

# CUR: Pros & Cons

## + Easy interpretation

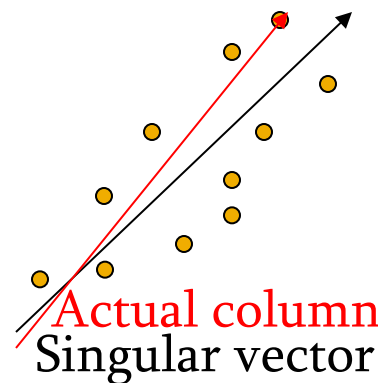
- Since the basis vectors are actual columns and rows

## + Sparse basis

- Since the basis vectors are actual columns and rows

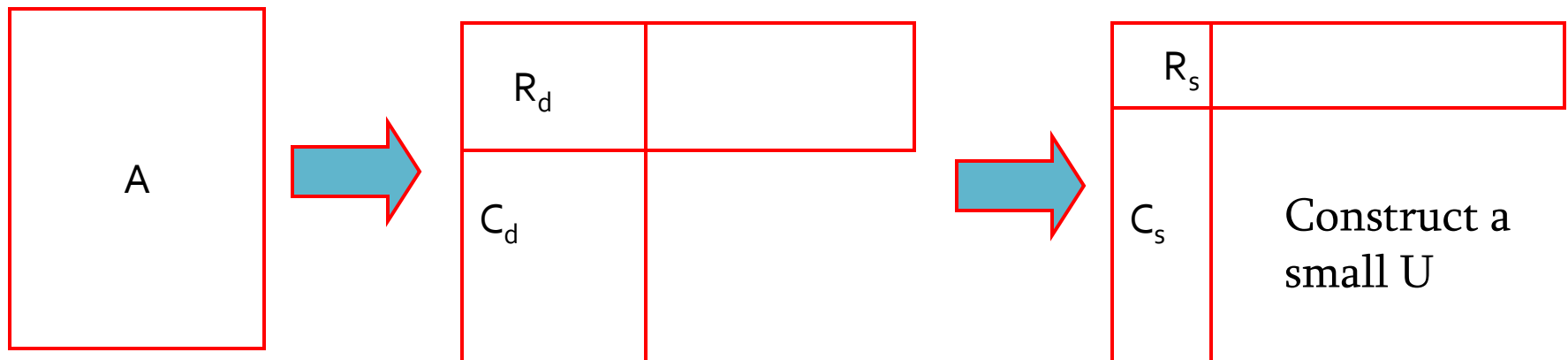
## - Duplicate columns and rows

- Columns of large norms will be sampled many times



# Solution

- If we want to get rid of the duplicates:
  - Throw them away
  - Scale (multiply) the columns/rows by the square root of the number of duplicates



# SVD vs. CUR

SVD:  $A = U \Sigma V^T$

Annotations for SVD:

- $A$ : Huge but sparse
- $U$ : Big and dense
- $\Sigma$ : sparse and small
- $V^T$ : Big and dense

CUR:  $A = C U R$

Annotations for CUR:

- $A$ : Huge but sparse
- $C$ : Big but sparse
- $U$ : dense but small
- $R$ : Big but sparse

# Simple Experiment

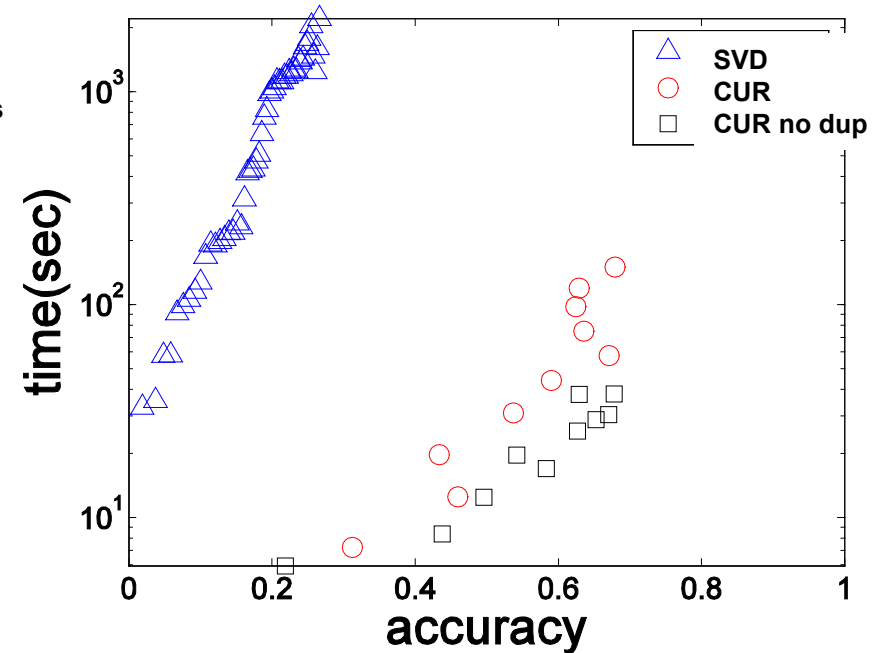
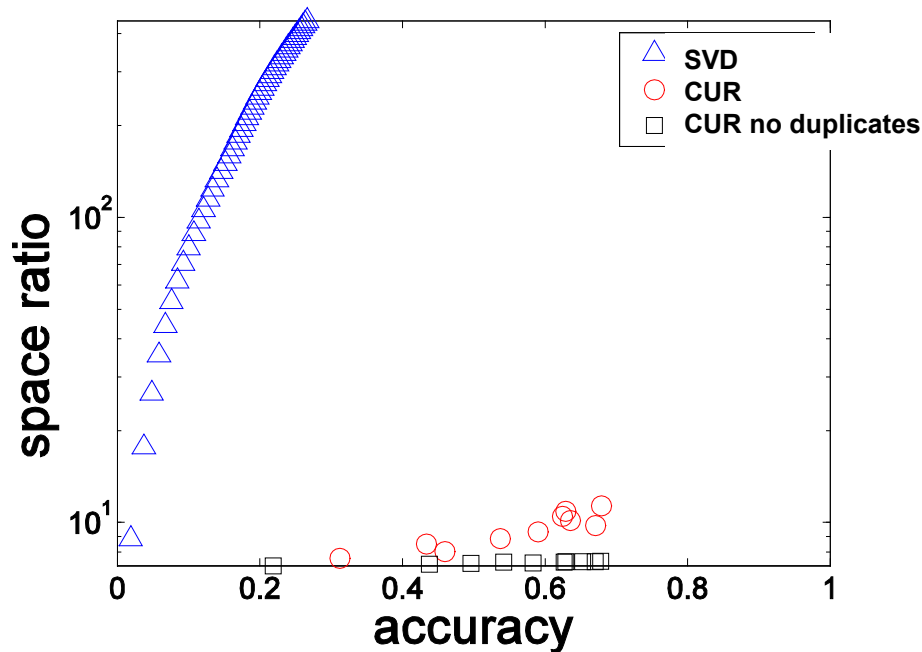
- **DBLP bibliographic data**

- Author-to-conference big sparse matrix
- $A_{ij}$ : Number of papers published by author  $i$  at conference  $j$
- 428K authors (rows), 3659 conferences (columns)
  - Very sparse

- **Want to reduce dimensionality**

- How much time does it take?
- What is the reconstruction error?
- How much space do we need?

# Results: DBLP- big sparse matrix



- **Accuracy:**
  - 1 – relative sum squared errors
- **Space ratio:**
  - $\# \text{output matrix entries} / \# \text{input matrix entries}$
- **CPU time**