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Usage and needs for sparse data in

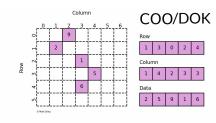


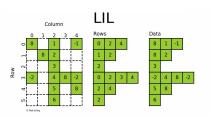
Sparse Data – Meeting 1 Monday, Sept. 26th 11AM - 12PM Pacific time Julien Jerphanion (@jjerphan)

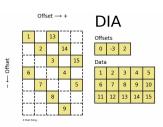












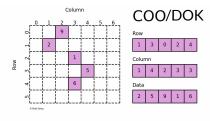
### 5% of use-cases, e.g.:

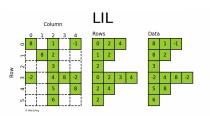
- Sparse matrices construction
- Generalized Linear Models
- Spectral{Biclustering, Embedding}
- AgglomerativeClustering

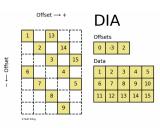
Used via SciPy's Python API. Use-cases' needs are covered.







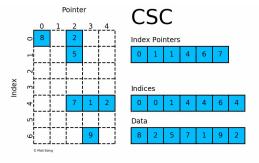


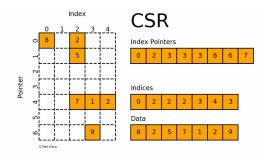


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### Used for performance:

- CSC: column-wise processing
- CSR: row-wise processing

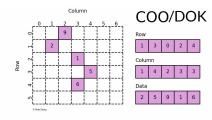
#### Used via:

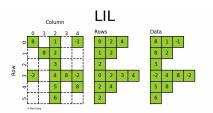
- SciPy's Python API
- Dedicated low-level Cython routines in scikit-learn working on the arrays directly, e.g.:

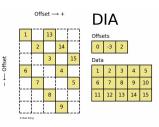
sklearn/utils/sparsefuncs fast DistanceMetrics.(r)dist csr {Dense,Sparse}2DatasetsPairs







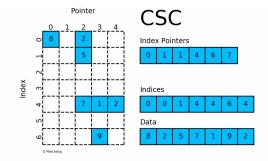


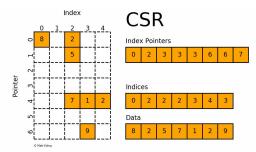


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95% of usages: a lot of transformers and machine learning algorithms

Use-cases' needs can better be addressed.

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sklearn/utils/sparsefuncs fast DistanceMetrics.(r)dist csr {Dense,Sparse}2DatasetsPairs

Sparse-Dense matrices operations: usage and needs









Sandwich product use case in Generalized Linear Models' solvers

$$\mathbf{X}^{\mathsf{T}} \mathrm{diag}(\mathbf{d}) \mathbf{X}$$

where  $\mathbf{X}$  : sparse and dense by blocks







Sandwich product use case in Generalized Linear Models' solvers

$$\mathbf{X}^{\top} \operatorname{diag}(\mathbf{d}) \mathbf{X}$$

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Generalized Matrix-Matrix Multiplication on dense-sparse matrices' pairs

$$\mathbf{C} \leftarrow \alpha \operatorname{op}(\mathbf{A}) \operatorname{op}(\mathbf{B}) + \beta \mathbf{C}$$

where 
$$\mathrm{op} \in \left\{\mathrm{Id}, \cdot^{ op}\right\}$$
  $\mathbf{C}$  : dense  $\mathbf{A}$   $\mathbf{B}$  : dense, CSR







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Needs: efficient low-level implementations for such operations

# Sparse-Dense matrices operations: possible solutions



- Recode the needed operations in Cython
  - V Pros:
    - full control on those implementations (tailorable to our use-cases)
  - X Cons:
    - maintenance complexity:
      - fused-type restrictions on Cython extension types
      - indptr, indices dtypes runtime dependence (<u>scipy#16774</u>)

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- Vendor/use some of <a href="SciPy's private C++ routines for CSR/CSC">SciPy's private C++ routines for CSR/CSC</a>:
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- Popendent (optionally) on another library like tabmat:
  - V Pros:
    - efficient and stable implementations
    - support block-wise sparse and dense structure arrays
  - Cons:
    - would add another dependency
    - no-public C/C++/Cython API
    - o potential costly data structures' adaptations



### **ONE Needs/wishes:**

- API UX uniformity across NumPy and SciPy usages
  - output containers' type returning match input containers' type
  - e.g.: np.{h,v}stack supporting SciPy matrices
- Ideally multi-thread and efficient implementations of the previous operations:
  - o usable via a Python API with the @ operator
  - usable via a Cython or C API
  - based on <u>SciPy's sparsetools (i.e. sparse matrices C++ routine)</u>?



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### ? Questions:

- Regarding indices and indptr types
  - Why have signed integers historical been chosen?
  - Does <u>scipy#16774</u> makes sense? If so, is it solvable?
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  - Would Sparse Arrays support this standard?



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  - o interesting extensions of sparse matrices to n-dimensional sparse arrays
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