Scal(a)ing up Machine Learning and Big Graph Analytics

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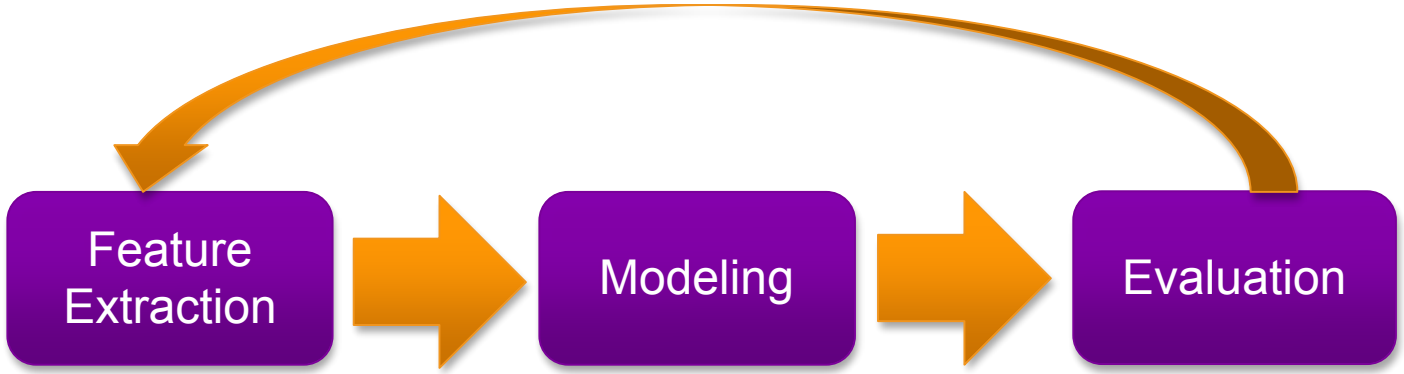
Develop a platform for Machine Learning and Graph analytics on a cluster of shared-nothing machines

- Programming environment
  - Specific to ML and Graph domain
- Data-parallel runtime
  - Supports ML and Graph analytic workflows

Characteristic Workflow for ML Analytics

- Feature Extraction
  - ETL workflow
- Modeling
  - Iterative algorithm that fits a model to the data
- Evaluation
  - Checks model fidelity



What is a Model?

- Global Model
  - Aggregate summary of all data points
  - Small in size compared to data set
  - e.g., regression, classification

- Local Model
  - Interdependent parameters for each data point
  - Size proportional to the data set
  - e.g., topic (graphical) models, clustering, PageRank

Outline

- Case Study
- Modeling in the Cloud
- Our work
- Project roadmap

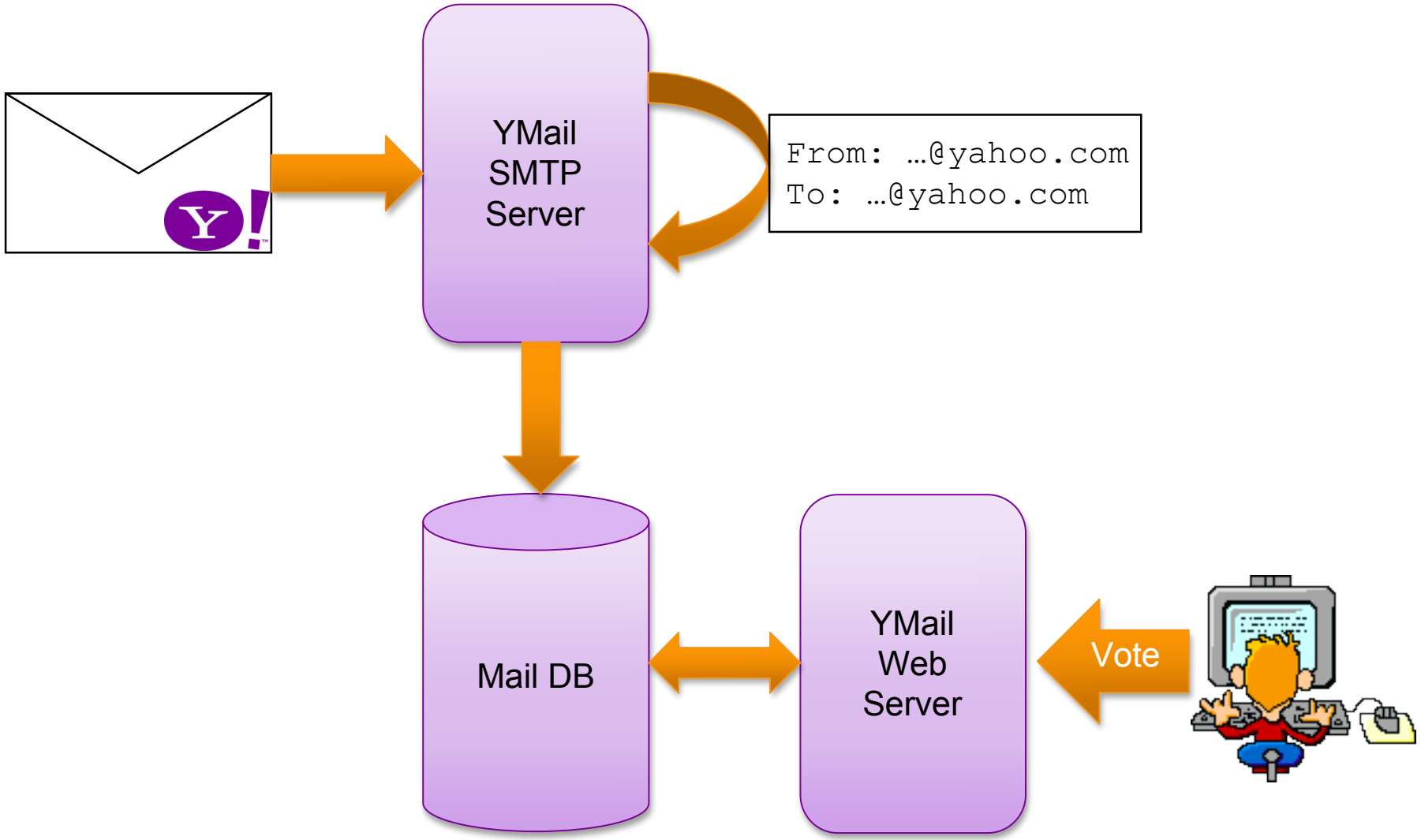
YAHOO! MAIL

Outbound Spam Filter for Yahoo! Mail

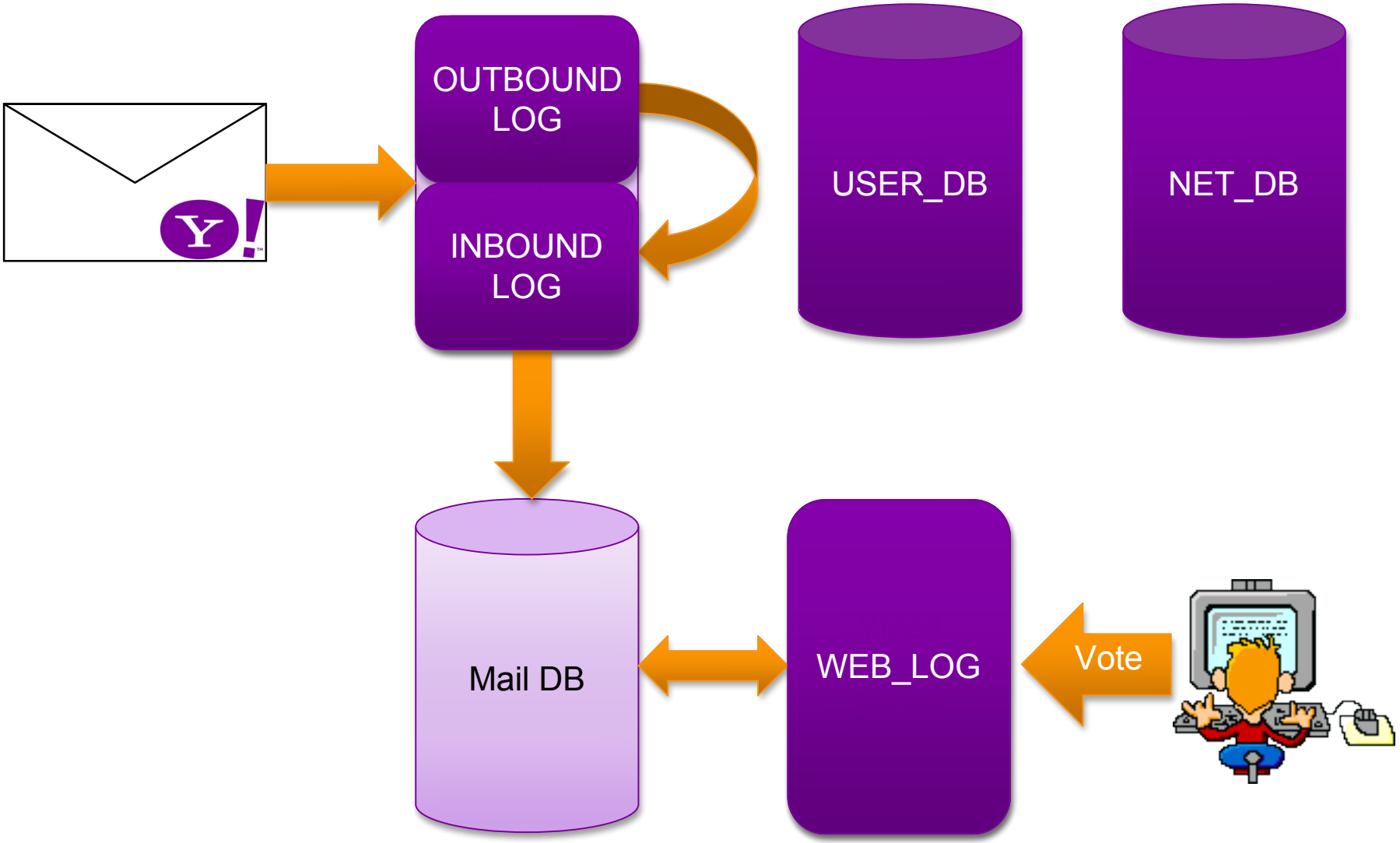
Ingredient: Client Classification

- **Goal:**
  - Train a spam classifier that can classify **outbound** messages
- **Problem:**
  - Other mail services won't tell us if our users send spam
- **Solution:**
  - Take the mail from Yahoo! to Yahoo! and observe how it was classified by our users

EMail Flow

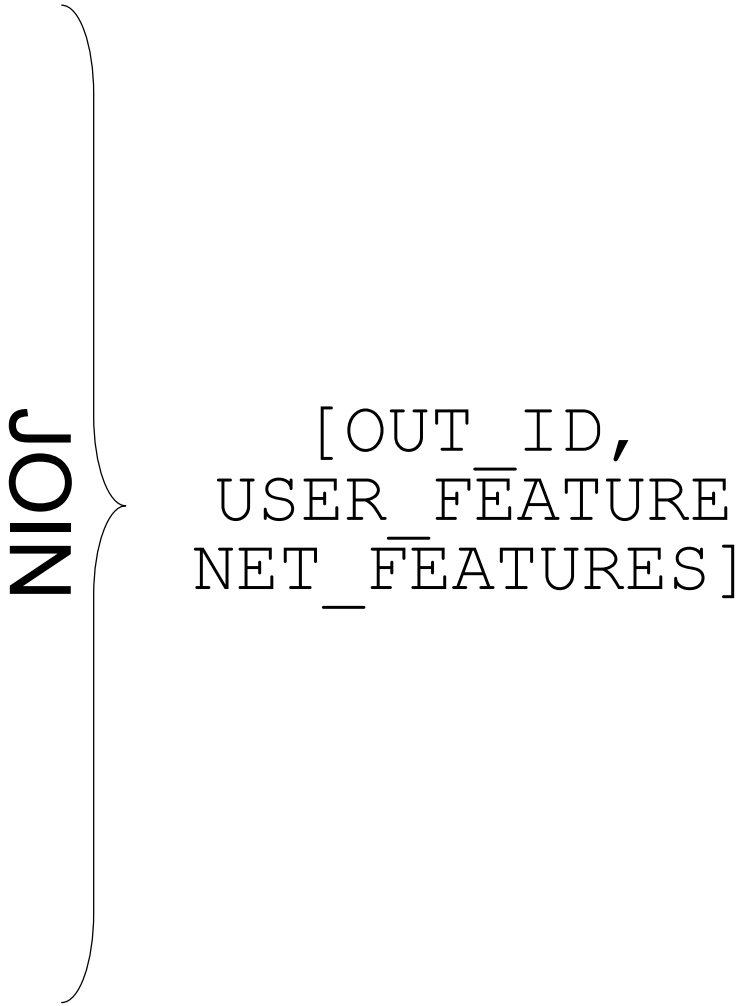

YMail
SMTP
Server
From: …@yahoo.com
To: …@yahoo.com
Mail DB
YMail
Web
Server
Vote

EMail Flow: Data Sets



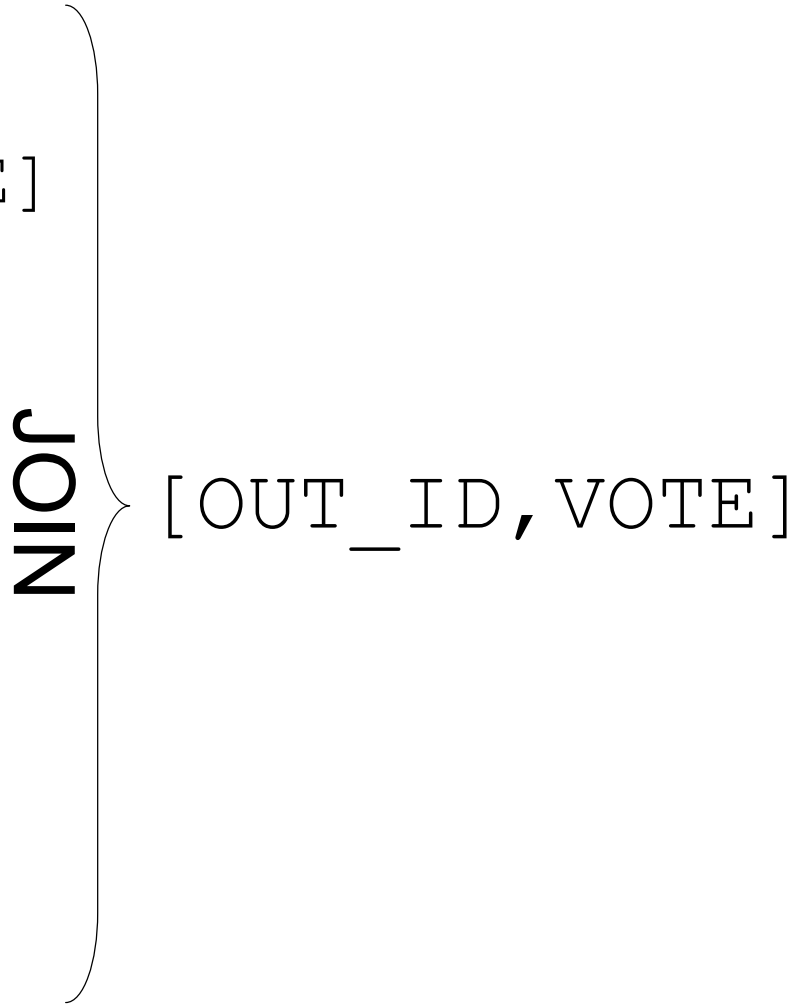
Step I Extract Features

- OUTBOUND_LOG
  - [OUT_ID, FROM, IP]
- USER_DB
  - [USER_ID, …]
- NET_DB
  - [IP, …]



Step II: Extract Labels

- OUTBOUND_LOG
  - [OUT_ID,FROM,TO,TIME]
- INBOUND_LOG
  - [IN_ID,FROM,TO,TIME]
- WEB_LOG
  - [IN_ID,VOTE]



Step II: Finding a Label

- OUTBOUND_LOG
  - [OUT_ID, **FROM, TO, TIME**]
- INBOUND_LOG
  - [IN_ID, **FROM, TO, TIME**]
- WEB_LOG
  - [IN_ID, VOTE]

JOIN

This needs a fuzzy join

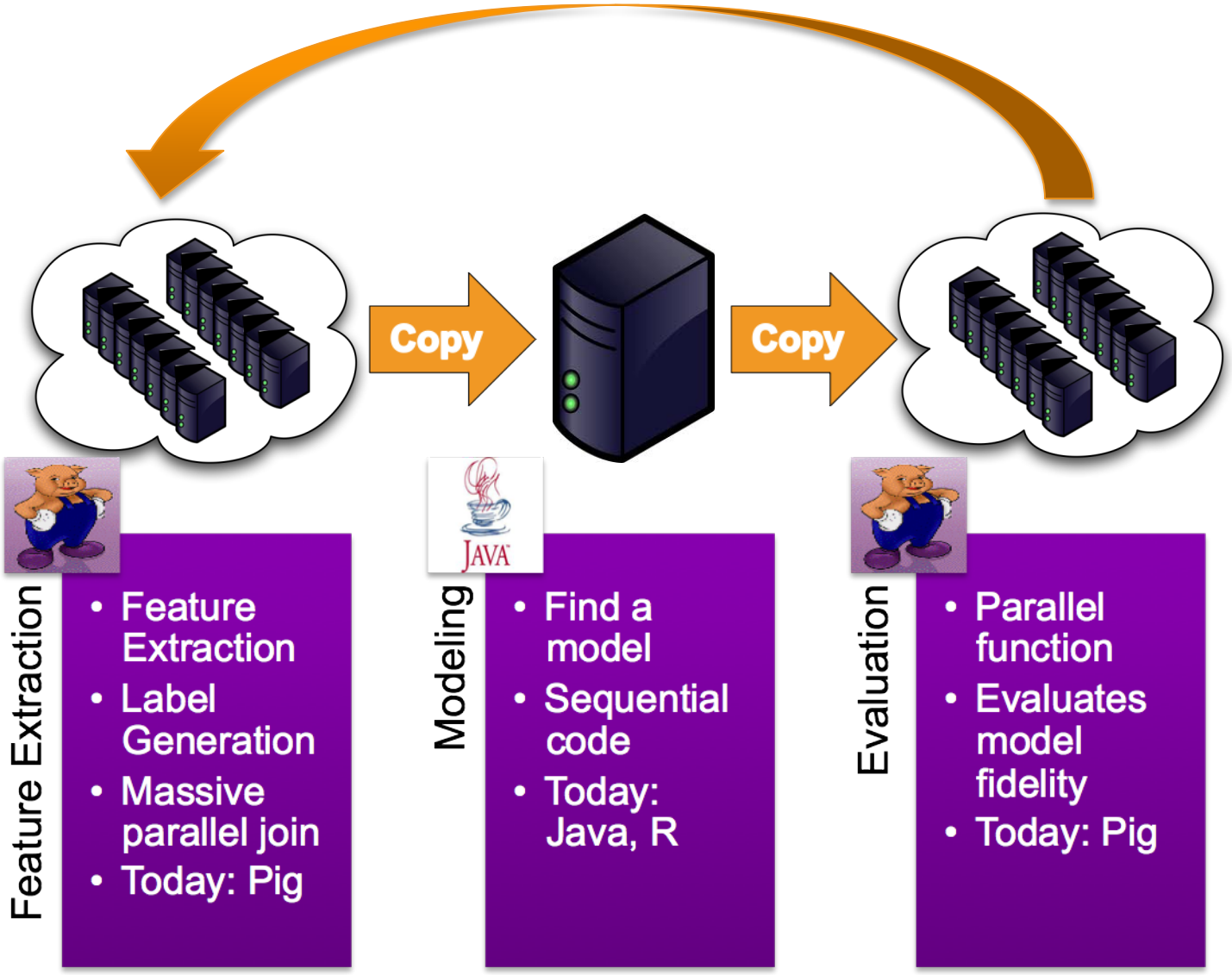
Step III: Creating the training data

- JOIN labels and features
- **Subsample** the training data
- Copy to a single machine

Step IV: Training the model

- Until a satisfactory model is found:
  - Train the model using sequential code
  - Evaluate the found model in Pig again
  - Apply insights to feature extraction, label generation and learning algorithm

Recap


Copy
Copy
Feature Extraction
• Feature Extraction
• Label Generation
• Massive parallel join
• Today: Pig
Modeling
• Find a model
• Sequential code
• Today: Java, R
Evaluation
• Parallel function
• Evaluates model fidelity
• Today: Pig

Take-Away

- **Usability is bad** (took an intern 3 months)
  - Many tools and technologies needed
  - Fractured workflow, captured in e.g. Oozie

- **Subpar solution**
  - Subsampling hurts classifier fidelity
  - Copying data to a single machine is slow

Now: Parallelize the middle

Feature Extraction

- Feature Extraction
- Label Generation
- Massive parallel join
- Today: Pig

Modeling

- Find a model
- Iterative data-parallel plan
- Cluster of machines
- Today: Hadoop

Evaluation

- Parallel function
- Evaluates model fidelity
- Today: Pig

What do people do?

- **Gradient Boosted Decision Trees**
  - Popular non-linear modeling algorithm
  - Used in Yahoo! search engine to learn the ranking function

- **Gradient Descent**
  - A method for minimizing objective functions
  - Written as a sum of differentiable functions

- **Latent Dirichlet Allocation (LDA)**
  - Example of a topic model
  - Usually expressed via Graphical Model

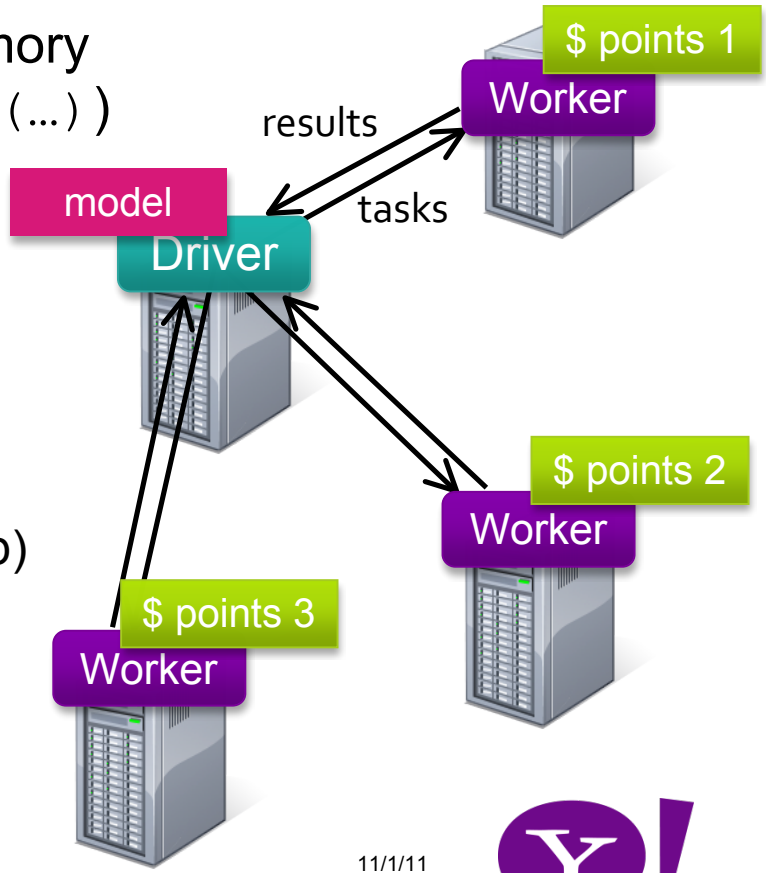
What do people do?

- **Gradient Boosted Decision Trees**
  - Popular non-linear modeling algorithm
  - Used in Yahoo! search engine to learn the ranking function
  - **Solution: Fake mappers that implement MPI**
- **Gradient Descent**
  - A method for minimizing objective functions
  - Written as a sum of differentiable functions
  - **Solution: Fake mappers that run aggregation trees**
- **Latent Dirichlet Allocation (LDA)**
  - Example of a topic model
  - Usually expressed via Graphical Model
  - **Solution: Fake mappers that implement this graphical model**

Framework I (Global Models): Spark

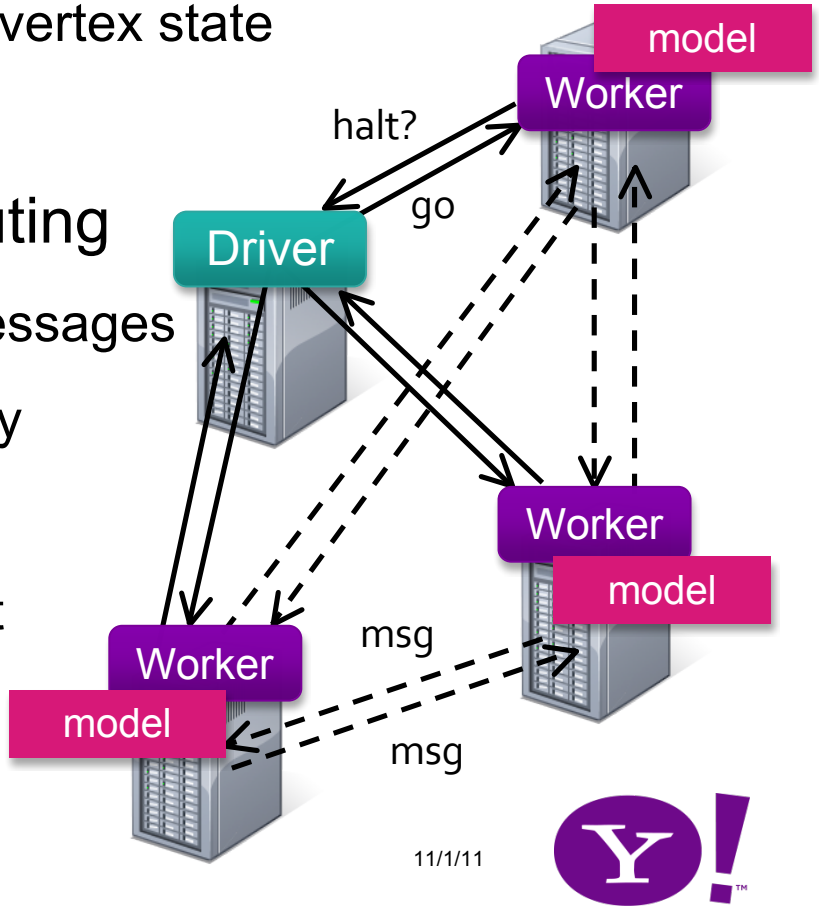
- Data Model: Resilient Distributed Datasets
  - Support for hash and range partitioning
  - Transformations or Actions can be added to them
  - The results can be materialized in memory (`RDD.cache()`) or to disk (`RDD.save(…)`)
- Caching allows fast iteration

```
points.cache()
var w = Vector.random(D)
for (i <- 1 to ITERATIONS) {
  val gradient = points.map { p => f(p, w) }
                       .reduce ((a, b) => a + b)
  w -= gradient
}
```



Framework II (Local Models): Pregel

- Graph-oriented API
  - UDF that implements single vertex update
  - Input messages from neighboring vertices
  - Output: outgoing messages and new vertex state
- Bulk synchronous parallel computing
  - Runtime executes all vertices with messages
  - Model updated and cached in memory
  - Checkpoint for fault-tolerance
  - Continues until everyone votes to halt

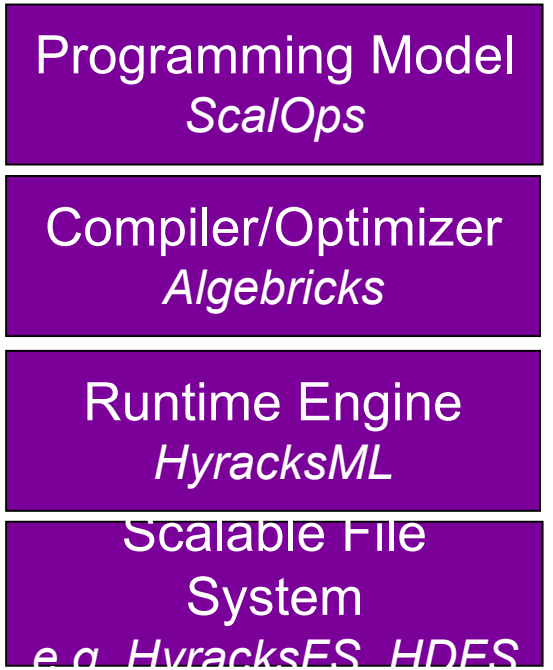


Framework: Pros/Cons

- **Pros**
  - Adds the notion of a working set for fast iterations
  - Exports a clean API specific to the problem domain
  - Abstracts (many) low-level implementation details

- **Cons**
  - Point solutions that mainly focus on modeling
  - Limited optimization support
  - No external memory operators

ScalOps + HyracksML



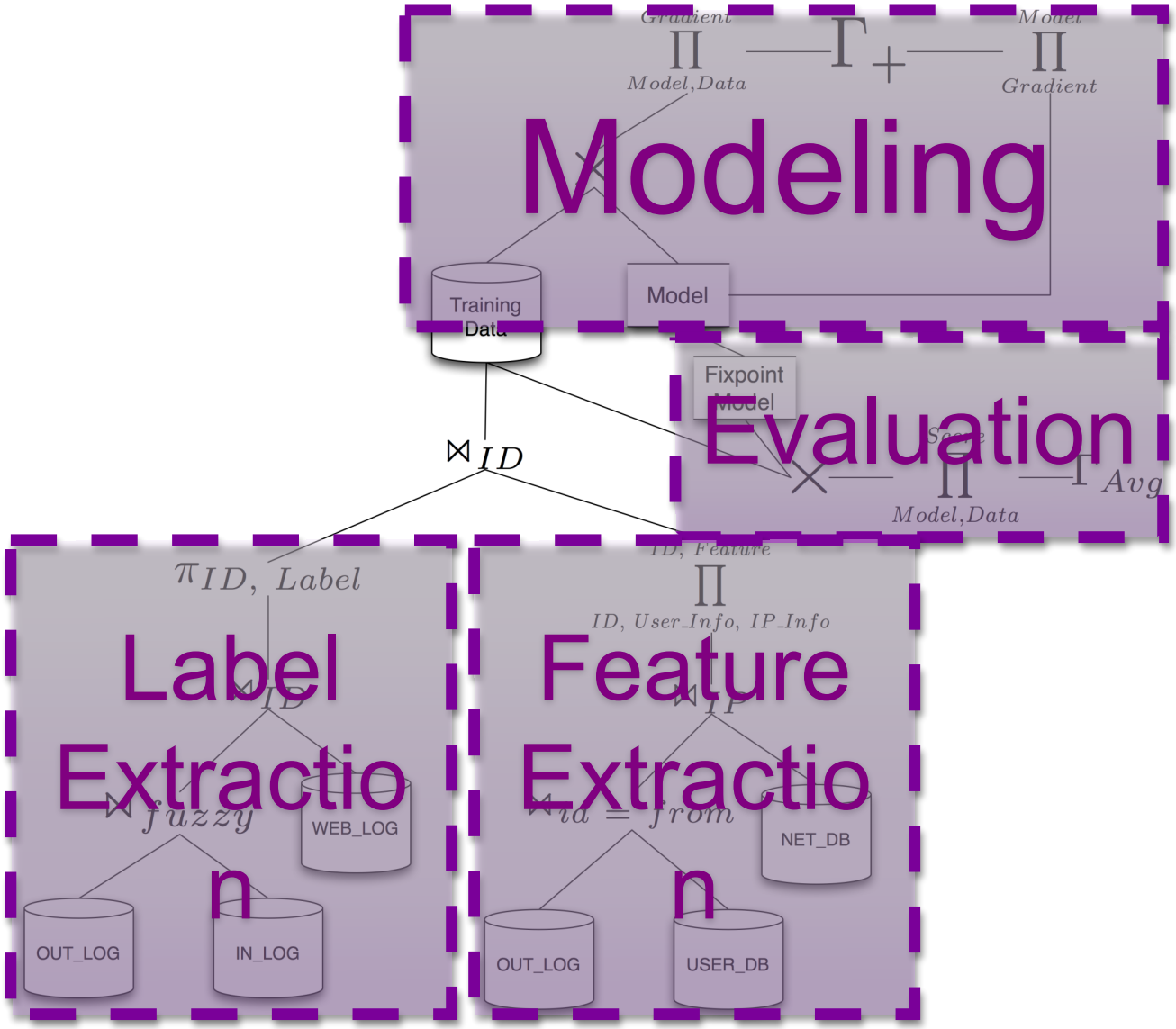
- ScalOps
  - Scala DSL for the entire analytic pipeline
  - Supports Pig Latin
  - Looping construct that captures iteration

- HyracksML + Algebricks
  - Data-parallel runtime that runs on a cluster of shared-nothing machines
  - Deductive database extensions to directly support iteration
  - Relational algebra and query optimizer that captures the entire workflow

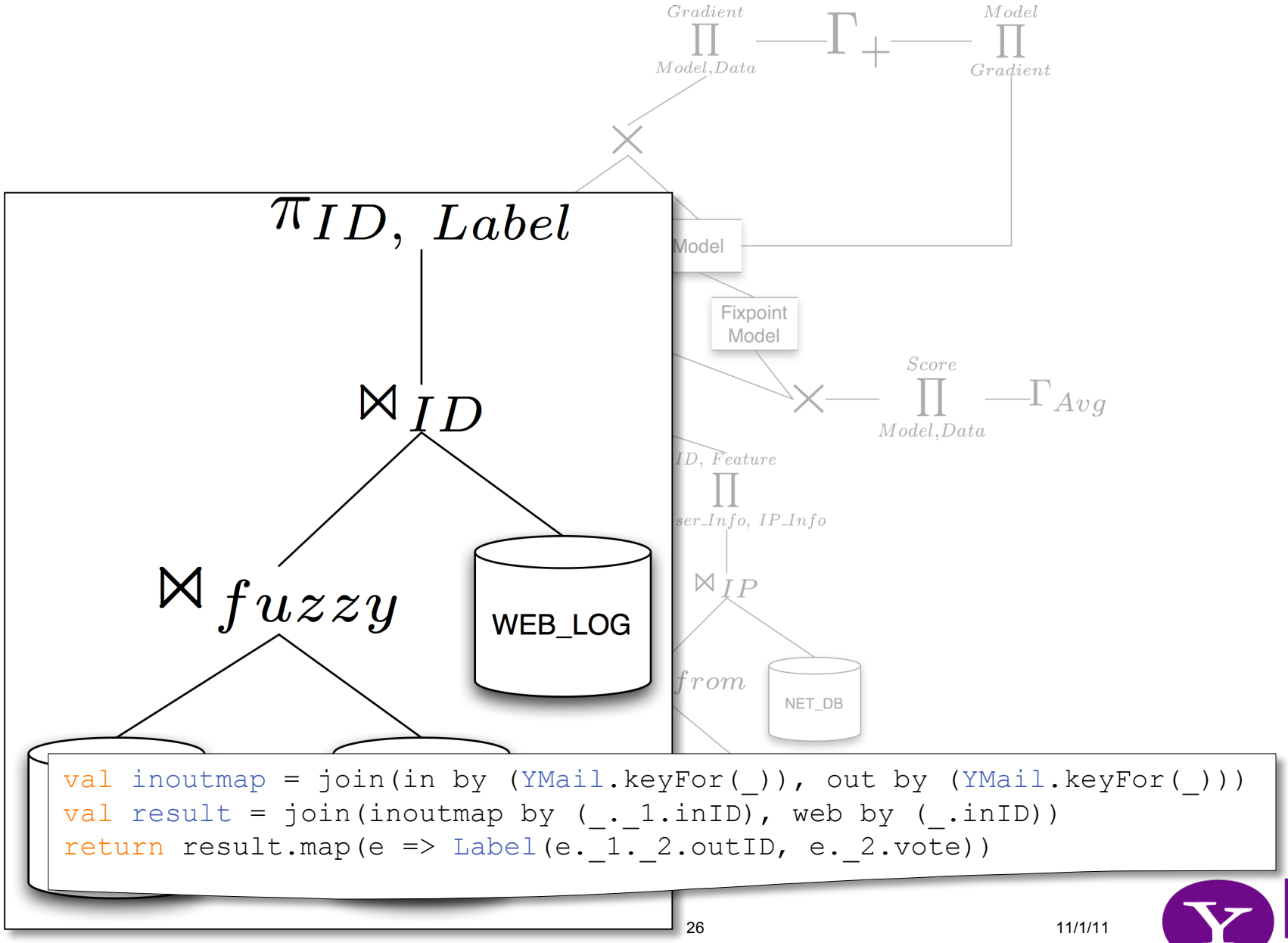
Spam Filter: ScalOps

```
object OutboundSpamFilter extends Query {

  // Join Targets
  case class Features(outID: String, features: Vector)
  case class Label(outID: String, label: Double)

  def getLabels(inboundLogs: Queryable[YMail.InboundRecord], outboundLogs: Queryable[YMail.OutboundRecord], webLogs: Queryable[YMail.WebRecord]) =
{
    val inoutmap = join(inboundLogs by (YMail.keyFor(_)), outboundLogs by (YMail.keyFor(_)))
    join(inoutmap by (_._1.inID), webLogs by (_.inID)).map(e => Label(e._1._2.outID, e._2.vote))
  }

  def getFeatures(outboundLogs: Queryable[YMail.OutboundRecord], userDB: Queryable[YMail.User], netDB: Queryable[YMail.IP]) = {
    case class IPInformation(outID: String, ipInfo: YMail.IP)
    case class UserInformation(outID: String, userInfo: YMail.User)
    val users = join(outboundLogs by (_.from), userDB by (_.id)).map(e => UserInformation(e._1.outID, e._2))
    val ips = join(outboundLogs by (_.ip), netDB by (_.ip)).map(e => IPInformation(e._1.outID, e._2))
    join(outboundLogs by (_.outID), users by (_.outID), ips by (_.outID)).map(e => Features(e._1.outID, YMail.extractFeatures(e._1, e._2.userInfo,
e._3.ipInfo)))
  }

  def run {
    val inboundLogs = load[YMail.InboundRecord]("hdfs://ymail/inbound.dat").filter(YMail.isYMail)
    val outboundLogs = load[YMail.OutboundRecord]("hdfs://ymail/outbound.dat").filter(YMail.isYMail)
    val webLogs = load[YMail.WebRecord]("hdfs://ymail/web.dat")
    val userDB = load[YMail.User]("hdfs://y/users.dat")
    val netDB = load[YMail.IP]("hdfs://y/network.dat")

    // Extract labels
    val labels = getLabels(inboundLogs, outboundLogs, webLogs)

    // Extract Features
    val features = getFeatures(outboundLogs, userDB, netDB)

    // Assemble a dataset
    val dataset = join(labels by (_.outID), features by (_.outID)).map(e => new Example(e._1.outID, e._1.label, e._2.features))

    // Train a model
    val model = ML.train(dataset)

    // Evaluate
    val score = dataset.map(ML.evaluate(model, _)).reduce(_ + _) / dataset.count

  }

}
```


Spam Filter: Hyracks RQ

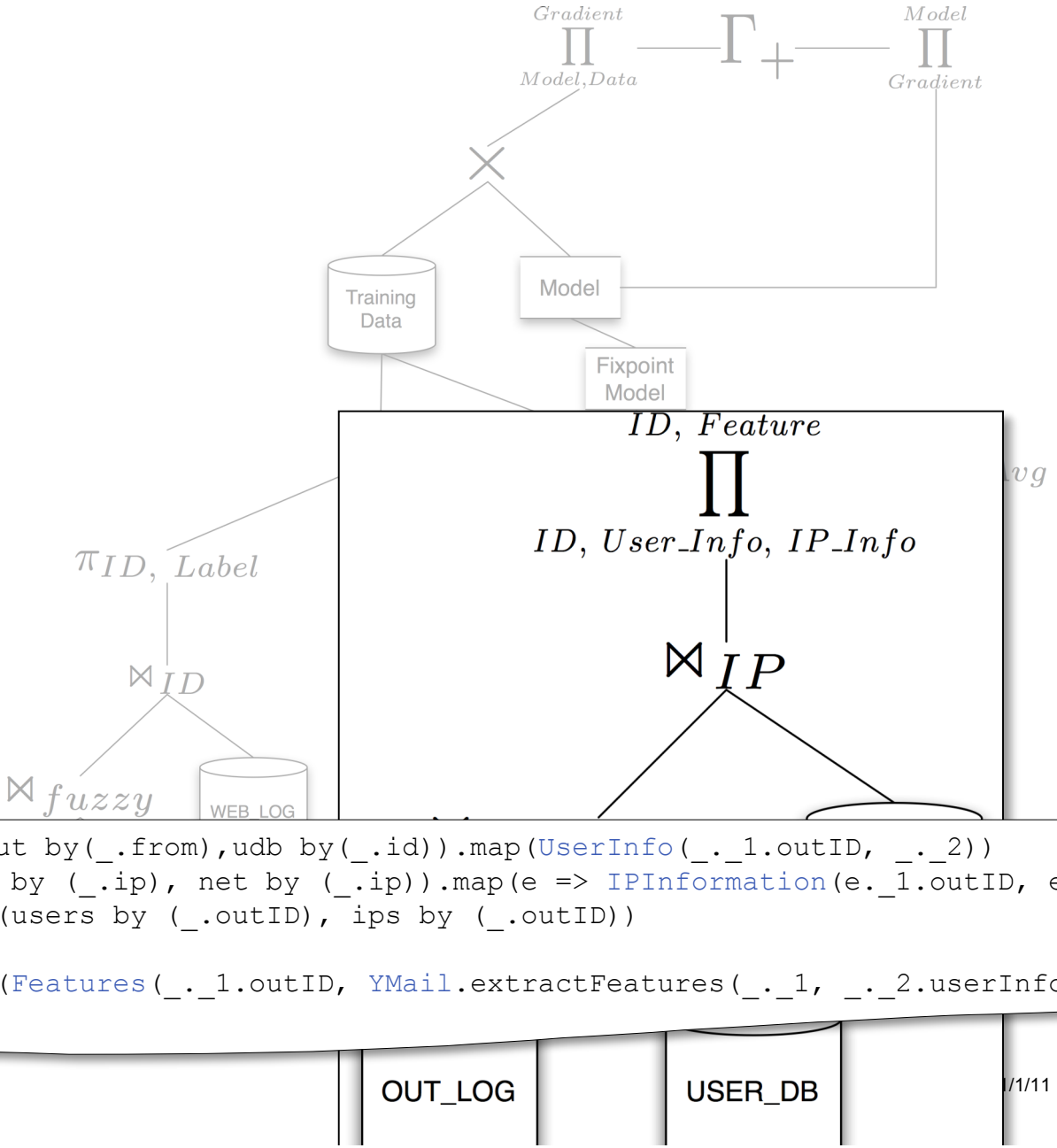


Spam Filter: Label Extraction



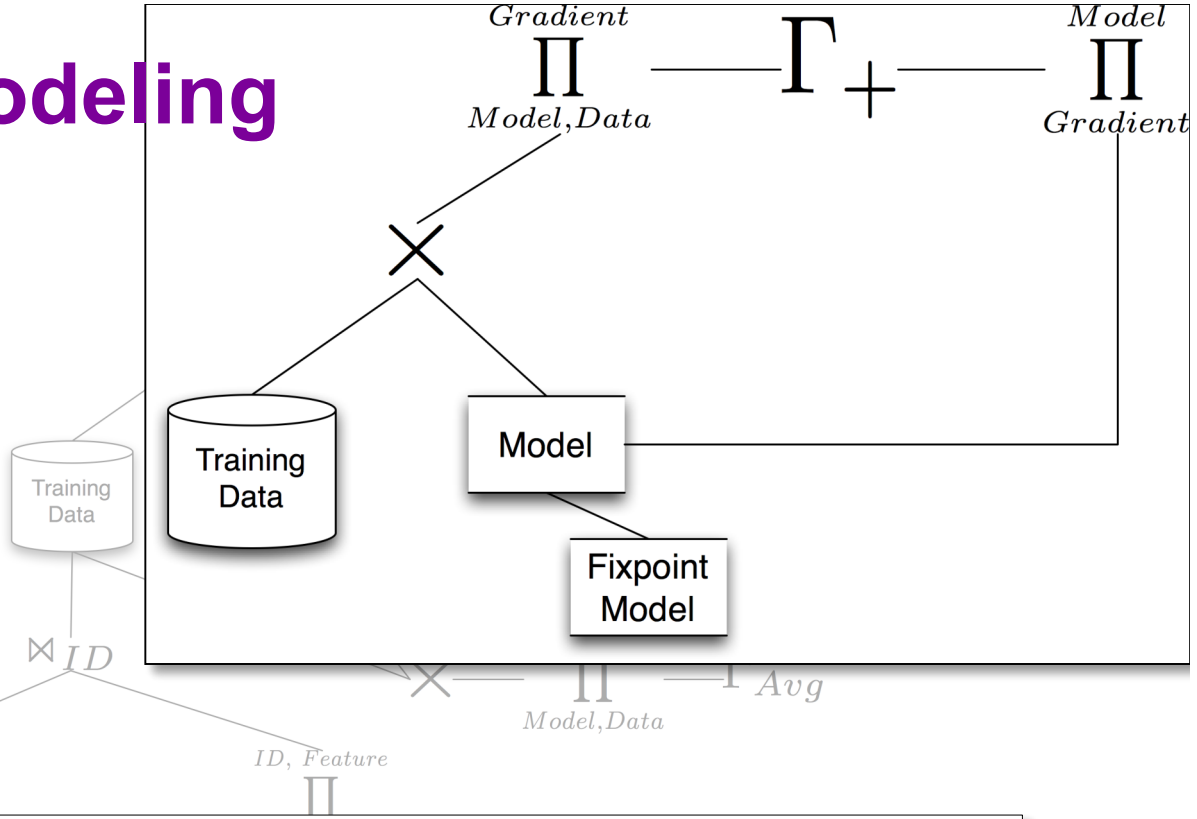

```
val inoutmap = join(in by (YMail.keyFor(_)), out by (YMail.keyFor(_)))
val result = join(inoutmap by (_._1.inID), web by (_.inID))
return result.map(e => Label(e._1._2.outID, e._2.vote))
```

Spam Filter: Feature Extraction



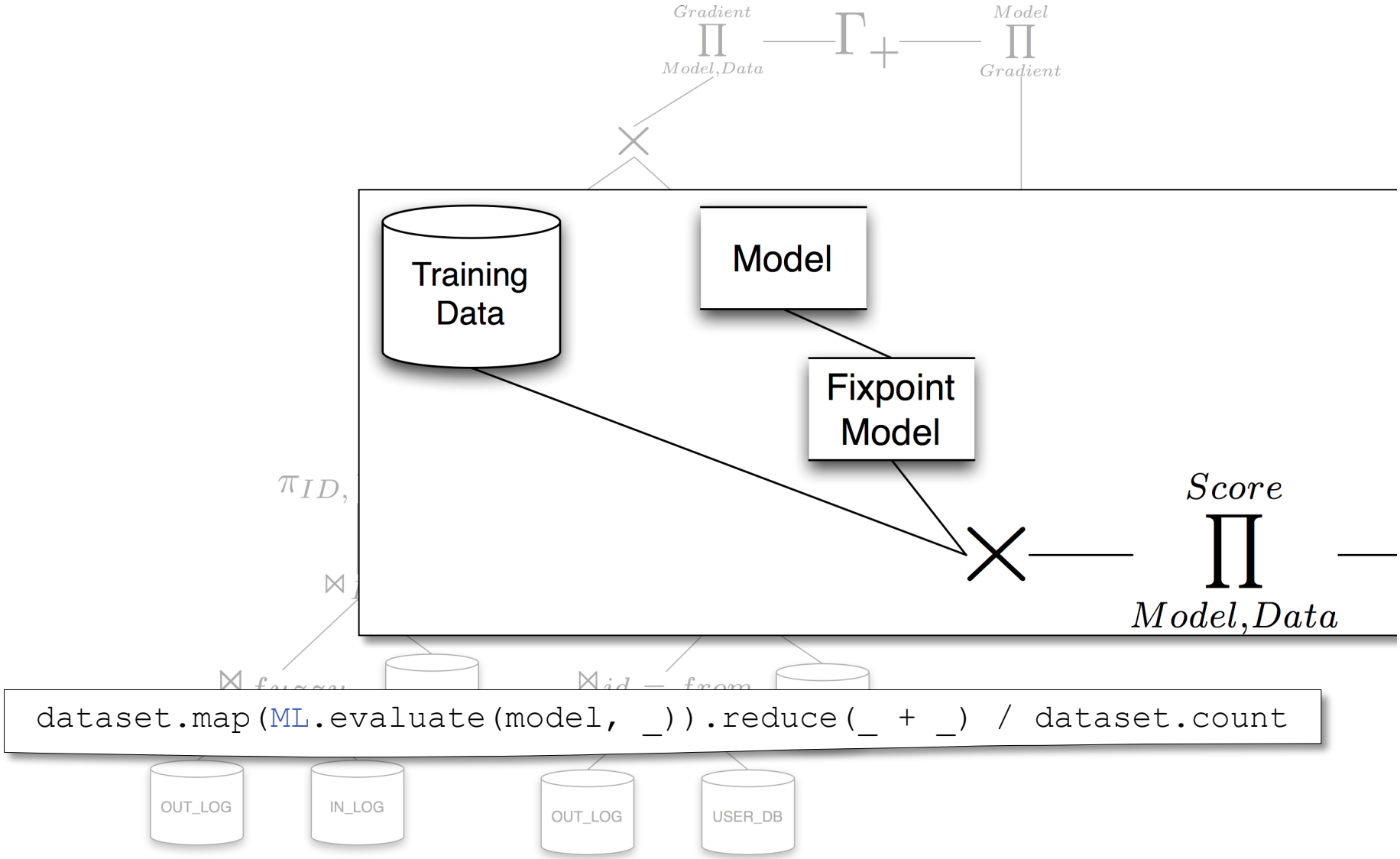

```
val users = join(out by(_.from),udb by(_.id)).map(UserInfo(_._1.outID, _._2))
val ips = join(out by (_.ip), net by (_.ip)).map(e => IPInformation(e._1.outID, e._2))
val results = join(users by (_.outID), ips by (_.outID))

return results.map(Features(_._1.outID, YMail.extractFeatures(_._1, _._2.userInfo, _._3.ipInfo)))
```

Spam Filter: Modeling




```
class MyModel(w: VectorType, funcValue: DoubleType) extends Model
val init = new MyModel(VectorType.zeros(1000), Double.MaxValue)
val result = loop(init, (mdl: Model) => mdl.funcValue > eps) { mdl =>
  val gradients = data.map(x => computeGradient(x, mdl))
  mdl.funcValue = gradients.map(x => x._1).reduce(_+_)
  mdl.funcValue += lambda * env.w.norm2
  mdl.w -= gradients.map(x => x._2).reduce(_+_) / gradients.count
  mdl.w *= (1.0 - 0.5 * lambda)
  mdl
}
return result
```

Spam Filter: Evaluation



Conclusion: Target Algorithms

- **Linear Models**
  - Batch Gradient Descent
  - Stochastic Gradient Descent
  - Logistic Regression
- **Clustering**
  - K-Means
- **Matrix Factorization**
- **Graph Analysis**
  - PageRank
  - LDA (Graphical Models)

Coming Attractions

- Recursive data-parallel runtime (HyracksML)
  - Deductive Databases, BOOM, Flying Fixed-Point

   Yingyi Bu and Joshua Rosen
- Extended Relational Algebra (Algebricks)
  - Captures the entire workflow in an optimizer friendly representation

   Vinayak Borkar
- High-level language (ScalOps)
  - Abstractions for Machine learning and Graph-based algorithms

   Markus Weimer

- Executive Producers

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