

# Embrace sparsity at web scale: Apache Spark\* MLlib algorithms optimization for sparse data

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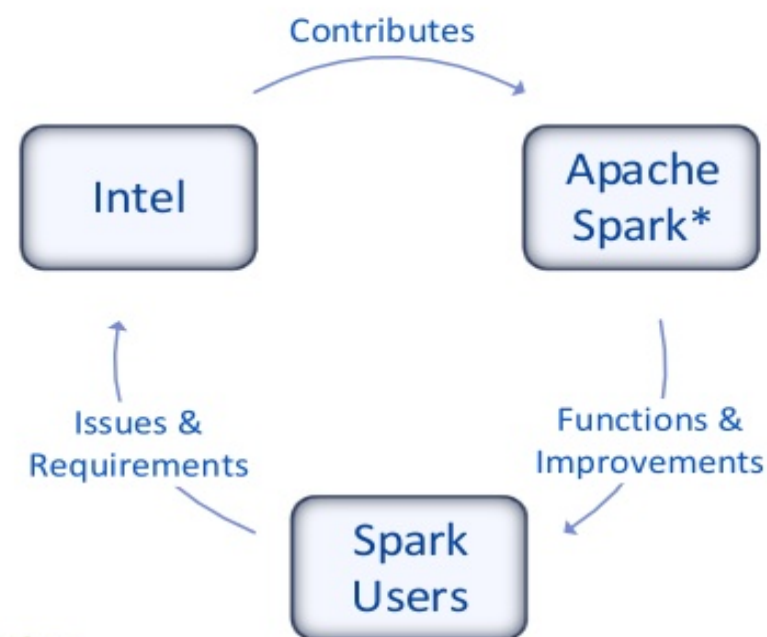
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**SPARK SUMMIT 2016**  
DATA SCIENCE AND ENGINEERING AT SCALE  
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# Intel & Big Data

- Contribution to big data community
  - Consistently and actively
  - Enthusiastic engineering team
  - <https://software.intel.com/en-us/bigdata>
- Wide cooperation and partnership
  - Consultations and co-development
  - Send to open source projects.



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# Sparse data is almost everywhere

- Data Source:
  - Movie ratings
  - Purchase history
- Feature engineering:
  - NLP: CountVectorizer, HashingTF
  - Categorical: OneHotEncoder
  - Image, video



# Sparse data support in MLlib

```
new DenseVector(  
  values = Array(1.0, 0.0, 0.0, 100.0))
```

```
new SparseVector(  
  size = 4,  
  indices = Array(0, 3),  
  values = Array(1.0, 100.0))
```



## First Tip: Anther option

- Hash Vector: a sparse vector backed by a hash array.
  - Mutable Sparse Vector
  - $O(1)$  random access
  - $O(\text{nnz})$  axpy, dot
- Available in Breeze and our package



## Sparse data support in MLlib

- Supporting Sparse data since v1.0
  - Load / Save, Sparse Vector, LIBSVM
  - Supporting sparse vector is one of the primary review focus.
  - Xiangrui's talk in Spark Summit 2014: Sparse data support in MLlib
  - [https://spark-summit.org/2014/wp-content/uploads/2014/07/sparse\\_data\\_support\\_in\\_mllib1.pdf](https://spark-summit.org/2014/wp-content/uploads/2014/07/sparse_data_support_in_mllib1.pdf)



## Gaps with some industry scenarios

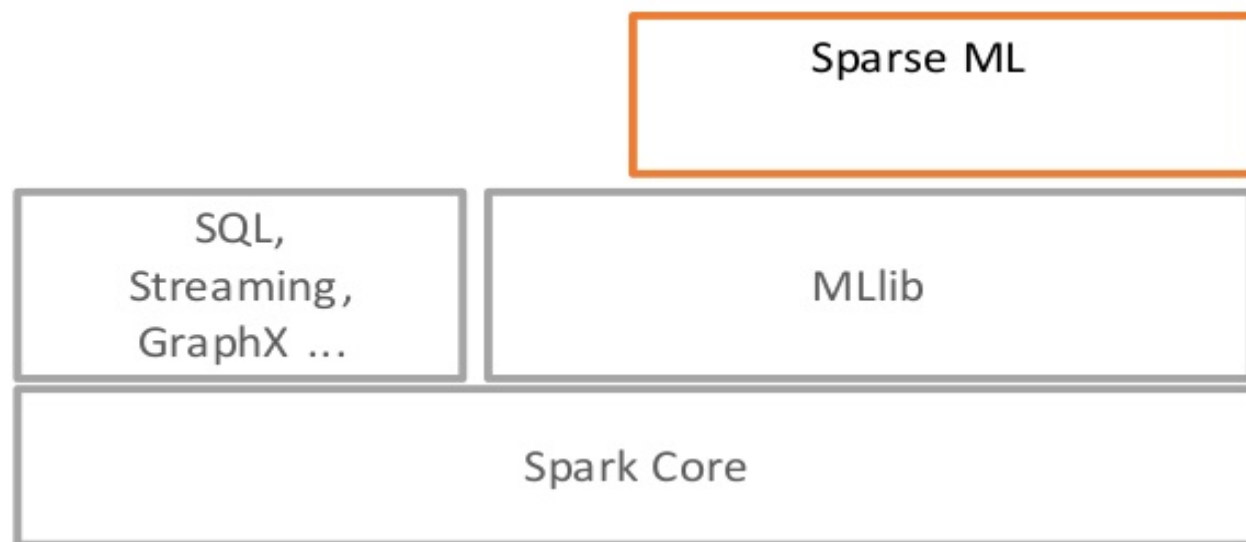
- Hi, I need
  - LR with 1 billion dimension
  - clustering with 10M dimension
  - Large scale documents classification/clustering
  - My data is quite sparse
- Yet with MLlib
  - OOM...
  - Can you help?





# Sparse ML for Apache Spark\*

- A Spark package containing algorithm optimization to support the sparse data at large scope





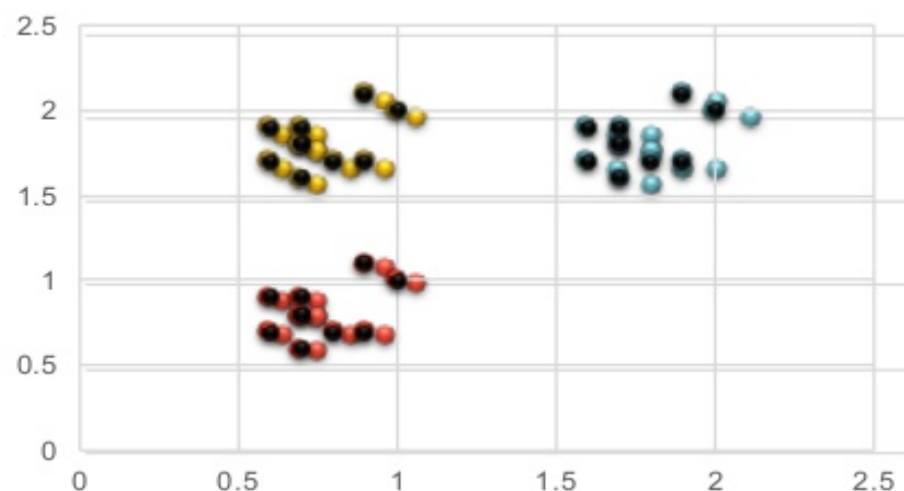
# Sparse ML for Apache Spark\*

- KMeans
- Linear methods (logistic regression, linear SVM, etc)
- HashVector
- MaxAbsScaler
- NaiveBayes
- Neural Network (WIP)



# KMeans

- Pick initial cluster centers
  - Random
  - KMeans++
- Iterative training
  - Points clustering, find nearest center for each point
  - Re-compute center in each cluster (avg.)
- Cluster centers are vectors with the same dimension of data



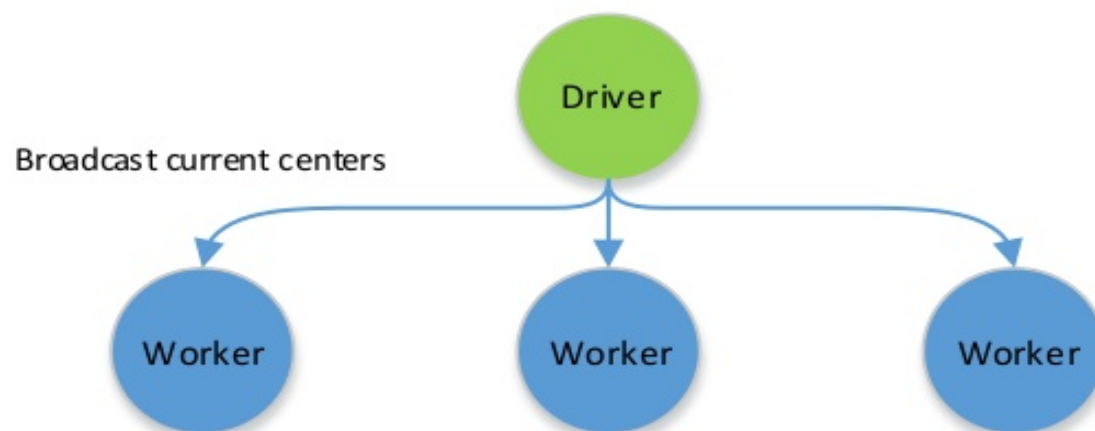
## KMeans scenario: e-commerce

- Cluster customers into 200 clusters according to purchase history:
  - 20M customers
  - 10M different products (feature dimension)
  - 200 clusters
  - Avg. sparsity  $1e-6$



# MLlib iteration

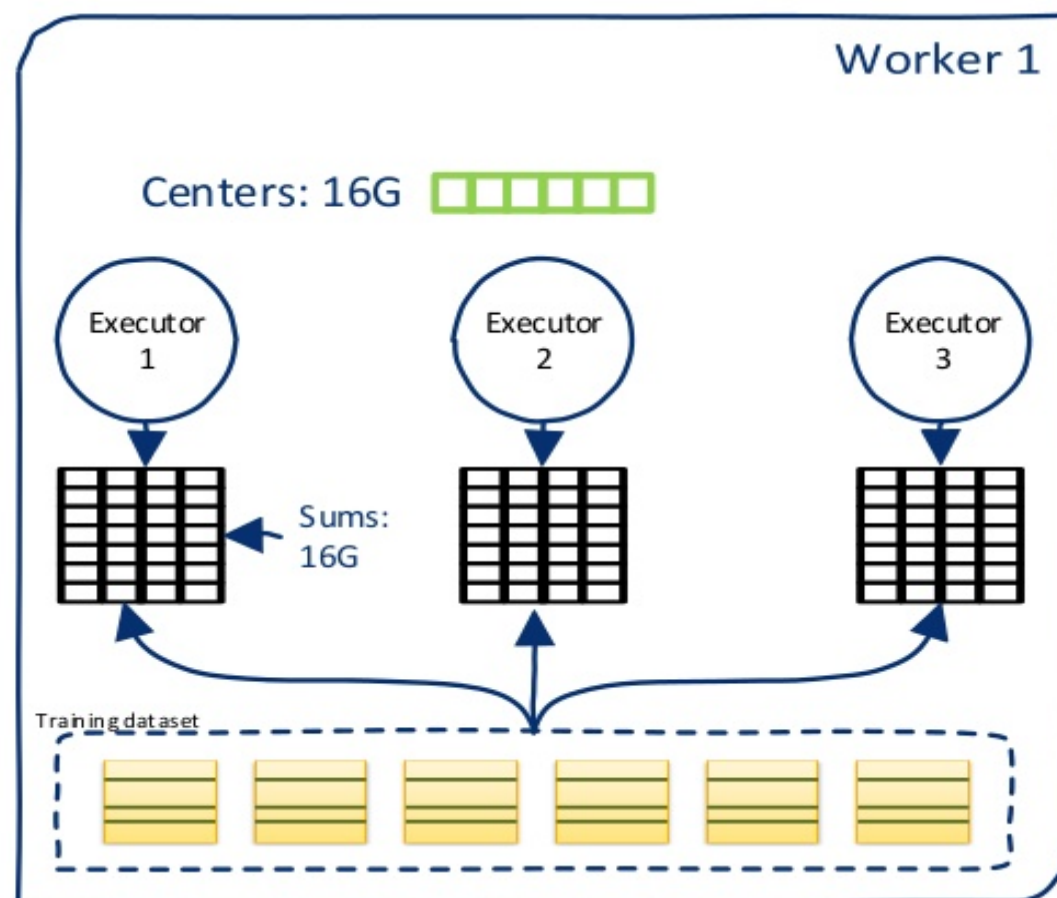
1. Broadcast current centers (**all dense vectors,  $200 * 10M * 8 = 16G$** ), to all the workers



# MLlib iteration

2. Compute a sum table for each partition of data

```
val sum = new Array[Vector](k)
for (each point in the partition) {
  val bestCenter = traverse()
  sum(bestCenter) += point
}
```



## Analysis: Data

- Are the cluster centers dense?
- Let's assume all the records have no overlapping features:
  - $20\text{M records} / 200 \text{ clusters} = 0.1\text{M records per cluster}$
  - $0.1\text{M} * 10 = 1\text{M non-zero in their sum/center}$
  - $1\text{M} / 10\text{M} = 0.1 \text{ center sparsity at most}$



# Analysis: operations



- Core linear algebra operation:

Operations		Sparse friendly
axpy	$Y += A * X$	No if Y is sparse, yet $X + Y$ is sparse-friendly
dot	$X \text{ dot } Y$	Yes
Sqdist	Square distance	Yes, sparse faster





# SparseKMeans

- Represent clustering centers with SparseVector
  - Reduce memory and time consumption



# Cluster centers

- What a center goes through in each iteration
  - Broadcast
  - Compute distance with all the points (sqdist , dot)
  - Discard (New centers are generated)
- Cluster centers can always use SparseVector
  - Without extra cost during computation



## Advanced: Sum table

- Use SparseVectors to hold the sum for each cluster
  - Reduce max memory requirement;
- Isn't it slower to compute with Sparse vectors?
  - SparseVector can not support axpy, but it supports  $x + y$
  - Modern JVM handles small objects efficiently
  - Automatically converts to DenseVector (sparseThreshold)



# Scalable KMeans

- What if you cluster centers are dense
  - Reduce max memory consumption
  - Break the constraint imposed by centers and sums
- Can we make the centers distributed?
  - `Array[Center] => RDD[Center]`
  - Each point vs. each cluster center.
  - That sounds like a join



# Scalable KMeans

```
val pointWithCenter = data.cartesian(centers).map { case (point, center) =>
  (point, (center, ScalableKMeans.fastSquaredDistance(point, center)))
}.reduceByKey { case((c1, d1), (c2, d2)) =>
  if(d1 < d2) (c1, d1) else (c2, d2)
}
```

```
val sumByCenter = pointWithCenter.map { case (point, (center, dist)) =>
  (center, (point.vector, 1L))
}.reduceByKey(mergeContribs)
```



# Scalable KMeans

- Scalable
  - No broadcast, no sum table
  - 200G  $\rightarrow$  20G \* 10
  - Remove memory constraint on single node
- Not only for Sparse data



# KMeans

- Sparse KMeans:
  - Cluster centers can be sparse:
- Scalable KMeans
  - Cluster centers can be distributed



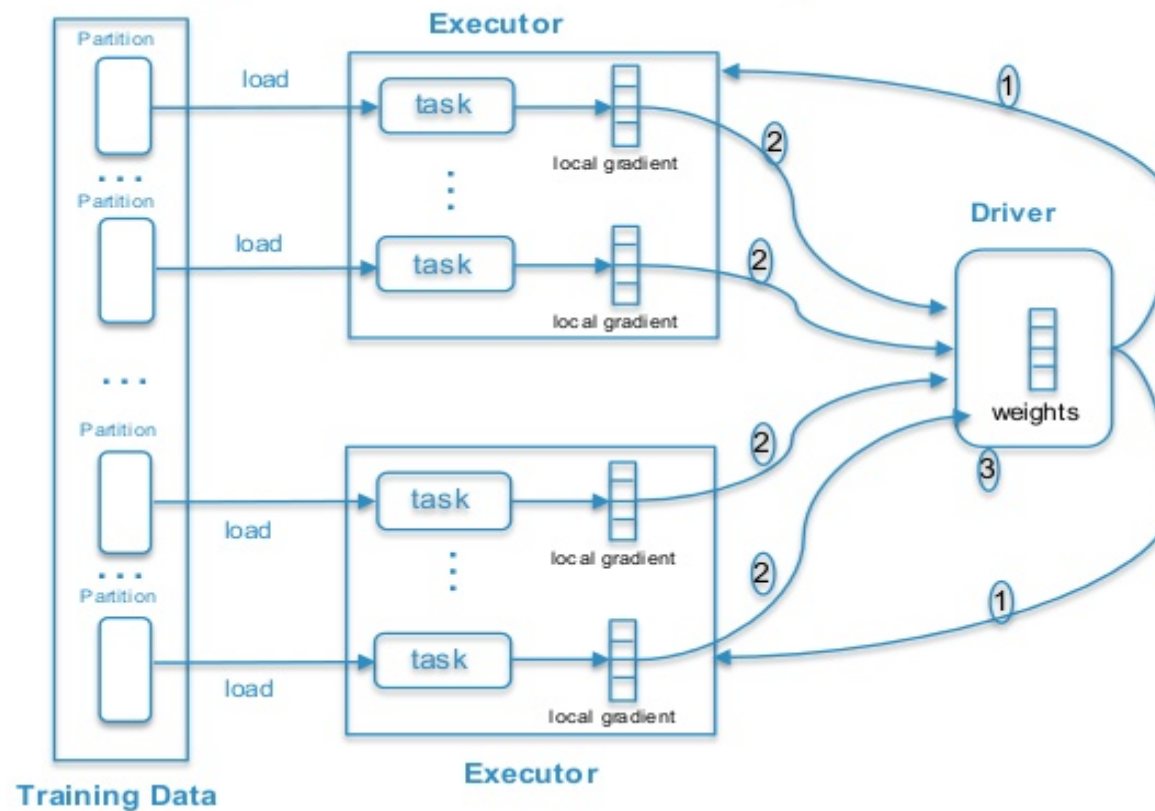


## Tip2: MaxAbsScaler for feature engineering

- MinMaxScaler destroys data sparsity
- StandardScaler does not support SparseVector with Mean



# Logistic Regression on Spark



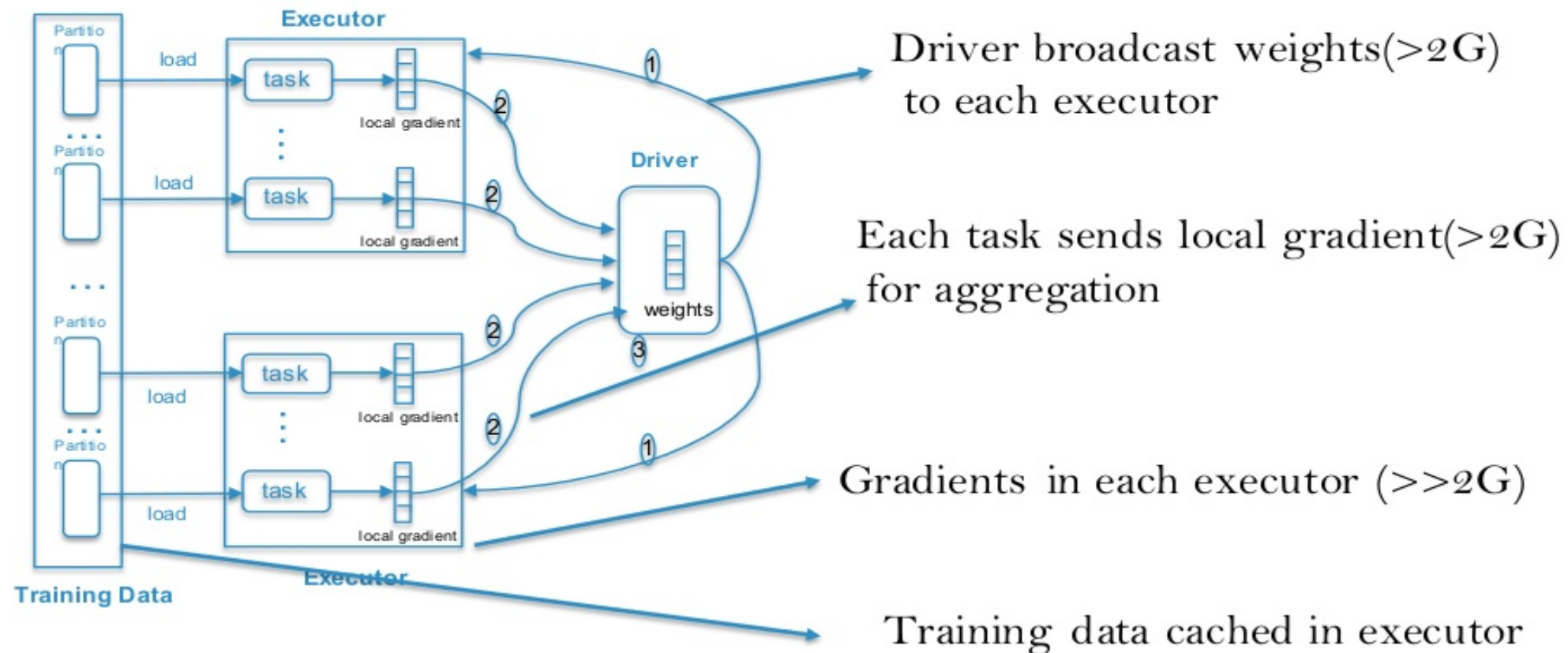
# Large Scale Logistic Regression

Customer's training set:

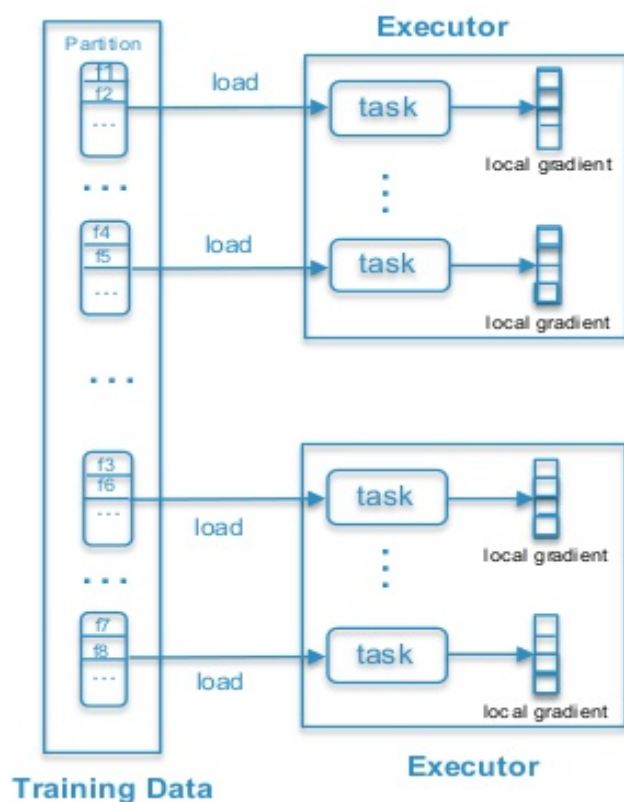
- Number of features : 200s million
- Billions  $\sim$  trillions training samples
- Each sample has 100s – 1000 non-zero elements



# Challenges: big data and big model



# Exploiting sparsity in gradients



$$g(w; x, y) = f(x^T w; y) \cdot x$$

The gradient is sparse as the feature vector is sparse



# Switch to sparse gradients

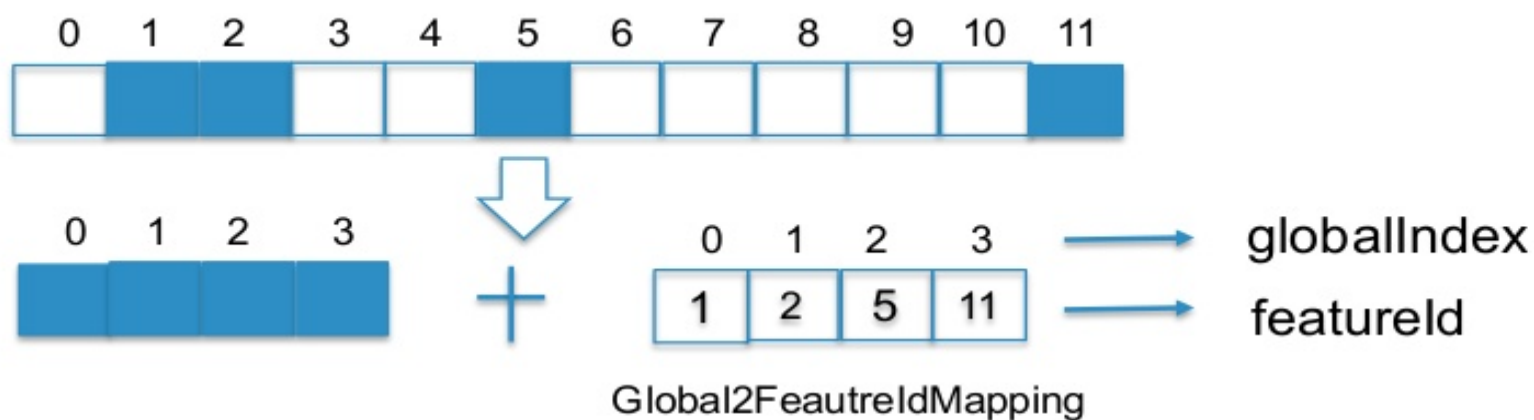
- `g = points.map(p => grad(w, p)).reduce(_ + _)`
- Gradients: `hashSparseVector`
- Adds gradients to an initial `hashSparseVector` :
  - ✓ Fast random access:  $O(1)$
  - ✓ Memory friendly:

Executor: 10G -> ~200M



# Exploiting sparsity in weights

- Weights is with great sparsity
  - Waste memory on meaningless 0
  - Use dense vector with non zero elements





# Prune weights

- Implementation:

```
val global2FeatureIdMapping =
```

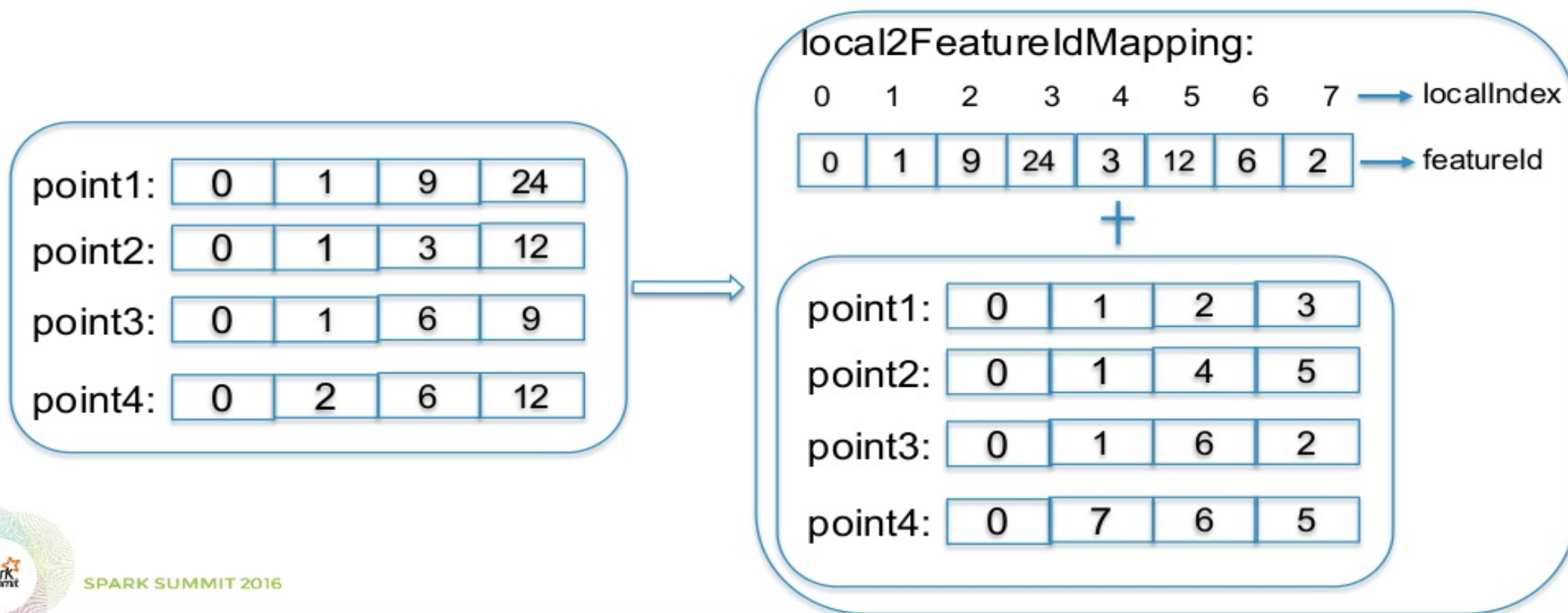
```
  points.mappartition {p => p.mapping}.collect().flatMap(t => t).distinct
```

- GlobalIndex is used during training
- Convert back to featureId after training



# Optimize cached training data

- Use localIndex as sparse vector indices



# Optimize cached training data

- Encode localIndex

featureId: 0 – 200 millions    localIndex: 0 – ~2 millions

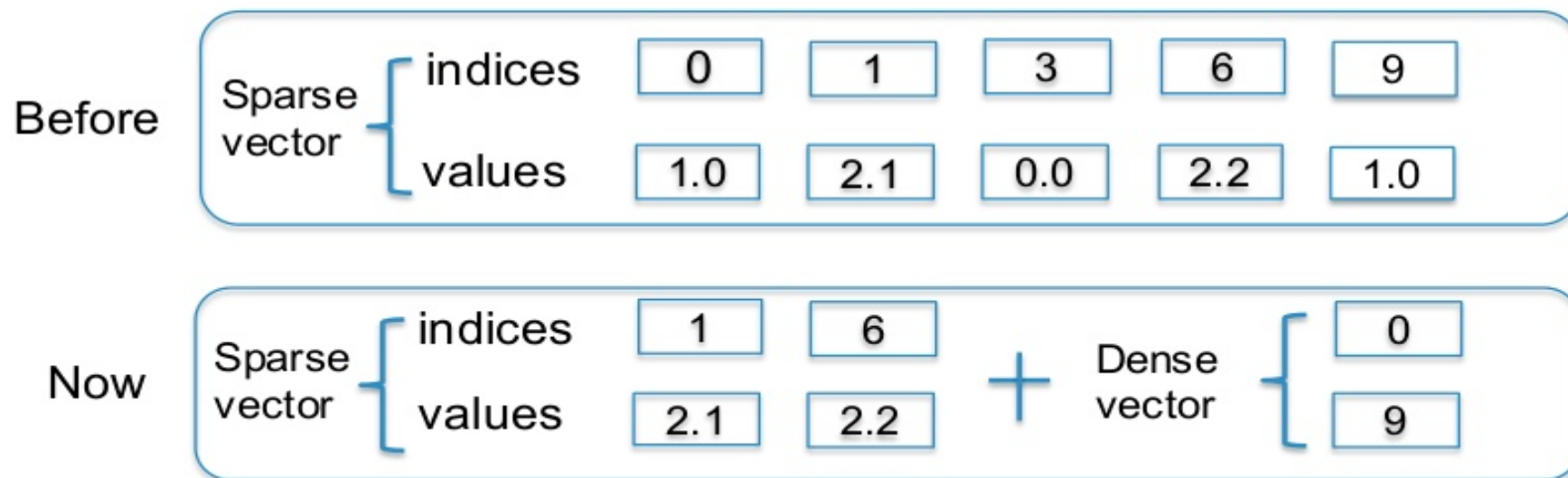
Use 1-3 bytes to store localIndex

- indices: `Array[Int]` -> ~~`Array[Array[Byte]]`~~ -> `Array[Byte]`
- use first bit to identify if the following byte is a new localIndex



# Optimize cached training data

- Support for binary(0 or 1) values



# Sparse Logistic Regression Performance

- Enviroment (12 executors with 8g memory in each)
  - ☐ Spark LR: OOM
  - ☐ Sparse LR: 90 seconds per epoch

Hardware : Intel(R) Xeon(R) CPU E5-2699 v3 @ 2.30GHz, 128GB DRAM

Software : Spark on yarn (Spark ver1.6.0 , Hadoop ver2.6.0)



# How to use SparseSpark

- <https://github.com/intel-analytics/SparseSpark>
- Consistent interface with MLlib
- Compile with application code.



# THANK YOU.

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