# Optimizing Sparse Matrix-Vector Multiplication Using Index and Value Compression

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## **Outline**

- Introduction and Motivation
- Index Compression (CSR-DU)
- Value Compression (CSR-VI)
- Performance Evaluation
- Conclusions

# **SpMxV**

#### Sparse Matrices:

- Larger portion of elements are 0's
- Efficient representation (storage and computation)
  - non-zero values (nnz)
  - indexing information structure

#### Formats:

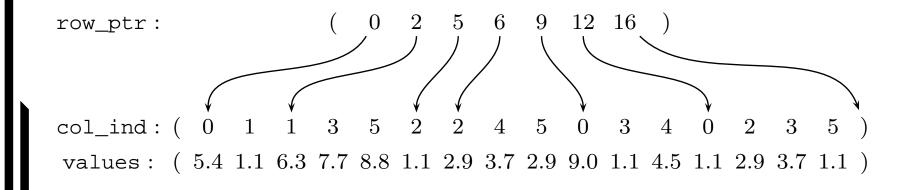
- CSR, CSC, COO
- BCSR
- JD, CDS, Elpack-Itpack

#### Sparse Matrix-Vector Multiplication (SpMxV):

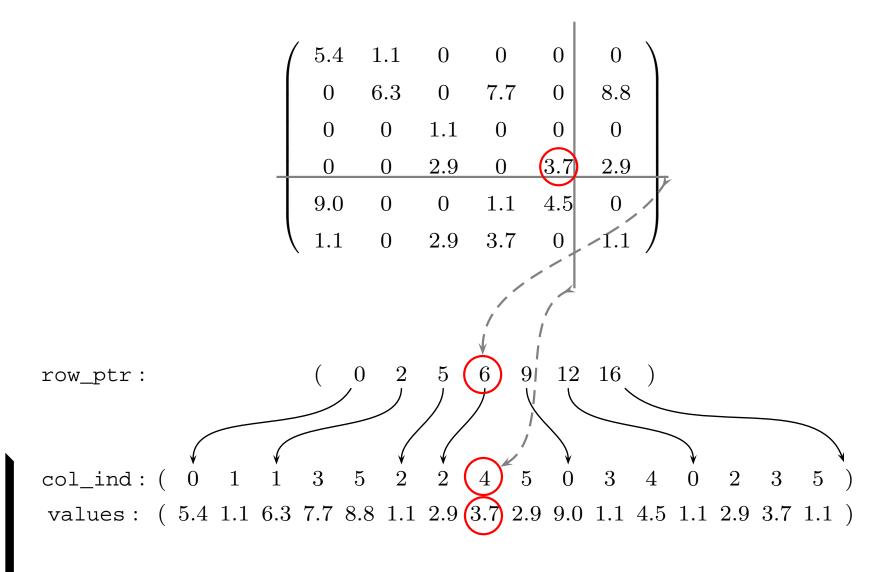
- $y = A \cdot x$ , A is sparse
- important, used in a variety of applications (eg, PDE solvers – CG, GMRES)

# Compressed Sparse Row (CSR)

```
\begin{pmatrix}
5.4 & 1.1 & 0 & 0 & 0 & 0 \\
0 & 6.3 & 0 & 7.7 & 0 & 8.8 \\
0 & 0 & 1.1 & 0 & 0 & 0 \\
0 & 0 & 2.9 & 0 & 3.7 & 2.9 \\
9.0 & 0 & 0 & 1.1 & 4.5 & 0 \\
1.1 & 0 & 2.9 & 3.7 & 0 & 1.1
\end{pmatrix}
```



# Compressed Sparse Row (CSR)



## CSR SpMxV

```
for (i=0; i<N; i++)
for (j=row_ptr[i]; j<row_ptr[i+1]; j++)
y[i] += values[j]*x[col_ind[j]];</pre>
```

## CSR SpMxV

```
for (i = 0; i < N; i++)
    for (j=row_ptr[i]; j< row_ptr[i+1]; j++)
        y[i] += values[j]*x[col_ind[j]];
  i = 3
                            0 \quad 2 \quad 5 \quad 6 \quad 9 \quad 12 \quad 16 \quad )
row_ptr:
                                                                 (row limits)
                                                0 3 4 0 2 3
                                           5
col_ind: ( 0 1 1 3 5 2 2 4
                                                              (indirect\ access)
                             x_0 \quad x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5 \quad x_6
   x:
\mathtt{values:} \ (\ 5.4\ 1.1\ 6.3\ 7.7\ 8.8\ 1.1\ 2.9\ 3.7\ 2.9\ 9.0\ 1.1\ 4.5\ 1.1\ 2.9\ 3.7\ 1.1\ )
                             y_0 y_1 y_2 y_3 y_4 y_5 y_6 )
   у:
```

# CSR SpMxV performance

- memory bandwidth is the main bottleneck (Goumas et al. PDP '08)
- spmv accesses:  $(N \times N \text{ sparse matrix}, nnz \gg N)$

Array	size	accesses	pattern	type
row_ptr	N	N	sequential	read
values	nnz	nnz	sequential	read
col_ind	nnz	nnz	sequential	read
X	N	nnz	random, ↑	read
У	N	N	sequential	write

- Thus, we target working set (ws) reduction
- allows better scaling for shared memory architectures
- values, col\_ind dominate working set

# CSR SpMxV working set

$$\text{ws} \approx \underbrace{\text{nnz} \cdot value\_size}_{\text{values}} + \underbrace{\text{nnz} \cdot index\_size}_{\text{col\_ind}}$$

32-bit indices, 64-bit values (common case)

64-bit indices, 64-bit values ( $\sim 1T \text{ ws size}$ )

# **Objective**

Explore the design space for accelerating SpMxV using working set reduction techniques

- Propose two methods (index / value compression)
- Evaluate on a rich matrix set
- Investigate issues, identify trade-offs
- Explore future directions

# **Compression Methods**

## **Methods overview**

- Compression ⇒ trade computation for data size
- data size reduction is not enough (SpMxV run-time)
- Index Compression: CSR-DU
  - general
  - coarse-grain delta encoding for column indices
- Value Compression: CSR-VI
  - specialized
  - exploits large number of common values

# **Index Compression**

- Blocking methods (BCSR, VBR) per block indexing ⇒ index data reduction
- Delta encoding for column indices
   (Willcock and Lumsdaine : DCSR, RPCSR ICS 06)

```
col_ind: 61311 61336 61390 61400 61428 deltas: ... 25 54 10 28
```

#### DCSR:

- byte-oriented
- 6 sub-operations for implementing SpMxV
- decoding overhead → performance degradation (branches)
- patterns of frequent used groups of sub-ops
- complex, non-portable, matrix-specific

## CSR-DU (CSR Delta Units)

- Exploit dense areas using delta encoding
- Coarse-grain approach:
  - matrix is partitioned into variable-length units
  - each unit has a delta size
  - less compression ratio
  - innermost loops without branches
- Compared to DCSR:
  - comparable performance
  - portable, easier to implement
  - suitable for matrices with large variation

## **CSR-DU** storage format

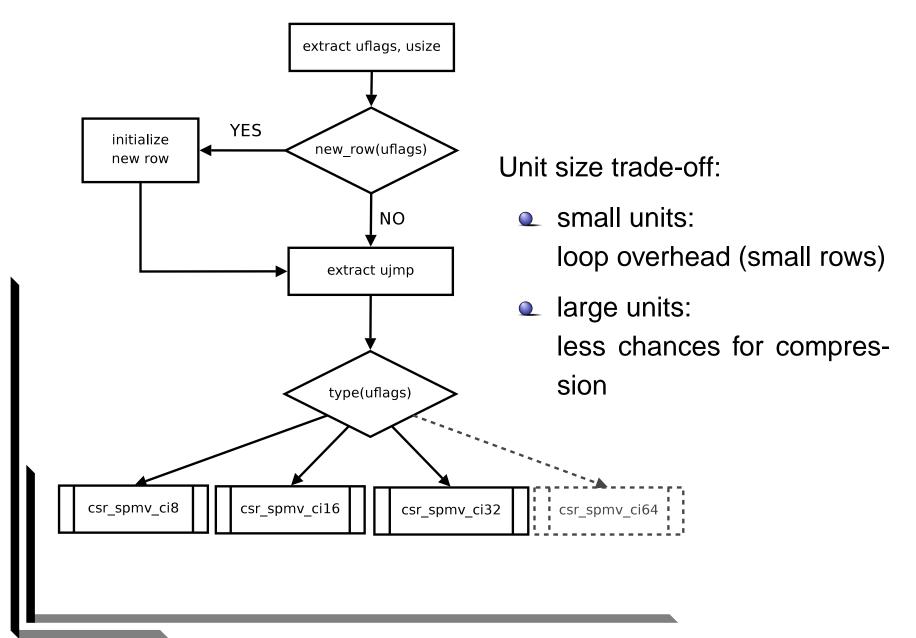
- ctl byte array replaces row\_ptr, col\_ind
- unit contents:

field	description	size
usize	size	1 byte
uflags	flags (new row, delta_size)	1 byte
ujmp	initial delta	variable length
ucis	subsequent deltas	$\mathtt{usize} \cdot delta\_size$

#### Example:

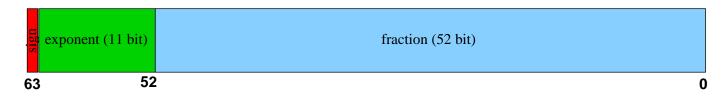
$$(7,1)(7,127)(7,250)(7,255)(8,10)(8,1021)$$
 uflags ucis 
$$\underbrace{[4,NR|U8,1,(126,123,5)]}_{\text{unit}} [2,NR|U16,10,(1011)]$$

# CSR-DU SpMxV



## **Value Compression**

- Values:
  - Typically the largest part of the ws (32i-64v)
  - (more) difficult to compress:
    - FP arithmetic produces rounded results
    - FP format



- significant number of matrices in our set with a small number of unique values.
- feasibility metric: total-to-unique ratio

$$(ttu = \frac{nnz}{unique\ values})$$

## **CSR-VI**

Indirect access for values:

```
values:

( 5.4 1.1 6.3 7.7 8.8 1.1 2.9 3.7 2.9 9.0 1.1 4.5 1.1 2.9 3.7 1.1 )

val_ind + vals_unique:

( 0 1 2 3 4 1 5 6 5 7 1 8 1 5 6 1 )

( 5.4 1.1 6.3 7.7 8.8 2.9 3.7 9.0 4.5 )
```

## **CSR-VI**

Indirect access for values:

```
values:

( 5.4 1.1) 6.3 7.7 8.8 1.1) 2.9 3.7 2.9 9.0 1.1) 4.5 1.1) 2.9 3.7 1.1) )

val_ind + vals_unique:

( 0 1) 2 3 4 1 5 6 5 7 1 8 1 5 6 1 )

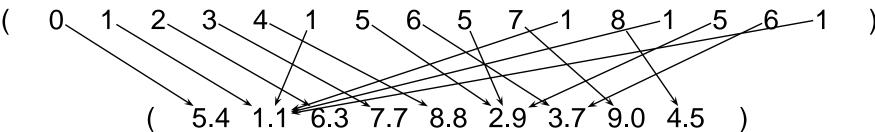
( 5.4 1.1) 6.3 7.7 8.8 2.9 3.7 9.0 4.5 )
```

## **CSR-VI**

#### Indirect access for values:

```
values:
( 5.4 1.1 6.3 7.7 8.8 1.1 2.9 3.7 2.9 9.0 1.1 4.5 1.1 2.9 3.7 1.1 )
```

val\_ind + vals\_unique:



format	values size
CSR	$nnz \cdot size\_v$
CSR-VI	$nnz \cdot size\_vi + uvals \cdot size\_v$

 $size\_vi \rightarrow \text{smallest integer that can address } uvals \text{ elements}$ (e.g.  $uvals \leq 256 \Rightarrow size\_vi = 1 \ byte$ )

# CSR-VI SpMxV

```
for(i=0; i<N; i++)
  for(j=row_ptr[i]; j<row_ptr[i+1]; j++){
    val = vals_unique[val_ind[j]];
    y[i] += val*x[col_ind[j]];
}</pre>
```

- one memory access added (indirect)
- access to vals\_unique is random

# **Experimental Evaluation**

## **Experimental Setup**

- System
  - Intel Core 2 Xeon (Woodcrest) @2.6 GHz, 4MB L2
  - 64-bit linux, gcc-4.2 -O3
- SpMxV Benchmark
  - 32-bit indices, 64-bit values
  - 128 iterations
- Matrix set
  - start: 100 matrices (Tim Davis, SPARSITY, ...)
  - memory bound set  $\mathcal{M}_0$ :  $ws > \frac{3}{4}L2$  (77 matrices)

## **CSR-DU Performance**

- Reject small row matrices: 59 remaining matrices (  $85\% \ \mathrm{nnz}$  in rows with  $\leq 6$  elements)
- Summary:

ma	trices		speed	dup (%)	
total	sp > 1	avg.	min	max	dense
64	59	8.1	-8.1	18.9	35

 $\bullet$  64-bit indices +36%

detailed results

## **CSR-VI Performance**

- Reject matrices with low ttu: 30 remaining matrices: (ttu < 5)
- Summary:

matrices		speedup (%)		
total	sp > 1	avg.	min	max
30	26	21.5	-31.1	74.1

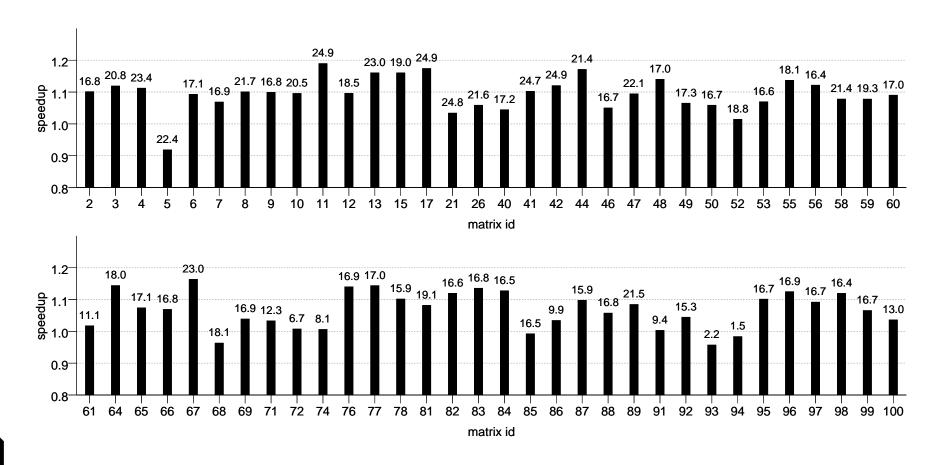
detailed results

### **Conclusions and Future Directions**

- Index compression:
  - limited perfomance gain for the 32i-64v case
  - "pure" computation (not hard-to-predict branches)
  - more aggressive compression (global)
  - expand the "unit" concept to support more types of regularities
  - matrix-specific code generation
- Value compression
  - common case: values largest part of ws
  - difficult (constrained regularity, nature of FP)
  - specialized schemes
- shared memory architectures
- working set reduction for other applications

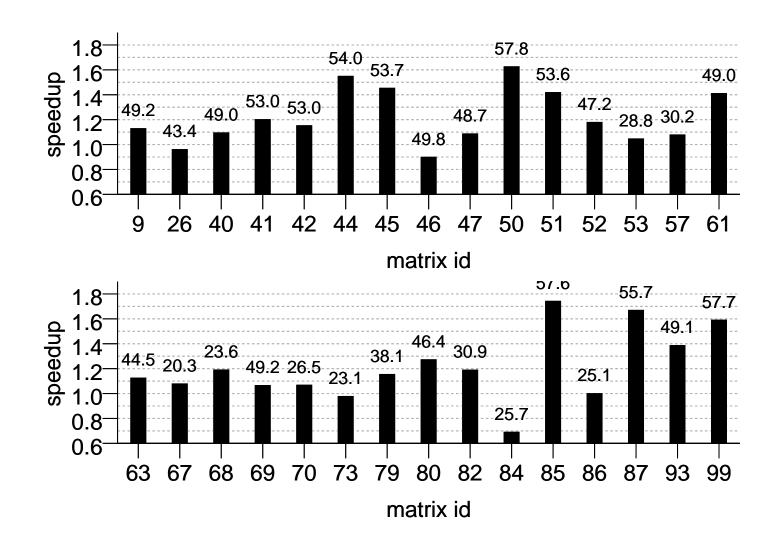
## **EOF**

## **CSR-DU Performance (2)**



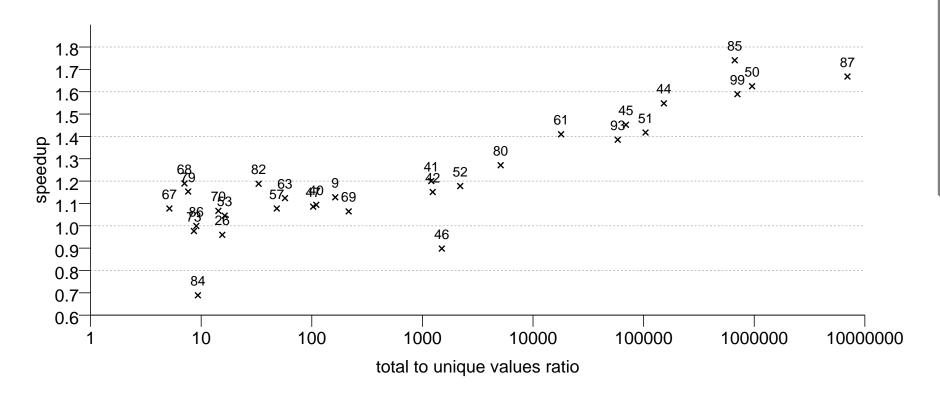
summarized results

## **CSR-VI Performance (2)**



summarized results

## **CSR-VI Performance (3 – ttu)**



summarized results