Distributed Computations for ML

Machine Learning and Data Mining

Maxim Borisyak

National Research University Higher School of Economics (HSE)

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Big Data

Big Data

Some industrial problems have too much data:

- it can not be stored on a one machine:
  - usually, meaning RAM;
- or, it can not be processed on one machine in an adequate amount of time:
  - video/music recommendations should be updates frequently.

Big Data

Problems:

- how to store ’big’ data;
- how to distribute data across computational cluster;
- how to compute whatever you need.

Storage

Usually it is a distributed database...

Examples:

- Any proper SQL DB (e.g. PostgreSQL);
- Cassandra;
- Hadoop Distributed File System (also HBase).

How to distribute data

Timescale of typical computer operations:

execute typical instruction	1 nanosec
fetch from L1 cache memory	0.5 nanosec
branch misprediction	5 nanosec
fetch from L2 cache memory	7 nanosec
Mutex lock/unlock	25 nanosec
fetch from main memory	100 nanosec
send 2K bytes over 1Gbps network	20,000 nanosec
read 1MB sequentially from memory	250,000 nanosec
fetch from new disk location (seek)	8,000,000 nanosec
read 1MB sequentially from disk	20,000,000 nanosec
send packet US to Europe and back	150,000,000 nanosec

How to distribute data

Humanized version (nanosec $\rightarrow$ sec):

execute typical instruction	1 sec
fetch from L1 cache memory	0.5 sec
branch misprediction	5 sec
fetch from L2 cache memory	7 sec
Mutex lock/unlock	25 sec
fetch from main memory	2 min
send 2K bytes over 1Gbps network	6 hours
read 1MB sequentially from memory	3 days
fetch from new disk location (seek)	3 month
read 1MB sequentially from disk	1 year
send packet US to Europe and back	5 years

How to distribute data

Answer:

- keep everything in RAM;
- send as little as possible data over network.

Question

Quite a typical operation is aggregation by key:

- a number of pairs `(K, V)` distributed across multiple machines;
- there can be multiple instances with the same key;
- the problem is to aggregate all values corresponding to one key, i.e. for some f produce:
  `(K, f(V1, V2, V3, ...))` for each key `K`.

How would you implement:

- counting words across a large text collection;
- computing personal recommendations for a large amount of users given their logs?

Distributed computations

How?

How can we implement framework for distributed computations?

A simple approach

- we known how to write sequential code;
- we known how to transmit data;
- just make a communication toolkit.

Example: MPI

```
my_result = /** computing something **/
MPI_Reduce(
  &my_result,
  &result,1,
  MPI_REAL,
  MPI_SUM,0,
  MPI_COMM_WORLD
);
```

Discussion

- low level.

Abstract view

- large datasets are usually more or less homogeneous (of the same type);
    - especially, for ML;
- a nice abstraction for it is **collection**.

Operations over collections: example

```
int* data = <receive numbers>;
int* result = (int* ) malloc(size of data);
...
for(int i = 0; i < n; ++i) {
  result[i] = f(data[i]);
}
```

Operations over collections: example

Humanized form:

- allocate and fill array `data`;
- allocate array `result`;
- allocate integer variable `i`;
- assign `i` to 0;
- check if `i < n`: continue if true; jump to ... otherwise;
- retrieve `data[i]`;
- compute `f(data[i])`;
- store result to `result[i]`;
- increase `i` by 1;

Operations over collections: example

What the author meant:

- apply `f` to each element of `data`;

What the author wrote:

- very specific instructions to traverse the array;
  - not essential to the meaning;
  - can be replaced by a number of other ways;
  - **intrinsically** sequential code.

Declarative programming

Imperative programming:

- code is a sequence of instructions:
  - increase **x** by 1;
  - add **a** and **b** store in **c**;
- code $\approx$ how to compute;

Declarative programming:

- code is a set of declarations/definitions;
  - let symbol **c** represent sum of **a** and **b**;
  - `x = x + 1` is absurd;
- code $\approx$ definition of the result.

Functional programming and collections

functional programming =

declarative programming+

high-order functions

Common collection functions

- defines a new collection with elements `f(e)` where `e` from `collection`;
  - fully isolates from the implementation;
  - makes all collection transformations uniform (including sets, trees, etc);

```
map(
  f : A -> B,
  collection : Collection[A]
) : Collection[B]
```

```
map((x) => x + 1, List(1, 2, 3)) // List(2, 3, 4)
```

Common collection functions

- allows function to produce multiple results:

```
flatMap(
  f : A -> Collection[B],
  collection : Collection[A]
) : Collection[B]
```

```
flatMap(
  x => if (x % 2 == 0) {
    List(x - 1, x, x + 1)
  } else { List() },
  List(1, 2, 3)
) // List(1, 2, 3)
```

Common collection functions

- folds collection from left to right;
  - computationally equivalent to any for-loop:

```
reduceLeft(
  f : (B, A) -> B,
  collection : Collection[A],
  init : B
) : B


reduceLeft(
  (acc : String, el : Int) => acc + el,
  List(1, 10, 100), ""
) // "110100"
```

Common collection functions

- folds collection from **right to left**:

```
reduceRight(
  f : (A, B) -> B,
  collection : Collection[A],
  init : B
) : B


reduceRight(
  (el : Int, acc : String) => acc + el,
  List(1, 10, 100), ""
) // "100101"
```

Common collection functions

- does not specify the traversing direction;
  - applicable for commutative operators

```
reduce(
  f : (A, A) -> A,
  collection : Collection[A]
) : A


reduce(
  (a, b) => a + b,
  List(1, 10, 100)
) // 111
```

Common collection functions

- produces collection with pairs from two collections:

```
zip(
  collection : Collection[A]
  collection : Collection[B]
) : Collection[(A, B)]
```

```
zip(List(1, 2, 3), List("one", "two", "three"))
// List((1, "one"), (2, "two"), (3, "three"))
```

Common collection functions

- filters collection according to a predicate:

```
filter(
  p : A => Boolean,
  collection : Collection[A]
) : Collection[A]
```

```
filter( x => x % 2 == 0, List(1, 2, 3)) // List(2)
```

Common collection functions

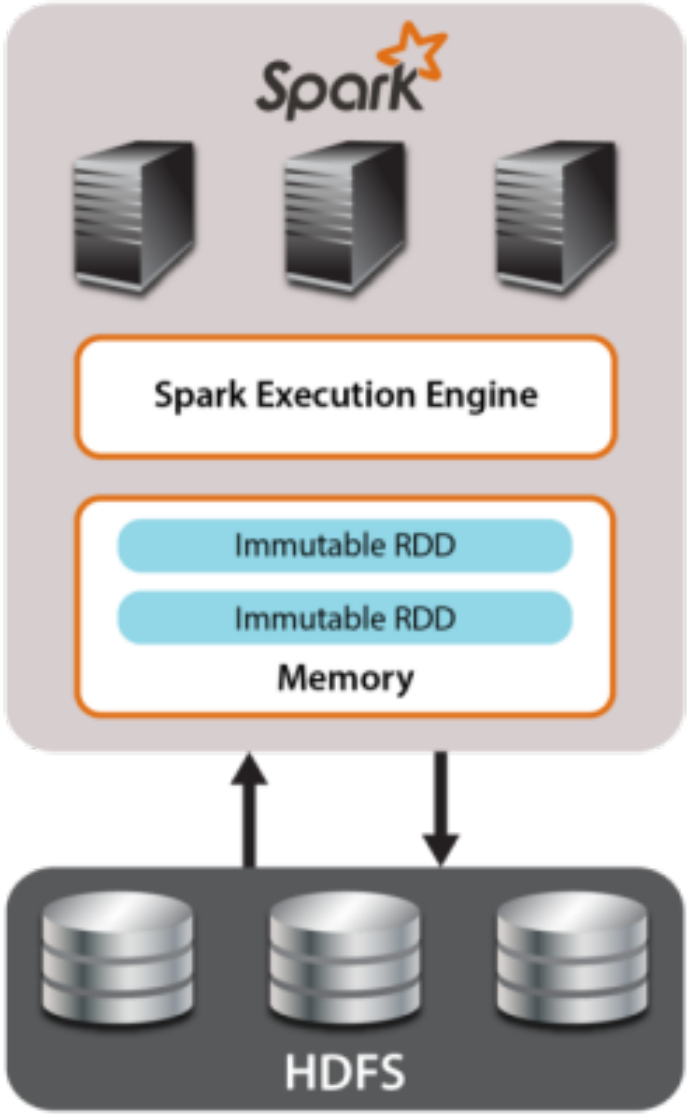
- 90% of the every-day programs can be implemented via `map`/`reduce`/...;
- each function only defines the result, not the way it can be obtained:
  - implementation details are hidden inside `map`, `reduce`, ...;
- **they can be implemented for distributed collections**:
  - code looks almost the same as for non-distributed collections.

Spark

Spark

Spark implements **distributed collections RDD**:

- Resilient;
- Distributed;
- Dataset.



RDD

RDD are immutable:

- they can not be changed;
- only new RDD can be produced;
- actual RDDs are just **definitions**.

RDD

Two types of operations:

- transformations: `RDD[A] -> RDD[B]` or `A -> RDD[B]`;
- actions: `RDD[A] -> B`.

Transformations:

- are not executed immediately;
- only store **definition**;

Action:

- reduce the entire RDD to a single value:
  - writing to a database also an action;
  - trigger execution of transformation.

RDD operations

```
trait RDD[T] {
  def map[U](f: T => U): RDD[U]

  def flatMap[U](f: T => Seq[U]): RDD[U]

  def filter(p: T => Boolean): RDD[T]

  def aggregate[U](zero: U)
    (f: (U, T) => U, g: (U, U) => U): U

  def fold(zero: T)(f: (T, T) => T): T

  def reduce(op: (T, T) => T): T
}
```

RDD operations

```
trait RDD[T] {
  def count(): Long

  def max(): T

  def min(): T

  def sample(fraction: Double): RDD[T]

  def take(n: Int): Array[T]

  def collect(): Array[T]
}
```

I/O RDD operations

```
trait SparkContext {
  def textFile(path: String): RDD[String]
  def objectFile[T](path: String): RDD[T]
  def parallelize[T](seq: Seq[T]): RDD[T]
  def union[T](rdds: Seq[RDD[T]]): RDD[T]
}

trait RDD[T] {
  def saveAsTextFile(path: String): Unit
  def saveAsObjectFile(path: String): Unit
}
```

PairRDD operations

```
trait PairRDD[K, V] extends RDD[(K, V)] {
  def aggregateByKey[U](zero: U)
    (f: (U, V) => U, g: (U, U) => U): RDD[(K, U)]

  def foldByKey(zero: V)
    (f: (V, V) => V): RDD[(K, V)]

  def reduceByKey(op: (V, V) => V): RDD[(K, V)]

  def groupByKey(): RDD[(K, Iterable[V])]
}
```

PairRDD operations

```
trait PairRDD[K, V] extends RDD[(K, V)] {
  def cogroup[U](other: RDD[(K, U)]):
    RDD[(K, (Iterable[V], Iterable[U]))]

  def fullOuterJoin[U](other: RDD[(K, U)]):
    RDD[(K, (Option[V], Option[U]))]

  def leftOuterJoin[U](other: RDD[(K, U)]):
    RDD[(K, (V, Option[U]))]

  def join[U](other: RDD[(K, U)]): RDD[(K, (V, U))]
}
```

Example: word count

```
texts : RDD[String] = sparkContext.fromFile("...")

texts.
  flatMap { x => x.split() }.
  map { x => (x, 1) }.
  reduceByKey { (a, b) => a + b }
```

Spark Execution Model

Master and workers

There are two type of nodes in Spark:

- master
  - launches main code;
  - sends commands to workers;
- workers:
  - just do masters commands.

Transformations and actions

RDD does not hold actual data:

- they are merely recipes for computations;
- actions trigger computations;
- if possible, no intermediate data collections are produced:
  - saving memory and time.

Examples

```
val data = {
  sparkContext.parallelize(0 until gazilion)
}

val sum = data.map( x => x * x ).
               map( x => x + 1 ).
               map( x => x / 3.0 ).
               reduce((a, b) => a + b)
```

The example would not produce 3 physical collections.
Instead, a constant amount of additional memory per machine would be required.

Example

```
val words: RDD[String] = ...

val counts = words.map(x => (x, 1)).reduceByKey{
  (a, b) => a + b
}.persist()

val total = counts.count()
val probabilities = counts.map {
  (word, count) => (word, count / total)
}
```

Find inefficiencies in the code.

Example

```
val words: RDD[String] = ...

val counts = words.map(x => (x, 1)).reduceByKey{
  (a, b) => a + b
}.persist()

val total = counts.count()
val probabilities = counts.map {
  (word, count) => (word, count / total)
}
```

`persist()` tells Spark to cache RDD so it can available after execution.

Balancing execution

Each RDD is split into partitions:

- a partition is processed by a one machine sequentially;
- number of partitions should be higher than number of CPUs;
- too many partitions cause overhead;
- partitioning might be selected during creation of RDD;
- manually invoke repartitioning by `repartition()` or `coalesce()`.

Cost of operations

Map-like operations:

- extremely fast as performed without any networking;
- essentially, each machine performs for-loop.

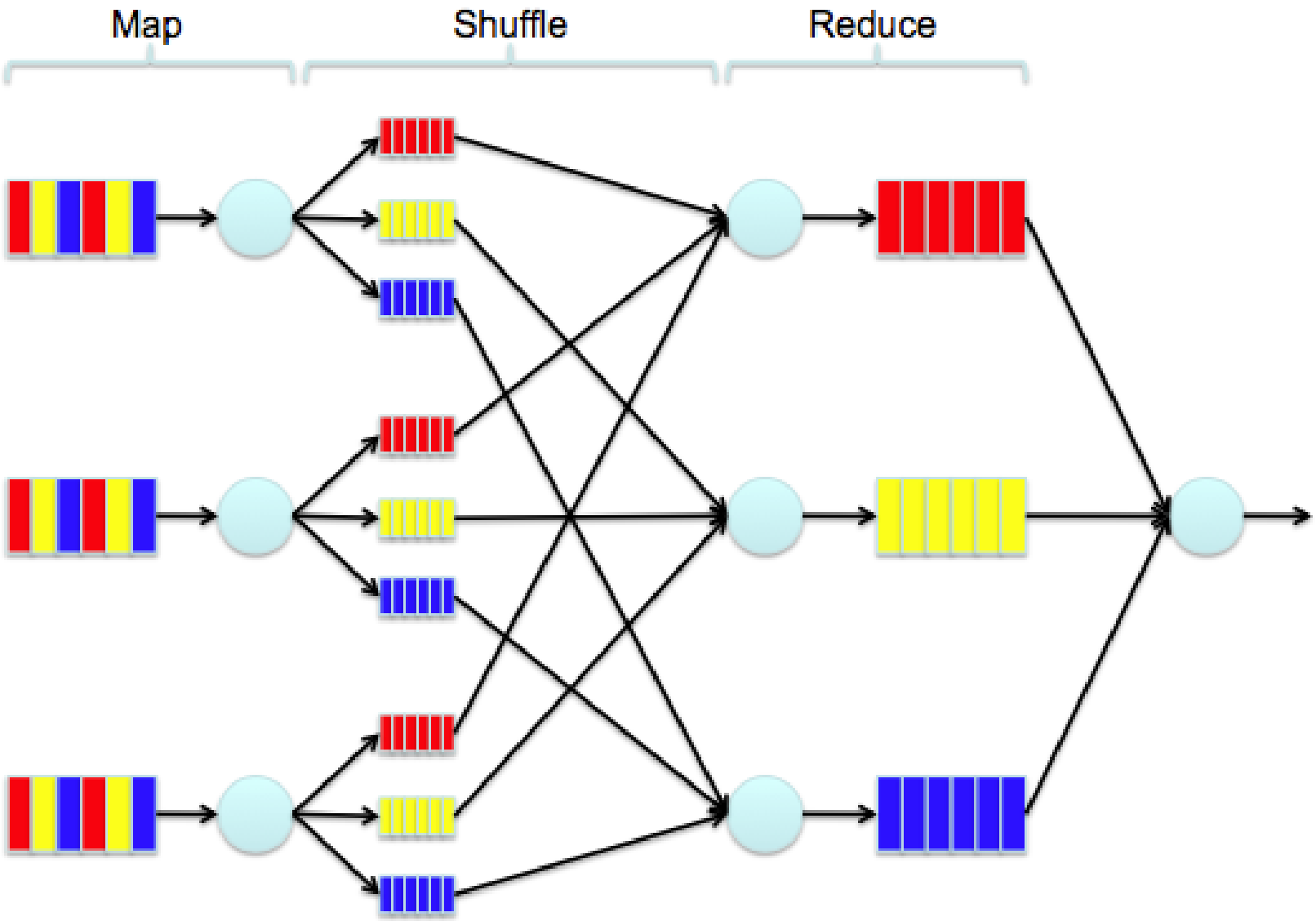
Reduce-like operations:

- somewhat fast;
- involves small transfer over network;

Join-like operations:

- might cause transfer of the whole dataset across machines;
- entries with the same key must be on the same machine.

Map-shuffle-reduce



Strange example

```
val largeTextCollection: RDD[String] = ...

val wordsAndTexts = largeTextCollection.flatMap{
  text => text.split().map( word => (word, text) )
}

wordsAndTexts.join(wordProbabilities).
              reduce(something)
```

What is wrong with this example?

ML examples

Logistic regression

```
val dataset: RDD[(Vector, Label)] = ...

var w = <some random vector>
var b = 0.0

for (i <- number_of_iterations) {
  val (grad_w, grad_b) = dataset.map { p =>
    ...
  }.reduce((a, b) => a + b)

  w += alpha * grad_w
  b += alpha * grad_b
}
```

Summary

Summary

Spark:

- based on functional programming;
- main abstraction is RDD;
- performs distributed computations;
- ...