# LightGBM算法研究

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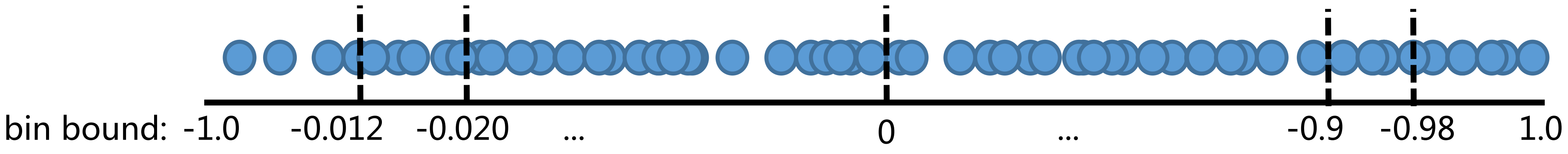
# 大纲

- 算法创新
  - bin & histogram
  - leaf-wise split
  - 分布式训练方法(communication efficient parallel voting)
  - DART(Dropout + GBDT)
  - GOSS(Gradient-based One-Side Sampling)
- 优点
- 缺点

# Bin & Histogram

- xgboost等传统实现: pre-sort + 精确查找/分位点近似查找
  - 找分裂点时速度慢
  - 精确
- LightGBM: bin & histogram近似查找
  - 找分裂点时速度贼快
  - 不那么精确
  - 实际效果不差

# Bin Mapper的构造



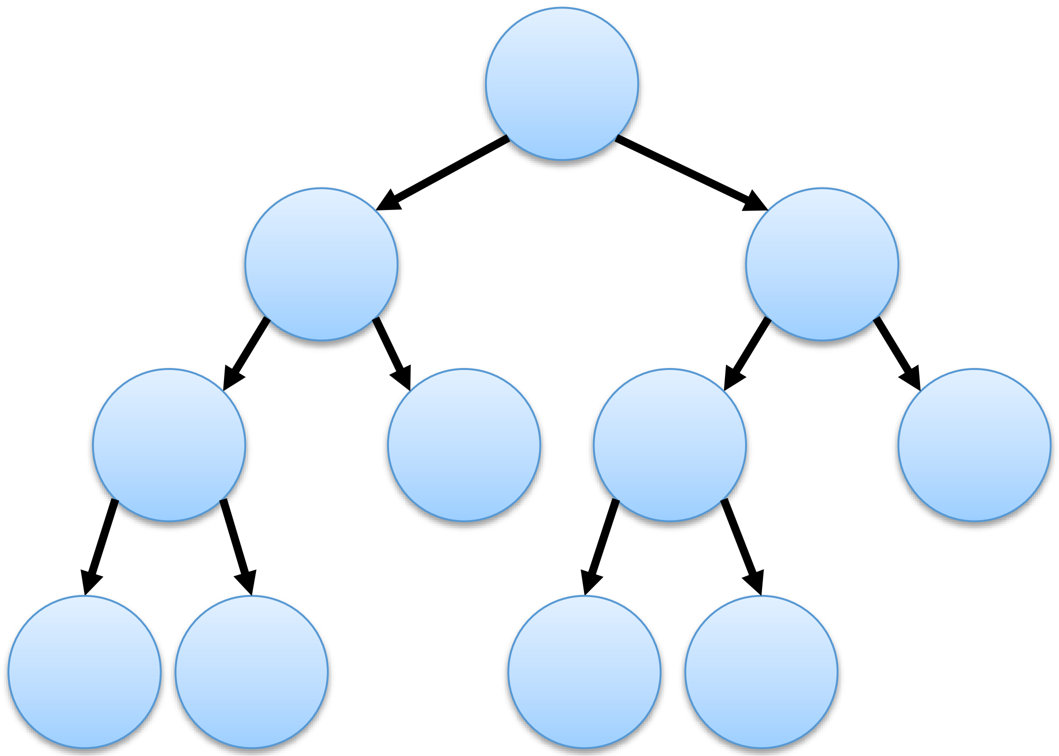

- 代码: DatasetLoader::ConstructBinMappersFromTextData

# Bin Mapper的使用

- 读取instance时, feature value被映射为bin index
- 内存中保存bin mapper和bin中的所有instance index
- 所有的bin bound(除了最小和最大)将作为split candidate

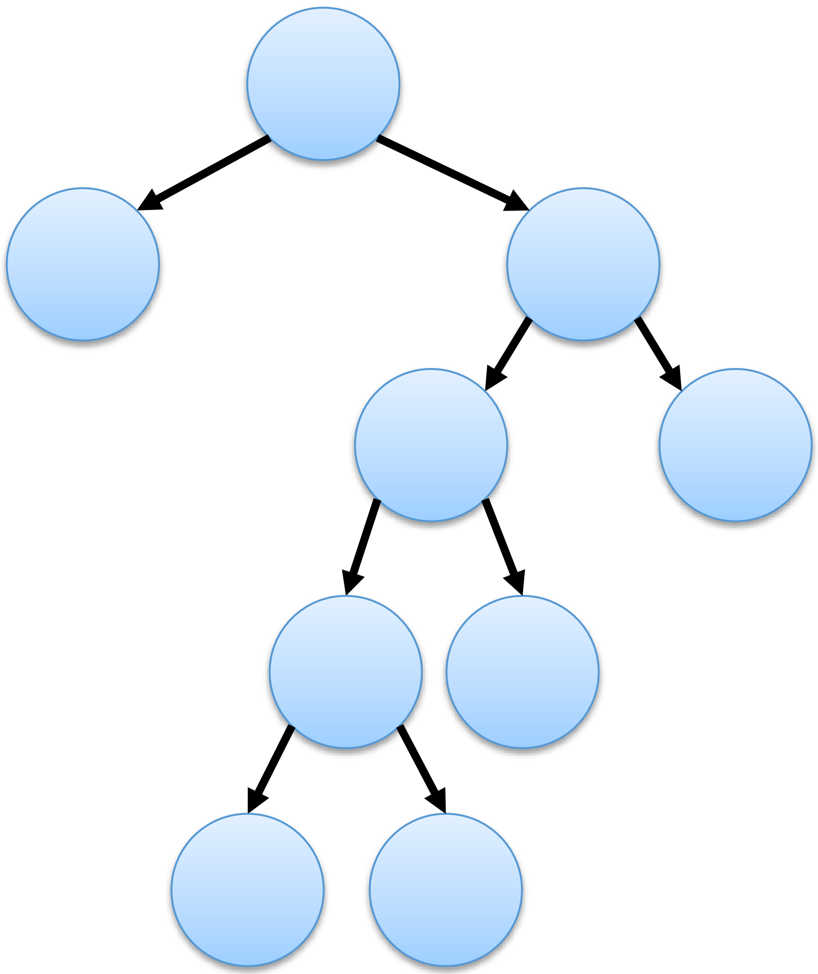
- 给听众的问题:
- 1. 如果某些特征值不在bin mappers的范围内如何处理?
- 2. 分布式情况下, 各个机器如何构造全局一致的bin mappers?

# 传统的Layer-wise Split



一层一层往下推进

# LightGBM的Leaf-wise Split



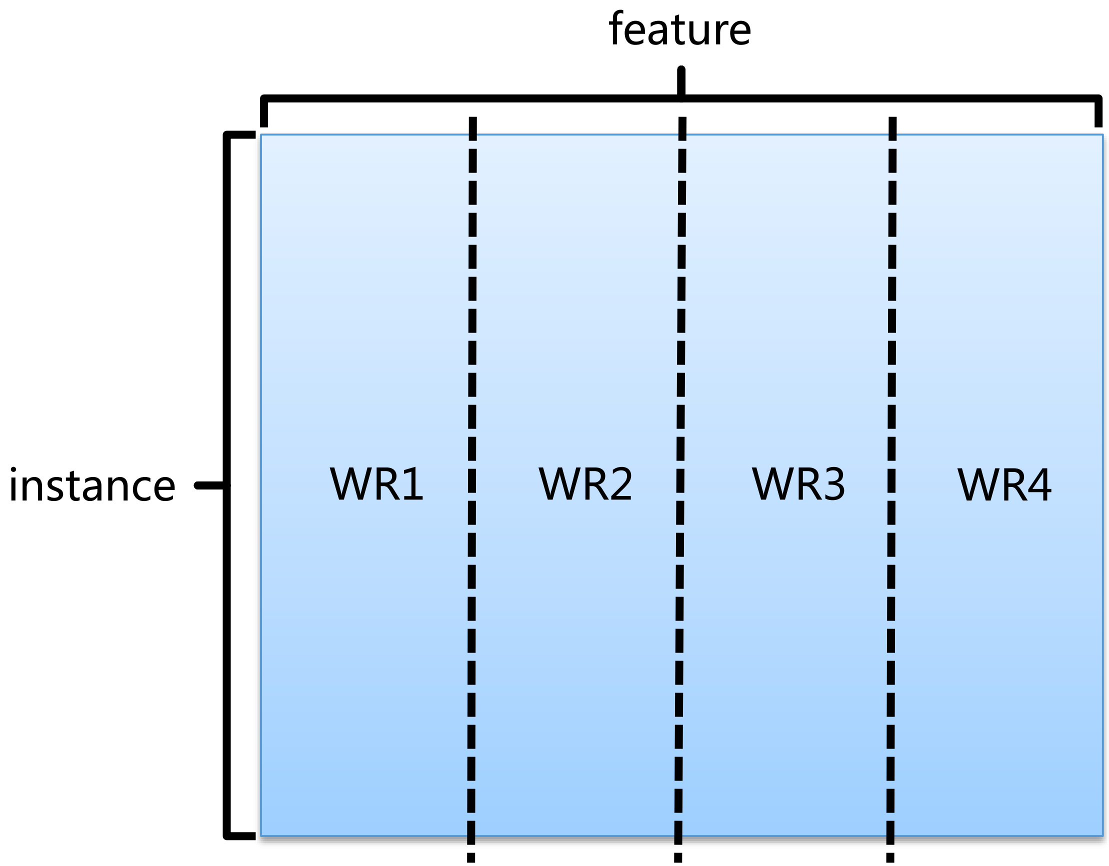
- 代码:
  - GBDT::TrainOneIter
  - SerialTreeLearner::Train
- 给听众的问题:
  - 每次分裂都要计算所有叶子节点的增益吗?

完全以增益为导向分裂
有更好的效果

# 分布式训练方法

- 传统的Attribute(Feature) Parallel
  - 通信量高
  - 精确
- LightGBM的Parallel Voting
  - 大部分计算在单个节点内, 通信量低
  - 不那么精确
  - 实际效果不差

# 传统的Feature Parallel




- 分布式分裂一个叶子节点的流程
  - WR并行找到local BSP(best split plan)
  - CD聚合并找到global BSP
  - 找到global BSP的worker进行instance切分, 将切分后的instance indices广播给所有WR

# LightGBM的Parallel Voting

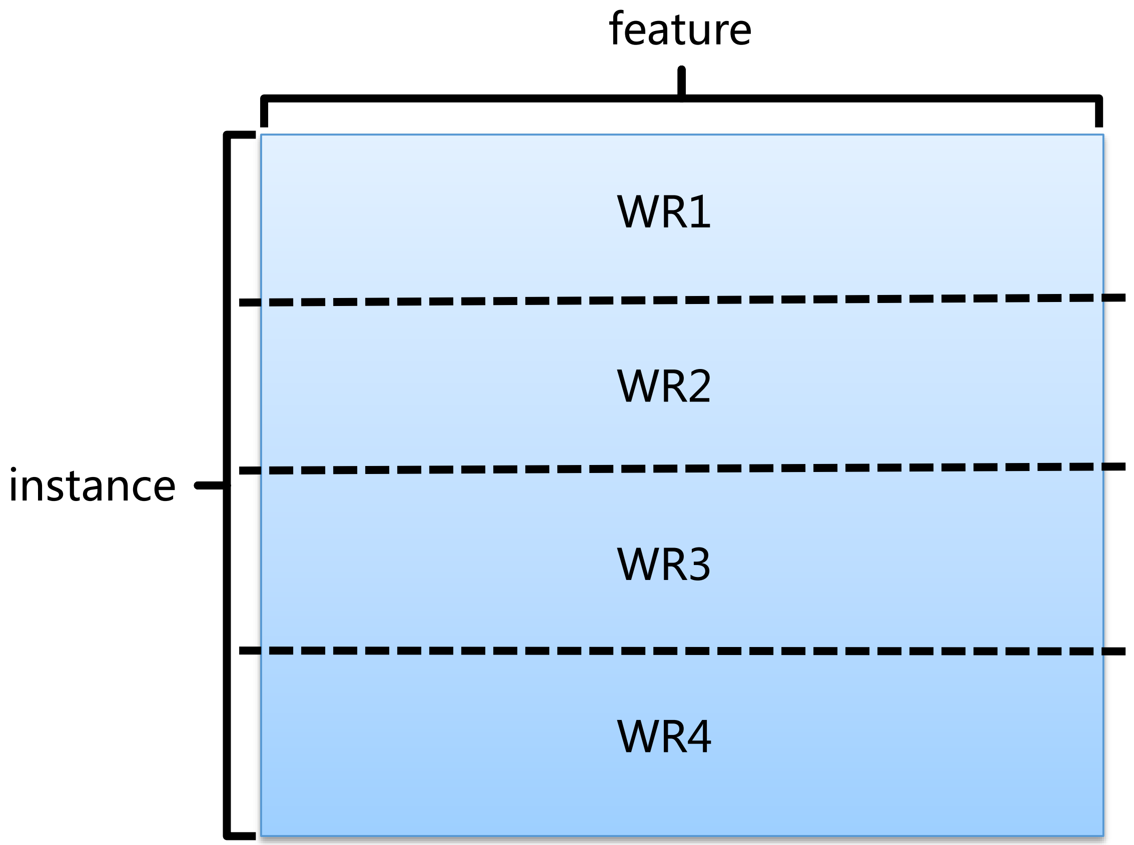
**Algorithm 2** FindBestSplit

```
Input: DataSet D
for all X in D.Attribute do
    ▷ Construct Histogram
    H = new Histogram()
    for all x in X do
        H.binAt(x.bin).Put(x.label)
    end for
    ▷ Find Best Split
    leftSum = new HistogramSum()
    for all bin in H do
        leftSum = leftSum + H.binAt(bin)
        rightSum = H.AllSum - leftSum
        split.gain = CalSplitGain(leftSum, rightSum)
        bestSplit = ChoiceBetterOne(split,bestSplit)
    end for
end for
return bestSplit
```

**Algorithm 3** PV-Tree_FindBestSplit

```
Input: Dataset D
localHistograms = ConstructHistograms(D)
▷ Local Voting
splits = []
for all H in localHistograms do
    splits.Push(H.FindBestSplit())
end for
localTop = splits.TopKByGain(K)
▷ Gather all candidates
allCandidates = AllGather(localTop)
▷ Global Voting
globalTop = allCandidates.TopKByMajority(2*K)
▷ Merge global histograms
globalHistograms = Gather(globalTop, localHistograms)
bestSplit = globalHistograms.FindBestSplit()
return bestSplit
```

# LightGBM的Parallel Voting




- 分布式分裂一个叶子节点的流程
  - WR并行找到k个local BSP
  - CD聚合保留top 2k个BSP
  - CD向所有WR收集这top 2k个BSP的histogram data
  - CD计算这top 2k个BSP的global 增益, 找到global BSP
  - CD将global BSP广播给所有WR
  - WR基于bin mapper做本地数据切分

# Histogram Data与Global增益

$$Gain = 2\mathcal{L}(\mathbf{b}^*, \mathbf{R}) - 2\mathcal{L}(\mathbf{b}^{*'}, \mathbf{R}')$$

$$= \frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} - \gamma$$

- 对于一个BSP, histogram data除了包含一些元信息外, 就是上面$G_L$, $G_R$, $H_L$, $H_R$.
- CD将收集到所有histogram data后, 可计算出global增益
- 核心代码: VotingParallelTreeLearner类

# DART

**Algorithm 1** The DART algorithm

Let N be the total number of trees to be added to the ensemble

$S_1 \leftarrow \{x, -L'_x(0)\}$

$T_1$ be a tree trained on the dataset $S_1$

$M \leftarrow \{T_1\}$

**for** $t = 2, \ldots, N$ **do**

随机丢掉一些树

$\quad D \leftarrow$ the subset of $M$ such that $T \in M$ is in $D$ with probability $p_{drop}$

$\quad$ **if** $D = \emptyset$ **then** $D \leftarrow$ a random element from $M$

$\quad$ **end if**

$\quad \hat{M} \leftarrow M \setminus D$

$\quad S_t \leftarrow \left\{x, -L'_x\left(\hat{M}(x)\right)\right\}$

$\quad T_t$ be a tree trained on the dataset $S_t$

$\quad M \leftarrow M \cup \left\{\frac{T_t}{|D|+1}\right\}$

$\quad$ **for** $T \in D$ **do**

修正丢弃掉树的预测值

$\quad\quad$ Multiply $T$ in $M$ by a factor of $\frac{|D|}{|D|+1}$

$\quad$ **end for**

**end for**

Output $M$

# DART效果

测试集square loss

| Ensemble size | 25 | 50 | 100 | 250 | 500 | 1000 |
|---|---|---|---|---|---|---|
| MART | 35.13 | 31.79 | 30.92 | 30.07 | 29.76 | 29.28 |
| DART | **32.50** | **30.50** | **29.66** | **28.14** | **28.11** | **27.98** |
| Random Forest | 32.76 | 33.21 | 32.88 | 32.36 | 32.66 | 32.33 |

测试集AUC

| Ensemble size | 50 | 100 | 250 | 500 | 1000 |
|---|---|---|---|---|---|
| MART | **0.9687** | **0.9699** | 0.9707 | **0.9704** | 0.9695 |
| DART | 0.9676 | 0.9692 | **0.9714*** | 0.9693 | **0.9699** |
| Random Forest | 0.9627 | 0.9629 | 0.9629 | 0.9630 | 0.9628 |

代码: DART::TrainOneIter

# GOSS

- Gradient-based One-Side Sampling
  - ➢一种新的Bagging(row subsample)方法
  - ➢前若干轮(1.0f / gbdt_config_->learning_rate)不Bagging
  - ➢之后Bagging时, 采样一定比例g(梯度)大的样本
- 直观解释: g越大, 降低loss的能力越大
- 代码: GOSS::Bagging

# 优点

- 目前最先进的GBDT工具包
- 支持分布式
- 速度快
- 效果好
- 省内存
- openmp和MPI使用的淋漓尽致

# 缺点

- 分布式没有fault tolerance
- typo非常非常非常多
- c++写的很junior
  - 作者很多best practice都不会
- 代码构架差
  - 部分代码结构混乱, 函数有些长, 看起来费劲

# 参考文献


- https://github.com/Microsoft/LightGBM
- Qi Meng, et al., A Communication-Efficient Parallel Algorithm for Decision Tree, NIPS, 2016.
- K. V. Rashmi, et al., DART: Dropouts meet Multiple Additive Regression Trees, arXiv, 2015.

# 谢谢聆听