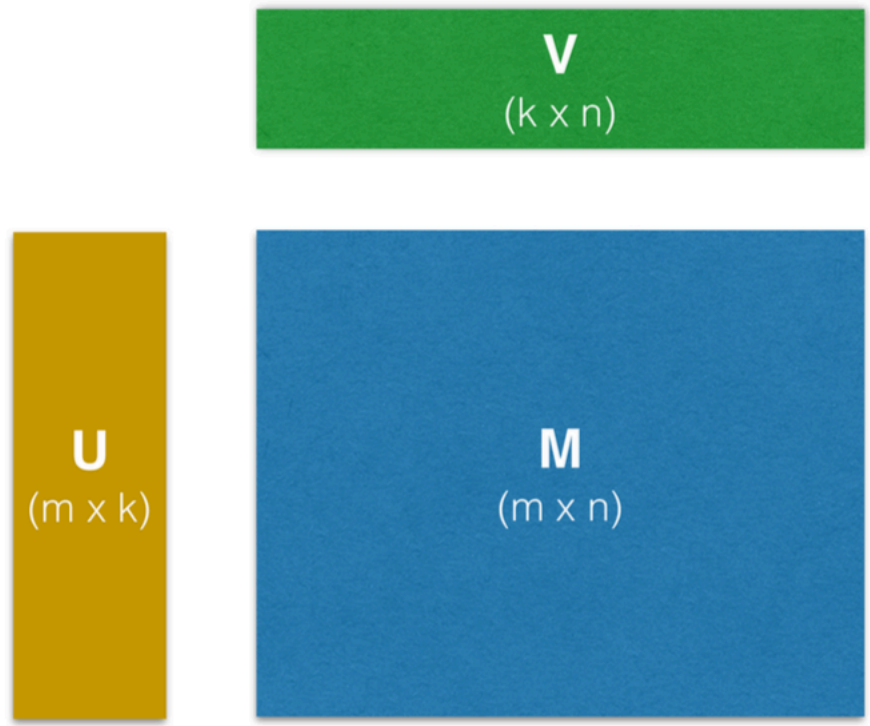
Factorbird: a Parameter Server Approach to Distributed Matrix Factorization

Sebastian Schelter, Venu Satuluri, Reza Zadeh

Distributed Machine Learning and Matrix Computations workshop in conjunction with NIPS 2014

Latent Factor Models

- Given M
  - sparse
  - n x m
- Returns U and V
  - rank k
- Applications
  - Dimensionality reduction
  - Recommendation
  - Inference



Seem familiar?

$$\min_{U,V} \sum_{(i,j)\in M} (m_{ij} - u_i^T v_j)^2 + \lambda \left(\|u_i\|^2 + \|v_j\|^2 \right)$$

- So why not just use SVD?

Problems with SVD

- (Feb 24, 2015 edition)

More detail....

$$M = \begin{pmatrix} 1 & 2 & \cdots & d \\ 2 & 3 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ d & 1 & \cdots & d-1 \end{pmatrix}$$

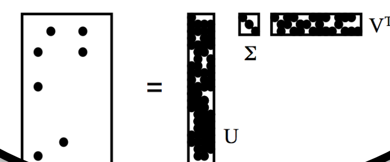
- Initialize W,H randomly
  - not at zero ☺
- Choose a random ordering (random sort) of the points in a stratum in each "sub-epoch"
- Pick strata sequence by permuting rows and columns of M, and using M'[k,i] as column index of row i in subepoch k
- Use "bold driver" to set step size:
  - increase step size when loss decreases (in an epoch)
  - decrease step size when loss increases
- Implemented in Hadoop and R/Snowfall

SVD: Drawbacks

\+ Optimal low-rank approximation in terms of Frobenius norm

\- Interpretability problem:
- A singular vector specifies a linear combination of all input columns or rows

\- Lack of sparsity:
- Singular vectors are dense!



Revamped loss function

- g – global bias term
- $b^U{}_i$ – user-specific bias term for user i
- $b^V{}_j$ – item-specific bias term for item j
- prediction function

$$p(i,j) = g + b^U{}_i + b^V{}_j + u^T{}_i v_j$$

- $a(i,j)$ – analogous to SVD's m_{ij} (ground truth)

- New loss function:

$$\min_{g,b^U,b^V,U,V} \frac{1}{2}\left(\sum_{i,j\in M} w(i,j)(p(i,j)-a(i,j))^2\right) + \frac{\lambda}{2}\left(g^2 + \|b^U\|^2 + \|b^V\|^2 + \|U\|_F^2 + \|V\|_F^2\right)$$

Algorithm

Algorithm 1: Matrix Factorization using SGD.

randomly initialize U and V

while *not converged* **do**

  randomly pick edge (i, j)

  `// compute weighted prediction error`

  $e_{ij} \leftarrow w(i,j)(a(i,j) - p(i,j))$

  `// update biases`

  $g \leftarrow g - \eta\,(e_{ij} + \lambda g)$

  $b_i^U \leftarrow b_i^U - \eta \left(e_{ij} + \frac{\lambda}{n_i} b_i^U \right)$

  $b_j^V \leftarrow b_j^V - \eta \left(e_{ij} + \frac{\lambda}{n_j} b_j^V \right)$

  `// update factors`

  $u_i \leftarrow u_i - \eta \left(e_{ij}\; v_j + \frac{\lambda}{n_i} u_i \right)$

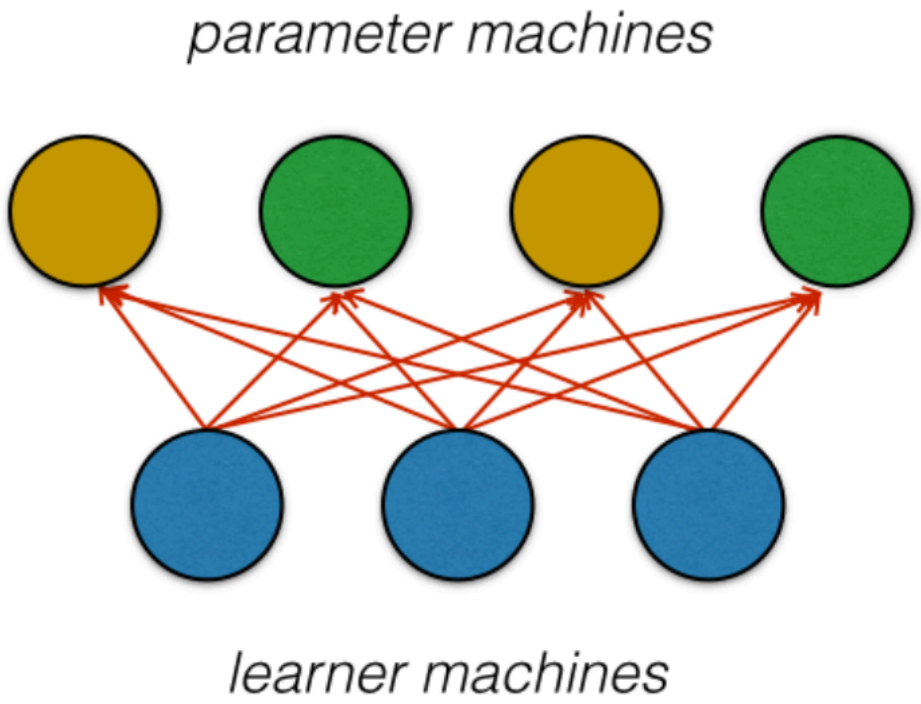
  $v_j \leftarrow v_j - \eta \left(e_{ij}\; u_i + \frac{\lambda}{n_j} v_j \right)$

Problems

1. Resulting U and V, for graphs with millions of vertices, still equate to hundreds of gigabytes of floating point values.
2. SGD is inherently sequential; either locking or multiple passes are required to synchronize.

Problem 1: size of parameters

- Solution: Parameter Server architecture



Problem 2: simultaneous writes

- Solution: *...so what?*

HOGWILD!: A Lock-Free Approach to Parallelizing Stochastic Gradient Descent

Feng Niu
leonn@cs.wisc.edu

Benjamin Recht
brecht@cs.wisc.edu

Christopher Ré
chrisre@cs.wisc.edu

Stephen J. Wright
swright@cs.wisc.edu
Computer Sciences Department
University of Wisconsin-Madison
Madison, WI 53706

Algorithm 1 HOGWILD! update for individual processors

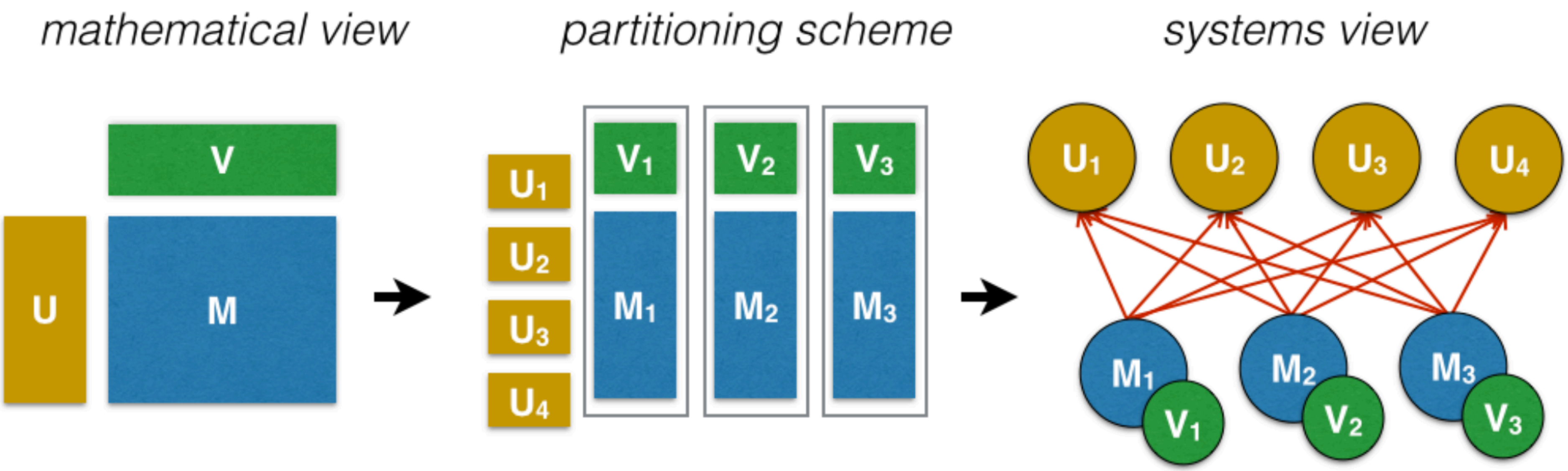
loop
    Sample e uniformly at random from E
    Read current state x_e and evaluate $G_e(x_e)$
    for $v \in e$ **do** $x_v \leftarrow x_v - \gamma G_{ev}(x_e)$
end loop

Lock-free concurrent updates?

- Assumptions

1. f is **Lipshitz continuously differentiable**
2. f is **strongly convex**
3. Ω (size of hypergraph) is **small**
4. Δ (fraction of edges that intersect any variable) is **small**
5. ρ (sparsity of hypergraph) is **small**

Factorbird Architecture

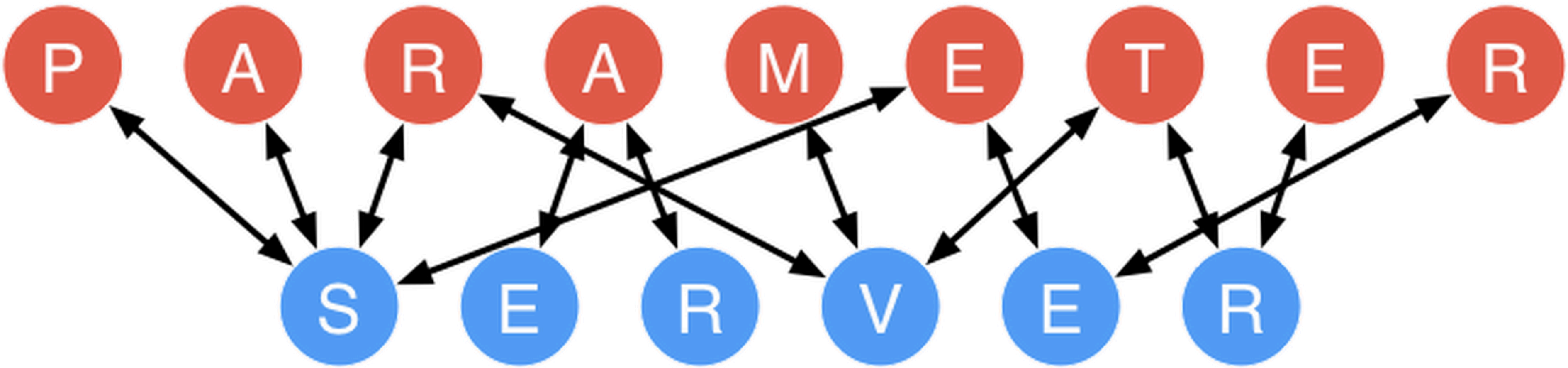


Co-partition M and V according to the number of learner machines

Co-locate partitions of M and V on learner machines

Parameter server architecture

- Open source!
  - http://parameterserver.org/



Factorbird Machinery

- memcached – Distributed memory object caching system
- finagle – Twitter's RPC system
- HDFS – persistent filestore for data
- Scalding – Scala front-end for Hadoop MapReduce jobs
- Mesos – resource manager for learner machines

Factorbird stubs

```scala
trait Learner {
  def initialize(factors: FactorVector): Unit
  def update(u_i: FactorVector, v_j: FactorVector,
             a_ij: Float, n_i: Int, n_j: Int, w_ij: Float): Float
}
```

```scala
trait Predictor {
  def predict(u_i: FactorVector, v_j: FactorVector): Float
}
```

```scala
trait LossEstimator {
  def estimateRegularizationComponent(
    numRowsOfU: Int, sampleOfU: Iterator[FactorVector],
    numColumnsOfV: Int, sampleOfV: Iterator[FactorVector]): Double

  def estimateErrorComponent(numEdges: Long,
    sampleOfEdges: Iterator[Edge], partitionOfU: FactorMatrix,
    partitionOfV: FactorMatrix): Double
}
```

Model assessment

- Matrix factorization using RMSE
  - Root-mean squared error

$$\operatorname{RMSD}(\hat{\theta}) = \sqrt{\operatorname{MSE}(\hat{\theta})} = \sqrt{\operatorname{E}((\hat{\theta} - \theta)^2)}.$$

- SGD performance often a function of hyperparameters
  - λ: regularization
  - η: learning rate
  - k: number of latent factors

[Hyper]Parameter grid search

- aka "parameter scans:" finding the optimal combination of hyperparameters
  - Parallelize!

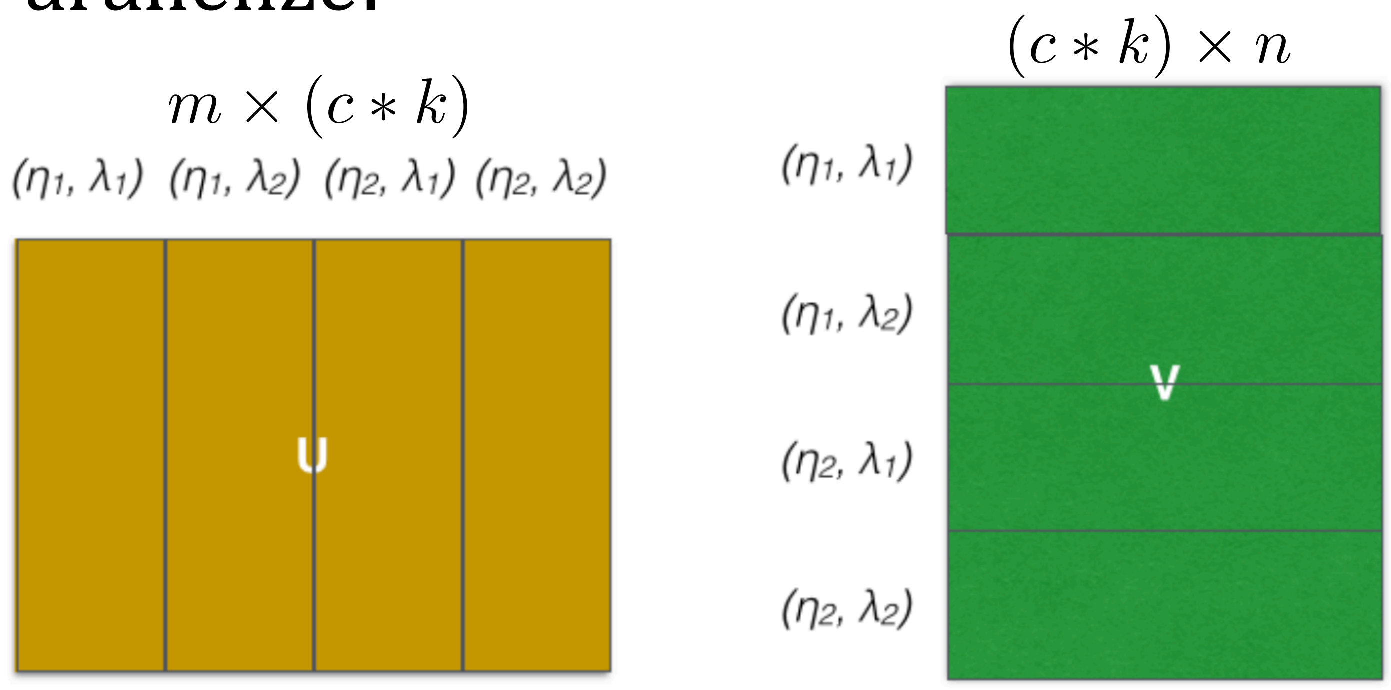


Figure 4: Packing many models into one for hyperparameter search.

Experiments

- "RealGraph"
  - Not a dataset; a framework for creating graph of user-user interactions on Twitter

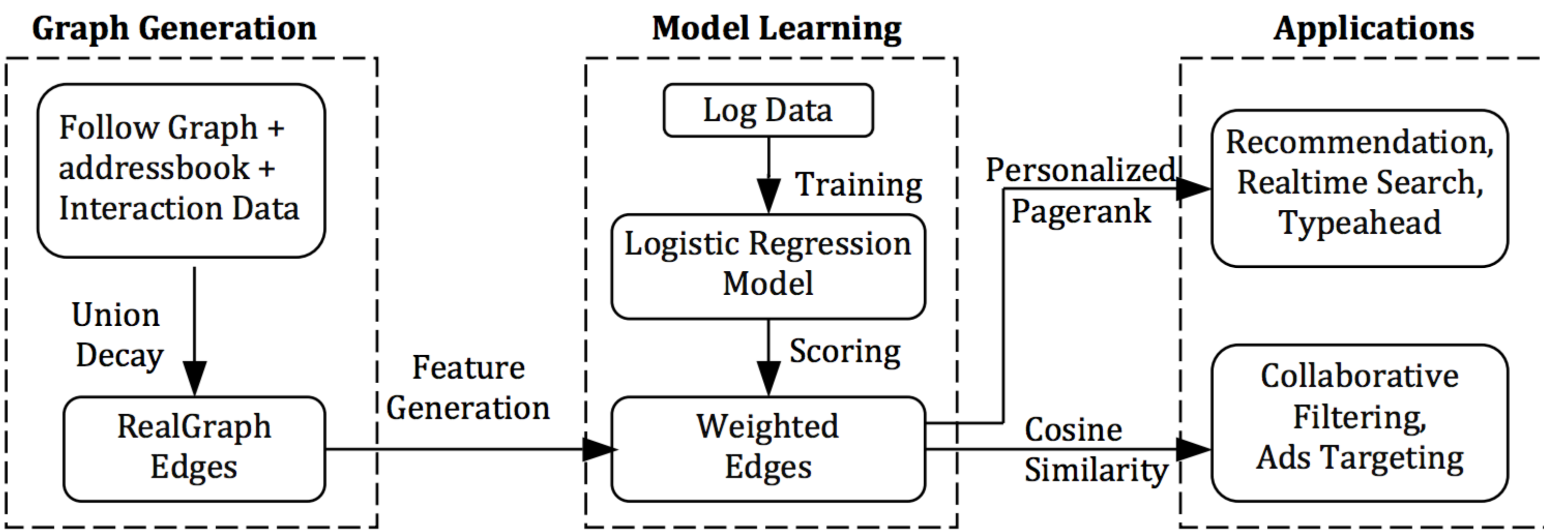


Figure 1: Twitter RealGraph Framework.

Kamath, Krishna, et al. "RealGraph: User Interaction Prediction at Twitter." User Engagement Optimization Workshop@ KDD. 2014.

Experiments

- Data: binarized adjacency matrix of subset of Twitter follower graph
  - $a(i, j) = 1$ if user i interacted with user j, 0 otherwise
- All prediction errors weighted equally ($w(i, j) = 1$)

- 100 million interactions
- 440,000 [popular] users

Experiments

- 80% training, 10% validation, 10% testing

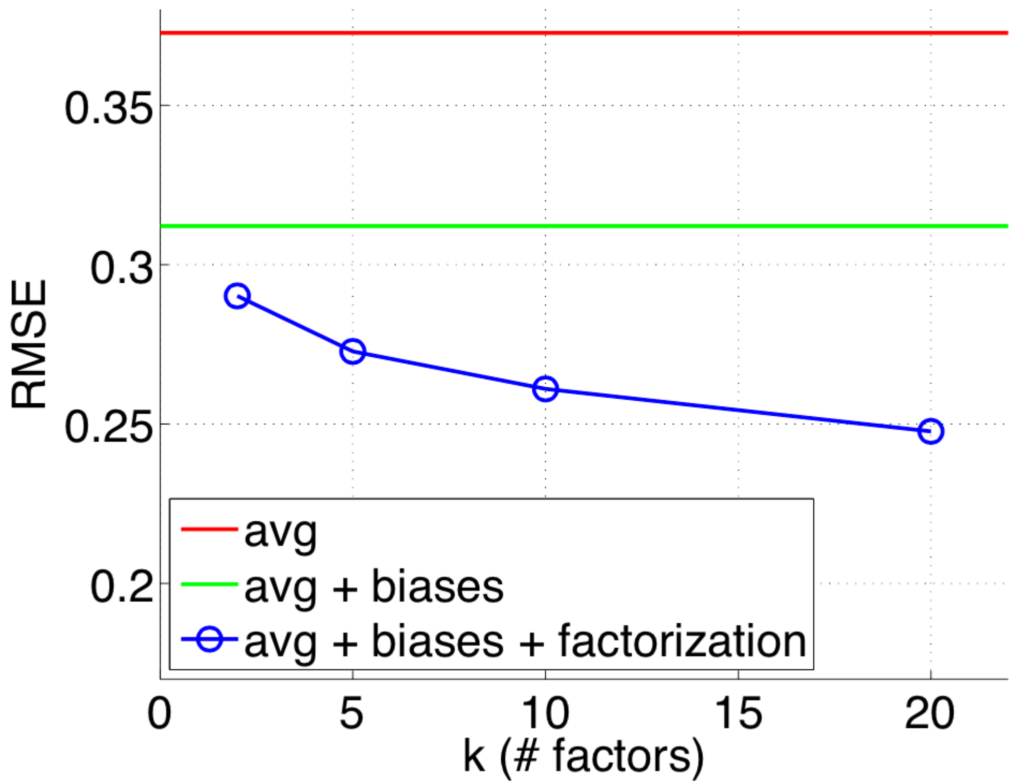


Figure 5: Prediction quality on held-out data with increasing model complexity.

Experiments

- $k = 2$
- Homophily

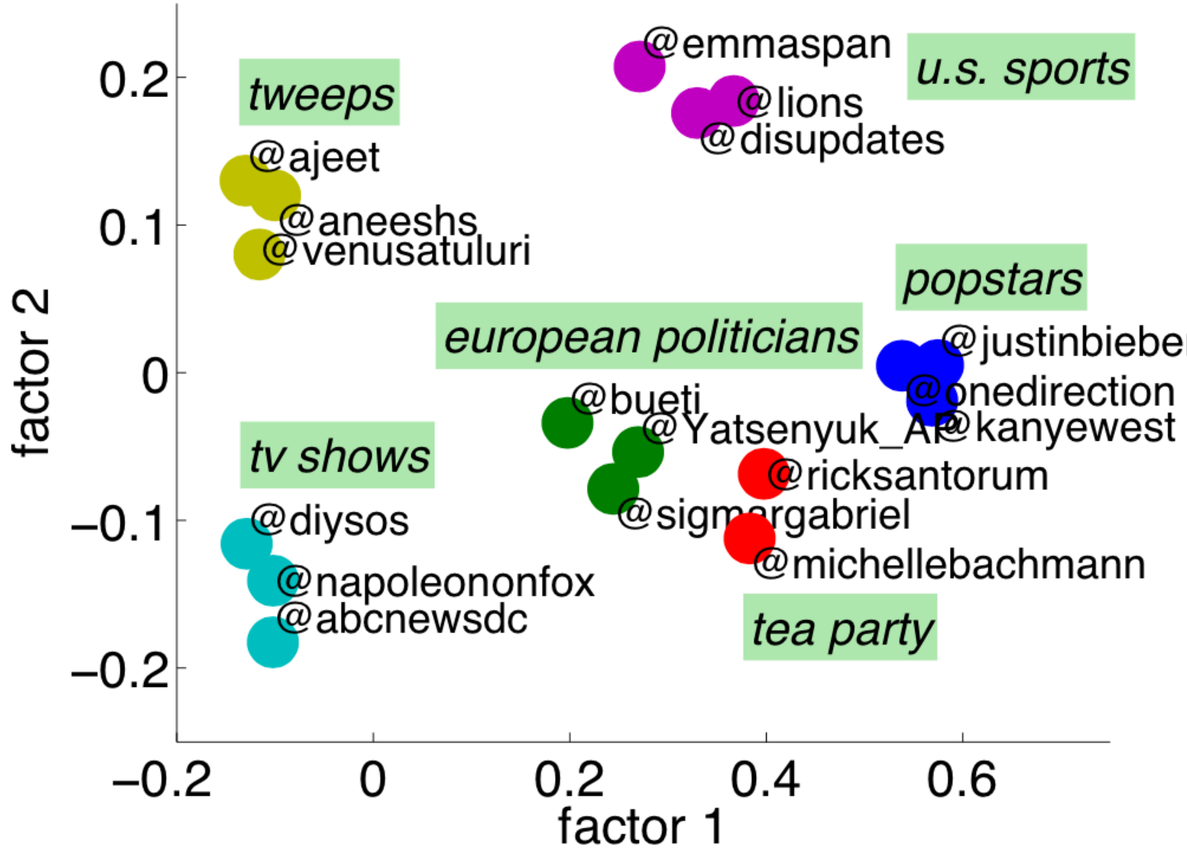


Figure 6: Plot of a selection of twitter users as positioned by a factorization with $k = 2$ of a sample of RealGraph.

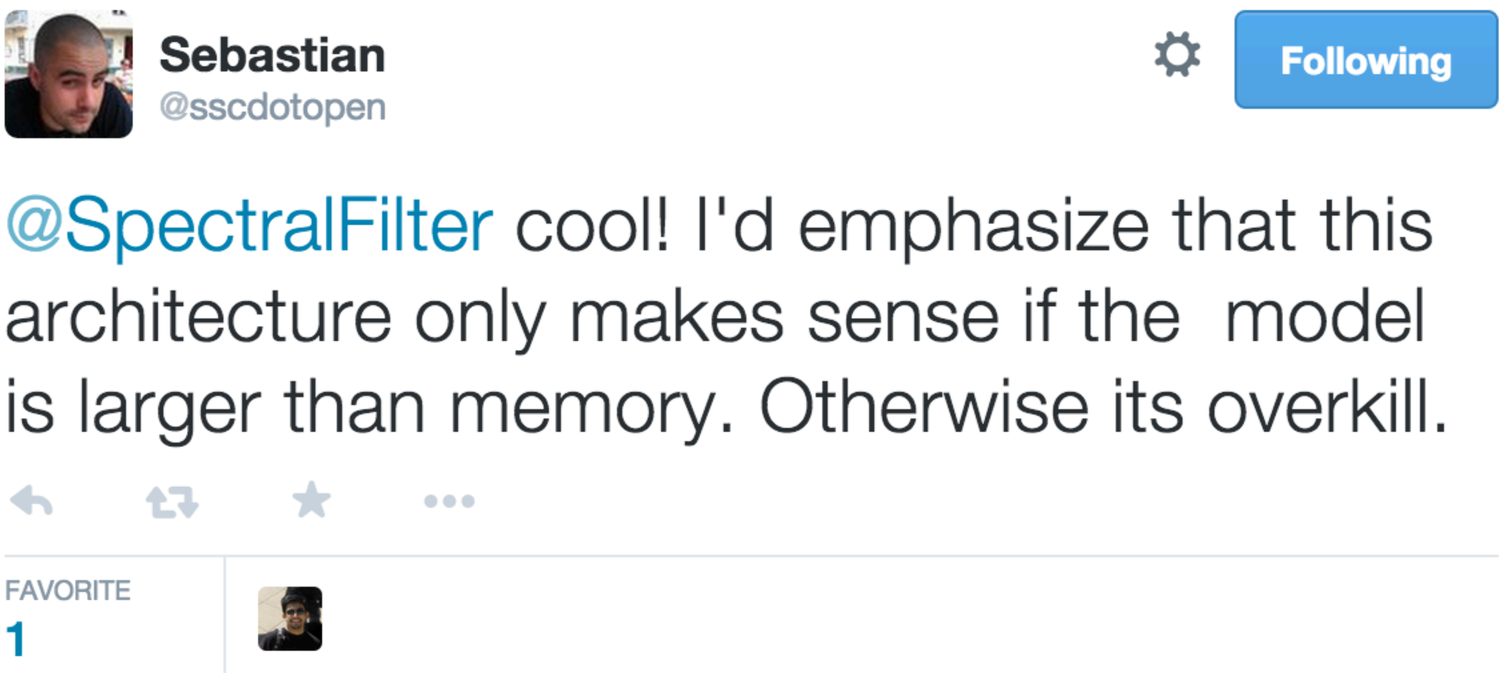
Experiments

- Scalability of Factorbird
  - large RealGraph subset
  - 229M x 195M (44.6 *quadrillion*)
  - 38.5 billion non-zero entries

- Single SGD pass through training set: ~2.5 hours
- ~ 40 billion parameters

Important to note

- As with most (if not all) distributed platforms:



Future work

- Support streaming (user follows)
- Simultaneous factorization
- Fault tolerance
- Reduce network traffic
- s/memcached/custom application/g
- Load balancing

Strengths

- Excellent extension of prior work
  - Hogwild, RealGraph
- Current and [mostly] open technology
  - Hadoop, Scalding, Mesos, memcached
- Clear problem, clear solution, clear validation

Weaknesses

- Lack of detail, lack of detail, lack of detail
  - How does number of machines affect runtime?
  - What were performance metrics of the large RealGraph subset?
  - What were some of the properties of the dataset (when was it collected, how were edges determined, what does “popular” mean, etc)?
  - How did other factorization methods perform by comparison?

Questions?