SCALING FACTORIZATION MACHINES ON APACHE SPARK WITH PARAMETER SERVERS

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SPARK SUMMIT EUROPE 2016

About

- About me
  - *@MLnick*
  - Principal Engineer at IBM working on machine learning & Spark
  - Apache Spark PMC
  - Author of *Machine Learning with Spark*

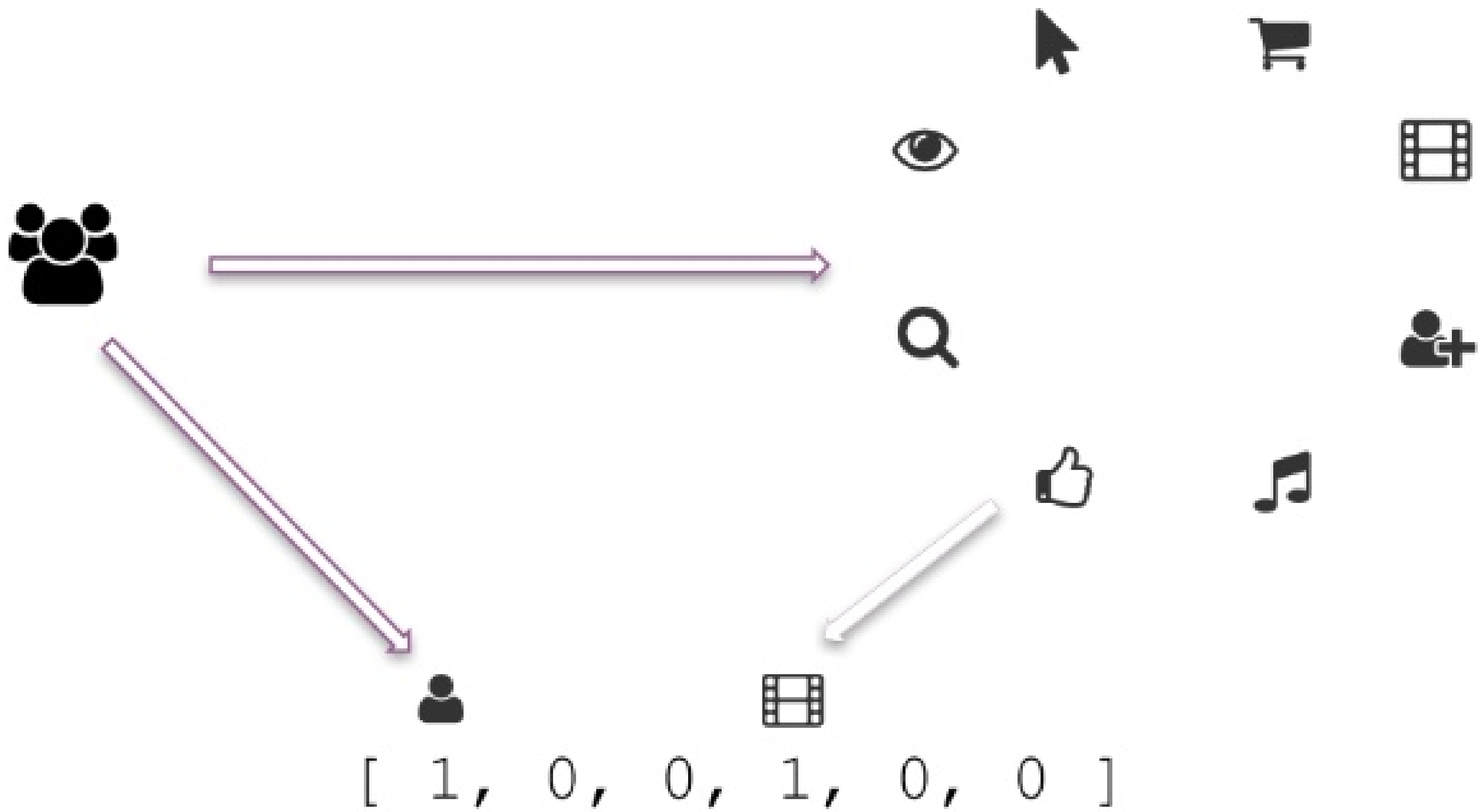
Agenda

- Brief Intro to Factorization Machines
- Distributed FMs with Spark and Glint
- Results
- Challenges
- Future Work

FACTORIZATION MACHINES

Factorization Machines

Feature interactions



Factorization Machines

Linear Models

$$w_0 + \sum_{i=1}^{n} w_i x_i \Longrightarrow w_0 + [\underbrace{w_u, 0, 0, w_i}_{\text{Bias terms}}, \ldots]$$

Not expressive enough!

Factorization Machines

Polynomial Regression

$$w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_{ij} x_i x_j \Longrightarrow w_0 + [\underbrace{w_u, 0, 0, w_i}_{\text{Bias terms}}, \ldots, \underbrace{w_{ui}}_{\text{Interaction term}}, \ldots]$$

$O(d^2)$

$n << d$

Factorization Machines

Factorization Machine

$$w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle \vec{v_i}\, \vec{v_j} \rangle x_i x_j \Rightarrow w_0 + [\underbrace{w_u, 0, 0, w_i}_{\text{Bias terms}}, \ldots, \underbrace{<\mathbf{v}_u \mathbf{v}_i>}_{\text{Factorized interaction term}}, \ldots]$$

$O(d^2 k)$

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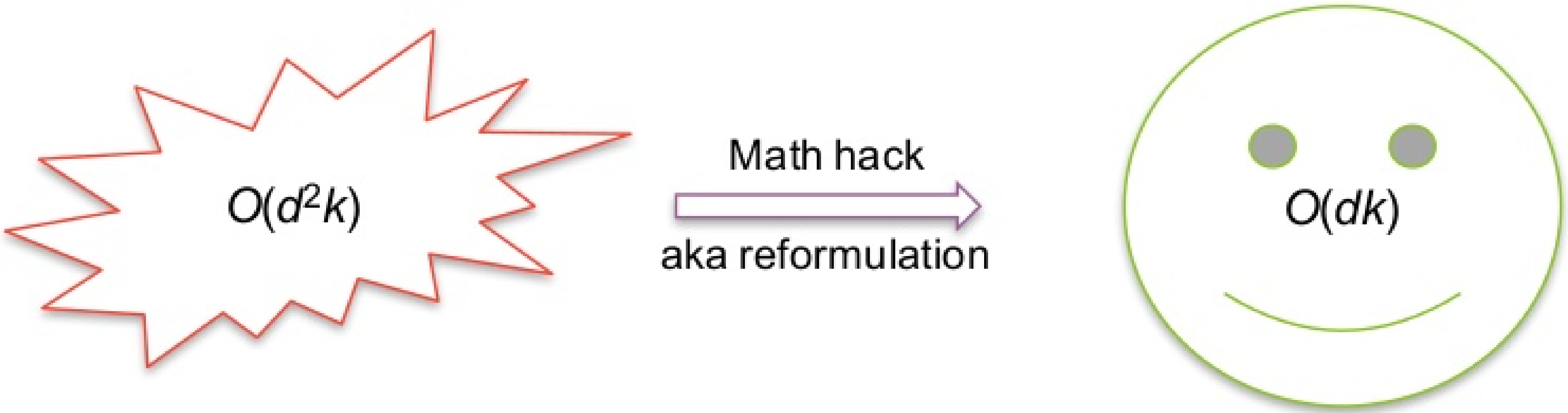
Factorization Machines

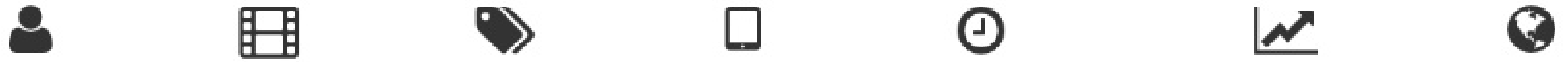
Factorization Machine



Not convex, but efficient to train using SGD, coordinate descent, MCMC

Factorization Machines

Factorization Machine



`[1,....,1,....,1,....,1,....,1,....,3.14,....1,....]`

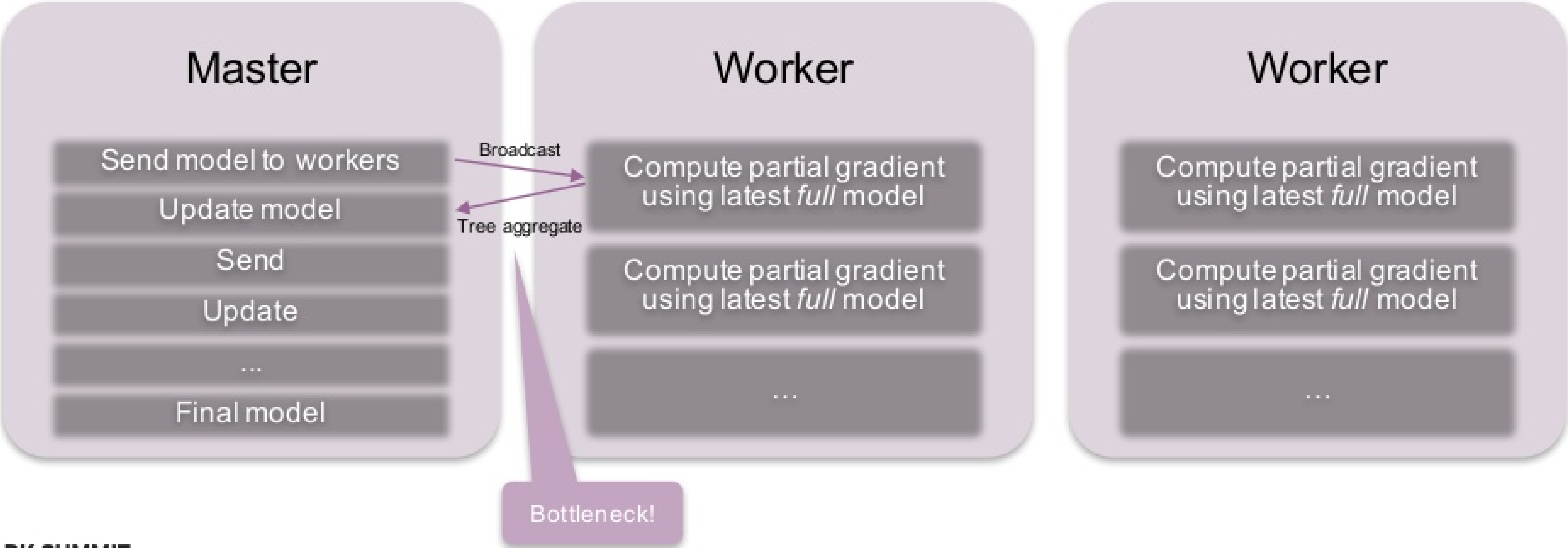
Standard matrix factorization (with biases) | Metadata features | Contextual features

Model size can still be very large! e.g. video sharing, online ads, social networks

DISTRIBUTED FM MODELS ON SPARK

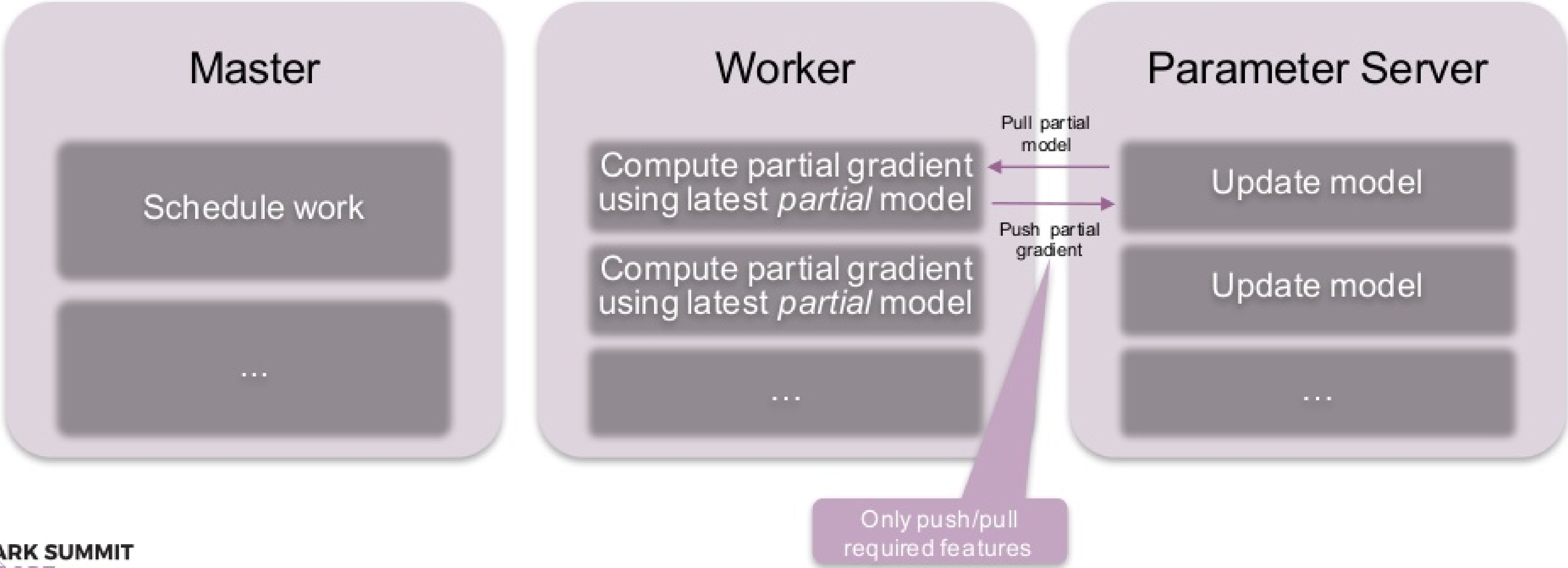
Linear Models on Spark

- Data parallel



Parameter Servers

- Model & data parallel



Distributed FMs

- spark-libFM
  - Uses old MLlib `GradientDescent` and `LBFGS` interfaces
- DiFacto
  - Async SGD implementation using parameter server (ps-lite)
  - Adagrad, L1 regularization, frequency-adaptive model-size
- Key is that most real-world datasets are *highly sparse* (especially high-cardinality categorical data), e.g. online ads, social network, recommender systems
- Workers only need access to a small piece of the model

Glint is a parameter server built using Akka
For more info, see Rolf's talk at 17:15!

GlintFM

- Procedure:
  1. Construct Glint Client
  2. Create distributed parameters
  3. Pre-compute required feature indices (per partition)
  4. Iterate:
     - Pull partial model (blocking)
     - Compute partial gradient & update
     - Push partial update to parameter servers (can be async)
  5. Done!

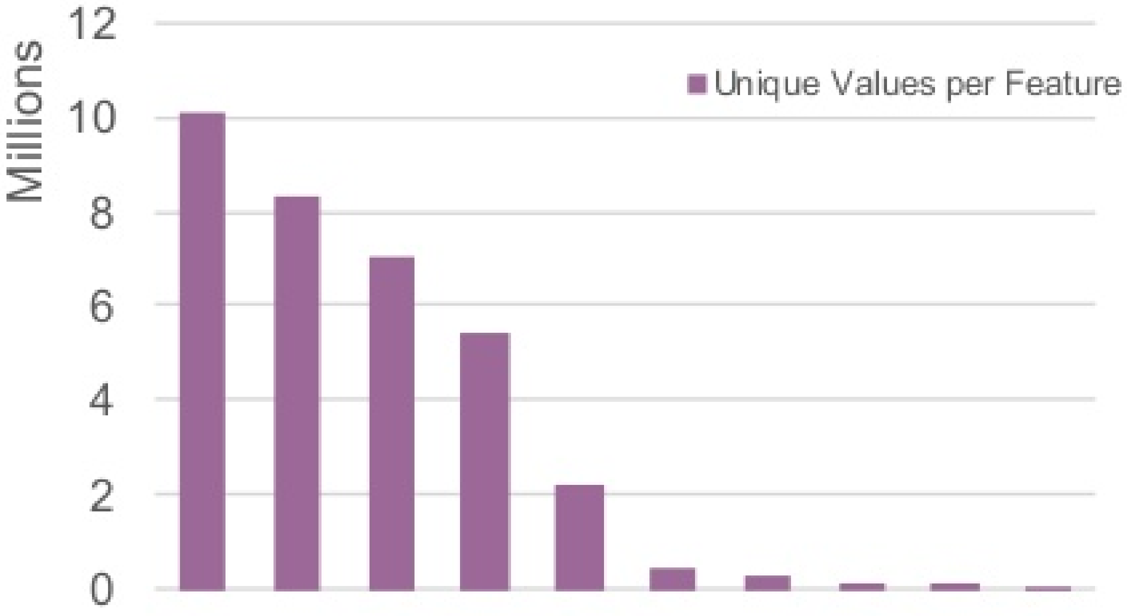
```
val client = Client(config)
val w = client.vector[Double](d)
val V = client.matrix[Double](d, k)
// training
train.foreachPartition { iter =>
  // compute partition statistics
  val localKeys = { ... }
  // iterate
  for (i <- 1 to numIterations) {
    // pull latest model for l local keys
    val localW = w.pull(localKeys) // 1 x l vector
    val localV = V.pull(localKeys) // l x k matrix
    // compute gradient
    partitionData.foldLeft(new FMAggregator(...)) { case (agg, features, label) =>
      agg.add(features, label, localW, localV)
    }
    // compute and push update
    val updates = ...
    w.push(...)
    V.push(...)
  }
}
```

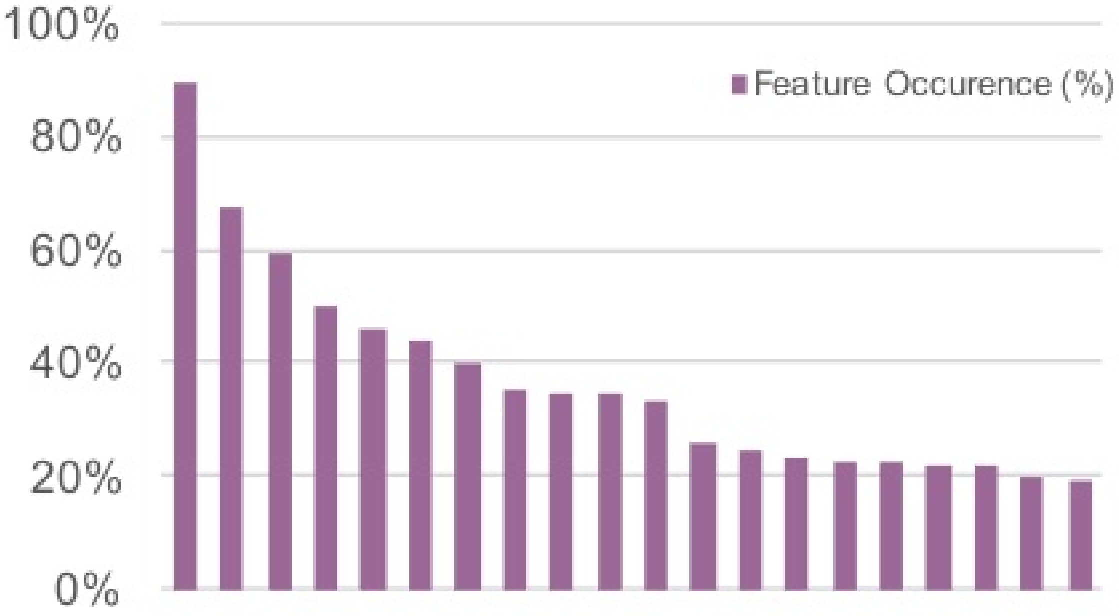
RESULTS

Data

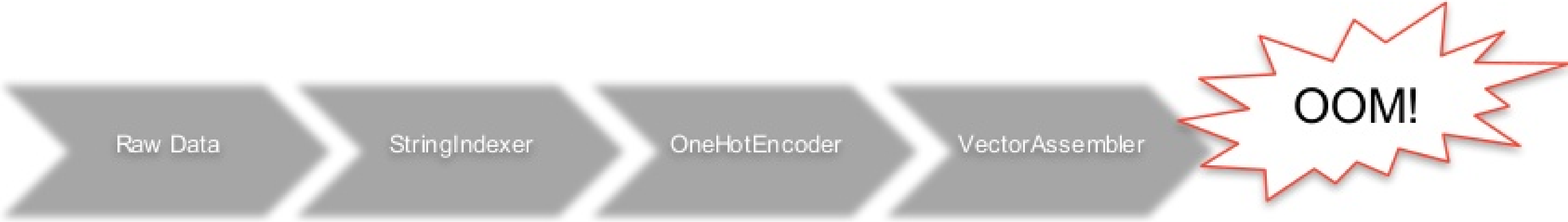
Criteo Display Advertising Challenge Dataset

- 45m examples, 34m unique features, 48 nnz /example





Feature Extraction



label	i1	i2	i3	i4	i5	i6	i7	i8	i9
0	1	1	5	0	1382	4	15	2	181
0	2	0	44	1	102	8	2	2	4
0	2	0	1	14	767	89	4	2	245
0	NULL	893	NULL	NULL	4392	NULL	0	0	0
0	3	-1	NULL	0	2	0	3	0	0

label	i1_idx	i1_ohe	features
0	2.0	(152,[2],[1.0])	(273492,[2,153,28...
0	3.0	(152,[3],[1.0])	(273492,[3,152,28...
0	3.0	(152,[3],[1.0])	(273492,[3,152,28...
0	0.0	(152,[0],[1.0])	(273492,[0,923,28...
0	4.0	(152,[4],[1.0])	(273492,[4,154,28...

Feature Extraction

Solution? “Stringify” + `CountVectorizer`

```
from pyspark.sql import Row
cols = df.columns
def convert_row(row):
    l = row.label
    i = 1
    v = []
    for c in cols[1:]:
        if row[i] is not None:
            v.append("%s=%s" % (c, row[i]))
        i += 1
    return Row(label=l, raw=v)

df_stringified = spark.createDataFrame(df.rdd.map(lambda row: convert_row(row)))
```

```
Row(i1=u'1', i2=u'1', i3=u'5', i4=u'0', i5=u'1382',... )
```

Convert set of `String` features into `Seq[String]`

```
Row(raw=[u'i1=1', u'i2=1', u'i3=5', u'i4=0', u'i5=1382', ...)
```

Feature Extraction

label	i1	i2	i3	i4	i5	i6	i7	i8	i9
0	1	1	5	0	1382	4	15	2	181
0	2	0	44	1	102	8	2	2	4
0	2	0	1	14	767	89	4	2	245
0	NULL	893	NULL	NULL	4392	NULL	0	0	0
0	3	-1	NULL	0	2	0	3	0	0

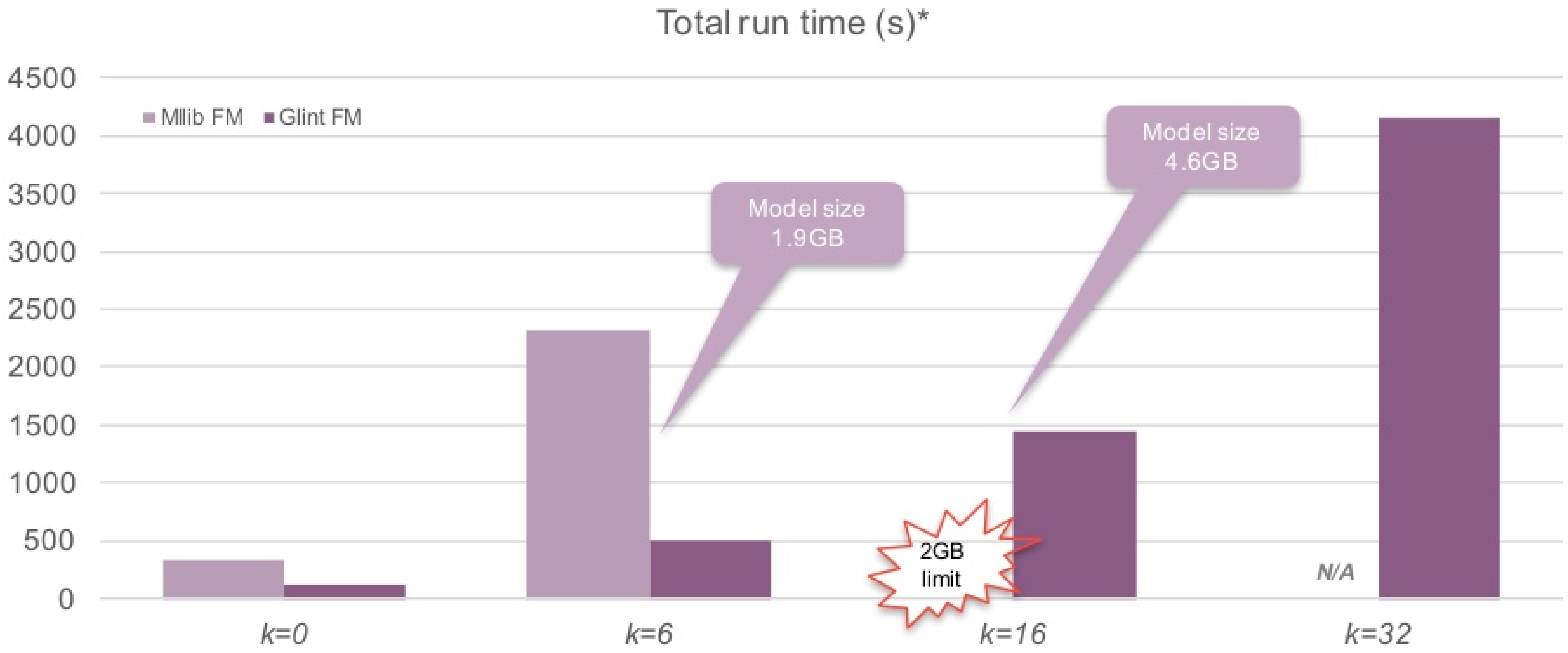
label	raw	features
0	[i1=1, i2=1, i3=5...	(273531,[0,1,2,3,...
0	[i1=2, i2=0, i3=4...	(273531,[0,1,2,3,...
0	[i1=2, i2=0, i3=1...	(273531,[0,3,4,6,...
0	[i1=NULL, i2=893,...	(273531,[0,1,2,3,...
0	[i1=3, i2=-1, i3=...	(273531,[0,1,2,3,...

Feature Extraction

label	i1	i2	i3	i4	i5	i6	i7	i8	i9
0	1	1	5	0	1382	4	15	2	181
0	2	0	44	1	102	8	2	2	4
0	2	0	1	14	767	89	4	2	245
0	NULL	893	NULL	NULL	4392	NULL	0	0	0
0	3	-1	NULL	0	2	0	3	0	0

label	raw	features
0	[i1=1, i2=1, i3=5...	(262144,[2411,726...
0	[i1=2, i2=0, i3=4...	(262144,[5352,934...
0	[i1=2, i2=0, i3=1...	(262144,[14069,15...
0	[i1=NULL, i2=893,...	(262144,[4201,693...
0	[i1=3, i2=-1, i3=...	(262144,[6935,140...

Performance



*10 iterations, 48 partitions, fit intercept

Performance

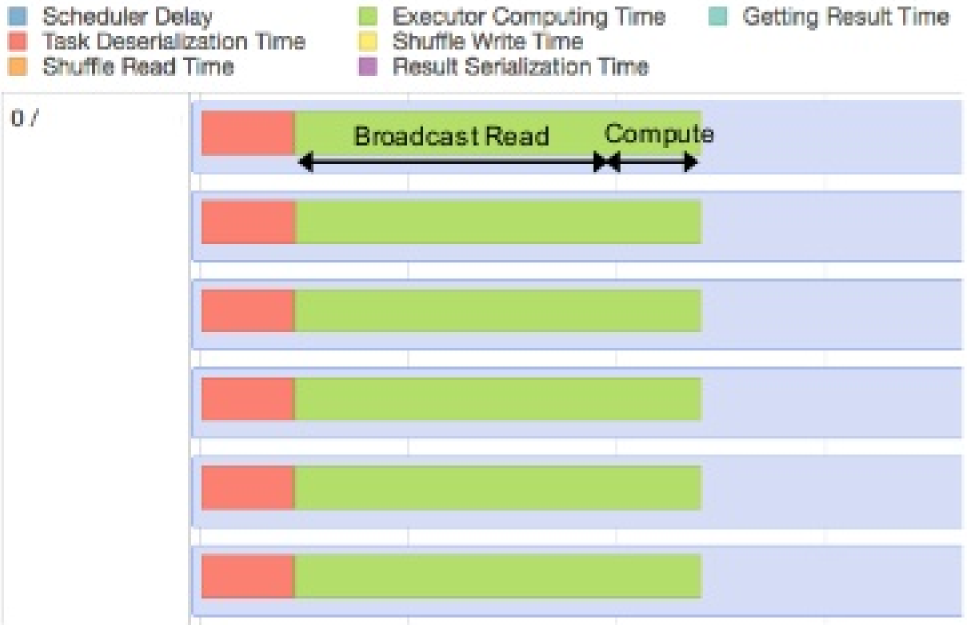
Details for Stage 23 (Attempt 0)

Total Time Across All Tasks: 41 min
Locality Level Summary: Process local: 48
Input Size / Records: 18.9 GB / 36671573
Shuffle Write: 4.1 GB / 48

Gradient computation

- DAG Visualization
- Show Additional Metrics
- Event Timeline

Enable zooming



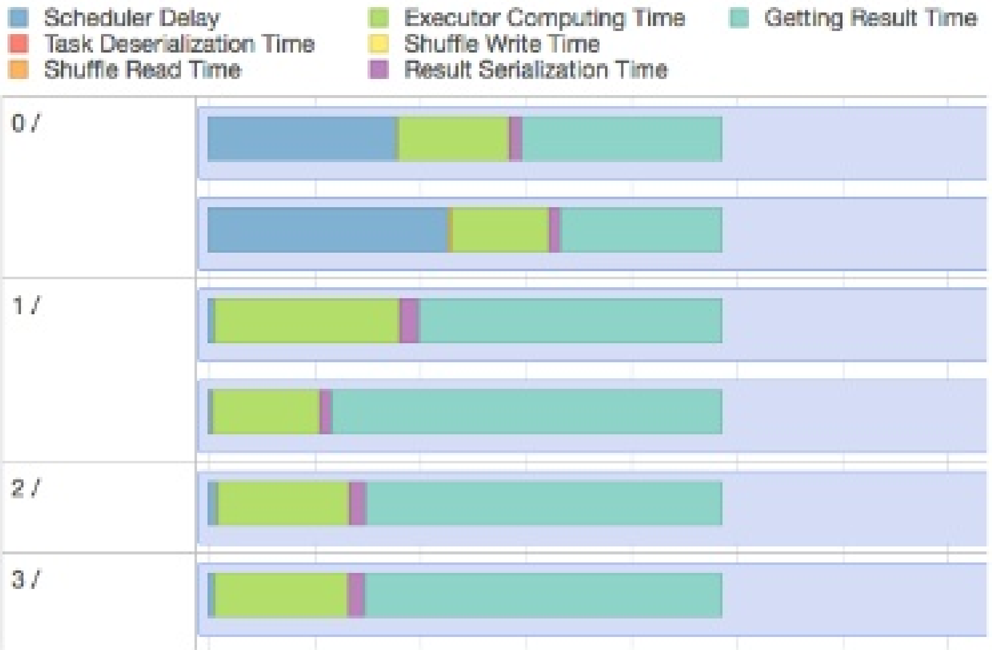
Details for Stage 24 (Attempt 0)

Total Time Across All Tasks: 2.6 min
Locality Level Summary: Node local: 6
Shuffle Read: 4.1 GB / 48

Aggregation & collect

- DAG Visualization
- Show Additional Metrics
- Event Timeline

Enable zooming



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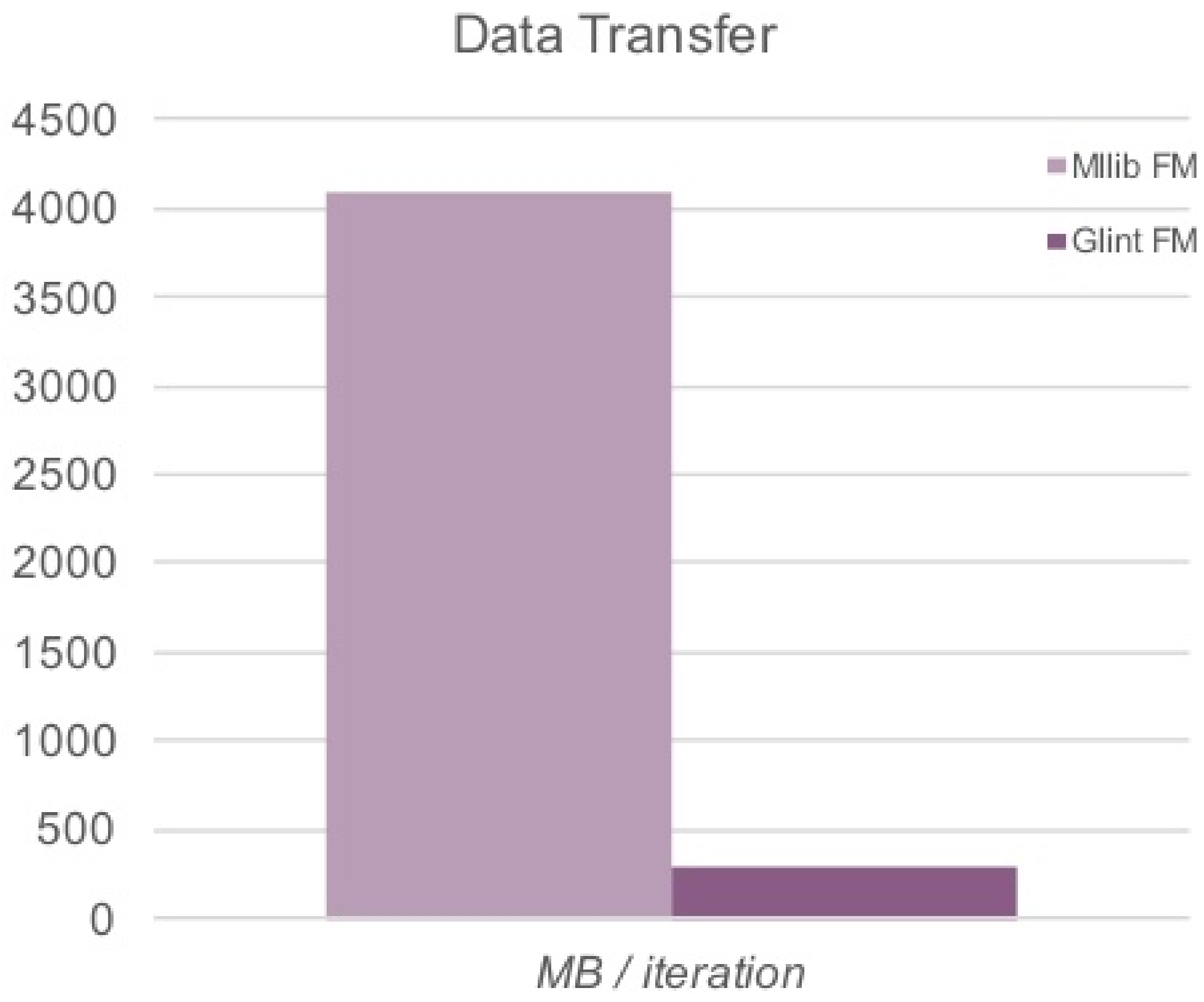
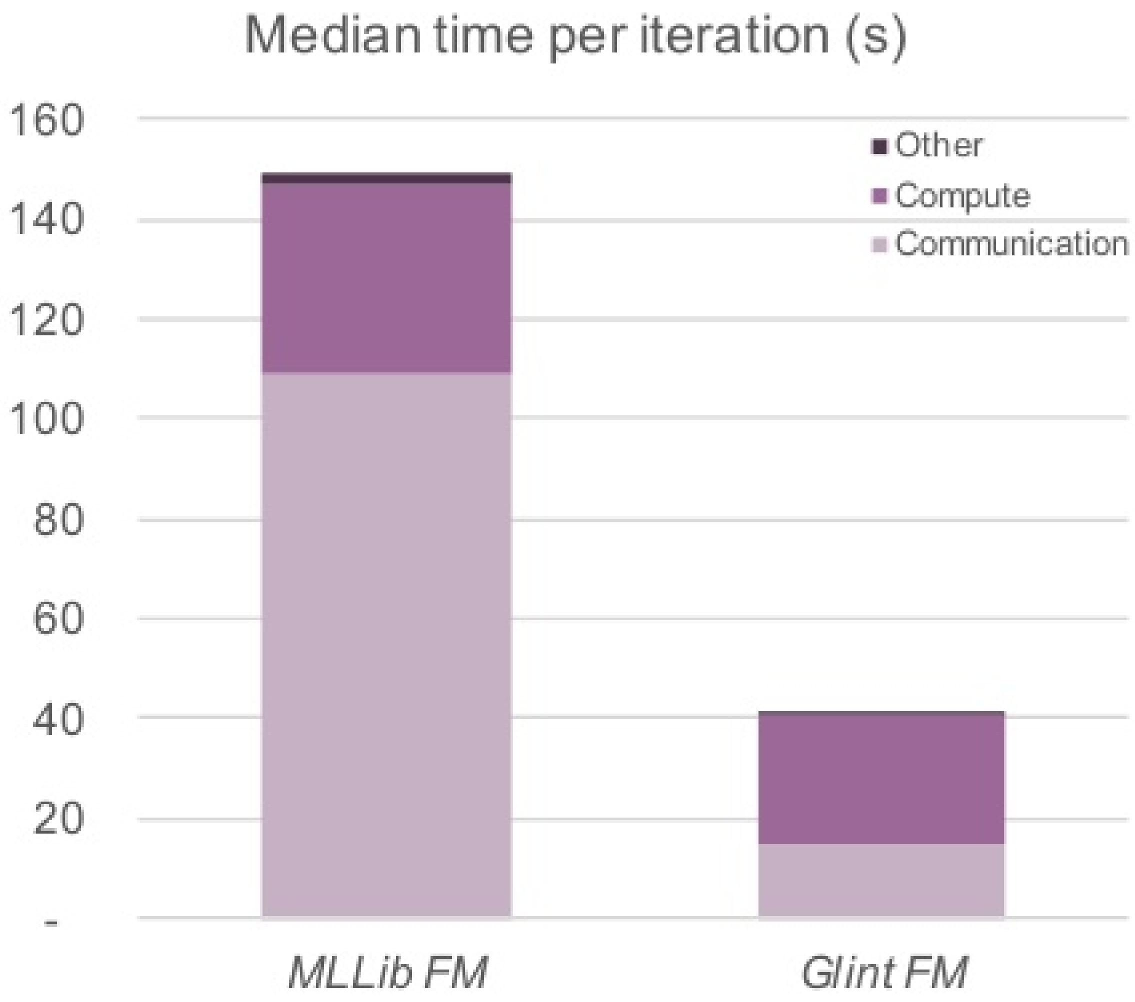
**k = 6, 10 iterations, 48 partitions, fit intercept*

Performance





**k = 6*, *10 iterations, 48 partitions, fit intercept*

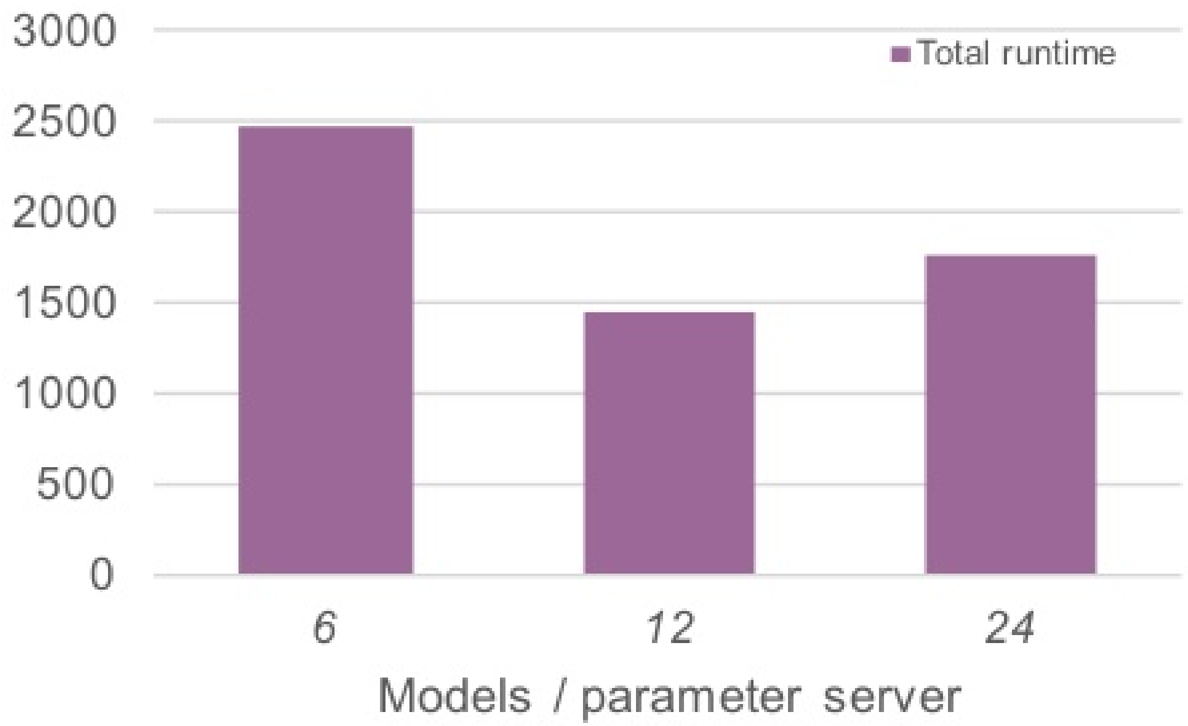
CHALLENGES & FUTURE WORK

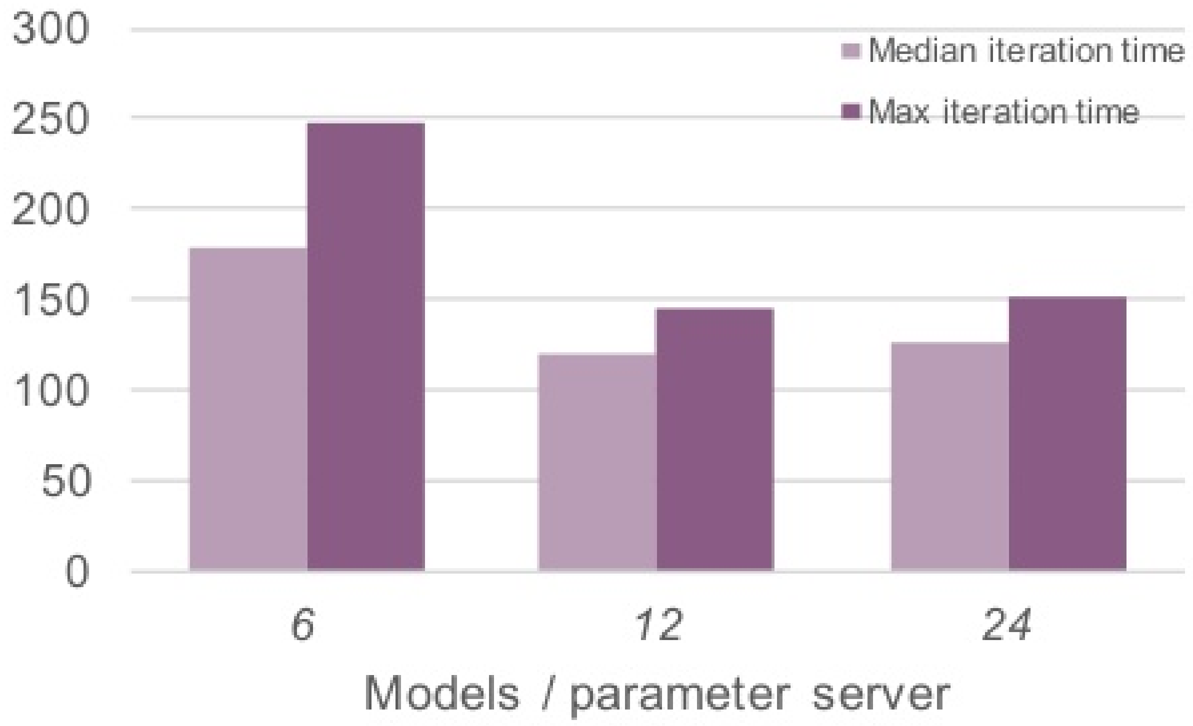
Challenges

- Tuning configuration
  - Glint - models/server, message size, Akka frame size
  - Spark - data partitioning (can be seen as “mini-batch” size)
- Lack of server-side processing in Glint
  - For L1 regularization, adaptive sparsity, Adagrad
  - These result in better performance, faster execution
- Backpressure / concurrency control

Challenges

- Tuning models / server

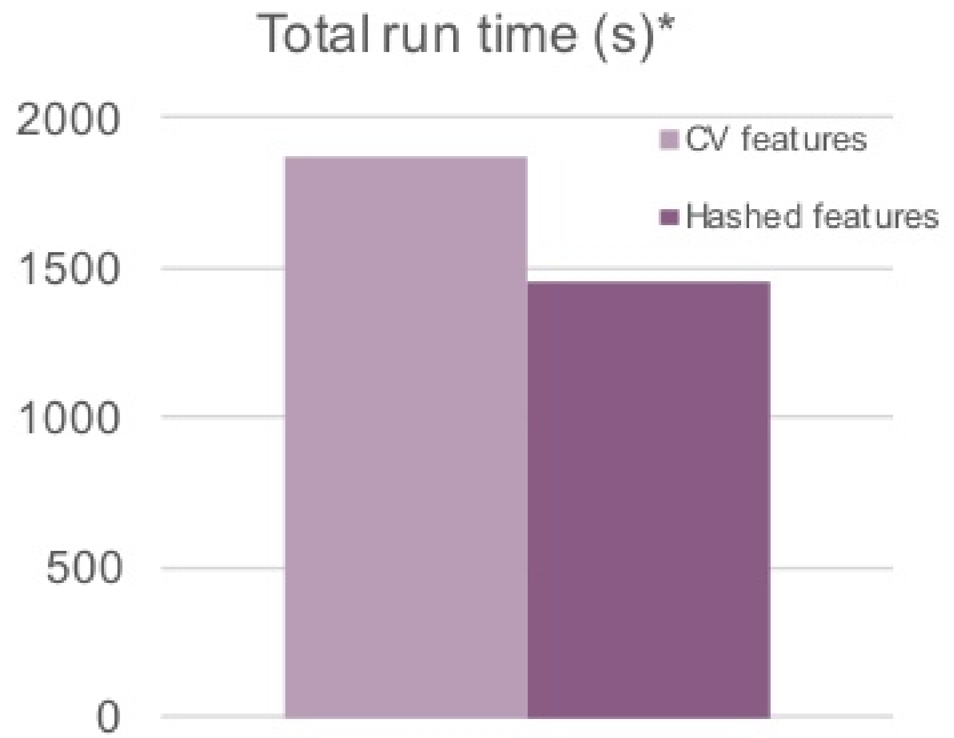




**k = 16, 10 iterations, 48 partitions, fit intercept*

Challenges

- Index partitioning for "hot features"
  - `CountVectorizer` for features leads to hot spots & straggler tasks due to sorting by occurrence
  - `OneHotEncoder` OOMed... but can also face this problem
  - Spreading out features is critical (used feature hashing)



*k = 16, 10 iterations, 48 partitions, fit intercept

Future Work

- Glint enhancements
  - Add features from DiFacto, i.e. L1 regularization, Adagrad & memory-adaptive *k*
  - Requires support for UDFs on the server
  - Built-in backpressure (Akka Artery / Streams?)
  - Key caching – 2x decrease in message size
- Mini-batch SGD within partitions
- Distributed solvers for ALS, MCMC, CD
- Relational data / block structure formulation
  - www.vldb.org/pvldb/vol6/p337-rendle.pdf

References

- Factorization Machines
  - http://www.csie.ntu.edu.tw/~b97053/paper/Rendle2010FM.pdf
  - https://github.com/ibayer/fastFM
  - www.libfm.org
  - https://github.com/zhengruifeng/spark-libFM
  - https://github.com/scikit-learn-contrib/polylearn
- DiFacto
  - https://github.com/dmlc/difacto
  - www.cs.cmu.edu/~yuxiangw/docs/fm.pdf
- Glint / parameter servers
  - https://github.com/rjagerman/glint
  - https://github.com/dmlc/ps-lite

THANK YOU.

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github.com/MLnick/glint-fm
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