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#### Data-driven applications

Sparse data is dominant

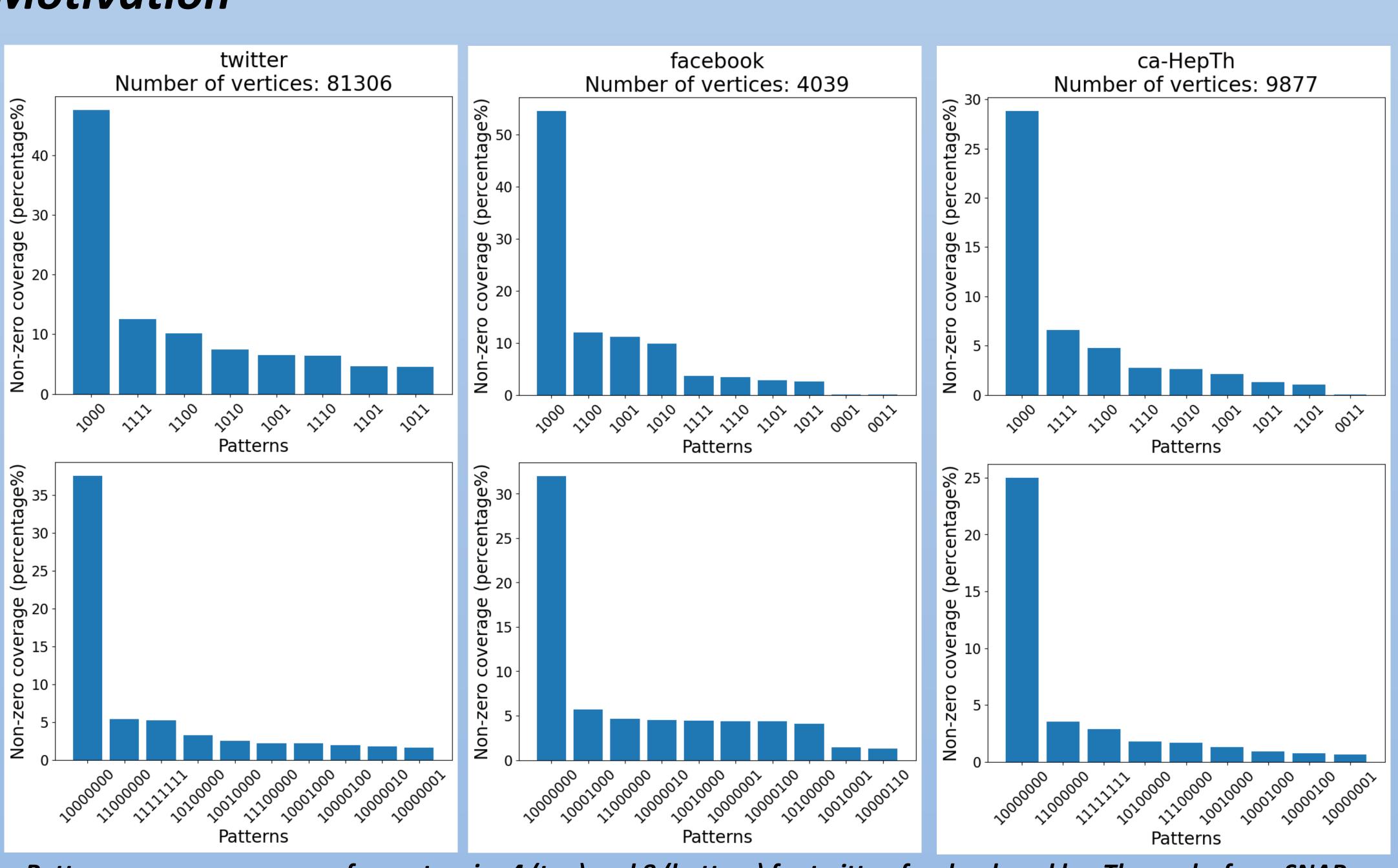
- **Big Data Analytics**
- Social Networks
- Scientific Computing
- Machine Learning

#### **Efficient storage and computation algorithms needed**

### **Objective**

Fast, low-overhead computations on sparse matrices

#### Motivation



Patterns non-zero coverage for vector size 4 (top) and 8 (bottom) for twitter, facebook and hepTh graphs from SNAP

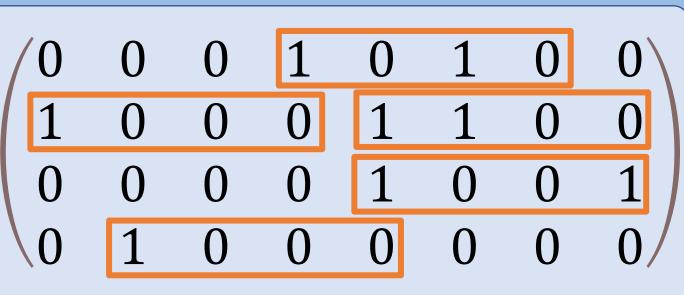
- Potential for vectorization
- Patterns with a single non-zero coverage drops by extending vector size
- Focusing on only a few patterns for vectorization covers most of the matrix

# Pattern-Aware Vectorization for S

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### **Related Work Limitations**

- Accelerators (i.e., GPUs) provide high speedups but limited memory capacity.
- Unified with memory automatic host/device paging degrades performance
- Limited compiler support (i.e., GCC) for automatic vectorization on sparse structures
- Existing storage formats for sparse matrices automatically extract dense not do segments, not seizing the potential for aggressive vectorization



Sample patterns of vector size 4 in a sparse 4 x 8 matrix

Sparse Matrix Technology Versity	Computatio Martin Kong School of Computer Scier University of Oklahom
pproach	
<ul> <li>Generate a list of dense regions within the sparse matrix</li> <li>Efficient scanning algorithm (or user input)</li> </ul>	<ul> <li>Data-level parallelism (SIMD) for sparse matrix computations</li> <li>Control-flow free vector code</li> </ul>
Dense Segments Extraction	Vector Code Generation
<ul> <li>Use hierarchical representations of sparse matrices to enable fast exploration</li> </ul>	Use Gather (load NNZ from sparse matrix using index vectors) and Scatte (store results to sparse

## **Evaluation**

**Kernel:** Sparse matrix-dense vector multiplication **Sparse matrix**: facebook adjacency matrix from SNAP (4039 x 4039), 176468 Single FP NNZs Memory: main 16 GB, L3 cache: 12 MB, L2 cache 1.5 MB, L1 cache: 192 KB

*locations*)

- Compiler: clang++ v10.0
- CPU: 12 cores (only sequential execution used) **Metric:** Speedup over naïve dense multiplication Proposed vec (dense segments start locations metadata + vectorization using <u>AVX256</u> intrinsics) achieves around 4.95x speedup over patt (clang auto-vectorization with metadata). COO achieves 1.5x speedup over proposed vec

#### Conclusion

- A new approach to enable more efficient sparse data computation using:
- Extraction and exploitation of metadata such as dense segments locations
- Generation of vector code to use data-level parallelism
- Efficiently visiting patterns using codelets
- Preliminary results
- Potential of exploiting additional metadata
- Potential of generating vector code combined with efficient storage formats

### **DNS**

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