# Parallel and Distributed GBT

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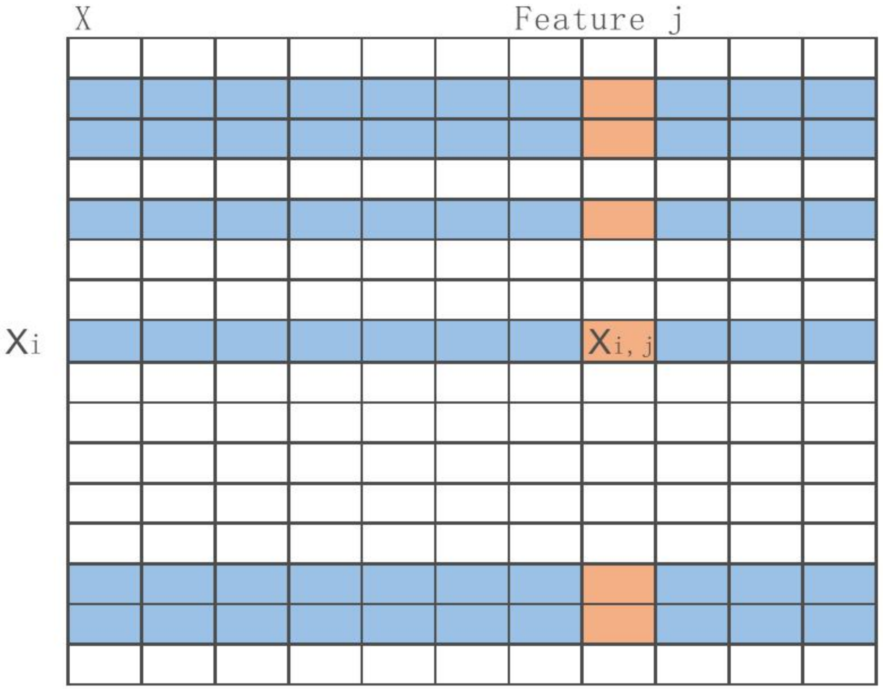
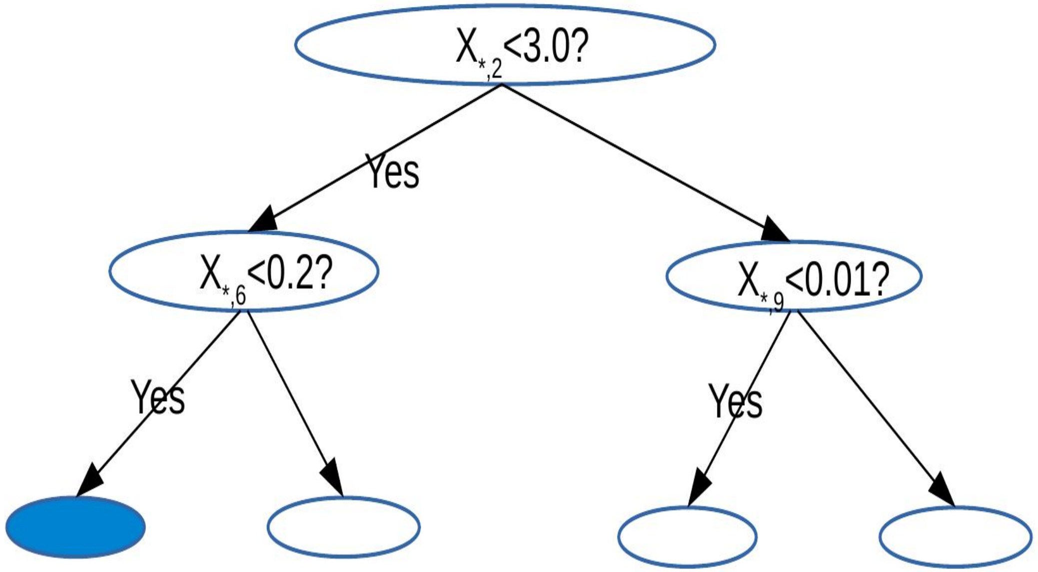
# Outline

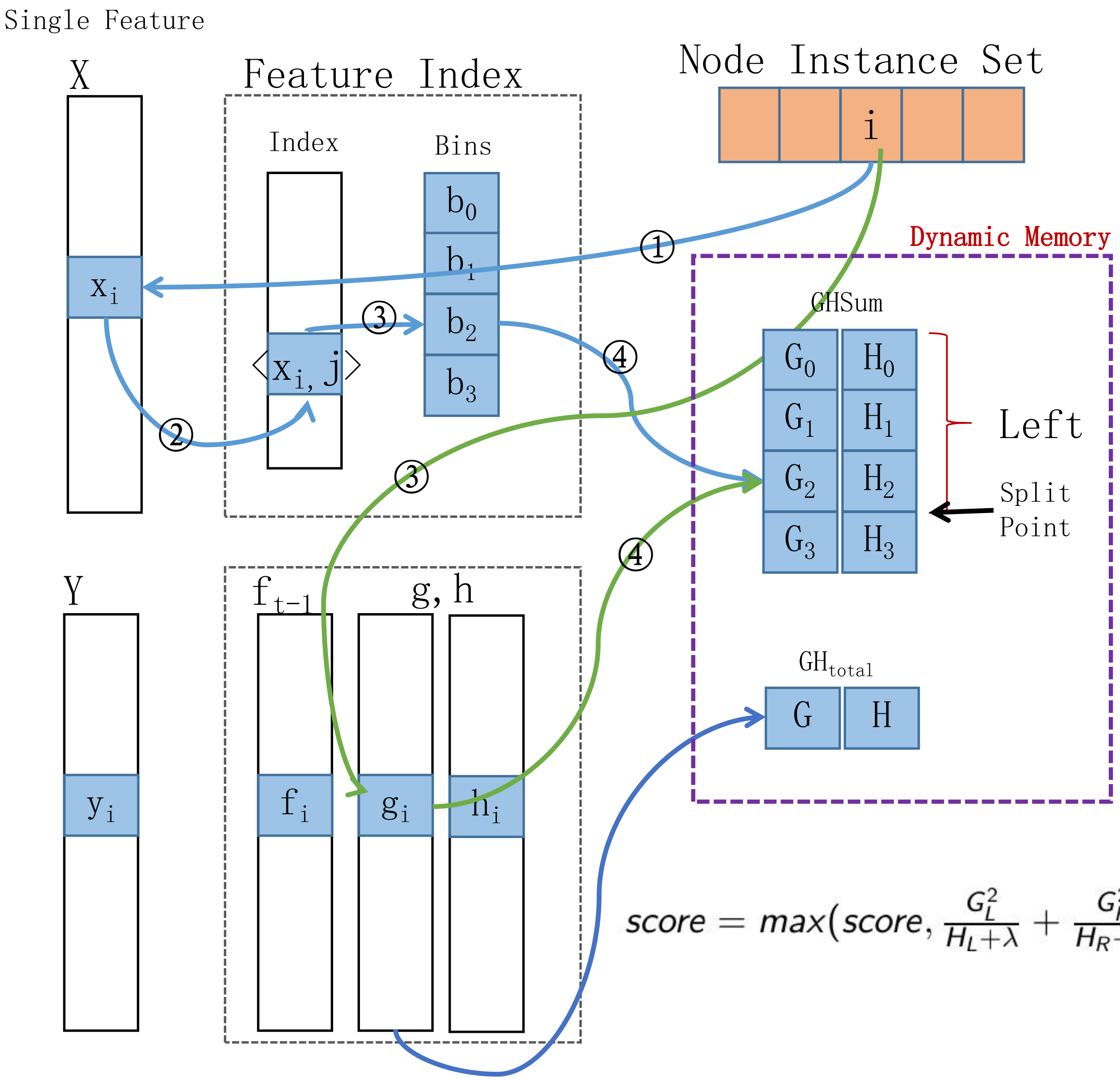
- Problem
- Related work
- Proposal

# Building a Tree



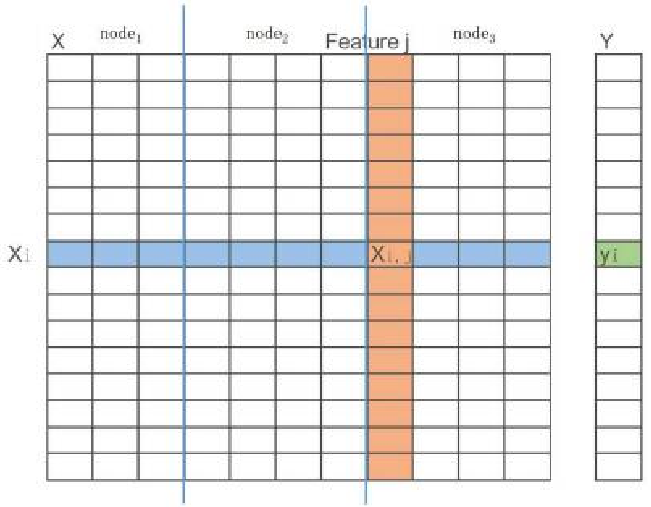

- findBestSplit is the bottleneck
  - For each node, go through all instances in the node and all features
  - parallelism: node level, feature level, inside single feature level




$$score = max(score, \frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda})$$

- findBestSplit is the bottleneck
  - GHSum is the core data structure
    - for each feature
    - bins, fixed split points
    - g,h summation on instances whose value fall into the bin

# Distributed Split


- Partition by rows (samples)
  - need gobal communication to build Bins, once if use global static Bins.
  - need gobal communication to build GHSum for each feature in findBestSplit() → allreduce(GHSum)
- Partition by columns (features)
  - Bins and GHSum are all local, no communication
  - need global communication to select the best feature in findBestSplit() → allreduce(maxscore), also need to broadcast(Split Instance Set)

# Issues

- irregular memory access
  - instances in tree nodes are dynamic sets
  - non-continuous memory access to g,h
  - read/write after write dependency,  GH[bin[id]] += g[id], will stall when cache miss on access g[id]
- spasity
  - missing values
  - frequent zero entries
  - artifacts of feature engineering such as one-hot-encoding
- high dimensionality
  - |features|

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# XGBoost[1]

- Standard baseline
- Algorithm
  - approximate algorithm with both local and global proposal methods (Bins)
  - sparsity-aware, only collect statistics of non-missing entries
- System
  - Column Block
    - each block is a subset of rows
    - in each block, data stored in compressed column(CSC) format, with each column sorted by corresponding feature value
    - support feature level parallelism
    - linear scan to find best split
  - Cache-aware access
    - choose correct block size to get gradient statistics(g,h) fit into the CPU cache. ($2^{16}$)

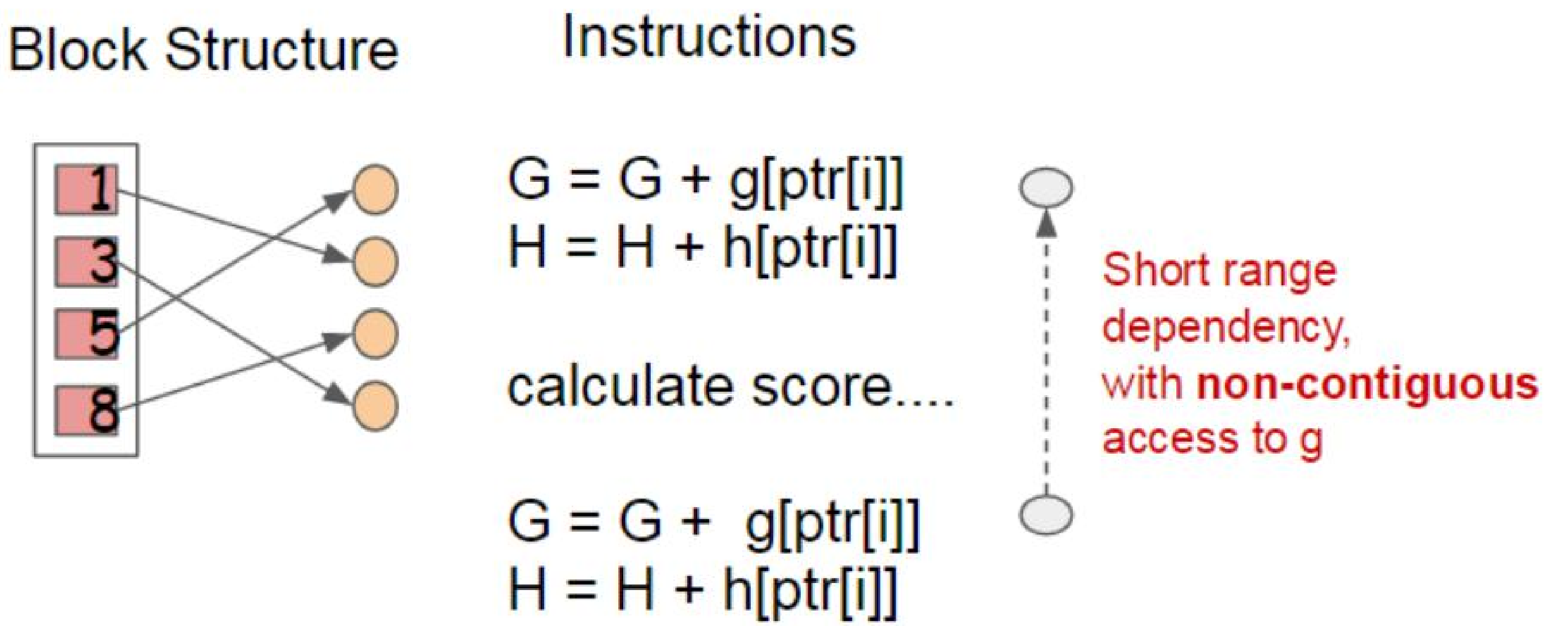


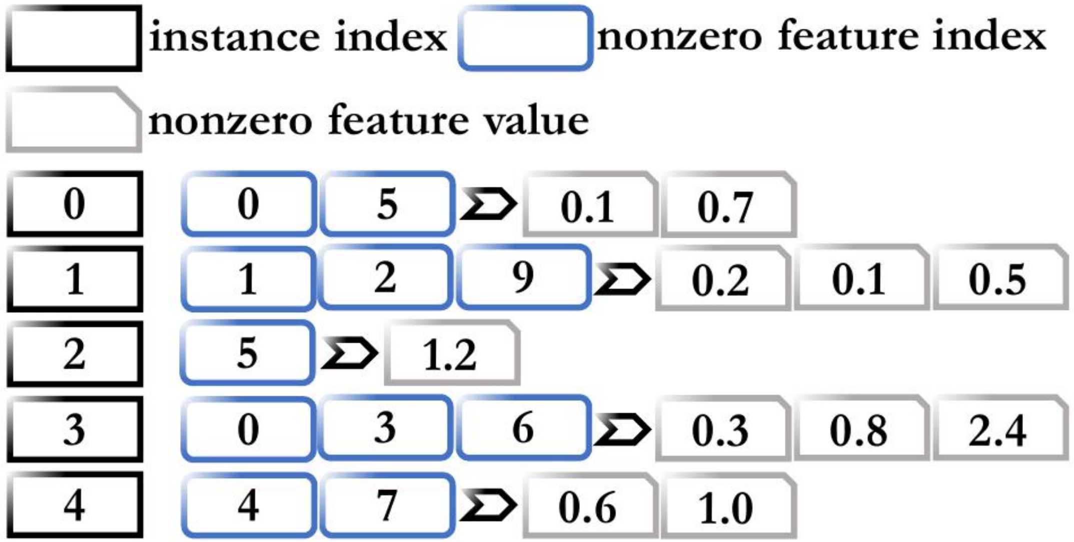

**Figure 8: Short range data dependency pattern that can cause stall due to cache miss.**

# LightGBM[2][3]

- high communication costs ~O(|features|*binSize)
  - PV-Tree (Parallel Voting Decision Tree)
    - local voting: select top-k features based on local data
    - global voting: select top-2k features by votings from local candidates
    - collect full-grained histograms of the globally top-2k, and findBestSplit
- high dimensionality
  - Gradient-based One-side sampling
    - exclude a significant proportion of data instances with small gradients in estimate the score
    - better than SGB(Stochastic GB) with the same sampling ratio
- Sparsity
  - Exclusive feature bundling
    - bundle mutually exclusive features(never nonzero values simultaneously) into a single feaure
    - letting exclusive features reside in different bins (adding offsets to original values)

# DimBoost[4][5]

- high dimensionality (industry application with 330K features)
- Optimize Communication
  - parameter server
    - claims to be one communication step and take less time (?)
  - two-phase-split finding
    - server-side split
  - round-robin task scheduler
    - schedule the splitting tasks among the workers
  - low-precision gradient histogram
    - each item q in a histogram, encode to a d-bit integer $q'=\text{floor}(q/|c|*2^d)$
    - d=8 often enough to obtain no loss on final accuracy
- Optimize Computation
  - parallel batch construction
    - divides a range into batches for the big nodes in the first few layers
  - spare histogram construction
    - only non-zero entries



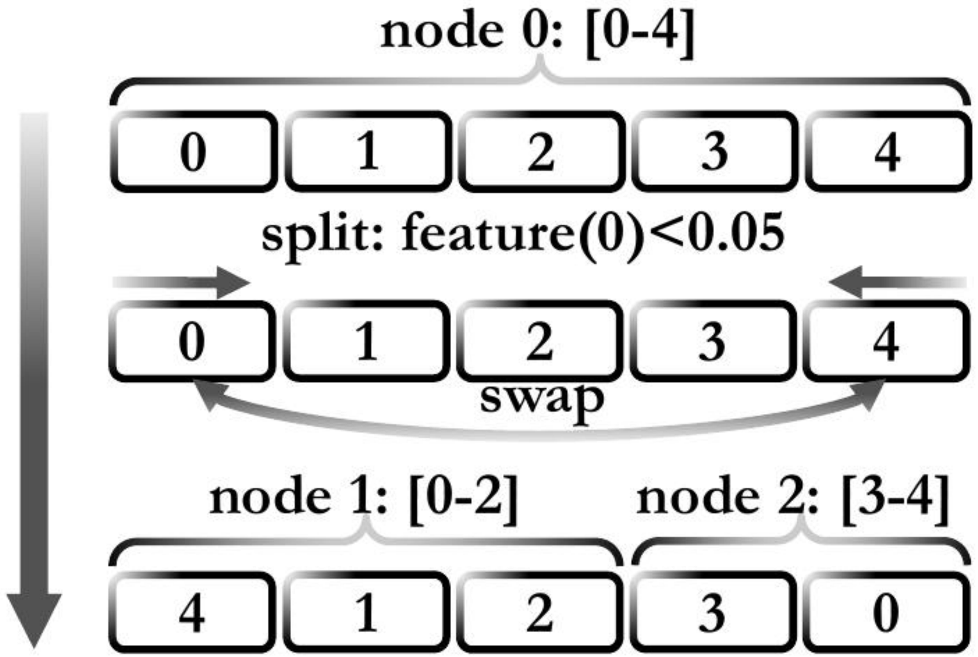




Figure 9: Node-to-instance Index.

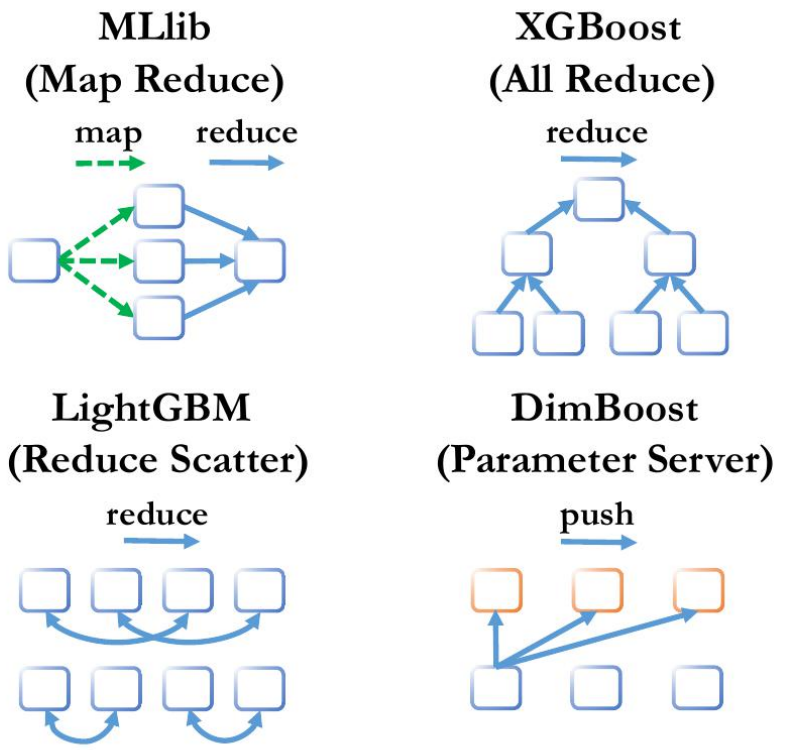



**Figure 3: Existing Model Aggregation Methods.**

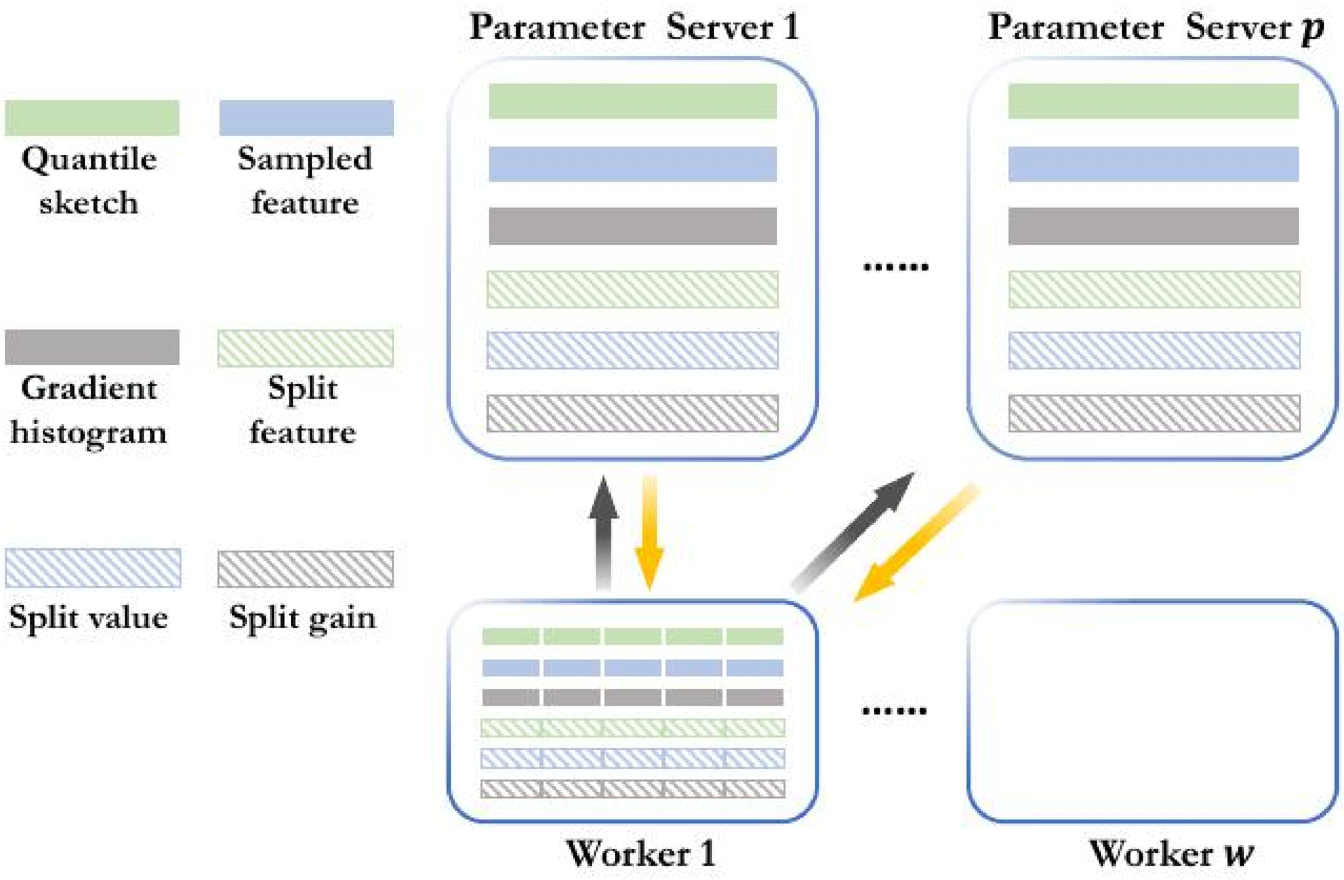



**Figure 6: Parameter layout.**

# GPU-GBDT[6]

- sparse representation
  - similar to Column Block
- fine-grain parallelism
  - parallelizing the score computation of each split point: segmented prefix sum --> GHSum
  - select best split point: semented reduction
  - splitting a node: maintain values of each feature in the new node in sorted order
- Run-length encoding compression
  - sorted by feature values
  - repeated values can be compressed
  - directly splitting RLE elements
- thread/block workload dynamic allocation
  - under a memory constrain

TABLE I
DENSE AND SPARSE DATA REPRESENTATION

| | Dense | Sparse |
|---|---|---|
| $\boldsymbol{x}_1$ | $\langle 0.0, 0.0, 0.1, 0.0 \rangle$ | $(a_3 : 0.1)$ |
| $\boldsymbol{x}_2$ | $\langle 1.2, 0.0, 0.1, 0.6 \rangle$ | $(a_1 : 1.2); (a_3 : 0.1); (a_4 : 0.6)$ |
| $\boldsymbol{x}_3$ | $\langle 0.5, 1.0, 0.0, 0.0 \rangle$ | $(a_1 : 0.5); (a_2 : 1.0)$ |
| $\boldsymbol{x}_4$ | $\langle 1.2, 0.0, 2.0, 0.0 \rangle$ | $(a_1 : 1.2); (a_3 : 2.0)$ |

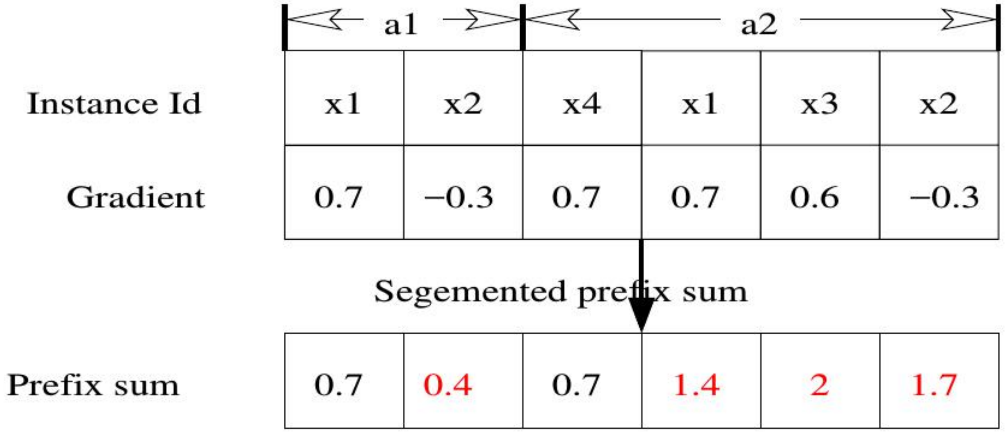


Fig. 1. Example results of segmented prefix sum

$$
\begin{aligned}
a_1 &= (\boldsymbol{x}_2 : 1.2); (\boldsymbol{x}_4 : 1.2); (\boldsymbol{x}_3 : 0.5) \\
a_2 &= (\boldsymbol{x}_3 : 1.0) \\
a_3 &= (\boldsymbol{x}_4 : 2.0); (\boldsymbol{x}_2 : 0.1); (\boldsymbol{x}_1 : 0.1) \\
a_4 &= (\boldsymbol{x}_2 : 0.6)
\end{aligned}
$$

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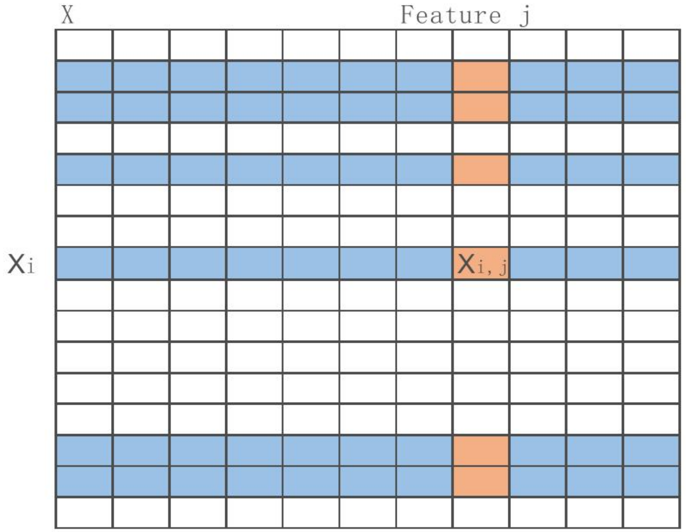
# Assumption

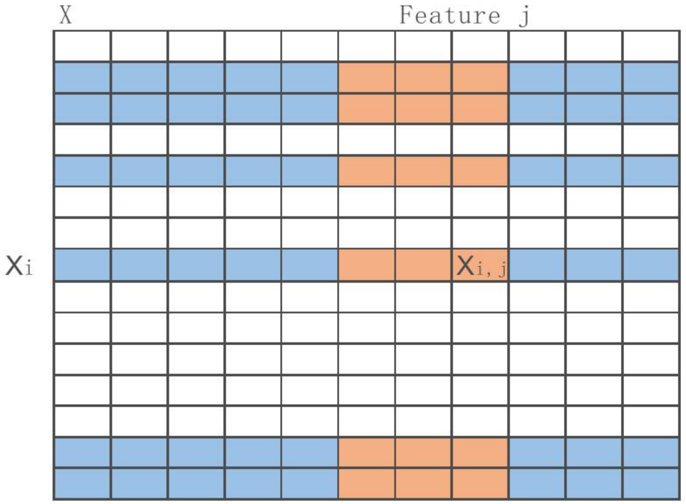
- Assumption:
  - Model: GHSum, (Bins, g, h)
  - Model size << Training Data size
- Training Data N samples, M Features, build tree with L levels
- Model GHSum with bin size B
  - at each node, size: B*M
  - at each level,size: $2^{L-1}$*B*M
- Most cases
  - M <1K, L<8, B~[20,100]
  - high dimension can be an issue
  - deep tree can be an issue (GBT prefers shallow trees)

# Assumption

- example:
  - Higgs: N = 10m, M = 28
    - L = 6, B = 128; model size at level L, 32*128*28 << 10m
  - KDD10: N=19M, M=29M
    - feature enginering: expand a categorical feature into a set of binary features, combination*

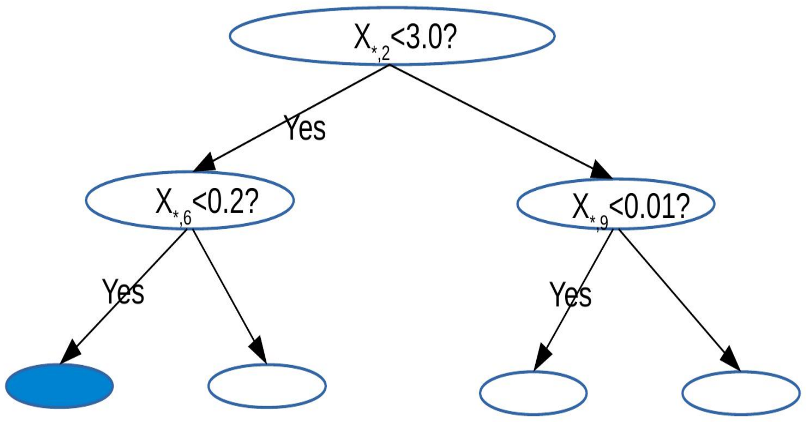
# Cache Friendly Data Orgnization



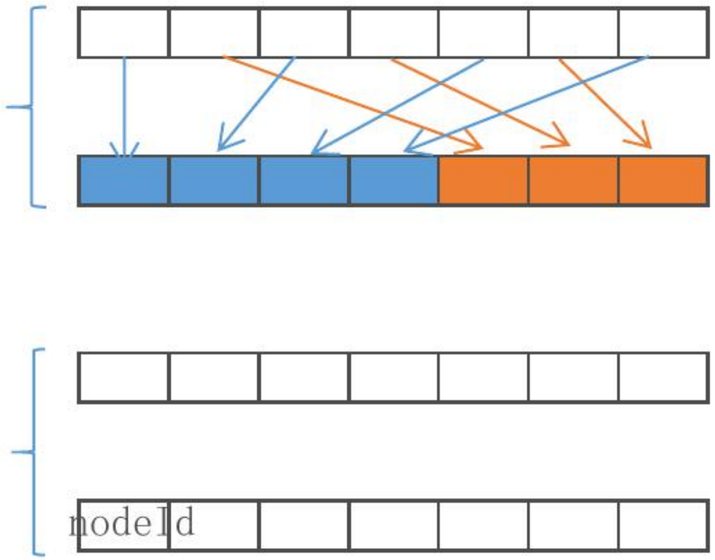

- Issue: non-continuous memory access in feature level parallelism
  - prefer column-wised data orgnization
  - dynamic instance set
  - N is large, (g,h) can not even fit into LLC cache
- Ideas
  - multi-columns to fit one cache line
  - clolumn block to get a small range of (g,h) access cache friendly

# Training data access



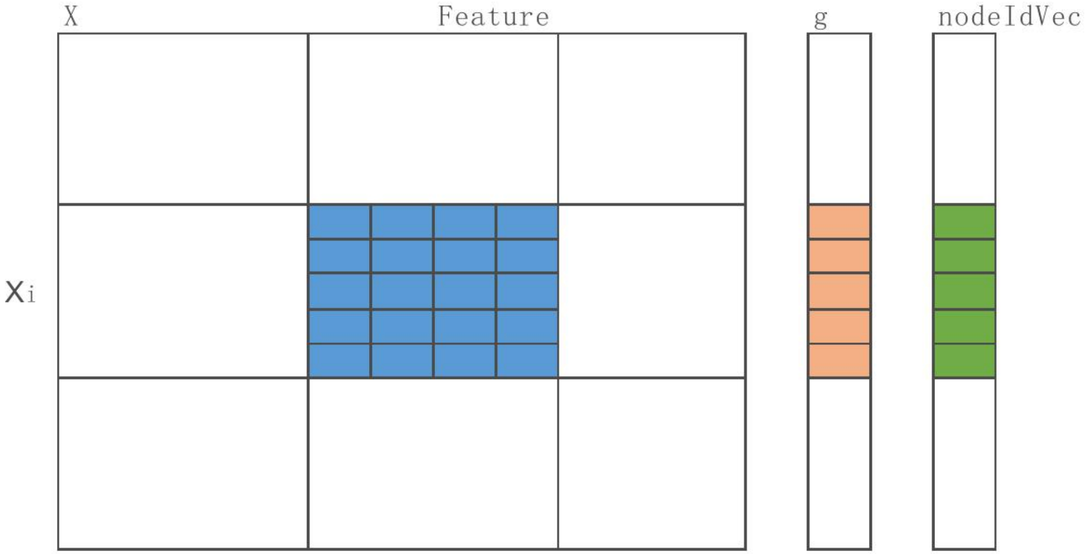

- Issue: redundent access to training data in node level parallelism
  - prefer row-wised data orgnization, however, it conflicts with feaure level parallelism
- Ideas
  - Keep column-wised orgnization
  - Keep all GHSum of the same level in cache
  - Single pass on train data for each level. (half when reuse $\text{GHSum}_{\_\text{parent}}$)

# Sequential Scan on the Instance Set




- Issue:Dynamic instance set
  - move instance id around after node split
- Ideas
  - encode <nodeid, level> into a uniq nodeID, (easy for binary tree)
  - a nodeID vector to maintain the current leaf level instance sets directly
  - sequential access to this vector

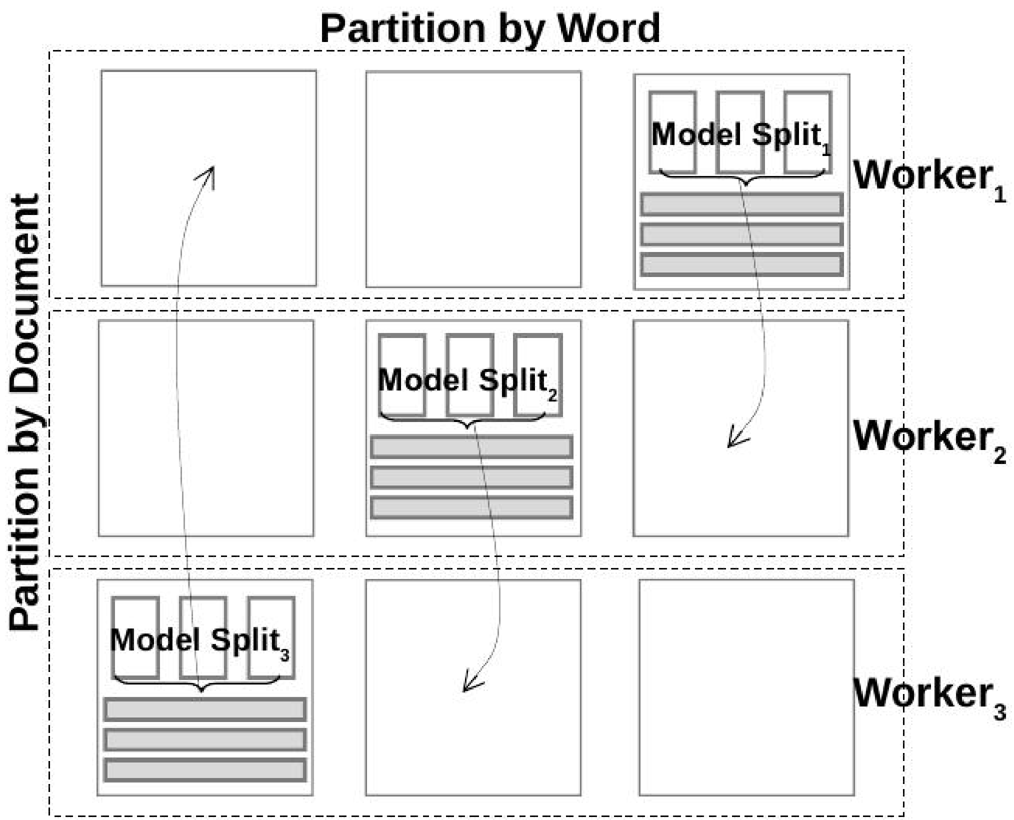
# Block-based Data Orgnization and Parallelsim




```
for j in column_block:
  for each x_{i,j} in the column X_{,j}:
    nodeid = nodeIDVec[i]
    bindid = Bins[j][x_{i,j}]
    GHSum[nodeid][j][binid] += g[i]
```

- Column Block
  - the basic unit for parallelism
  - column-wised data orgnization
  - dense/sparse support
  - sorted by feature values
- Set the block number/size to
  - fit all active <g,h>,nodeIDVec blocks in LLC
  - fit all active GHSum blocks in L2
  - loop order can be optimized

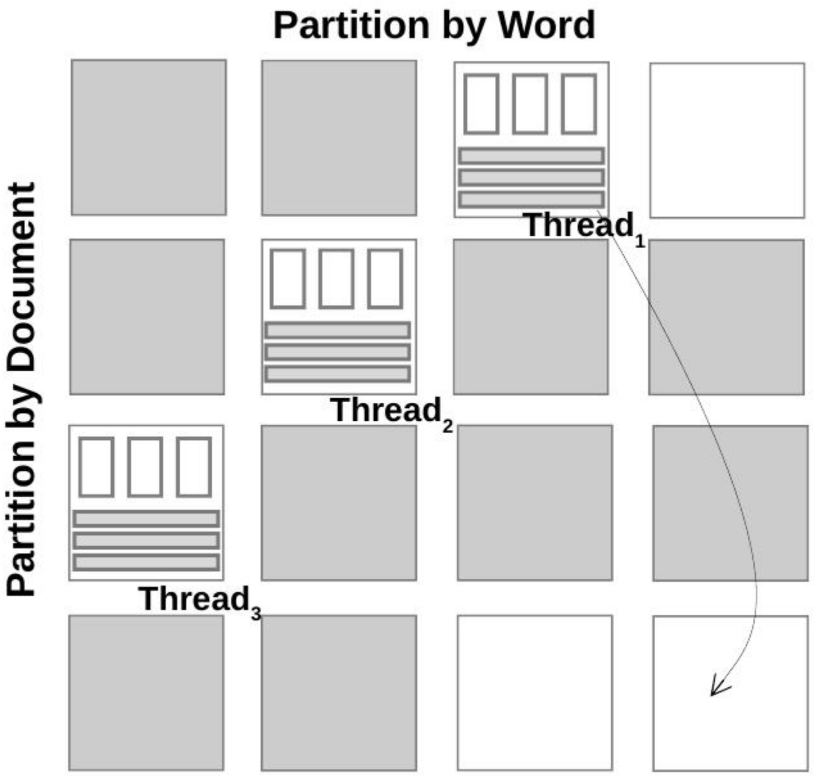
# Data and Model Parallelism by Model Rotation




(a) model rotation

- Proposal
  - use computation model : model rotation
- Data partitioned to blocks
  - Data Parallelsim:
  - Model parallelism: GHSum split by feature columns
- Scheduler to avoid update conflicts

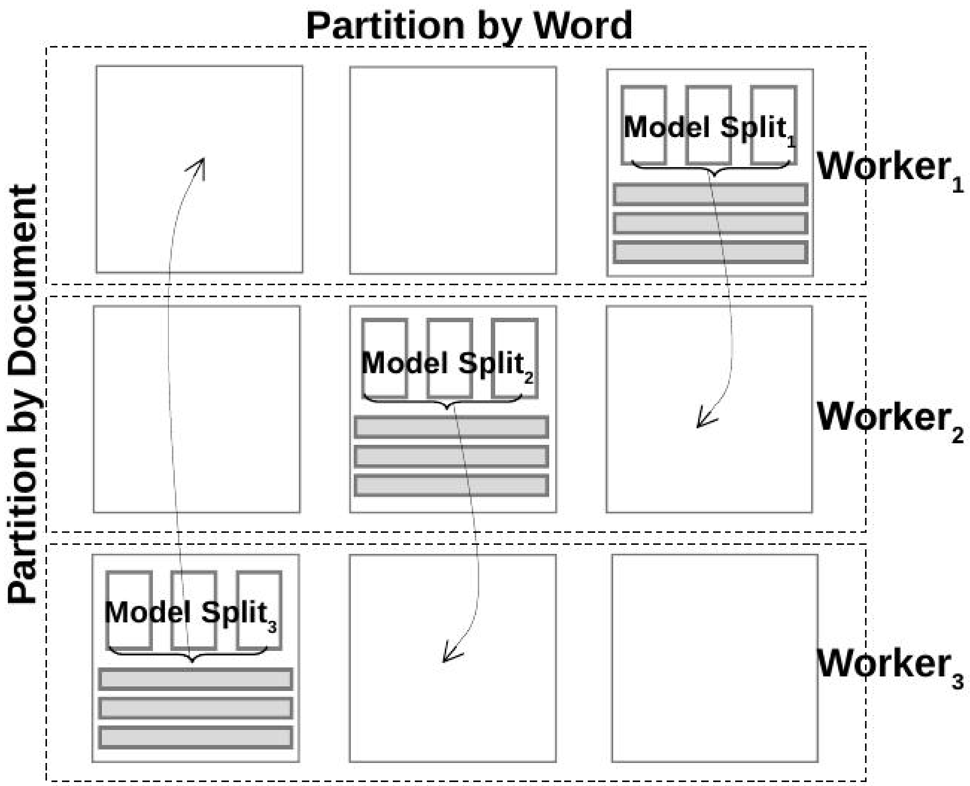
# Block Dynamic Scheduling in Shared Memory systems




(b) dynamic scheduling

- a low cost solution to remove synchronization overhead
- number of partitions is larger than the number of threads,
- always ‘free’ rows and columns avaliable when one thread finishes its current task.
- cache-aware block size
- sparse representation ready

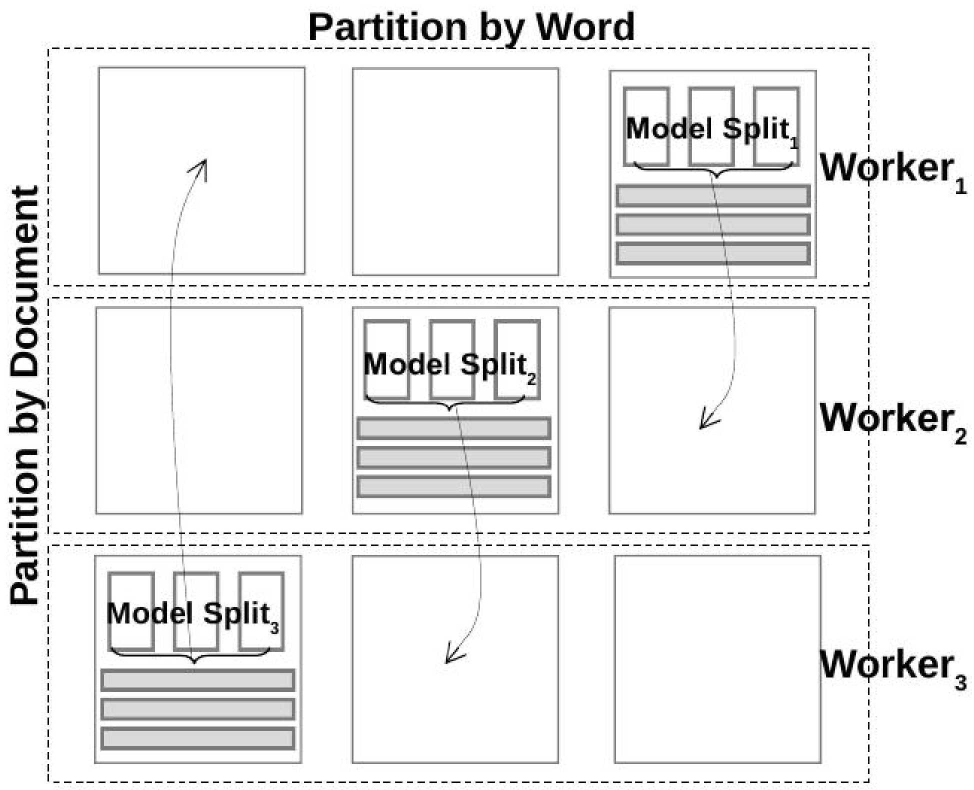
# Distributed Model Rotation




(a) model rotation

- Training data randomly partitioned among nodes
- Model partitioned among nodes
  - split by feature columns
- Scheduler to avoid update conflicts
  - rotate local model partition to neighbor at each sub-step
  - finish after K sub-steps(K nodes)
  - kind of a ring-allreduce

# Pipelining and Timer Control in Distributed Systems




(a) model rotation

- Each sampler only works for the same period of time and then the samplers do synchronization all together.
- They all use a timer to control the synchronization point rather than waiting until all the blocks to finish.
- This adjustment does not change the property of the uniform random selection of blocks.

# More to consider

- Feature Bundle
  - deal with category features
- Feature Sampling
  - design scheduler with Gradient-based priority
- Data Compression
  - model compression: low-precision compression
  - traning data compression: RLE

# References


- [1]T. Chen and C. Guestrin, “Xgboost: A scalable tree boosting system,” in Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, 2016, pp. 785–794.
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- [6]Z. Wen, B. He, R. Kotagiri, S. Lu, and J. Shi, “Efficient Gradient Boosted Decision Tree Training on GPUs,” in 2018 IEEE International Parallel and Distributed Processing Symposium (IPDPS), 2018, pp. 234–243.