## Lecture 20 - MPI Part 3

**DSE 512** 

Drew Schmidt 2022-04-07

#### From Last Time

- Homework 3
  - o Originally due Saturday April 9
  - Now due Wednesday April 13
  - THERE WILL BE NO ADDITIONAL EXTENSIONS
- Did I forget something?
- Questions?

### Today

- Data parallelism with MPI
  - $\circ$  SVD
  - o GLM's
  - Some other approaches

## Parallel SVD

## Recall: Connection to Eigendecomposition

$$egin{aligned} A^T A &= \left(U \Sigma V^T
ight)^T \left(U \Sigma V^T
ight) \ &= V \Sigma U^T U \Sigma V^T \ &= V \Sigma^2 V^T \end{aligned}$$

## Recall: Computing the "Normal Equations" Matrix

Choose b > 0 and split A into b blocks of rows:

$$A = egin{bmatrix} A_1 \ A_2 \ dots \ A_b \end{bmatrix}$$

Then

$$A^TA = \sum_{i=1}^b A_i^TA_i$$

### Recall: Crossproduct-Based SVD Algorithms

#### Out-of-core

- Inputs
  - $\circ$   $A_{m imes n}$
  - Number of blocks b
- Procedure
  - $\circ$  Initialize  $B_{n\times n}=0$
  - $\circ$  For each  $1 \le i \le b$ 
    - $\blacksquare$  Read block of rows  $A_i$
    - Compute  $B = B + A_i^T A_i$
  - $\circ$  Factor  $B = \Lambda \Delta \Lambda$

#### Parallel

- Inputs
  - $\circ$   $A_{m imes n}$
  - Number of cores c
- Procedure
  - $\circ$  Distribute matrix A among c workers into submatrices  $A_i$
  - $\circ$  Compute  $B_i = A_i^T A_i$
  - $\circ$  Compute  $B = \sum_{i=1}^{c} B_c$
  - $\circ$  Factor  $B = \Lambda \Delta \Lambda$

#### Parallel SVD

```
parsvd = function(A_local){
 B_local = crossprod(A_local)
 B = allreduce(B_local)
 e = eigen(B)
 sigma = sqrt(e$values)
 v = e$vectors
 u_local = sweep(v, STATS=1/sigma, MARGIN=2, FUN="*")
 u_local = A_local %*% u_local
 list(sigma=sigma,
   u_local = u_local,
   V = V
```

#### Cute Trick

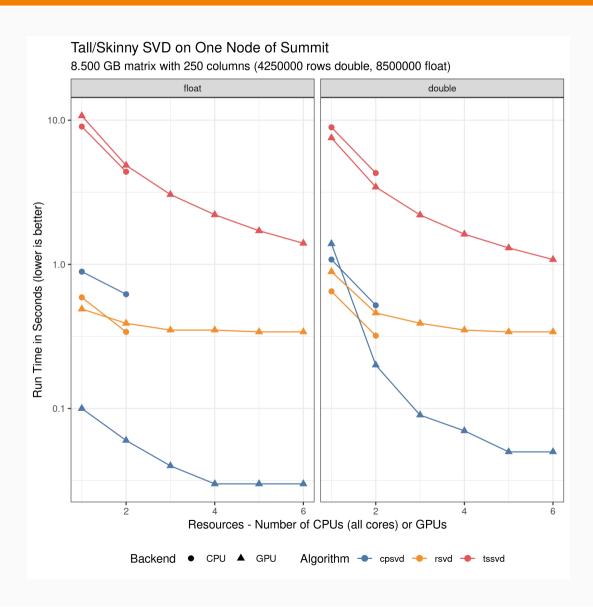
```
allreduce = identity
set.seed(1234)
A = matrix(rnorm(3*2), 3, 2)
parsvd(A)
```

```
## $sigma
## [1] 2.8602018 0.6868562
##
## $u local
## [,1]
                 [,2]
## [1,] -0.9182754 -0.359733536
## [2,] 0.1786546 -0.003617426
## [3,] 0.3533453 -0.933048068
##
## $v
##
           [,1]
                 [,2]
## [1,] 0.5388308 -0.8424140
## [2,] 0.8424140 0.5388308
```

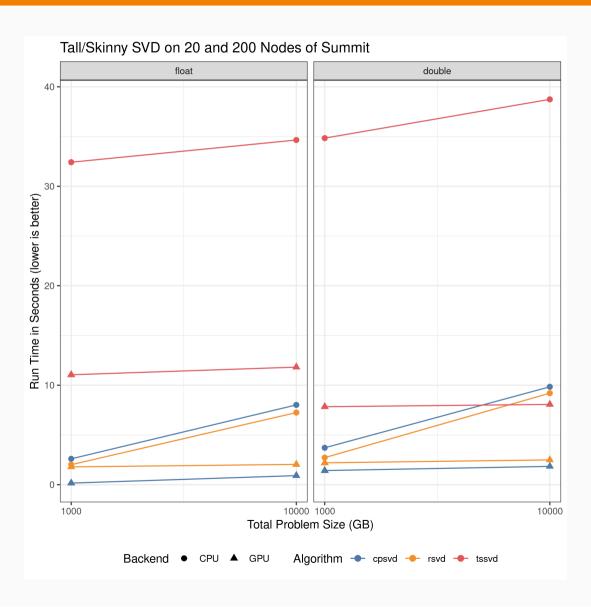
#### svd(A)

```
## $d
## [1] 2.8602018 0.6868562
##
## $u
##
         [,1]
                        [,2]
## [1,] -0.9182754 -0.359733536
## [2,] 0.1786546 -0.003617426
## [3,] 0.3533453 -0.933048068
##
## $v
           [,1]
##
                      [,2]
## [1,] 0.5388308 -0.8424140
## [2,] 0.8424140 0.5388308
```

### Comparing SVD Implementations



## Comparing SVD Implementations



#### More Information

See: Schmidt, D., 2020, November. A Survey of Singular Value Decomposition Methods for Distributed Tall/Skinny Data. In 2020 IEEE/ACM 11th Workshop on Latest Advances in Scalable Algorithms for Large-Scale Systems (ScalA) (pp. 27-34). IEEE.

# Parallel Regression

## Recall: Regression

- Normal equations
- QR
- SVD
- Solving the optimization problem

#### Recall: Solving the Regression Optimization Problem

$$\min_{eta \in \mathbb{R}^n} rac{1}{2m} \sum_{i=1}^m \left( (Xeta)_i - y_i 
ight)^2$$

```
cost_gaussian = function(beta, x, y){
    m = nrow(x)
    (1/(2*m))*sum((x%*%beta - y)^2)
}

reg.fit = function(x, y, maxiter=100){
    control = list(maxit=maxiter)
    beta = numeric(ncol(x))
    optim(par=beta, fn=cost_gaussian, x=x, y=y, method="CG", control=control)
}
```

```
reg.fit(X, y)$par
```

### Regression: Serial to Parallel

```
cost_gaussian = function(beta, x, y){
  m = nrow(x)
  J = (1/(2m))sum((x%*%beta - y)^2)
  J
}
```

```
cost_gaussian = function(beta, x, y){
  m = nrow(x)
  J_local = (1/(2m))sum((x%*%beta - y)^2)
  J = allreduce(J_local)
  J
}
```

- Global: beta
- Distributed: x, y

#### Logistic Regression

$$\min_{ heta \in \mathbb{R}^n} rac{1}{m} \sum_{i=1}^m -y \log(g^{-1}(X heta)) - (1-y) \log(1-g^{-1}(X heta))$$

```
linkinv_logistic = binomial(logit)$linkinv
cost_logistic = function(theta, x, y)
 m = nrow(x)
 eta = x%*%theta
 h = linkinv_logistic(eta)
 (1/m)*sum((-y*log(h)) - ((1-y)*log(1-h)))
logistic.fit = function(x, y, maxiter=100)
 control = list(maxit=maxiter)
 theta = numeric(ncol(x))
 optim(par=theta, fn=cost_logistic, x=x, y=y, method="CG", control=control)
```

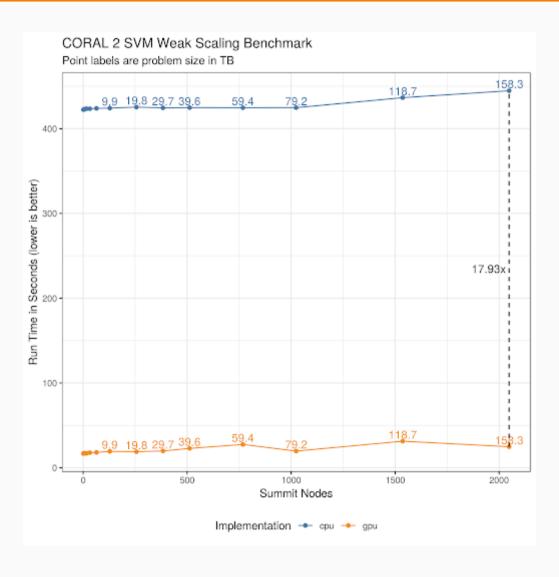
#### Logistic Regression: Serial to Parallel

```
cost_logistic = function(theta, x, y)
{
    m = nrow(x)
    eta = x%%theta
    h = linkinv_logistic(eta)
    J = (1/m)sum((-ylog(h)) - ((1-y)log(1-h))
}
```

```
cost_logistic = function(theta, x, y)
{
    m = nrow(x)
    eta = x%%theta
    h = linkinv_logistic(eta)
    J_local = (1/m)sum((-ylog(h)) - ((1-y)log(h))) = allreduce_dbl(J_local)
    J
}
```

- Global: theta
- Distributed: x, y

#### Linear 2-Class SVM Benchmark



# Other Approaches

## Distributing a Matrix

	$x_{11}$	$x_{12}$	$x_{13}$	$x_{14}$	$x_{15}$	$x_{16}$	$x_{17}$	$x_{18}$	$x_{19}$
	$x_{21}$	$x_{22}$	$x_{23}$	$x_{24}$	$x_{25}$	$x_{26}$	$x_{27}$	$x_{28}$	$x_{29}$
	$x_{31}$	$x_{32}$	$x_{33}$	$x_{34}$	$x_{35}$	$x_{36}$	$x_{37}$	$x_{38}$	$x_{39}$
	$x_{41}$	$x_{42}$	$x_{43}$	$x_{44}$	$x_{45}$	$x_{46}$	$x_{47}$	$x_{48}$	$x_{49}$
x =	$x_{51}$	$x_{52}$	$x_{53}$	$x_{54}$	$x_{55}$	$x_{56}$	$x_{57}$	$x_{58}$	$x_{59}$
	$x_{61}$	$x_{62}$	$x_{63}$	$x_{64}$	$x_{65}$	$x_{66}$	$x_{67}$	$x_{68}$	$x_{69}$
	$x_{71}$	$x_{72}$	$x_{73}$	$x_{74}$	$x_{75}$	$x_{76}$	$x_{77}$	$x_{78}$	$x_{79}$
	$x_{81}$	$x_{82}$	$x_{83}$	$x_{84}$	$x_{85}$	$x_{86}$	$x_{87}$	$x_{88}$	$x_{89}$
	$x_{91}$	$x_{92}$	$x_{93}$	$x_{94}$	$x_{95}$	$x_{96}$	$x_{97}$	$x_{98}$	$x_{99}  \rfloor_{9 \times 9}$

### Distributing a Matrix: Blocking by Rows

### Distributing a Matrix: Blocking by Columns

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} & x_{18} & x_{19} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} & x_{28} & x_{29} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} & x_{38} & x_{39} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} & x_{48} & x_{49} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} & x_{58} & x_{59} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} & x_{68} & x_{69} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} & x_{78} & x_{79} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} & x_{87} & x_{88} & x_{89} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} & x_{97} & x_{98} & x_{99} \end{bmatrix}_{9 \times 9}$$

$$Processors = \begin{bmatrix} 0 & 1 & 2 & 3 \end{bmatrix}$$

### Distributing a Matrix: Cycling by Rows

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} & x_{18} & x_{19} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} & x_{28} & x_{29} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} & x_{38} & x_{39} \\ \hline x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} & x_{48} & x_{49} \\ \hline x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} & x_{58} & x_{59} \\ \hline x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} & x_{68} & x_{69} \\ \hline x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} & x_{78} & x_{79} \\ \hline x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} & x_{87} & x_{88} & x_{89} \\ \hline x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} & x_{97} & x_{98} & x_{99} \end{bmatrix}_{9 \times 9}$$

$$\text{Processors} = \begin{bmatrix} 0 & 1 & 2 & 3 \end{bmatrix}$$

### Distributing a Matrix: Cycling by Columns

$$x_{11} \begin{vmatrix} x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} & x_{18} & x_{19} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} & x_{28} & x_{29} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} & x_{38} & x_{39} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} & x_{48} & x_{49} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} & x_{58} & x_{59} \\ x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} & x_{68} & x_{69} \\ x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} & x_{78} & x_{79} \\ x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} & x_{87} & x_{88} & x_{89} \\ x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} & x_{97} & x_{98} & x_{99} \end{bmatrix}_{9 \times 9}$$

$$Processors = \begin{bmatrix} 0 & 1 & 2 & 3 \end{bmatrix}$$

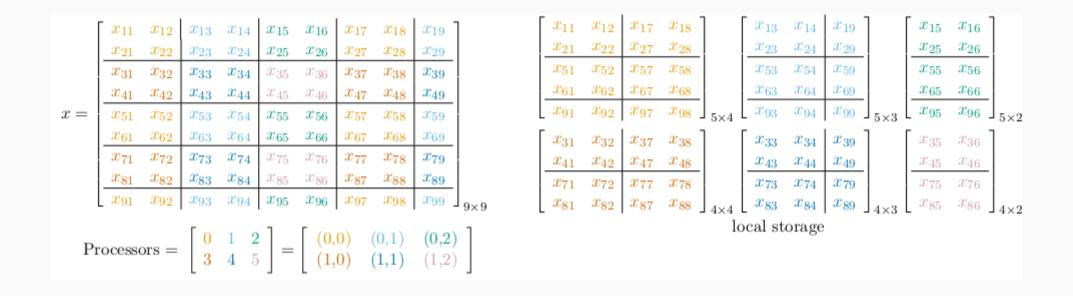
#### Distributing a Matrix: Blocking by Rows AND Columns

#### Distributing a Matrix: Cycling by Rows AND Columns

$$x = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{17} & x_{18} & x_{19} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{27} & x_{28} & x_{29} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} & x_{36} & x_{37} & x_{38} & x_{39} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} & x_{46} & x_{47} & x_{48} & x_{49} \\ \hline x_{51} & x_{52} & x_{53} & x_{54} & x_{55} & x_{56} & x_{57} & x_{58} & x_{59} \\ \hline x_{61} & x_{62} & x_{63} & x_{64} & x_{65} & x_{66} & x_{67} & x_{68} & x_{69} \\ \hline x_{71} & x_{72} & x_{73} & x_{74} & x_{75} & x_{76} & x_{77} & x_{78} & x_{79} \\ \hline x_{81} & x_{82} & x_{83} & x_{84} & x_{85} & x_{86} & x_{87} & x_{88} & x_{89} \\ \hline x_{91} & x_{92} & x_{93} & x_{94} & x_{95} & x_{96} & x_{97} & x_{98} & x_{99} \end{bmatrix}_{9 \times 9}$$

$$Processors = \begin{bmatrix} 0 & 1 \\ 2 & 3 \end{bmatrix}$$

### Distributing a Matrix: The 2-dimensional Block-Cyclic Layout



#### ScaLAPACK

- The scalable LAPACK
- Uses 2-d block-cyclic layout
- Created in the 90's
- Several attemps to replace it

## Bindings

- Julia
  - ScaLAPACK.jl
- Python
  - scalapy
- R
  - $\circ \ pbdDMAT$
  - o fmlr

#### SVD with fmlr

```
suppressMessages(library(fmlr))

g = grid()
x = mpimat(g, 5, 5, 1, 1)
x$fill_rnorm()
x$info()

s = cpuvec()
linalg_svd(x, s)
if (g$rank0()){
    s
}
```

```
mpirun -np 4 Rscript x.r
```

# mpimat 5x5 with 1x1 blocking on 2x2 grid type=d
3.1585 2.6992 1.2946 0.9501 0.5486

#### SVD with fmlr

```
suppressMessages(library(fmlr))

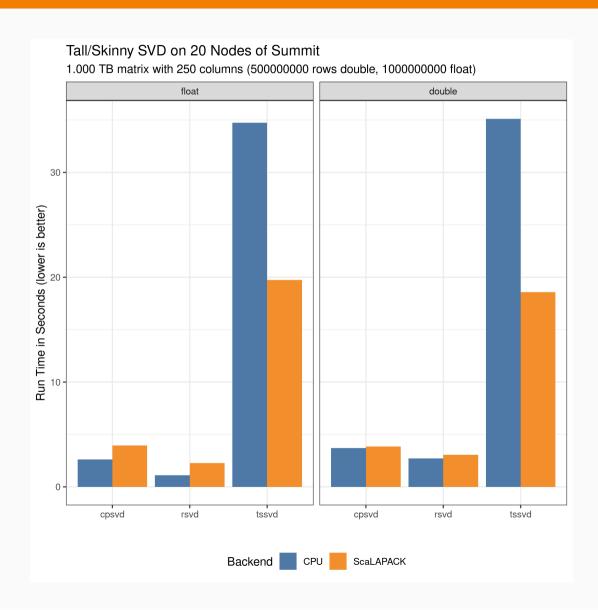
g = grid()
x = mpimat(g, 5, 5, 1, 1)
x$fill_rnorm()
x$info()

s = cpuvec()
linalg_rsvd(1234, 1, 2, x, s)
if (g$rank0()){
    s
}
```

```
mpirun -np 4 Rscript x.r
```

# mpimat 5x5 with 1x1 blocking on 2x2 grid type=d
3.1162

## Comparing SVD Implementations



# Wrapup

#### Wrapup

- SPMD makes short work of data parallelism problems.
- The allreduce() collective is *very* powerful.
- Distributing by row/col is easy, but not always appropriate.
- Next time: the MapReduce algorithm

## Questions?