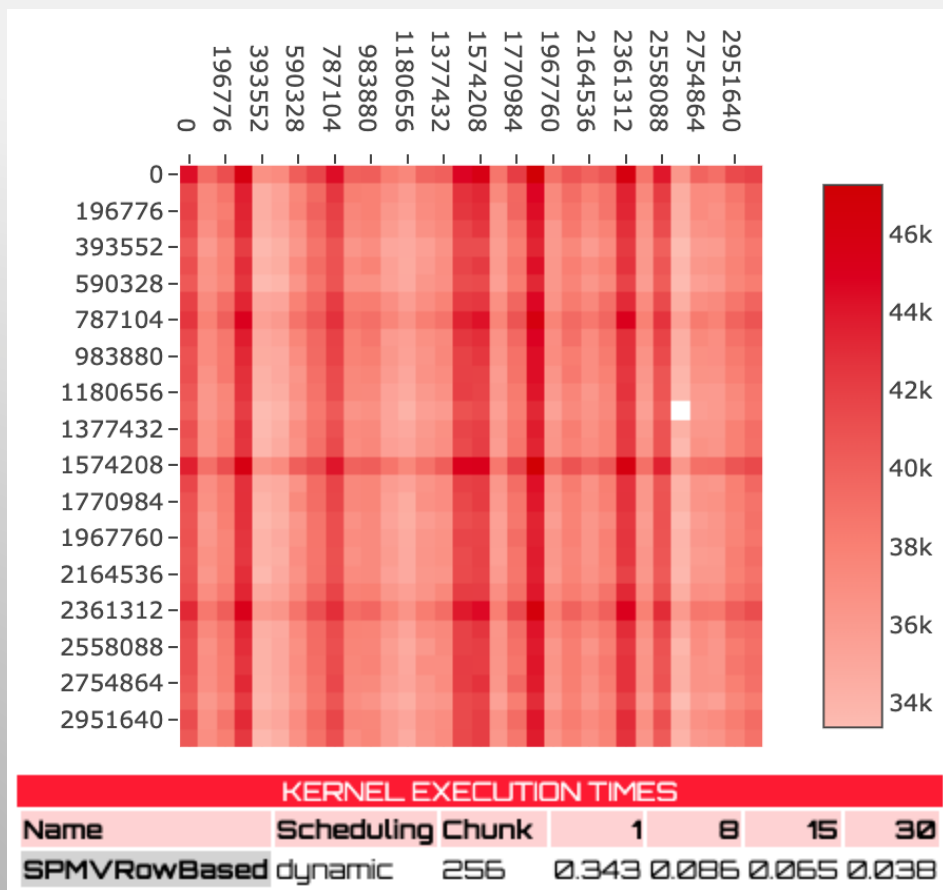
    int num_rows = row_ptr.size() - 1; // Number of rows in the sparse matrix

    // Resize the output vector to match the number of rows in the matrix
    y.resize(num_rows, 0.0);

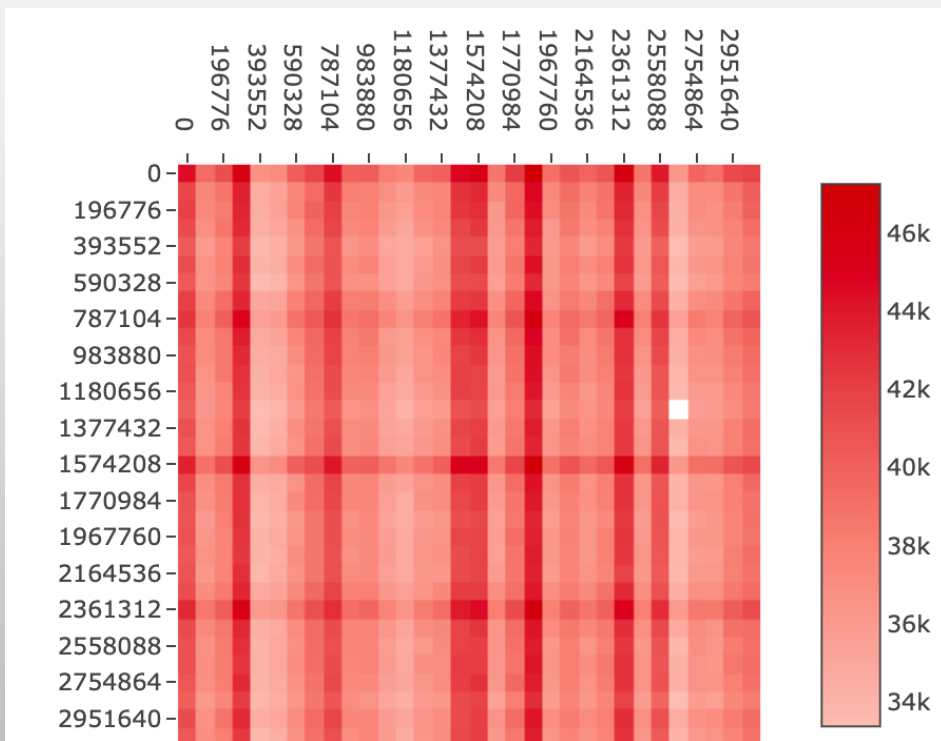
    // Perform SpMV
    for (int i = 0; i < num_rows; ++i) {
        double sum = 0.0;
        for (int j = row_ptr[i]; j < row_ptr[i + 1]; ++j) {
            sum += values[j] * x[col_idx[j]];
        }
        y[i] = sum;
    }
}
```

SpMV

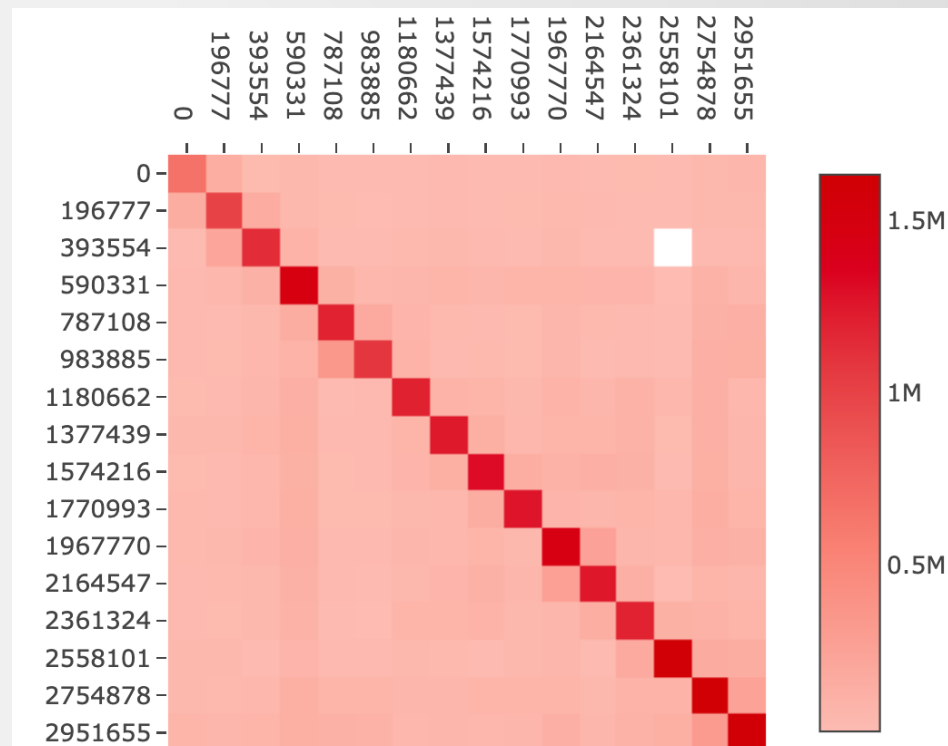
Sparse Matrix Ordering



Sparse Matrix Ordering

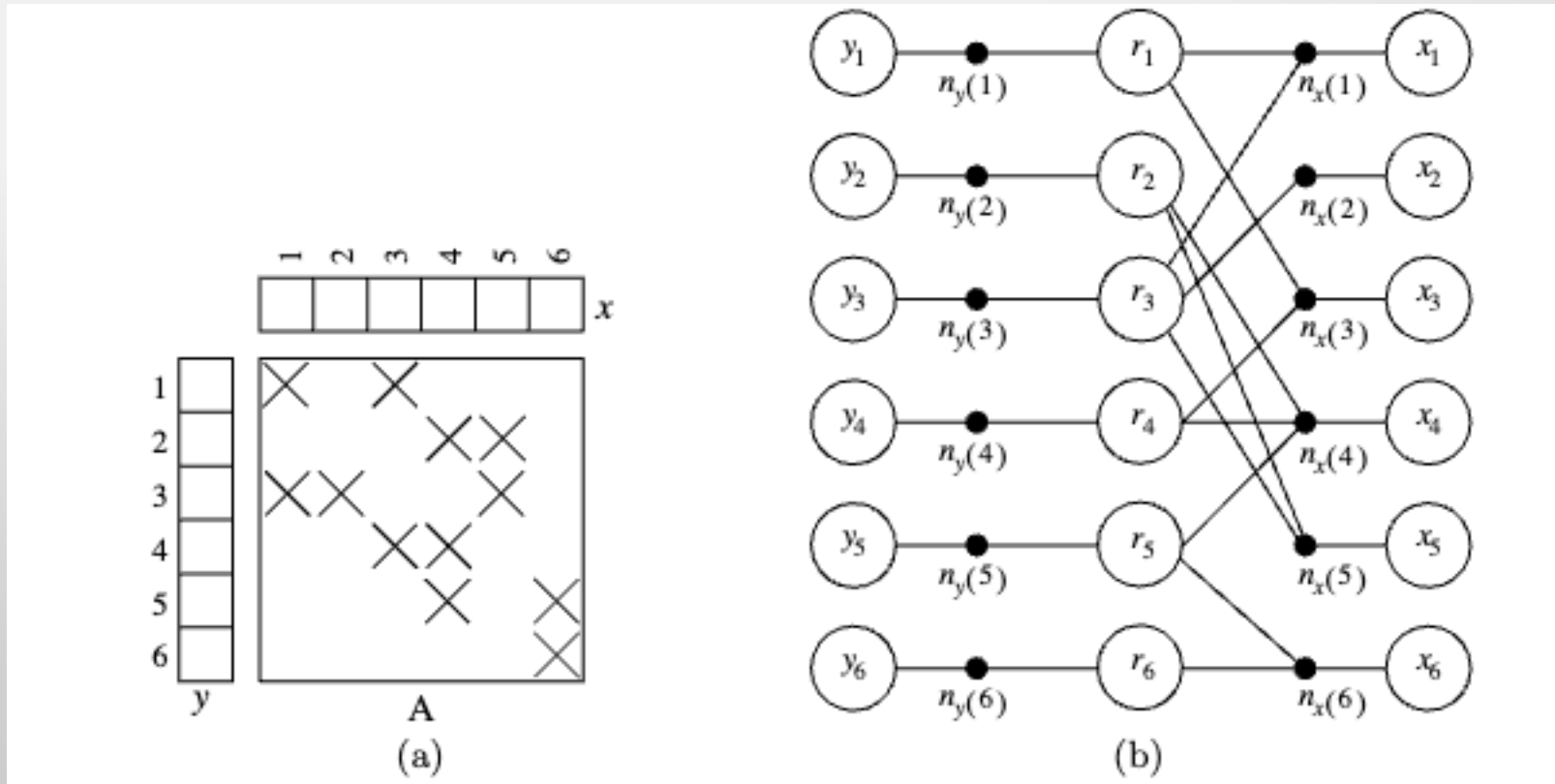


KERNEL EXECUTION TIMES						
Name	Scheduling Chunk	1	8	15	30	
SPMVRowBased	dynamic	256	0.343	0.086	0.065	0.038



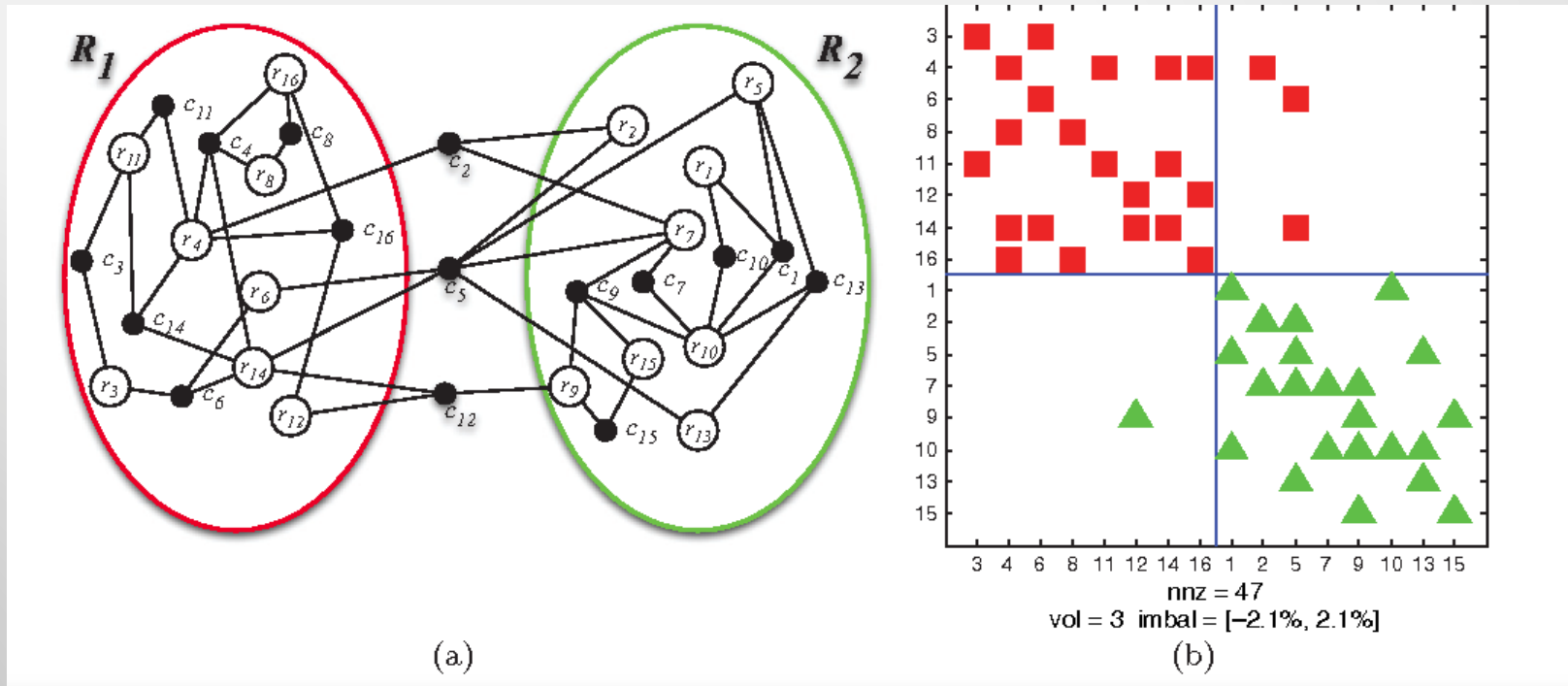
KERNEL EXECUTION TIMES						
Name	Scheduling Chunk	1	8	15	30	
SPMVRowBased	dynamic	256	0.361	0.057	0.030	0.022

Sparse Matrix Partitioning



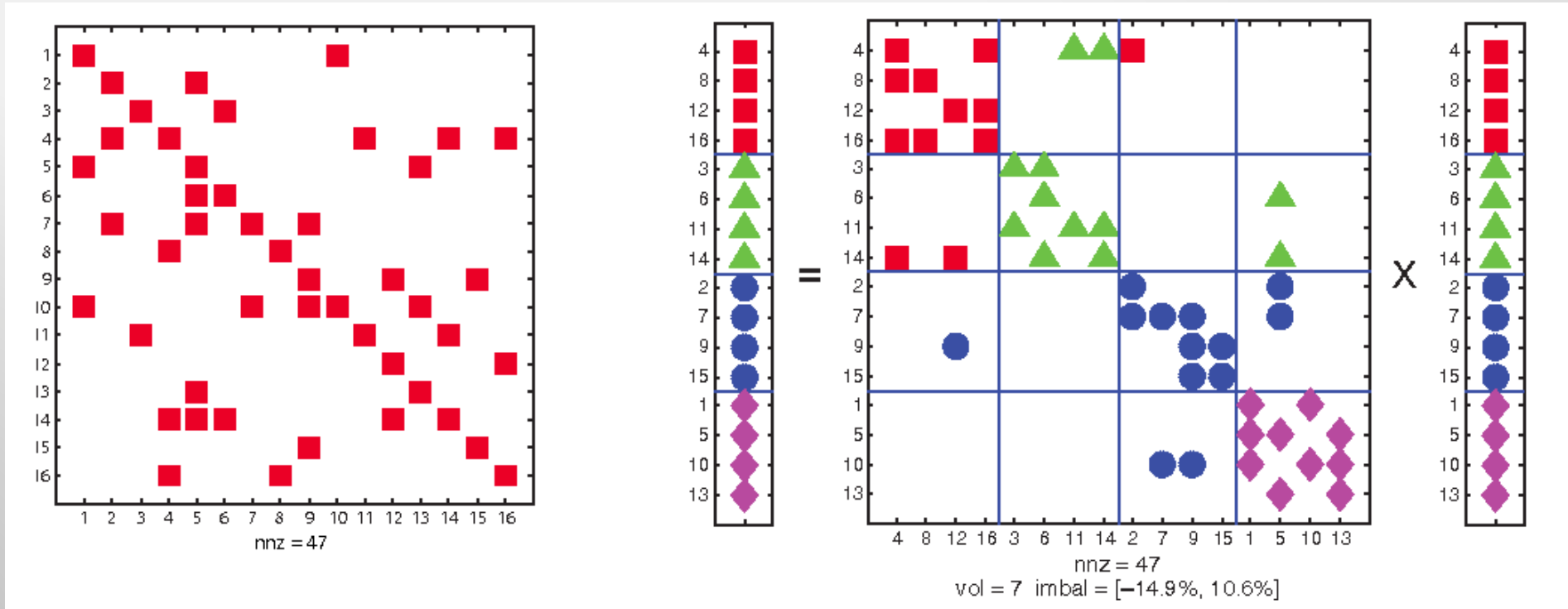
Bora Uçar, Cevdet Aykanat. Revisiting Hypergraph Models for Sparse Matrix Partitioning. SIAM Review, 2007, 49 (4), pp.595–603. 10.1137/060662459. hal-00803507

Sparse Matrix Partitioning



SIAM Journal on Scientific Computing 2010 On Two-Dimensional Sparse Matrix Partitioning: Models, Methods, and a Recipe Ümit V. Çatalyürek, C. Aykanat, B. Uçar

Sparse Matrix Partitioning



SIAM Journal on Scientific Computing 2010 On Two-Dimensional Sparse Matrix Partitioning: Models, Methods, and a Recipe Ümit V. Çatalyürek, C. Aykanat, B. Uçar

Sparse Matrix Partitioning

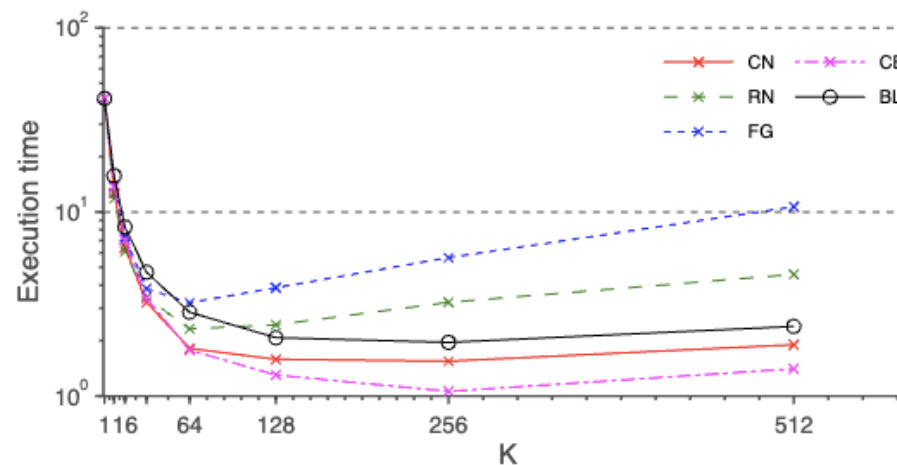
Metric	$8 \leq K \leq 64$			$128 \leq K \leq 512$		
	SPMV	PETSc	Trilinos	SPMV	PETSc	Trilinos
MaxNnz	8.02	7.81	6.80	0.49	0.44	0.83
TotVol	0.18	0.38	1.00	0.39	0.36	1.06
MaxSV	1.66	1.53	2.20	0.00	0.00	0.11
TotMsg	0.15	0.28	0.00	7.90	8.03	4.51
MaxSM	0.00	0.00	0.00	1.22	1.18	3.49

Table 2: Regression analysis of SPMV, PETSc and Trilinos with all matrices and models CN and BL.

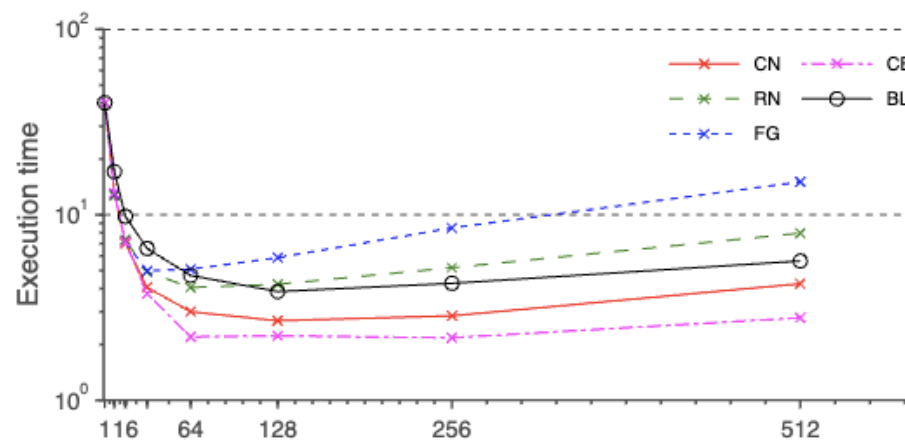
Kamer Kaya, Bora Uçar, Umit Catalyurek. Analysis of Partitioning Models and Metrics in Parallel Sparse Matrix-Vector Multiplication, 10th PPAM - Parallel Processing and Applied Mathematics, Sep 2013, Varsovie, Poland. Springer, pp.174–184, 2014

Sparse Matrix Partitioning

SPMV



Trilinos



Thanks



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