Easy* Python wrappers for RandBLAS and RandLAPACK

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RandBLAS in action: subset selection

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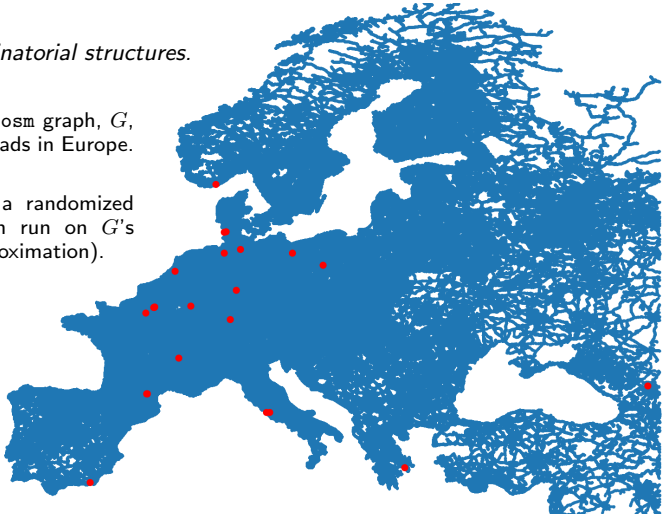
Matrices often encode combinatorial structures.

Right: the DIMACS10 `europe-osm` graph, G, representing 50 million major roads in Europe.

Red nodes were obtained by a randomized Golub-Klema-Stewart algorithm run on G's adjacency matrix (rank-32 approximation).

Algorithm ingredients:

- ⋆ Gaussian sampling
- ⋆ SPMM
  - QR & QRCP
  - dense BLAS



Householder QRCP with randomized, block pivoting

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Independently discovered by Duersch and Gu [DG17] and Martinsson [Mar15].

Refined in [MOHvdG17] and [XGL17]. Recently revitalized by [MMK+25].

Given $\mathbf{M} \in \mathbb{R}^{m \times n}$, find $\mathbf{Q}$, $\mathbf{R}$, $\boldsymbol{J}$

- Select a block size b (big, but $\ll n$) and tuning parameter $1 \leq \gamma < 2$ (recommend $= 1$).
- Sample a Gaussian operator $\mathbf{S} \in \mathbb{R}^{\gamma b \times m}$, and sketch $\mathbf{M}^{\mathrm{sk}} = \mathbf{S}\mathbf{M}$.

Main loop for $i = 1 : n/b$

1. $[\sim, \mathbf{R}^{\mathrm{sk}}, \boldsymbol{J}_i] = \texttt{qrcp\_wide}(\mathbf{M}^{\mathrm{sk}})$
2. $\mathbf{M}^{\mathrm{perm}} = \texttt{col\_perm}(\mathbf{M}, \boldsymbol{J}_i)$
3. $k = \texttt{rank\_est}(\mathbf{R}^{\mathrm{sk}})$
4. $[\mathbf{Q}_i, \mathbf{R}_i^{11}] = \texttt{qr\_tall}(\mathbf{M}^{\mathrm{perm}}, k)$
5. $[\mathbf{M}^{\mathrm{update}}, \mathbf{R}_i^{12}] = \texttt{apply\_trans\_q}(\mathbf{Q}_i, \mathbf{M}^{\mathrm{perm}})$
6. Update $\mathbf{M}$ with $\mathbf{M}^{\mathrm{update}}$
7. Update $\mathbf{Q}$ with $\mathbf{Q}_i$; $\mathbf{R}$ with $\mathbf{R}_i^{11}$ and $\mathbf{R}_i^{12}$; $\boldsymbol{J}$ with $\boldsymbol{J}_i$
8. Check termination criteria
9. Update $\mathbf{M}^{\mathrm{sk}}$

Speed of QR and QRCP algorithms

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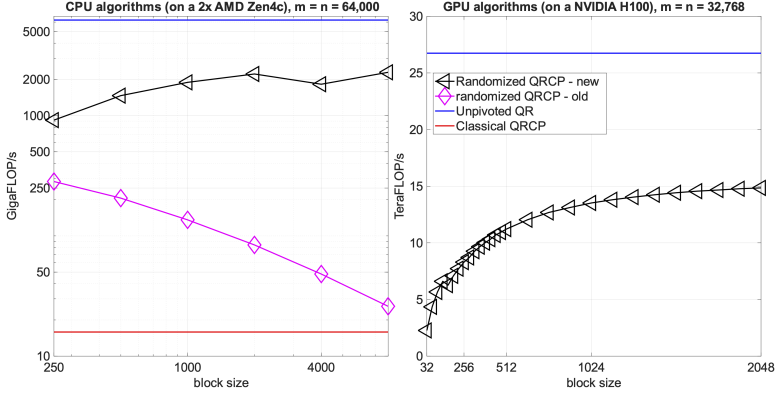
"**Randomized QRCP – new**" is our implementation described in [MMK+25].



We can get a **100x speedup** over a classical algorithm – for a *full matrix decomposition*.

The algorithm – which is notoriously hard to parallelize – runs beautifully on GPUs.

A glimpse of the RandBLAS API

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```
using namespace RandBLAS; using namespace blas;
// step 1
RNGState state();
// step 2
DenseDist D(10000, 50);
DenseSkOp<double> S(D, state);
// step 3
double B* = new double[20000 * 50];
sketch_general(
      Layout::ColMajor, Op::NoTrans, Op::NoTrans,
      20000, 50,  10000, 1.0, A, 20000, S, 0.0, B, 20000
); // B = AS
```

RandBLAS types involved in sketching:

- Templated `RNGState` structs.
- Implementations of ...
  - `SketchingDistribution`
  - `SketchingOperator`

Three powerful aspects of RandBLAS' API:

1. No hidden machine state affects $\mathbf{S} = \{\texttt{dist}, \texttt{state}\}$ as a mathematical object.
2. `SketchingOperator` objects are constructed in $O(1)$ time and space.
3. We have procedural, random(ish) access to submatrices of sketching operators.

This tutorial

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1. `git clone https://github.com/rileyjmurray/midwest-randnla-2026.git`
2. Look at `project_instructions.md`.
   - Pull the Docker image and launch a container.
   - Setup conda. Build and install RandLAPACK within the container.
3. A "Hello World"
   - change directory into `bindings`
   - run `pip install -e .`
   - run `pytest tests`
   - Prompt: Please read AGENTS.md, then create a function ‘`suparla.add(a, b)`‘ that takes two float64 scalars and returns their sum.
4. Making real bindings!
   - Prompt: Help me expose RandLAPACK's `BQRRP` algorithm to Python so it can operate on NumPy arrays.
   - If you encounter errors, paste them into the chat window and ask how to proceed.
5. Possible next steps:
   - Make a demo script that compares speed of SciPy's QR with `pivoting=True` to `BQRRP`.
   - Expose some of `BQRRP`'s subroutine options to the Python interface.
   - Modify `BQRRP`'s C++ source so that it can terminate at a prescribed rank.

Thank you!

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Example: pivot quality with randomized and classical QRCP

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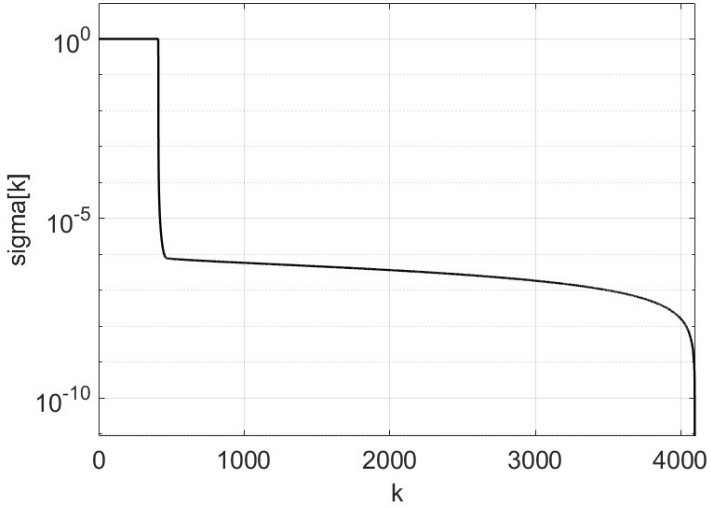

Figure: True singular values of test matrix $\mathbf{M}$.

Example: pivot quality with randomized and classical QRCP

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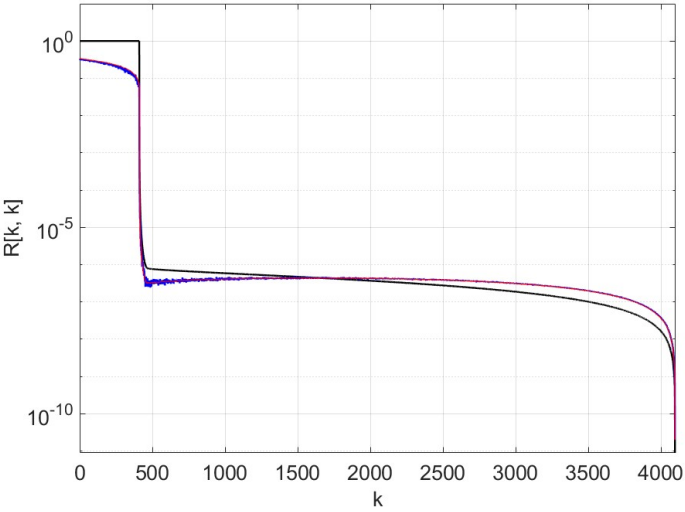

Figure: BQRRP and **classical QRCP**: diagonal entries of **R**.

Example: pivot quality with randomized and classical QRCP

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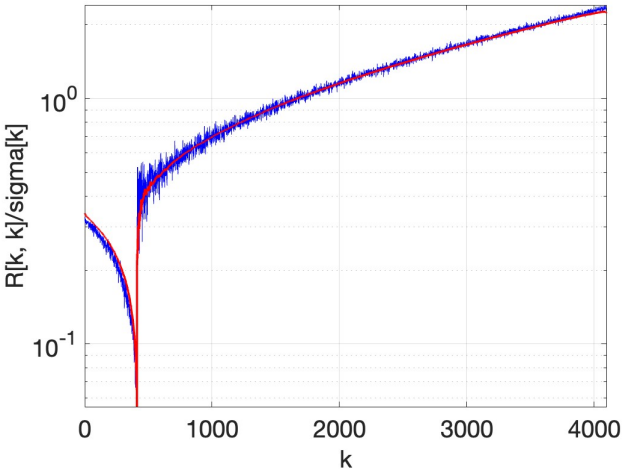

Figure: BQRRP and **classical QRCP**: ratios of $\mathrm{diag}(\mathbf{R})$ and singular values of $\mathbf{M}$.

RandBLAS' sparse matrix datastructures

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In RandBLAS 1.0:

- The common interface for our sparse matrix types
- COOMatrix
- CSRMatrix
- CSCMatrix

Operations with sparse matrices

Sketching

- $\mathbf{B} = \alpha \cdot \mathrm{op}(\mathrm{submat}(\mathbf{S})) \cdot \mathrm{op}(\mathbf{A}) + \beta \cdot \mathbf{B}$
- $\mathbf{B} = \alpha \cdot \mathrm{op}(\mathbf{A}) \cdot \mathrm{op}(\mathrm{submat}(\mathbf{S})) + \beta \cdot \mathbf{B}$

Deterministic operations

- $\mathbf{C} = \alpha \cdot \mathrm{op}(\mathbf{A}) \cdot \mathrm{op}(\mathbf{B}) + \beta \cdot \mathbf{C}$, with sparse $\mathbf{A}$
- $\mathbf{C} = \alpha \cdot \mathrm{op}(\mathbf{A}) \cdot \mathrm{op}(\mathbf{B}) + \beta \cdot \mathbf{C}$, with sparse $\mathbf{B}$

Flexible memory ownership policies:

Public Functions

inline **CSRMatrix**(int64_t n_rows, int64_t n_cols)

Standard constructor. Initializes n_rows and n_cols at the provided values. The vals, rowptr, and colidxs members are set to null pointers; nnz is set to zero, index_base is set to Zero, and CSRMatrix::own_memory is set to true.

This constructor is intended for use with reserve_csr(int64_t nnz, CSRMatrix &A).

inline **CSRMatrix**(int64_t n_rows, int64_t n_cols, int64_t nnz, T *vals, sint_t *rowptr, sint_t *colidxs, IndexBase index_base = IndexBase::Zero)

Expert constructor. Arguments passed to this function are used to initialize members of the same names; CSRMatrix::own_memory is set to false.

On RandBLAS' main branch, to appear in version 1.1:

$$\mathbf{B} = \alpha \cdot \mathrm{op}(\mathbf{A})^{-1} \cdot \mathbf{B}$$

where $\mathbf{A}$ is sparse triangular (upper or lower, CSC or CSR) and $\mathbf{B}$ is dense.

The BLAS data model

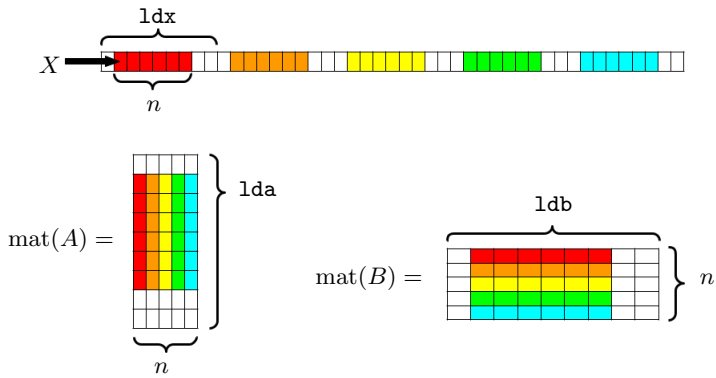

Figure: Visualization of how a buffer, pointed to by X, can be read in different ways to obtain two different matrices. We get $\mathrm{mat}(A)$ by setting $A = X$ and reading in column-major order with stride $\texttt{lda} = \texttt{ldx}$. We get $\mathrm{mat}(B)$ by setting $B = X$ and reading in row-major order with stride $\texttt{ldb} = \texttt{ldx}$. Mathematically, we have $\mathrm{mat}(A)^* = \mathrm{mat}(B)$.

Considerations in high-performance sketching

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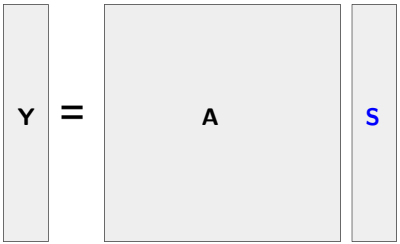
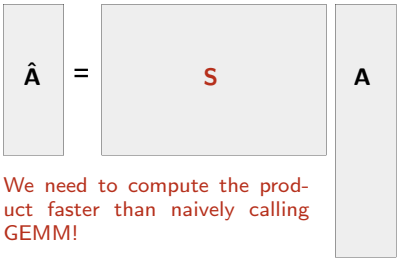
There are two regimes for sketching: and *sampling* and *embedding*





We need to compute the product faster than naively calling GEMM!

- ✓ Use vendor BLAS to multiply when both $(\mathbf{S}, \mathbf{A})$ are dense.
- ✓ Use OpenMP for sparse matrix multiplies and generating $\mathbf{S}$.
- ✓ Beware cache effects and row-major vs column-major memory layout.