TensorFrames:
Google Tensorflow with Apache Spark

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About Databricks

Why Us

- Created Apache Spark to enable big data use cases with a single engine.
- Contributes 75% of Spark's code - 10x more than others.

Our Product

- Bring Spark to the enterprise: The just-in-time data platform.
- Fully managed platform powered by Apache Spark.
- A unified solution for data science and engineering teams.

About me

Software engineer at Databricks

Apache Spark contributor

Ph.D. UC Berkeley in Machine Learning

(and Spark user since Spark 0.2)

Outline

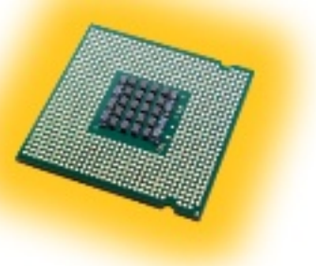
- **Numerical computing with Apache Spark**
- Using GPUs with Spark and TensorFlow
- Performance details
- The future

Numerical computing for Data Science

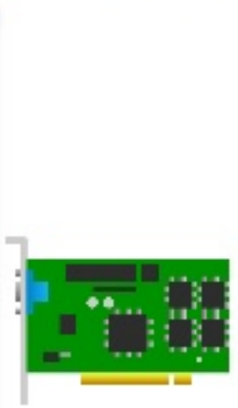
- Queries are data-heavy
- However algorithms are computation-heavy
- They operate on simple data types: integers, floats, doubles, vectors, matrices

The case for speed

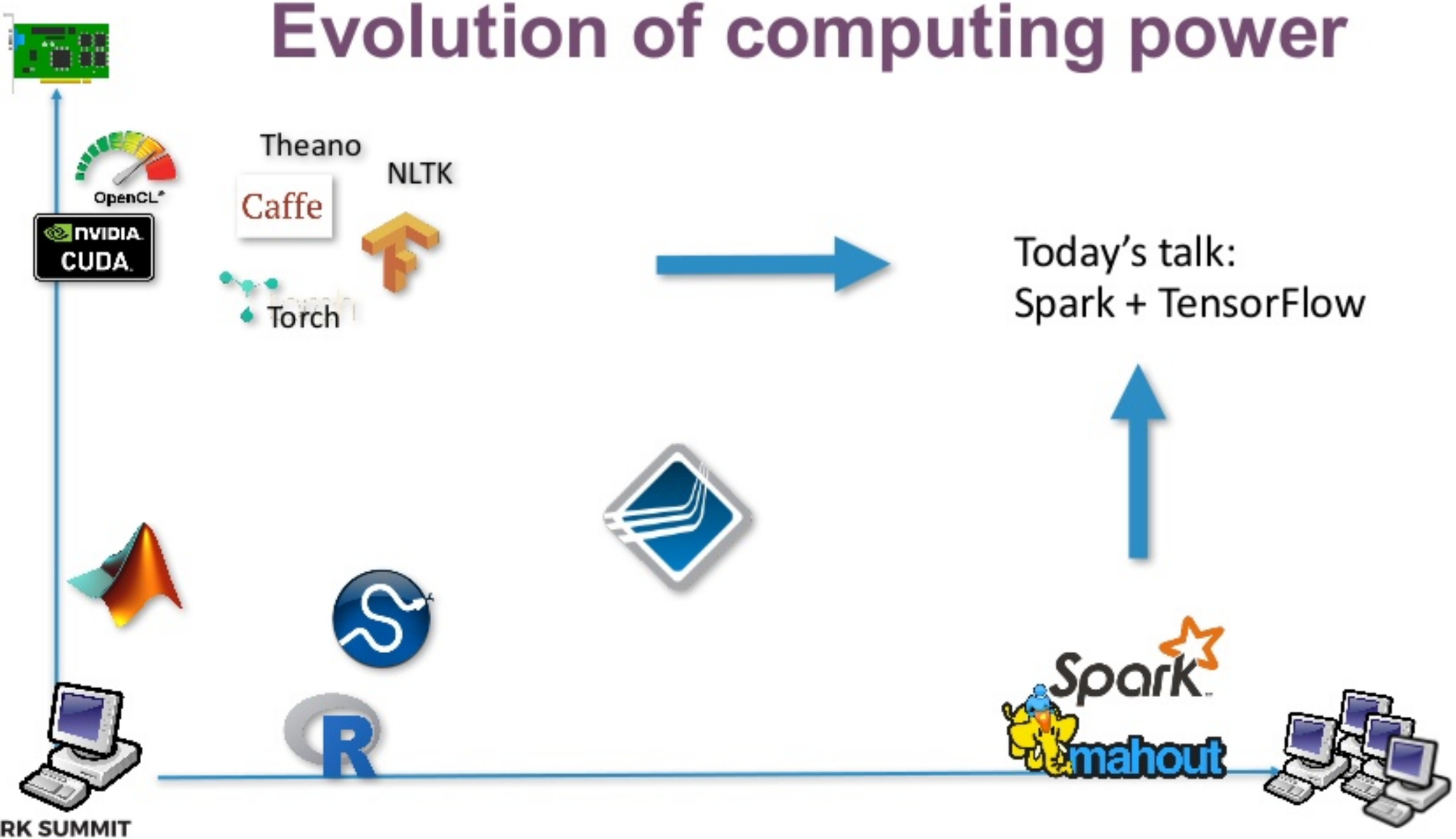
- Numerical bottlenecks are good targets for optimization
- Let data scientists get faster results
- Faster turnaround for experimentations
- How can we run these numerical algorithms faster?



Evolution of computing power



Evolution of computing power



Evolution of computing power

- Processor speed cannot keep up with memory and network improvements
- Access to the processor is the new bottleneck
- Project Tungsten in Spark: leverage the processor's heuristics for executing code and fetching memory
- Does not account for the fact that the problem is *numerical*

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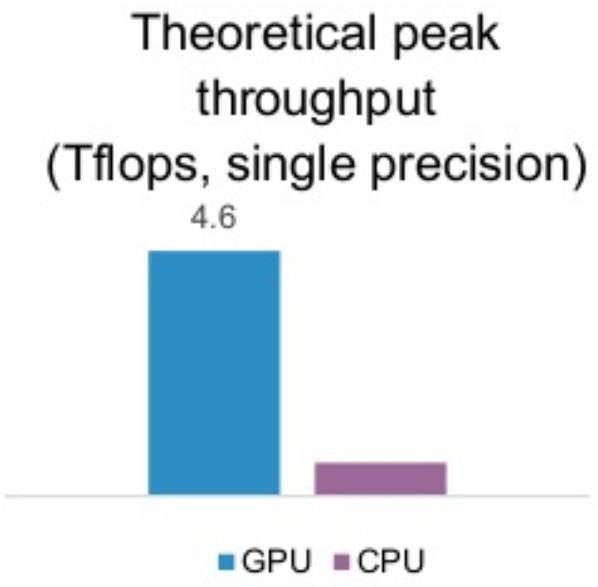
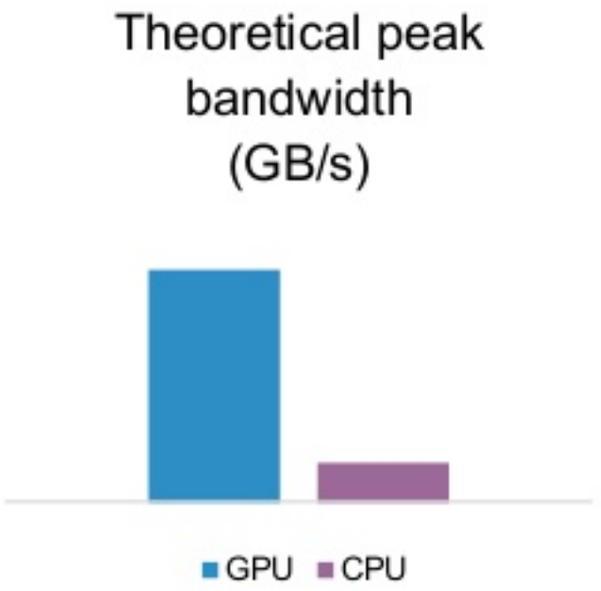
GPGPUs

- Graphics Processing Units for General Purpose computations



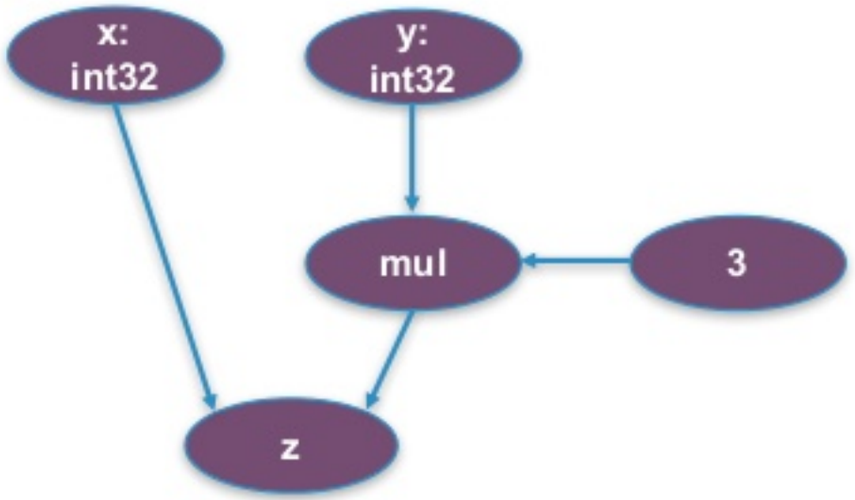


Google TensorFlow

- Library for writing “machine intelligence” algorithms
- Very popular for deep learning and neural networks
- Can also be used for general purpose numerical computations
- Interface in C++ and Python

Numerical dataflow with Tensorflow

```
x = tf.placeholder(tf.int32, name="x")
y = tf.placeholder(tf.int32, name="y")
output = tf.add(x, 3 * y, name="z")
```




```
session = tf.Session()
output_value = session.run(output,
  {x: 3, y: 5})
```

Numerical dataflow with Spark

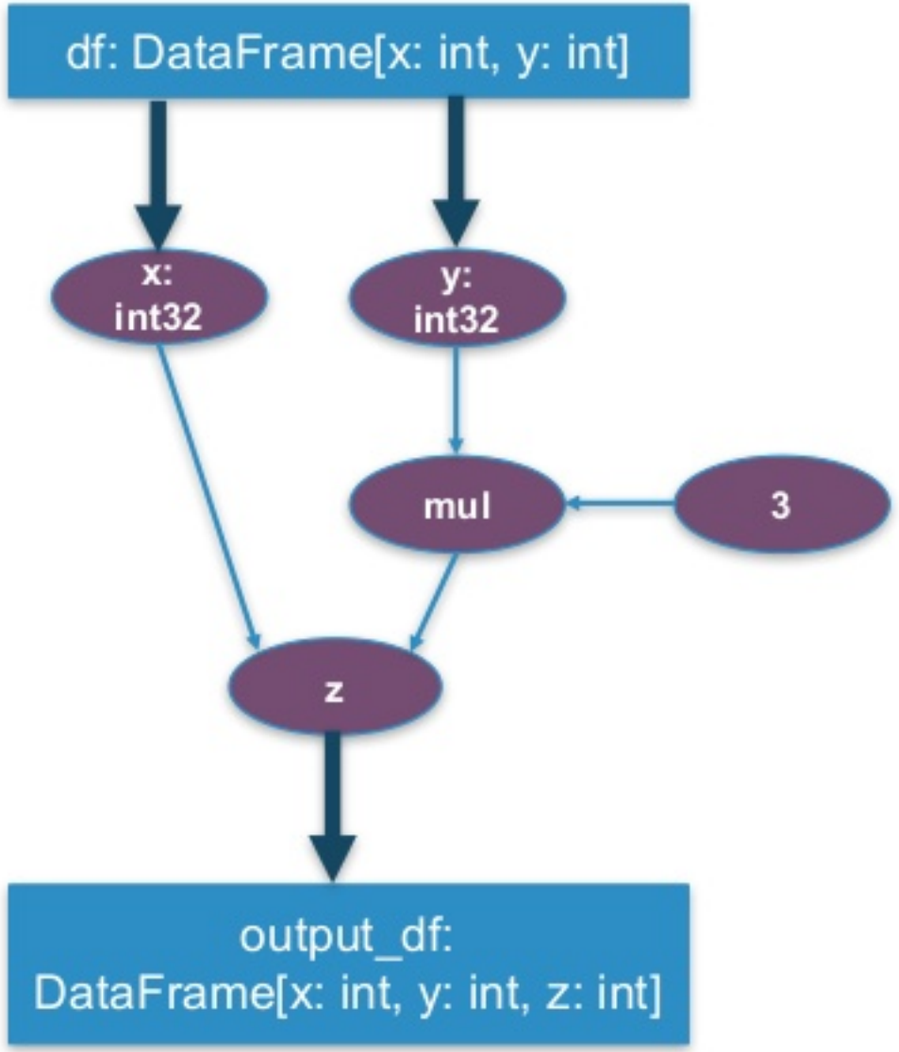
```
df = sqlContext.createDataFrame(…)

x = tf.placeholder(tf.int32, name="x")
y = tf.placeholder(tf.int32, name="y")
output = tf.add(x, 3 * y, name="z")

output_df = tfs.map_rows(output, df)



   output_df.collect()
```



Demo

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- Using GPUs with Spark and TensorFlow
- **Performance details**
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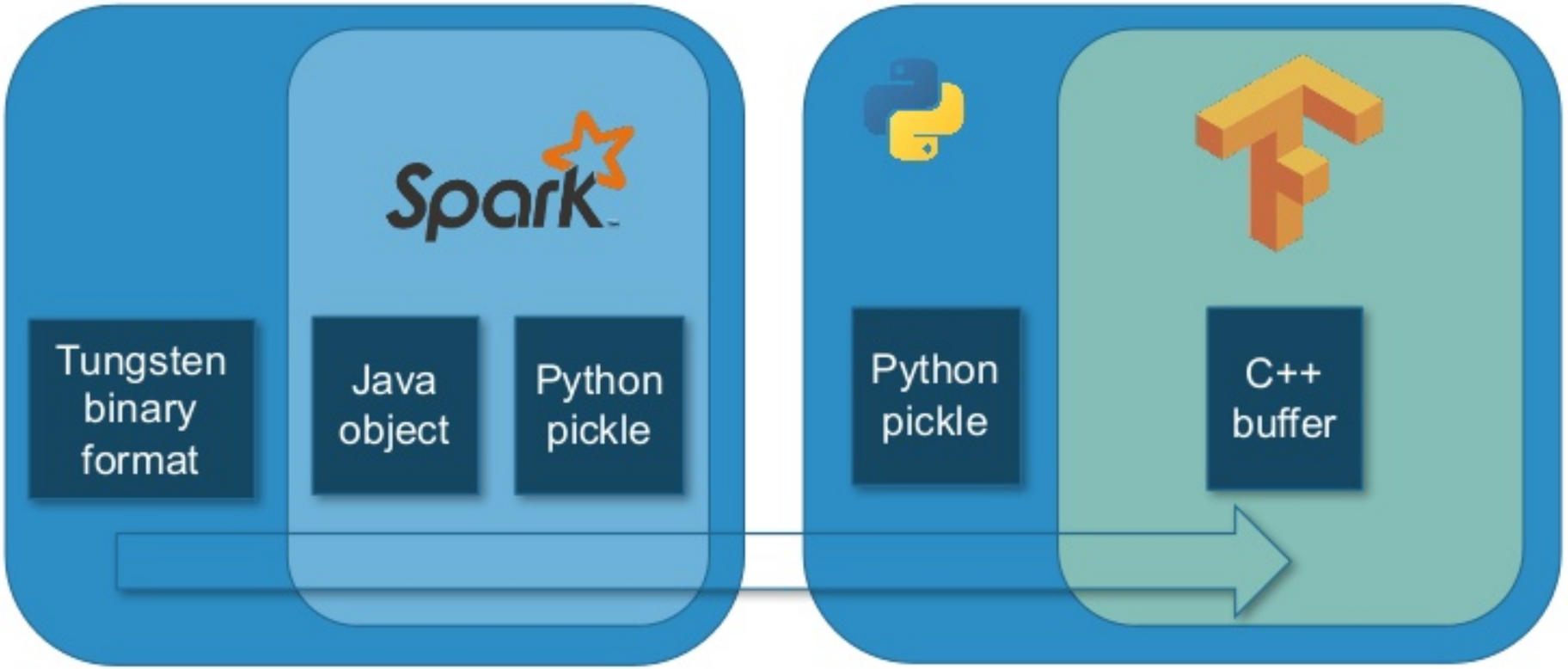
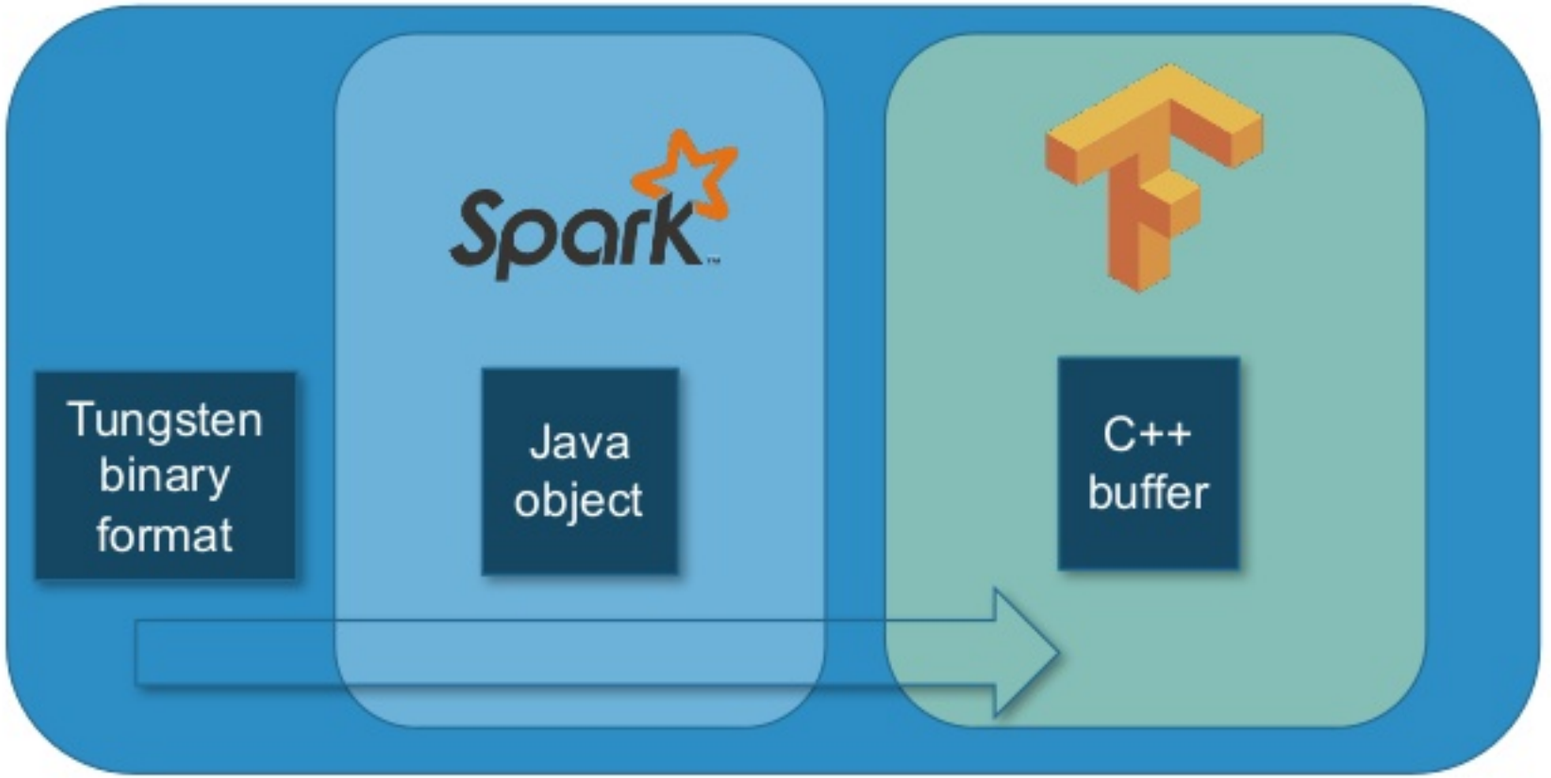
It is a communication problem

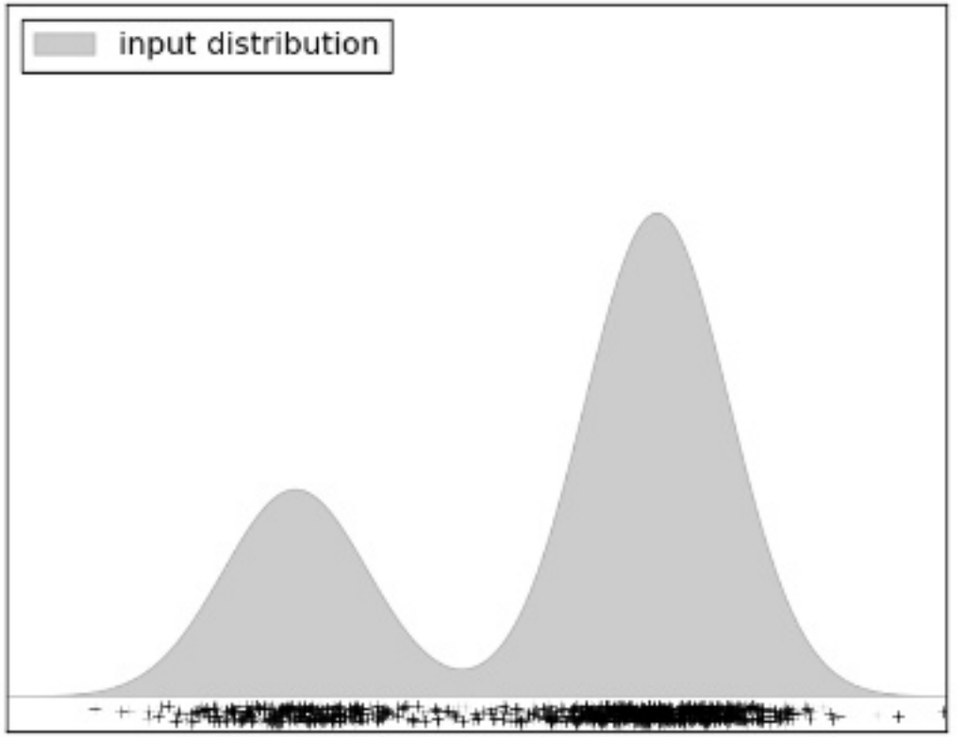


TensorFrames: native embedding of TensorFlow



An example: kernel density scoring

- Estimation of distribution from samples
- Non-parametric
- Unknown bandwidth parameter
- Can be evaluated with goodness of fit



An example: kernel density scoring

- In practice, compute:

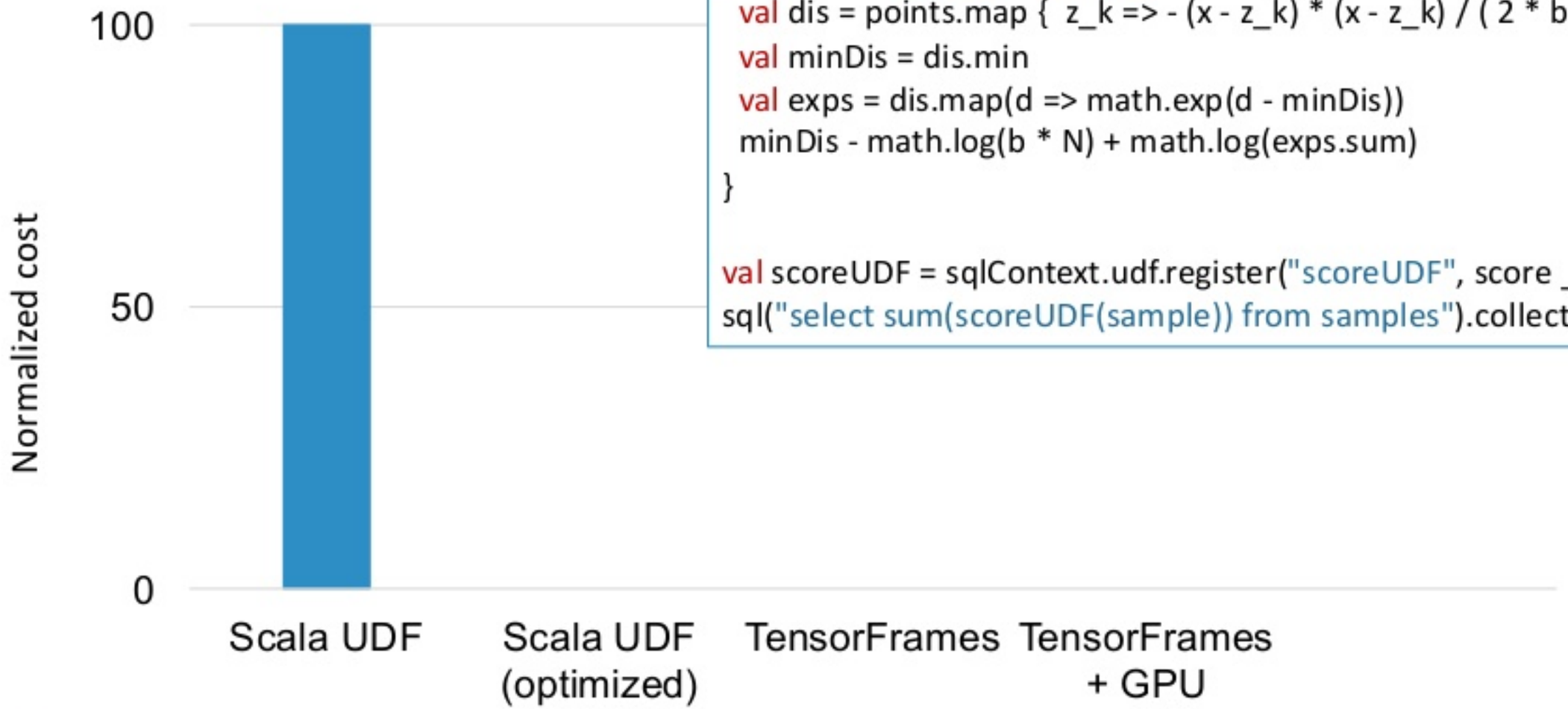
$$\frac{1}{L}\sum_{x} score\,(x)$$

with:

$$score\,(x) = \log\left[\frac{1}{N}\sum_{k=1}^{N}\exp\left(-\frac{(x-z_k)^2}{\sqrt{2\pi}b}\right)\right]$$

- In a nutshell: a complex numerical function

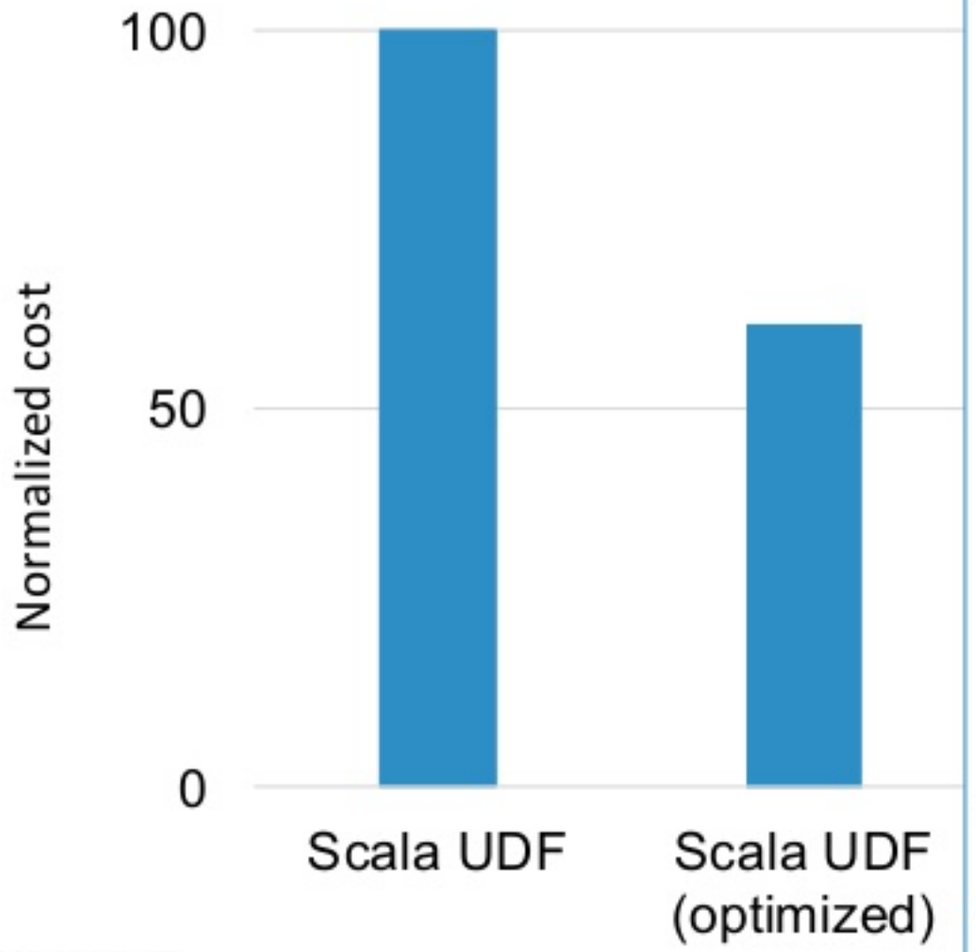
Speedup




```
def score(x: Double): Double = {
  val dis = points.map {  z_k => - (x - z_k) * (x - z_k) / ( 2 * b * b) }
  val minDis = dis.min
  val exps = dis.map(d => math.exp(d - minDis))
  minDis - math.log(b * N) + math.log(exps.sum)
}

val scoreUDF = sqlContext.udf.register("scoreUDF", score _)
sql("select sum(scoreUDF(sample)) from samples").collect()
```

Speedup




```
def score(x: Double): Double = {
 val dis = new Array[Double](N)
 var idx = 0
 while(idx < N) {
  val z_k = points(idx)
  dis(idx) = - (x - z_k) * (x - z_k) / ( 2 * b * b)
 idx += 1
 }
 val minDis = dis.min
 var expSum = 0.0
 idx = 0
 while(idx < N) {
  expSum += math.exp(dis(idx) - minDis)
  idx += 1
 }
 minDis - math.log(b * N) + math.log(expSum)
}

val scoreUDF = sqlContext.udf.register("scoreUDF", score _)
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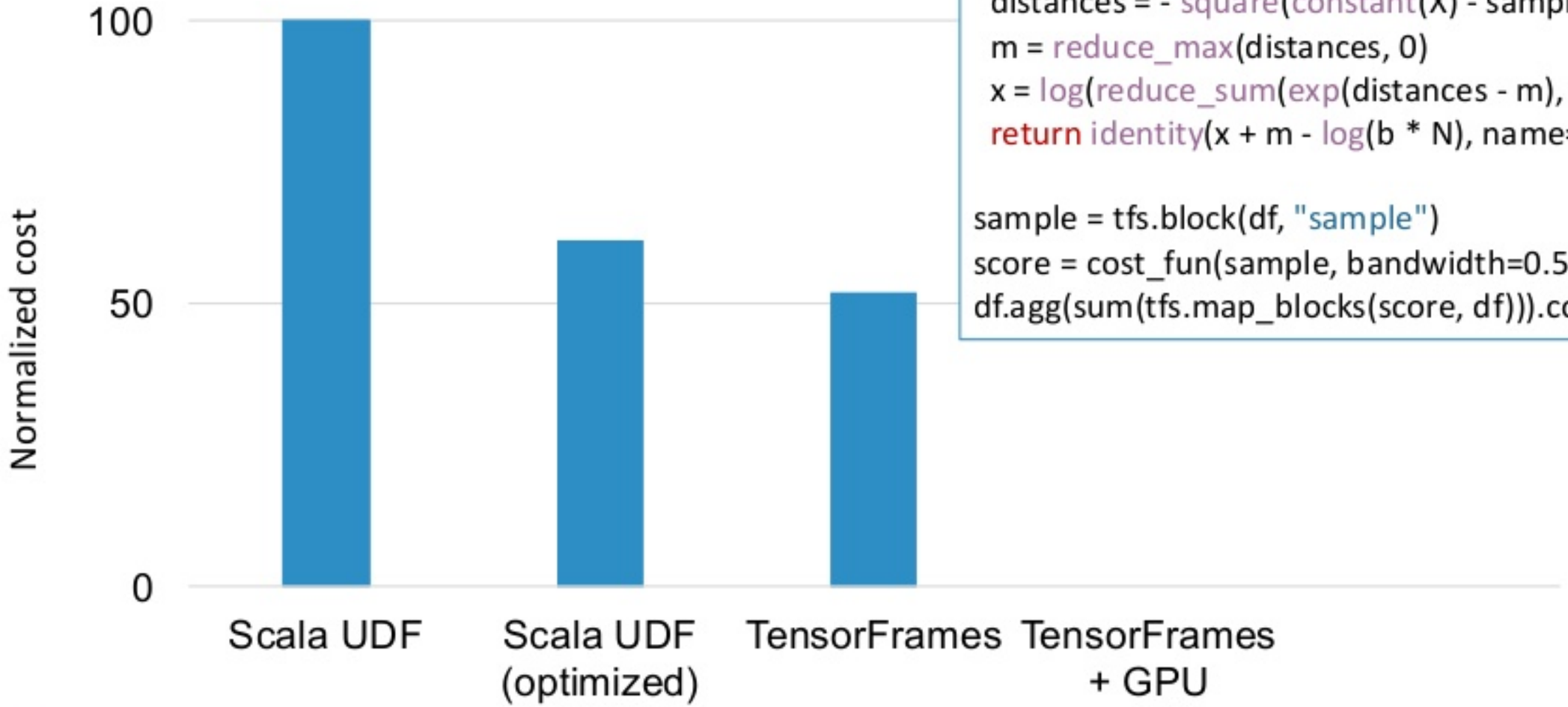
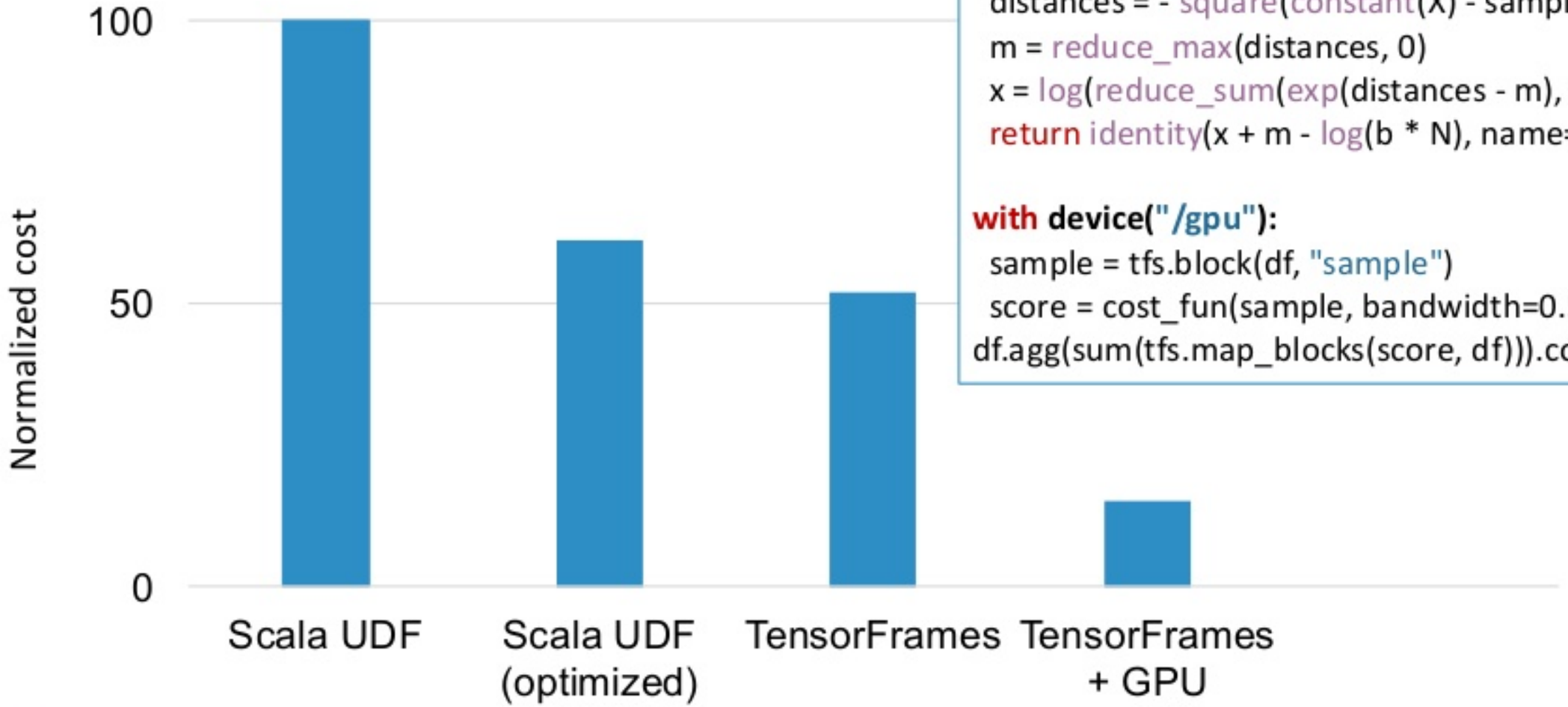
Speedup




```
def cost_fun(block, bandwidth):
  distances = - square(constant(X) - sample) / (2 * b * b)
  m = reduce_max(distances, 0)
  x = log(reduce_sum(exp(distances - m), 0))
  return identity(x + m - log(b * N), name="score")

sample = tfs.block(df, "sample")
score = cost_fun(sample, bandwidth=0.5)
df.agg(sum(tfs.map_blocks(score, df))).collect()
```

Speedup




```
def cost_fun(block, bandwidth):
  distances = - square(constant(X) - sample) / (2 * b * b)
  m = reduce_max(distances, 0)
  x = log(reduce_sum(exp(distances - m), 0))
  return identity(x + m - log(b * N), name="score")

with device("/gpu"):
  sample = tfs.block(df, "sample")
  score = cost_fun(sample, bandwidth=0.5)
df.agg(sum(tfs.map_blocks(score, df))).collect()
```

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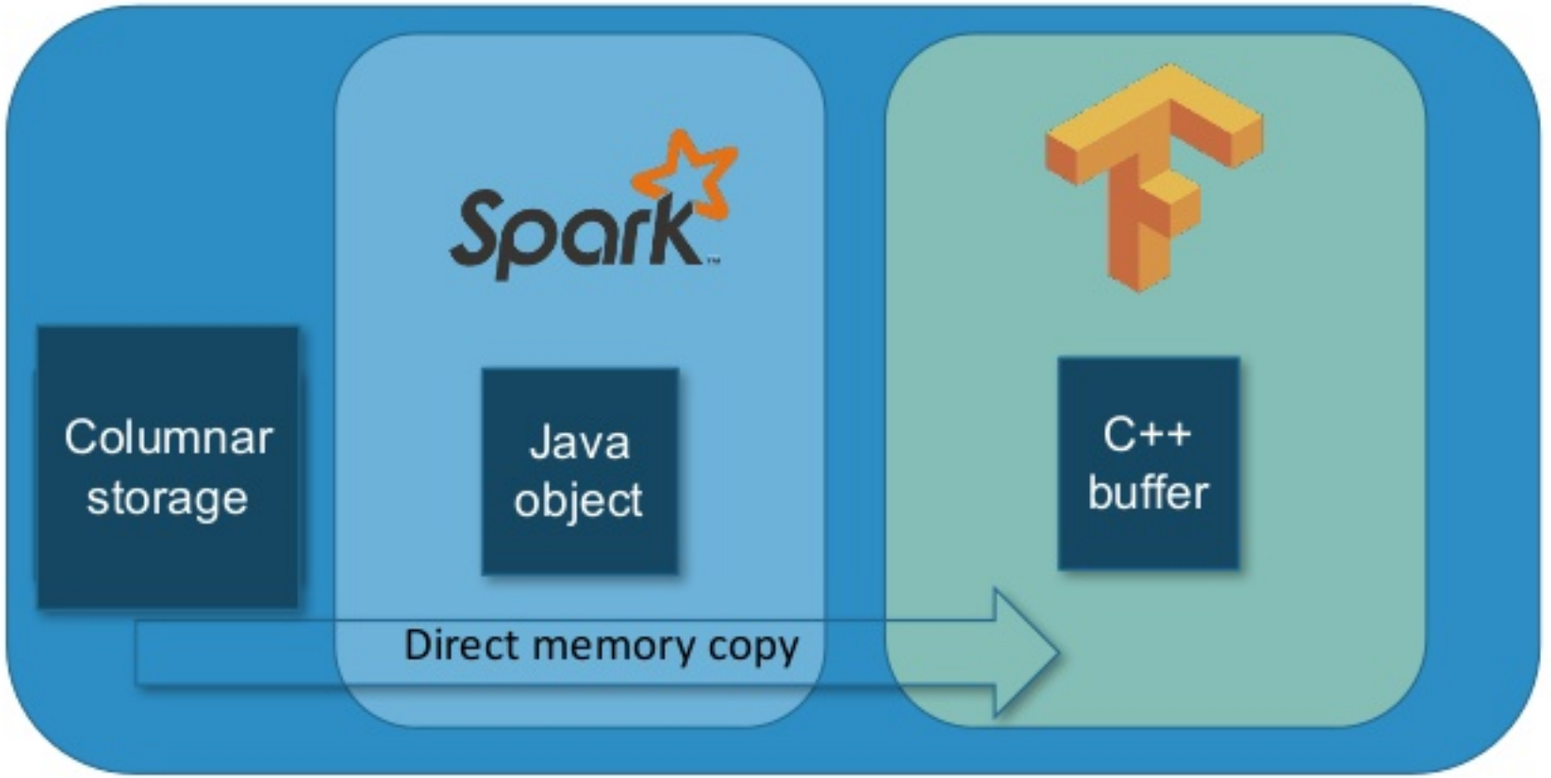
Improving communication



The future

- Integration with Tungsten:
  - Direct memory copy
  - Columnar storage

- Better integration with MLlib data types

Recap

- Spark: an efficient framework for running computations on thousands of computers
- TensorFlow: high-performance numerical framework
- Get the best of both with TensorFrames:
  - Simple API for distributed numerical computing
  - Can leverage the hardware of the cluster

Try these demos yourself

- TensorFrames source code and documentation:
  github.com/databricks/tensorframes
  spark-packages.org/package/databricks/tensorframes
- Demo notebooks available on Databricks
- The official TensorFlow website:
  www.tensorflow.org

Thank you.

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