Mining Large-scale Social Networks
Challenges & Scalable Solutions

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Google Research

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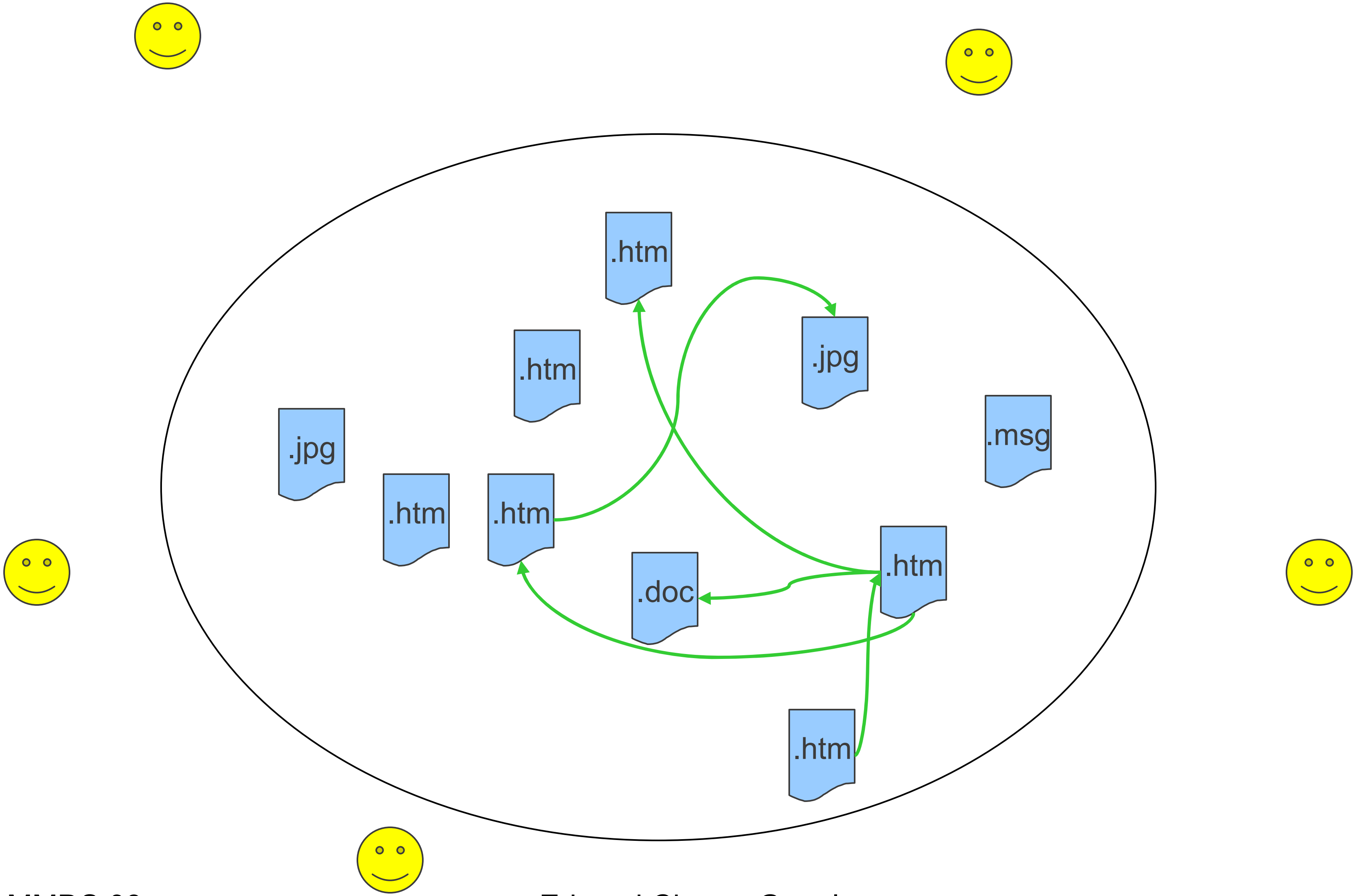
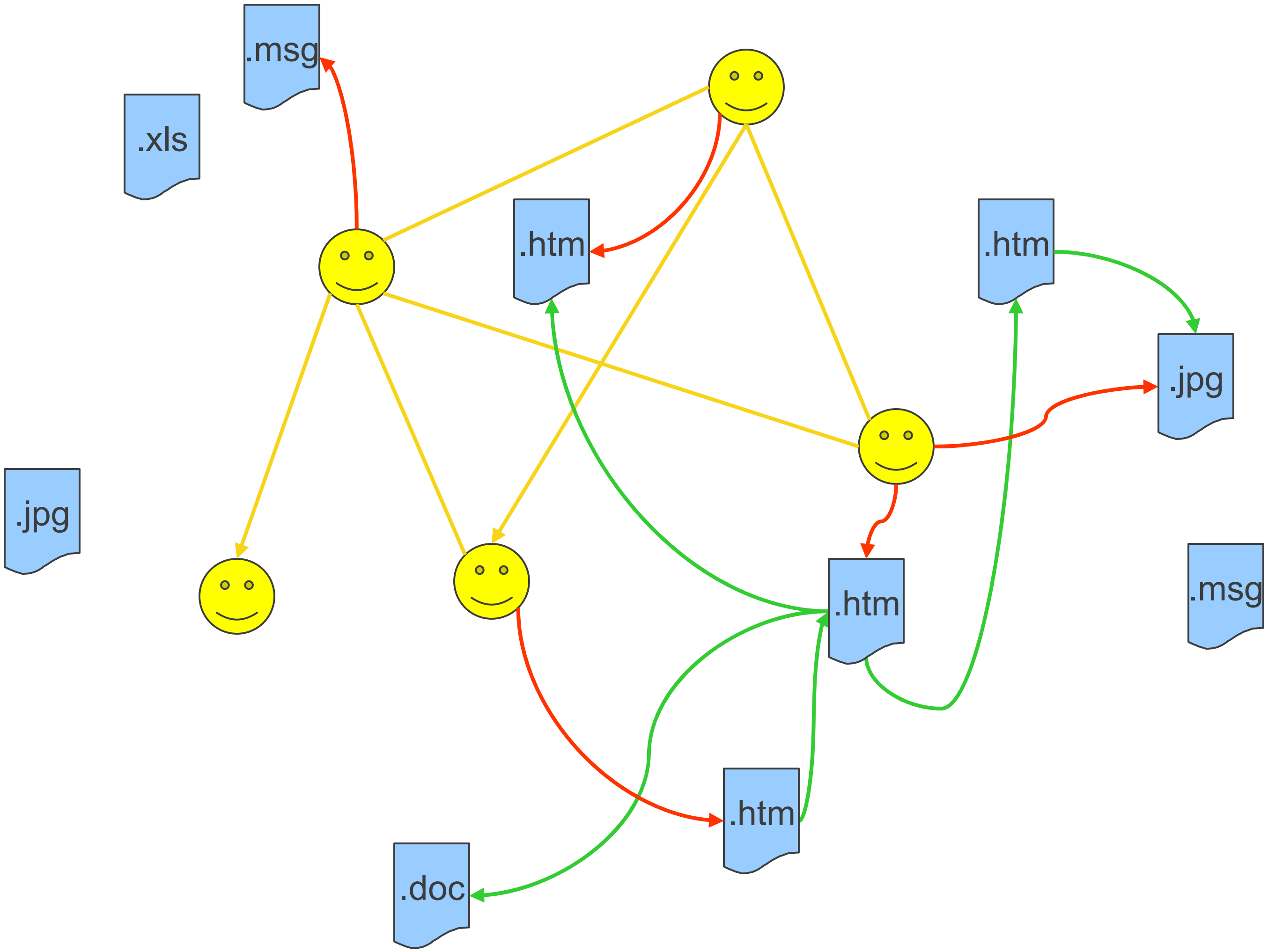
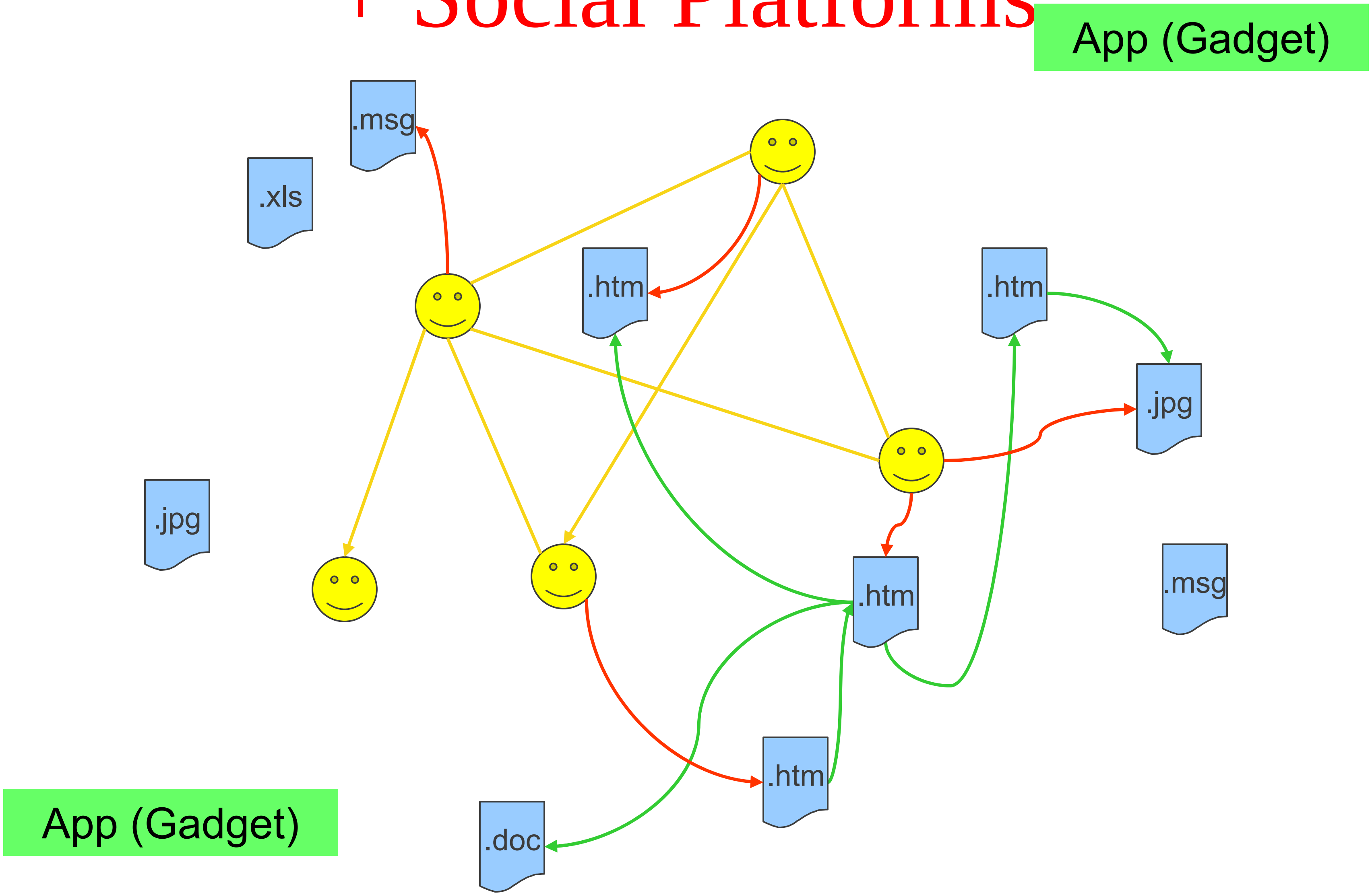
Web 1.0



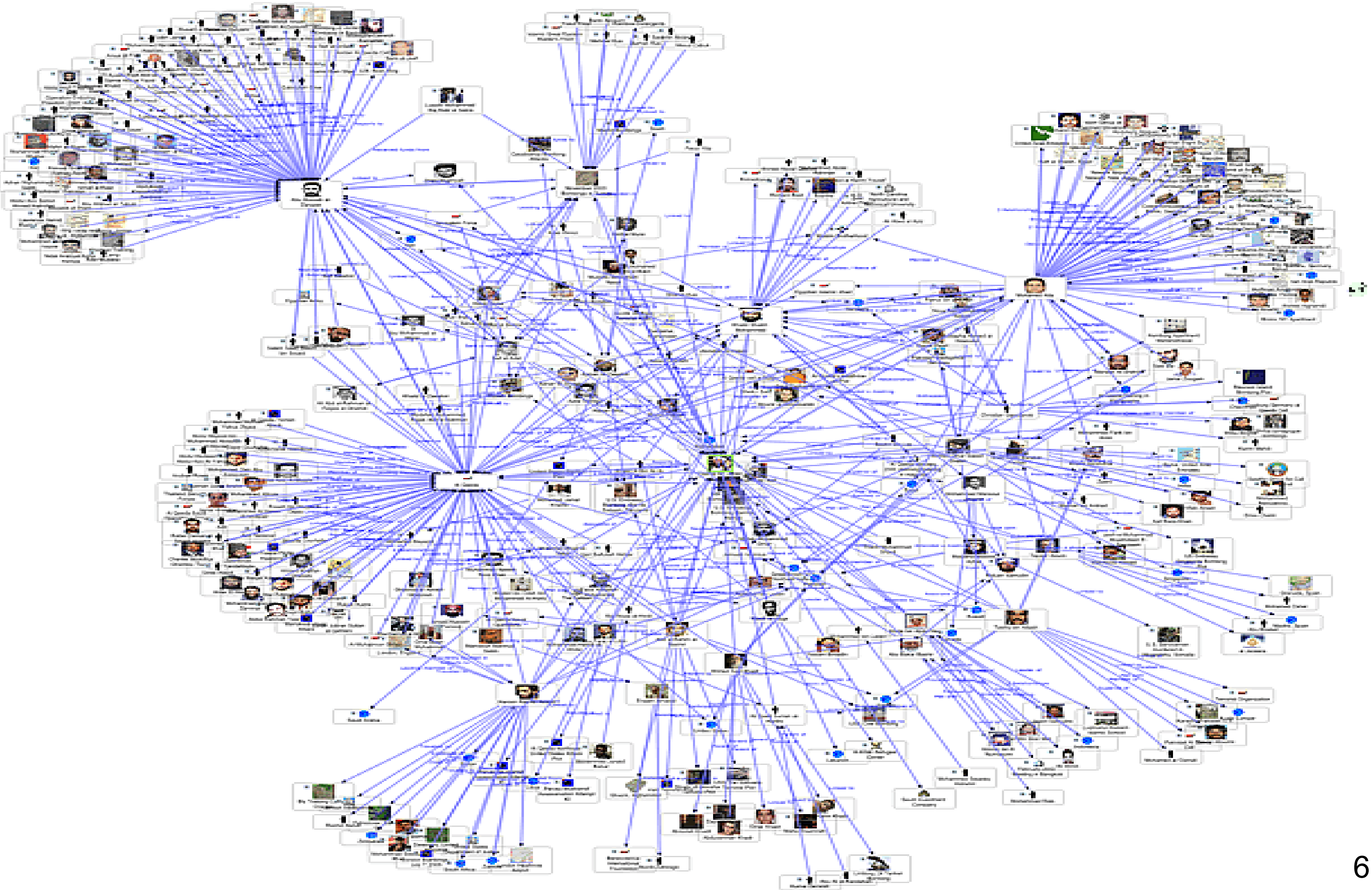
Web 2.0 --- Web with People



+ Social Platforms



People Centric Web



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上一步 |
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机械舞
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暗香浮月
沉网
武汉牛牛
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Recommendation Systems

- Friend Recommendation
- Application Recommendation
- Community/Forum Recommendation
- Ads Matching

- Performance Requirements
  - Scalability, scalability, scalability

Google Data Centers

Outline

- Emerging Applications
  - Social networks
  - Personalized Information retrieval
- Key Subroutines for Mining Massive SNS
  - Clustering [ECML 08]
  - Frequent Itemset Mining [Google Tech Report 08]
  - Combinational Collaborative Filtering [KDD 08]
    - with PLSA
    - with LDA
  - Support Vector Machines [NIPS 07]

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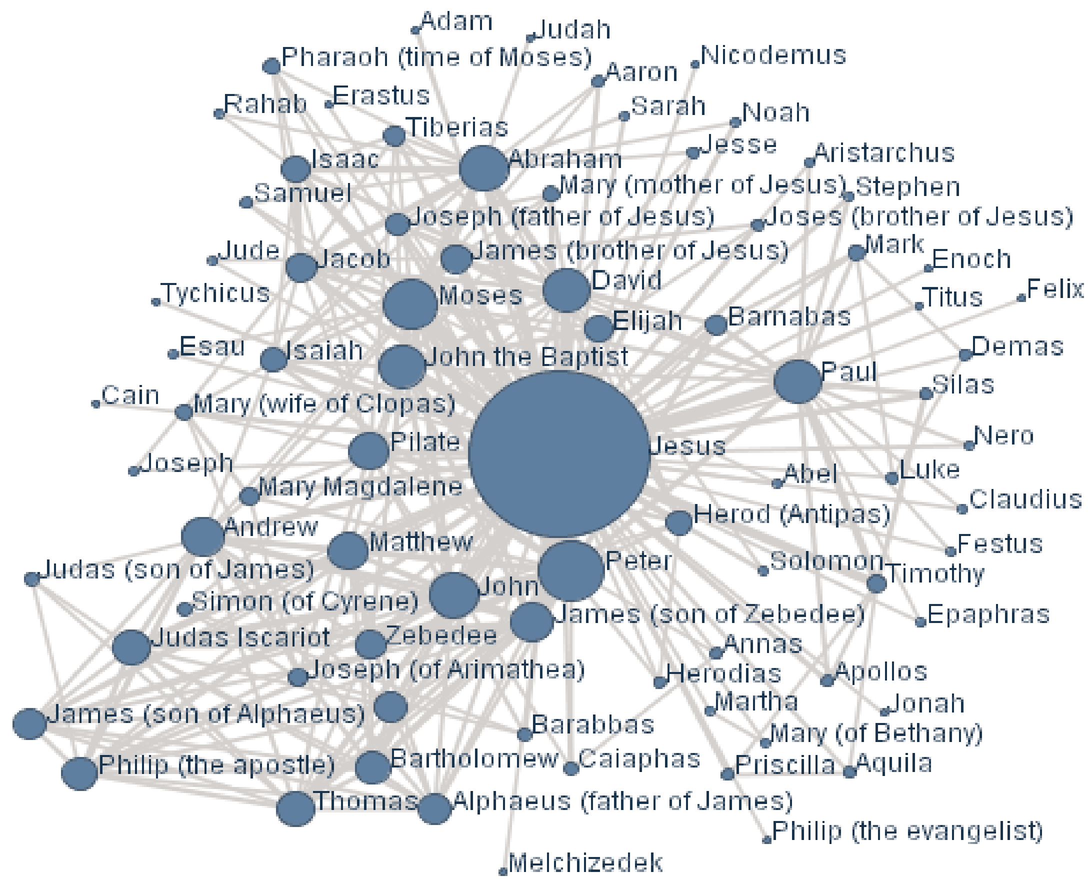
Clustering for SNS Analysis

- Centrality
- Degree Centrality
- Closeness
- Betweenness

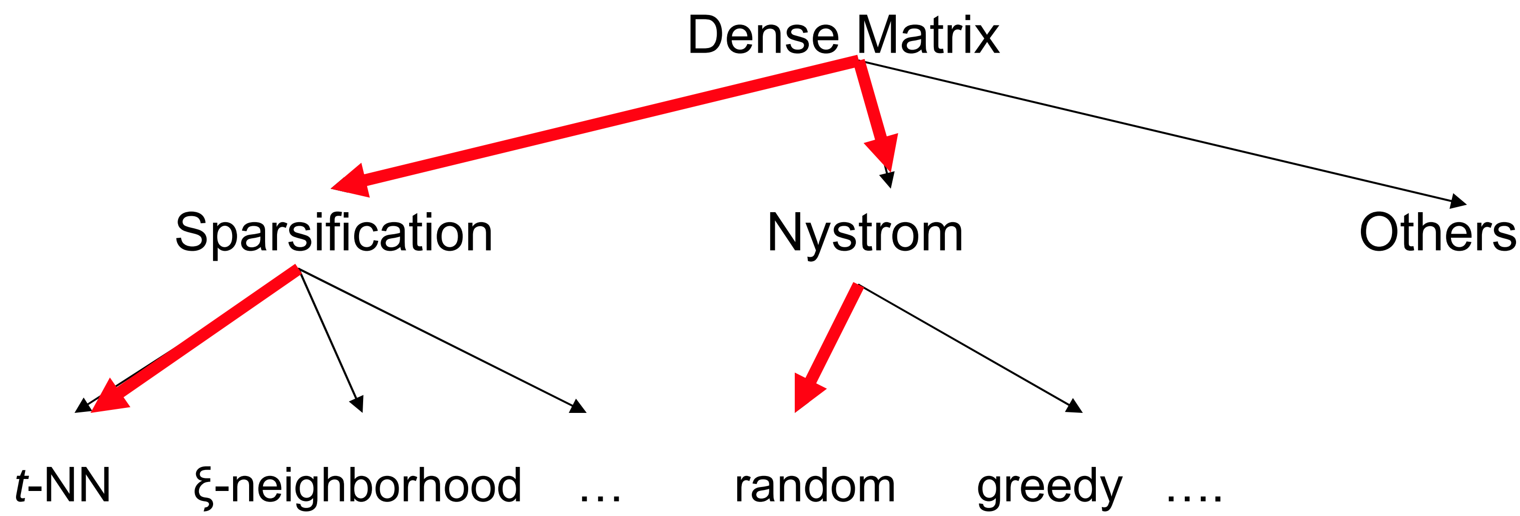


Spectral Clustering [A. Ng, M. Jordan]

- Important subroutine in tasks of machine learning and data mining
  - Exploit *pairwise similarity* of data instances
  - More effective than traditional methods e.g., k-means
- Key steps
  - Construct pairwise similarity matrix
  - Compute the Laplacian matrix
  - Apply eigendecomposition
  - Perform *k*-means

Scalability Problem

- Quadratic computation of nxn matrix
- Approximation methods



Sparsification vs. Sampling

- Construct the dense similarity matrix S
- Sparsify S
- Compute Laplacian matrix L

$$L = I - D^{-1/2} S D^{-1/2}, \quad D_{ii} = \sum_{j=1}^{n} S_{ij}$$

- Apply *ARPACLK* on L
- Use *k*-means to cluster rows of V into *k* groups

- Randomly sample *l* points, where *l* << *n*
- Construct dense similarity matrix [A B] between *l* and *n* points
- Normalize A and B to be Laplacian form
- $R = A + A^{-1/2}BB^{T}A^{-1/2}$; $R = U\Sigma U^{T}$
- *k*-means

Single Machine

- Nystrom approximation by random sampling
  - Random sampling is least costly
  - Trade clustering quality for speed
- Sparsification with t-NN
  - Keep only t-NN of each instance
  - O(n^2) computation and storage

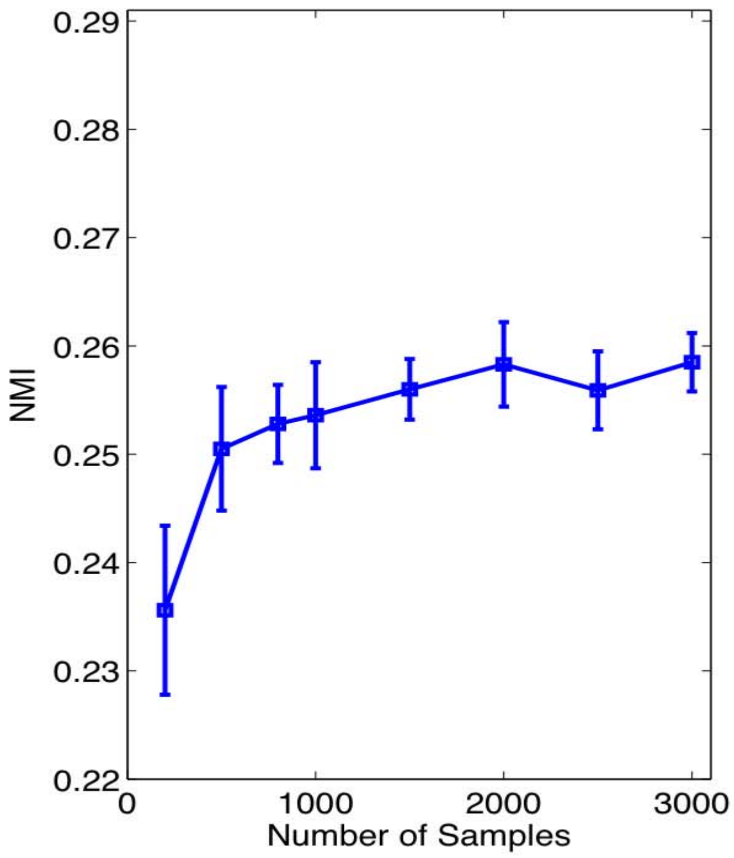
Empirical Study

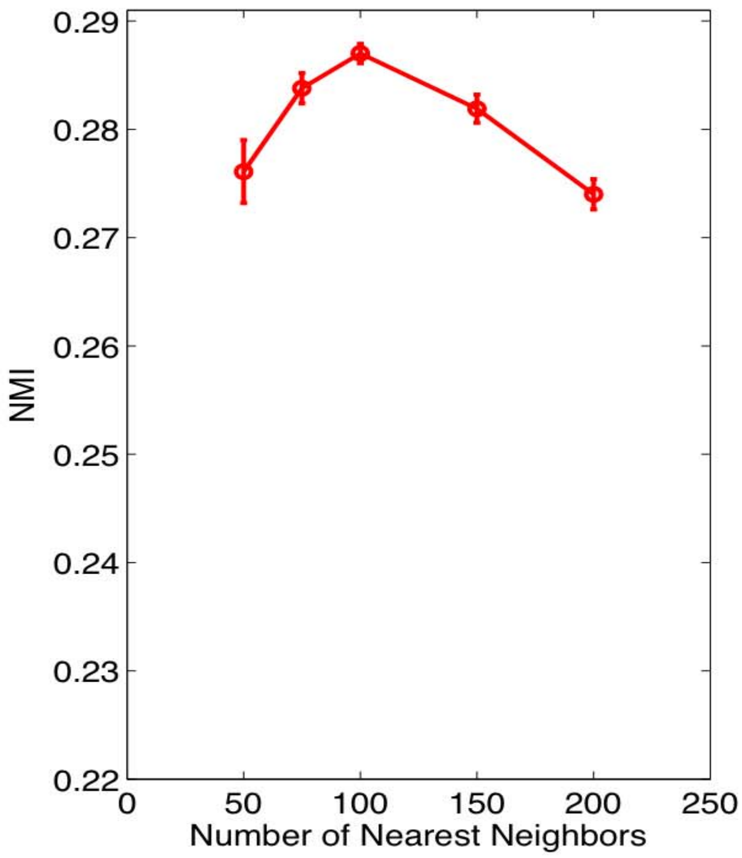
- Dataset: RCV1 (Reuters Corpus Volume I)
  - A filtered collection of *193,944* documents in*103* categories
- Photo set: PicasaWeb
  - *637,137* photos
- Experiments
  - Clustering quality vs. computational time
    - Measure the similarity between CAT and CLS
    - Normalized Mutual Information (NMI)

$$NMI(CAT;CLS) = \frac{I(CAT;CLS)}{\sqrt{H(CAT)H(CLS)}}$$

  - Scalability

NMI Comparison (on RCV1)





Nystrom method **Sparse matrix approximation**

Speedup Test on RCV1

	Eigensolver		k-means	
Machines	Time (sec.)	Speedup	Time (sec.)	Speedup
1	1.870×10^3	1.00	1.557×10^2	1.00
2	8.529×10^2	2.19	1.433×10^2	1.09
4	4.765×10^2	3.92	8.565×10^1	1.82
8	3.094×10^2	6.04	3.235×10^1	4.81
16	2.352×10^2	7.95	4.579×10^1	3.40
32	2.150×10^2	8.70	4.318×10^1	3.61
64	2.563×10^2	7.30	5.008×10^1	3.11

Speedup Test on *637,137* Photos

- K = 1000 clusters

	Eigensolver		k-means	
Machines	Time (sec.)	Speedup	Time (sec.)	Speedup
1	—	—	—	—
2	8.074×10^4	2.00	3.609×10^4	2.00
4	4.427×10^4	3.65	1.806×10^4	4.00
8	2.184×10^4	7.39	8.469×10^3	8.52
16	9.867×10^3	16.37	4.620×10^3	15.62
32	4.886×10^3	33.05	2.021×10^3	35.72
64	4.067×10^3	39.71	1.433×10^3	50.37
128	3.471×10^3	46.52	1.090×10^3	66.22
256	4.021×10^3	40.16	1.077×10^3	67.02

- Achiever linear speedup when using 32 machines, after that, sub-linear speedup because of increasing communication and sync time

Sparsification vs. Sampling

	Sparsification	Nystrom, random sampling
Information	Full n x n similarity scores	None
Pre-processing Complexity (bottleneck)	$O(n^2)$	$O(nl)$, $l \ll n$
Effectiveness	Good	Not bad (Jitendra M., PAMI)

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Collaborative Filtering

Given a matrix that "*encodes*" data

Many applications (collaborative filtering):

- User – Community
- User – User
- Ads – User
- Ads – Community
- etc.

Communities

Users

	2		1			4				5	
	5		4				?		1		3
		3		5			2				
4			?			5		3		?	
		4		1	3				5		
			2				1	?			4
	1					5		5		4	
		2		?	5		?		4		
	3		3		1		5		2		1
	3				1			2		3	
	4			5	1			3			
		3				3	?			5	
2	?		1		1						
		5			2	?		4		4	
	1		3		1	5		4		5	
1		2			4				5	?	

FIM-based Recommendation

"Growing" the knowledge-base

- $\{\text{BMW}, \text{Volkswagen}\} \rightarrow \{\text{BMW}, \text{Volkswagen}, \text{Volvo}, \text{Benz}, \text{QQ}, \ldots\}$
- $\{\text{T72}, \text{iPhone}\} \rightarrow \{\text{Nokia}, \text{T72}, \text{Apple}, \text{iPhone}, \ldots\}$
- $\{\text{Java}, \text{C++}\} \rightarrow \{\text{Java}, \text{C++}, \text{Python}, \text{Perl}, \text{Javascript}, \ldots\}$

To grow the base, we need association rules

- An association rule: $a, b, c \longrightarrow d$
- A Bayesian interpretation: $P(d \mid a, b, c) = \frac{N(a,b,c,d)}{N(a,b,c)}$
- The key is to count the occurrences (*support*) of itemsets $N(\ldots)$

FIM Preliminaries

- Observation 1: If an item A is not frequent, any pattern contains A won't be frequent [R. Agrawal]

  ➔ use a threshold to eliminate infrequent items

  ~~{a}~~ → ~~{a,b}~~
- Observation 2: Patterns containing A are subsets of (or found from) transactions containing A [J. Han]

  ➔ divide-and-conquer: select transactions containing A to form a conditional database (CDB), and find patterns containing A from that conditional database

  {a, b}, {a, c}, {a} → {a, b, c}
- Observation 3: To prevent the same pattern from being found in multiple CDBs, all itemsets are sorted by the same manner (e.g., by descending support)

Preprocessing

	f: 4	
	c: 4	
	a: 3	
f a c d g i m p	b: 3	f c a m p
	m: 3	
a b c f l m o	p: 3	f c a b m
b f h j o	o: 2	f b
	d: 1	
b c k s p	e: 1	c b p
	g: 1	
a f c e l p m n	h: 1	f c a m p
	i: 1	
	k: 1	
	l : 1	
	n: 1	

- According to Observation 1, we count the support of each item by scanning the database, and eliminate those infrequent items from the transactions.
- According to Observation 3, we sort items in each transaction by the order of descending support value.

Parallel Projection

- According to Observation 2, we construct CDB of item A; then from this CDB, we find those patterns containing A
- How to construct the CDB of A?
  - If a transaction contains A, this transaction should appear in the CDB of A
  - Given a transaction {B, A, C}, it should appear in the CDB of A, the CDB of B, and the CDB of C
- However, this leads to *duplicates*
  - Suppose {B,A,C} is a frequent pattern, it will be found three times --- from the CDBs of A, B and C respectively
- Solution: using the order of items:
  - sort {B,A,C} by the order of items → <A,B,C>
  - Put <> into the CDB of A
  - Put <A> into the CDB of B
  - Put <A,B> into the CDB of C

Example of Projection

f c a m p	p: { f c a m / f c a m / c b }
f c a b m	m: { f c a / f c a / f c a b }
f b	b: { f c a / f / c }
c b p	a: { f c / f c / f c }
f c a m p	c: { f / f / f }

Example of Projection of a database into CDBs.
Left: sorted transactions;
Right: conditional databases of frequent items

Example of Projection

f c a m p	p: { f c a m / f c a m / c b }
f c a b m	m: { f c a / f c a / f c a b }
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f c a m p	c: { f / f / f }

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f c a b m	m: { f c a / f c a / f c a b }
f b	b: { f c a / f / c }
c b p	a: { f c / f c / f c }
f c a m p	c: { f / f / f }

Example of Projection of a database into CDBs.
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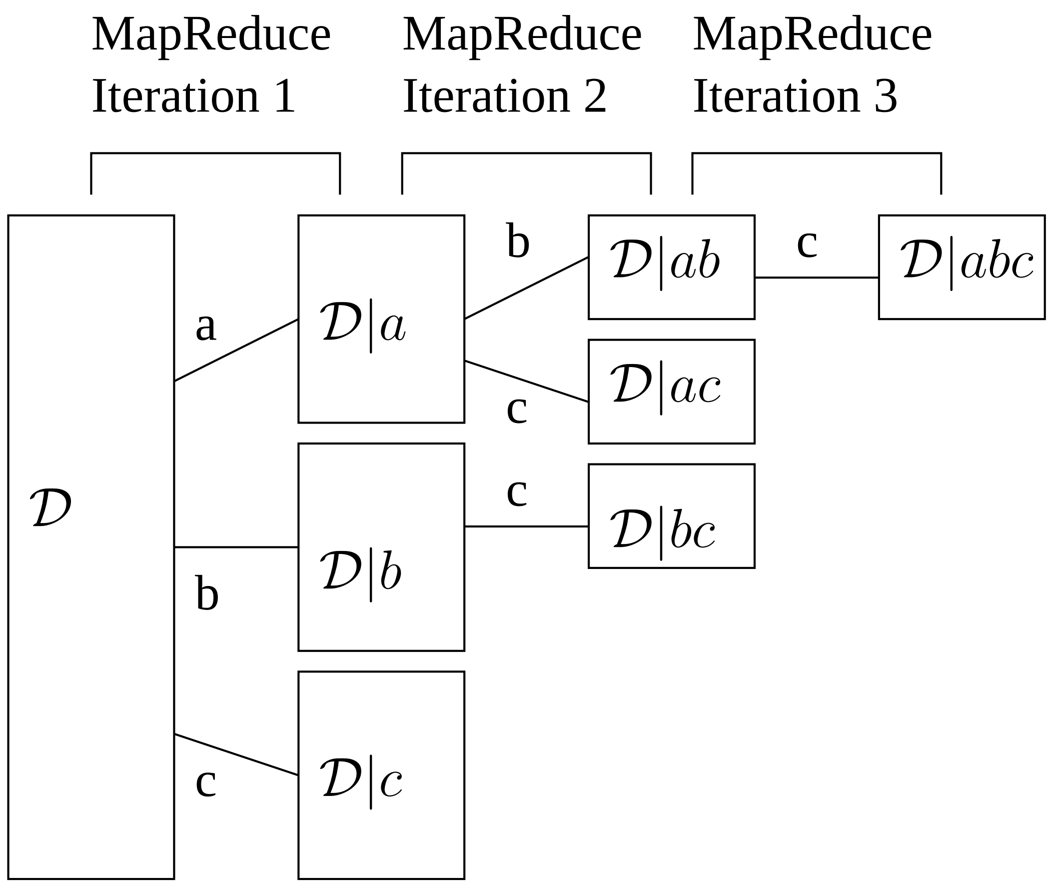
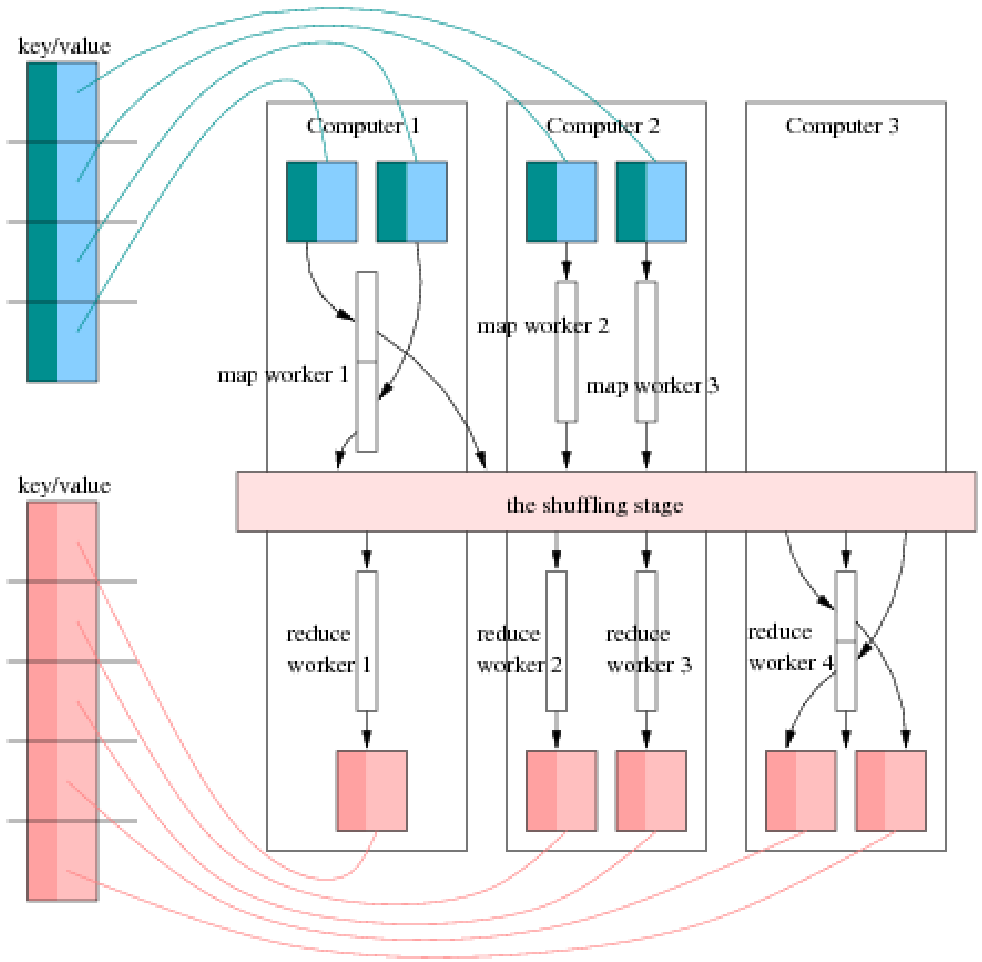
Recursive Projections



- Recursive projection form a search tree
- Each node is a CDB
- Using the order of items to prevent duplicated CDBs.
- Size(D|ac)=supp(ac)
- Each level of breath-first search of the tree can be done by a MapReduce iteration.
- Once a CDB is small enough to fit in memory, we can invoke FP-growth to mine this CDB, and no more growth of the sub-tree.

MapReduce



- Logically, the input transaction database is in one file, but physically distributed across many computers.
- Logically, the output pattern database is in one file, but physically distributed across many computers.

Projection using MapReduce

Map inputs (transactions) key="": value	Sorted transactions (with infrequent items eliminated)	Map outputs (conditional transactions) key: value
f a c d g i m p	f c a m p	p: f c a m m: f c a a: fc c: f
a b c f l m o	f c a b m	m: f c a b b: f c a a: f c c: f
b f h j o	f b	b: f
b c k s p	c b p	p: c b
a f c e l p m n	f c a m p	b: c p: f c a m m: f c a a: f c c: f

Reduce inputs (conditional databases) key: value	Reduce outputs (patterns and supports) key: value
p: { f c a m / f c a m / c b }	p : 3 p c : 3
m: { f c a / f c a / f c a b }	m f : 3 m c : 3 m a : 3 m f c : 3 m f a : 3 m c a : 3 m f c a : 3
b: { f c a / f / c }	b : 3
a: { f c / f c / f c }	a : 3 a f : 3 a c : 3 a f c : 3
c: { f / f / f }	c : 3 c f : 3

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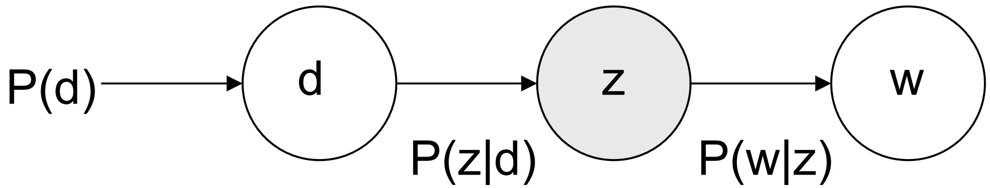
Notations

- Given a collection of co-occurrence data
  - Community: $C = \{c_1, c_2, \ldots, c_N\}$
  - User: $U = \{u_1, u_2, \ldots, u_M\}$
  - Description: $D = \{d_1, d_2, \ldots, d_V\}$
  - Latent aspect: $Z = \{z_1, z_2, \ldots, z_K\}$
- Models
  - Baseline models
    - Community-User (C-U) model
    - Community-Description (C-D) model
  - CCF: Combinational Collaborative Filtering
    - *Combines* both baseline models

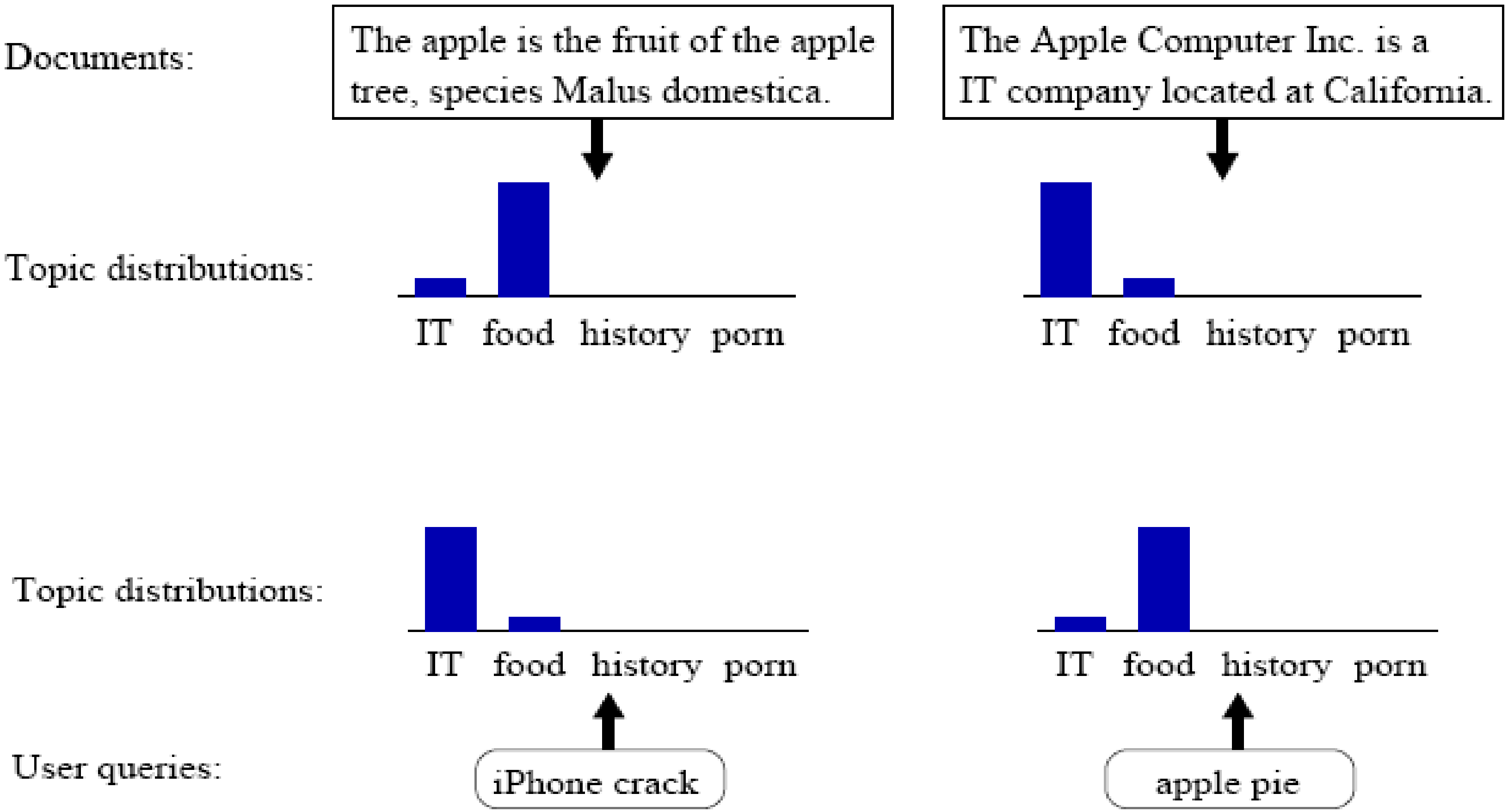
Probabilistic Latent Semantic Analysis (PLSA) [Hoffman 1999; Hoffman 2004]

- Document is viewed as a bag of words
- A *latent semantic layer* is constructed in between documents and words
- $P(w, d) = P(d)\,P(w|d) = P(d)\sum_z P(w|z)P(z|d)$



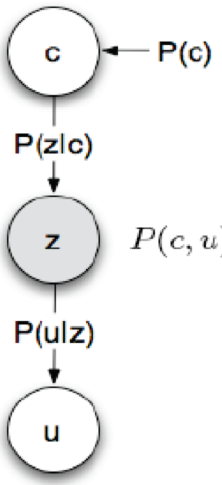
- Probability delivers explicit meaning
  - $P(w|w)$, $P(d|d)$, $P(d, w)$
- Model learning via EM or Gibbs sampling

Example of Latent Analysis



Baseline Models

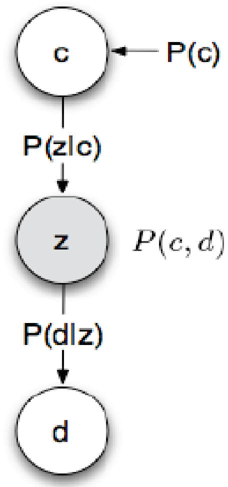
Community-User (C-U) model



$$P(c,u) = P(c)\sum_z P(u|z)P(z|c)$$

- Community is viewed as a bag of users
- ***c*** and ***u*** are rendered conditionally independent by introducing ***z***
- Generative process, for each user *u*
  1. A community *c* is chosen uniformly
  2. A topic *z* is selected from P(z|c)
  3. A user *u* is generated from P(u|z)

Community-Description (C-D) model

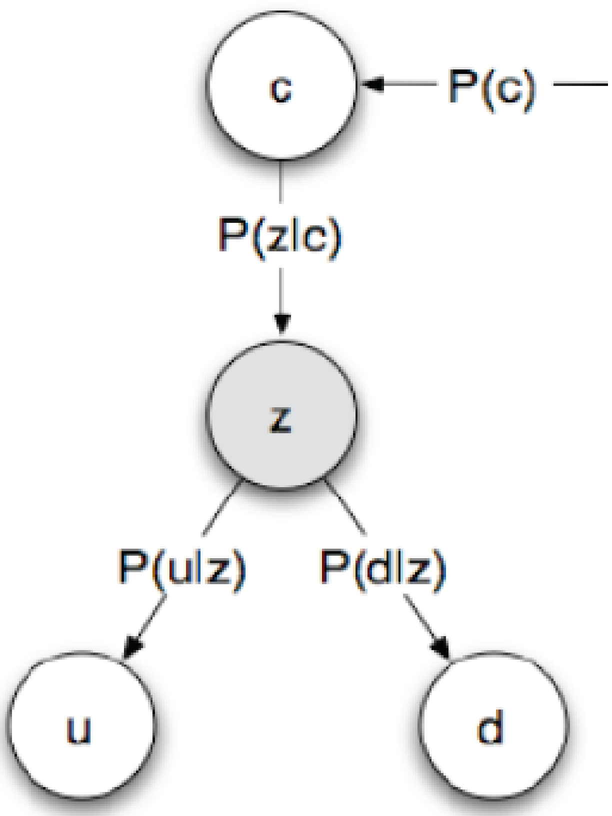


$$P(c,d) = P(c)\sum_z P(d|z)P(z|c)$$

- Community is viewed as a bag of words
- ***c*** and ***d*** are rendered conditionally independent by introducing ***z***
- Generative process, for each word *d*
  1. A community *c* is chosen uniformly
  2. A topic *z* is selected from P(z|c)
  3. A word *d* is generated from P(d|z)

CCF Model [Chen, et. al. KDD 08]

Combinational Collaborative Filtering (CCF) model



- CCF *combines* both baseline models
- A community is viewed as
  - a bag of users AND a bag of words
- By adding C-U, CCF can perform personalized recommendation which C-D alone *cannot*
- By adding C-D, CCF can perform better personalized recommendation than C-U alone, which may suffer from sparsity
- Things CCF can do that C-U and C-D cannot
  - P(d|u), relate user to word
  - Useful for user targeting ads

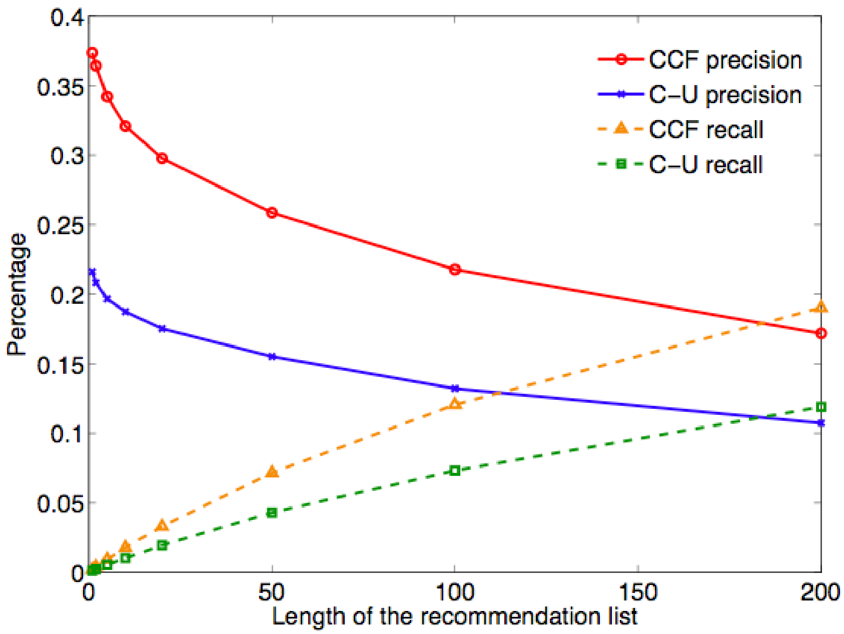
Empirical Study

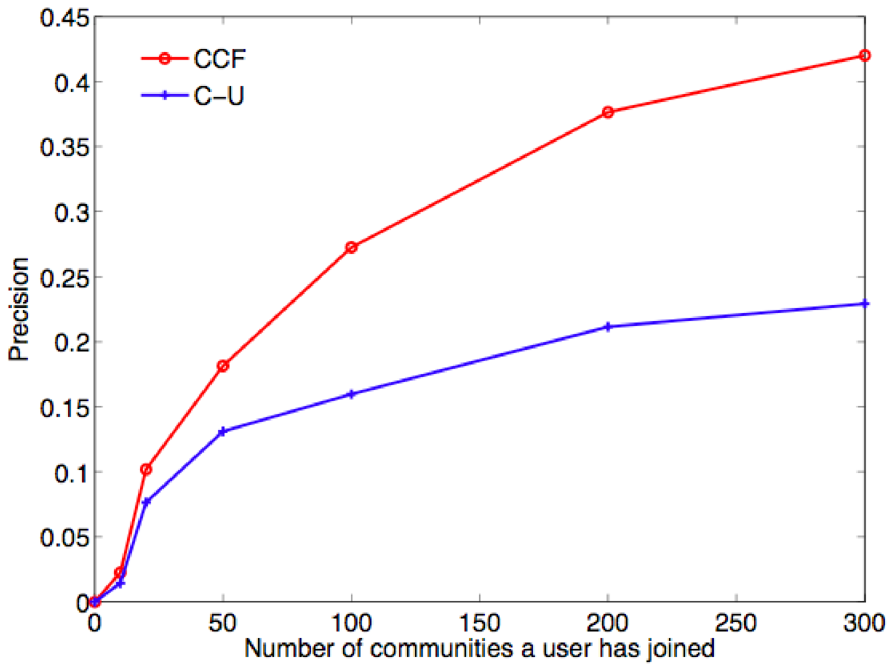
- Orkut Dataset
  - Collected in July, 2007
  - Two types of data were extracted
    - Community-user, community-description
  - 312,385 users
  - 109,987 communities
- Machine farm
  - Up to 200 machines in Google datacenters
  - Each machine is configured with:
    - A CPU faster than 2GHz
    - Memory larger than 4GBytes
- Evaluations
  - Community recommendation
  - Speedup

Community Recommendation

- Evaluation Method
  - Leave-one-out: randomly delete one community for each user
  - Whether a removed community can be recovered
- Evaluation metric
  - Precision and Recall

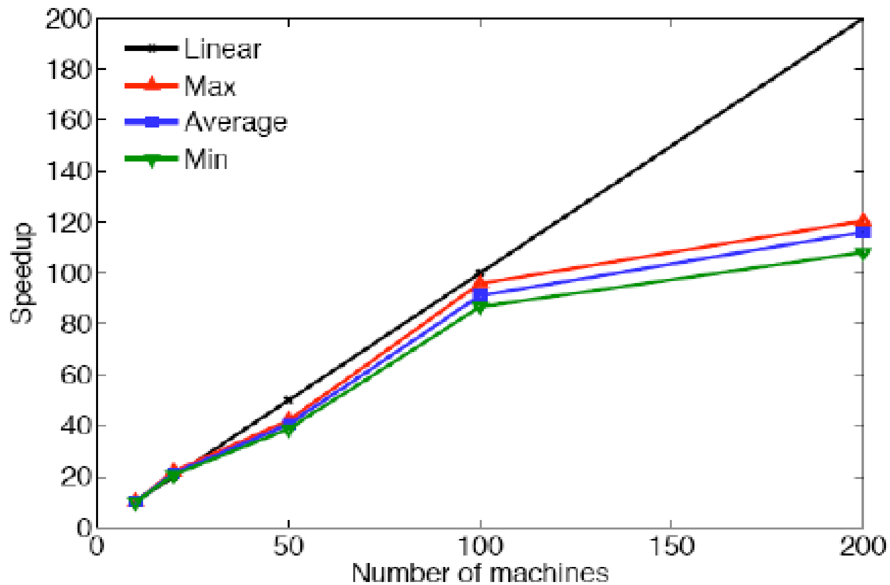
Results





- CCF outperforms C-U
- The more information, the higher accuracy

Gibbs Sampling MapRedue Speedup

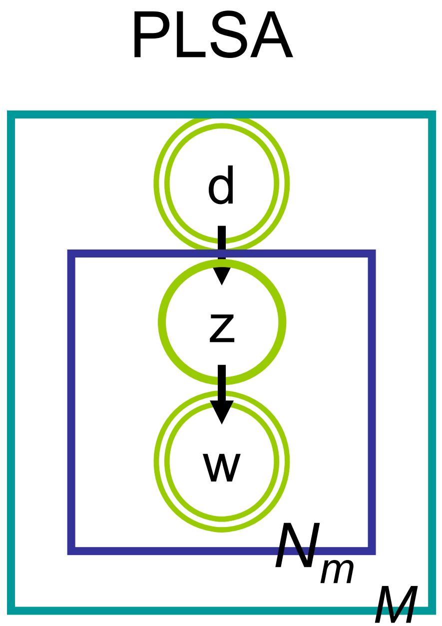


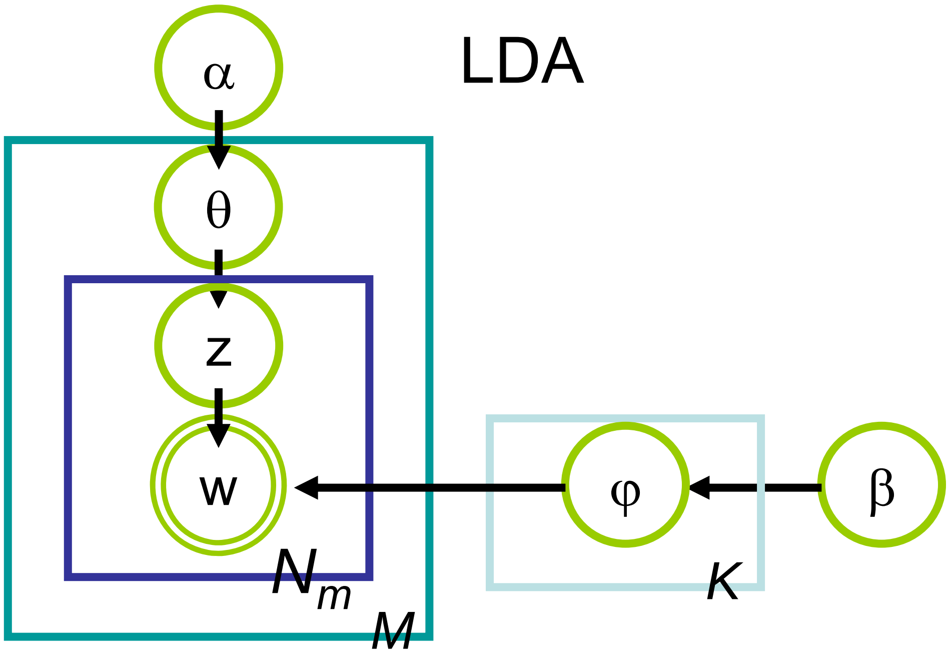
Machines	Time (sec.)	Speedup
10	9,233	10
20	4,326	21.3
50	2,280	40.5
100	1,014	91.1
200	796	116

- The Orkut dataset enjoys a linear speedup when the number of machines is up to 100
- Reduces the training time from one day to less than 14 minutes
- But, what makes the speedup slow down after 100 machines?

Extensions

- Expand CCF to incorporate more types of information
- Replace PLSA with LDA





…Extensions

- Fusing more information sources
- Considering time dimension
- Incremental learning
- Topic hierarchy
- Etc.

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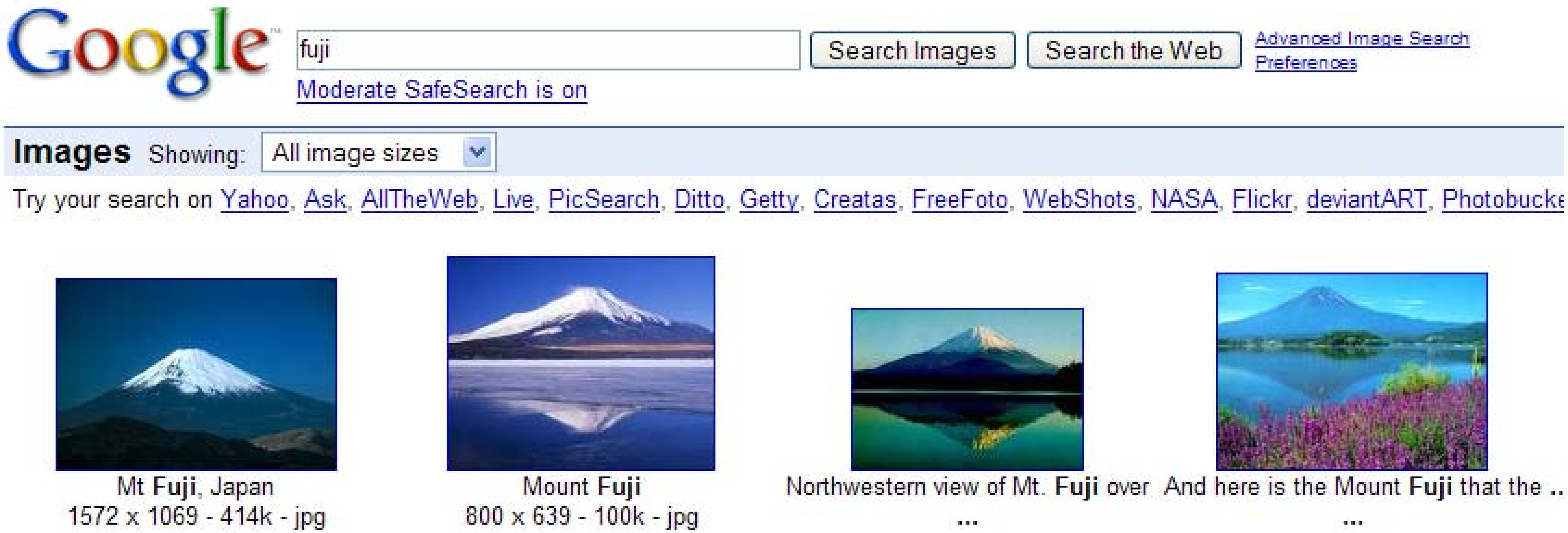
Personalized Search Example

- Infer relevance through social networks
- Query “fuji” can return
  - Fuji mountain
  - Fuji apples
  - Fuji cameras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Mount Fuji
800 x 639 - 100k - jpg
Northwestern view of Mt. Fuji over ...
And here is the Mount Fuji that the .. ...


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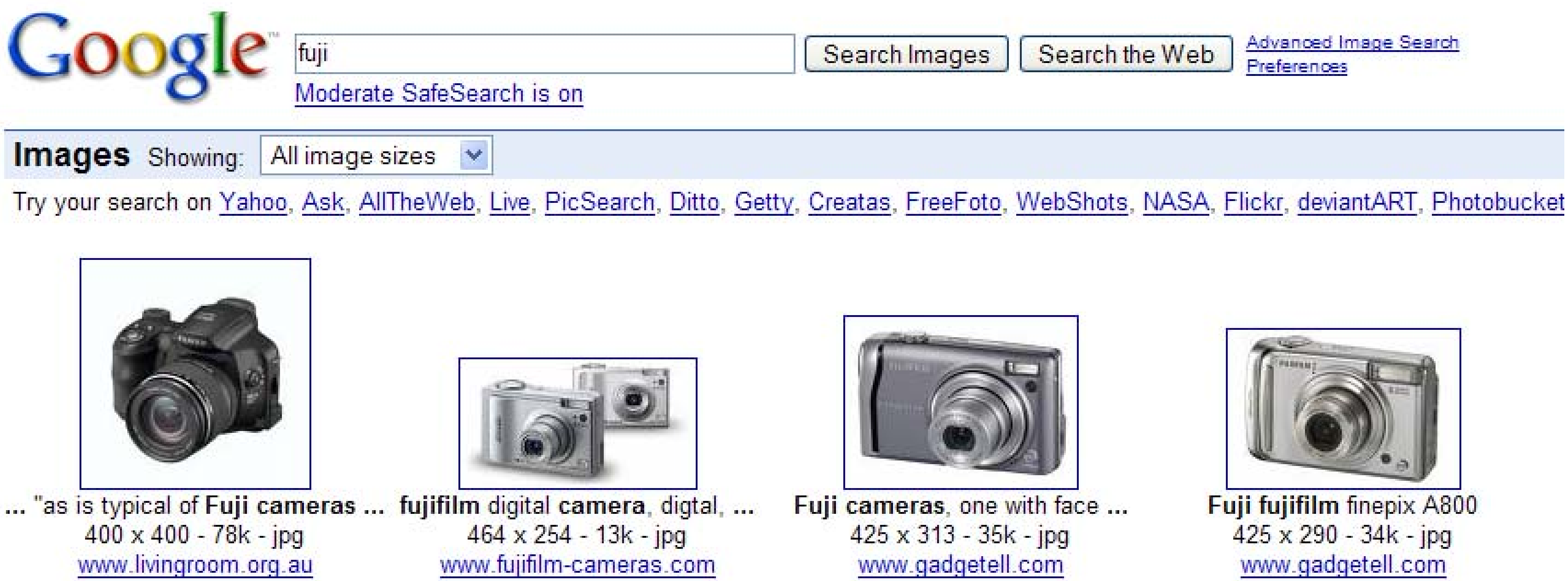
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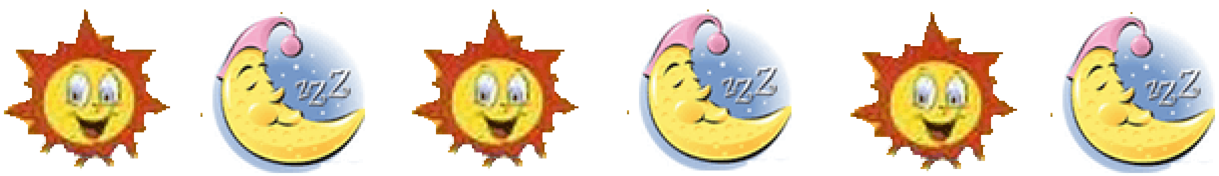
SVM Bottlenecks

Time consuming – 1M dataset, 8 days



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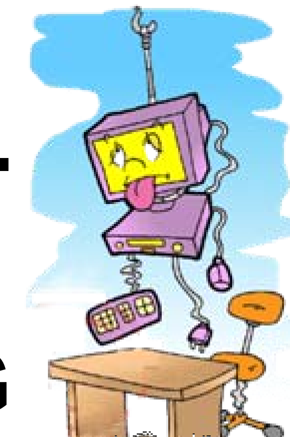


Memory consuming – 1M dataset, 10G

Matrix Factorization Alternatives

Factorization	Cost
QR	$O(\frac{4}{3}n^3)$
LU	$O(\frac{2}{3}n^3)$
Cholesky	$O(\frac{1}{3}n^3 + 2n^2)$
LDL^T	$O(\frac{1}{3}n^3)$
Incomplete Cholesky	$O(p^2 n)$
Kronecker	$O(2n^2)$

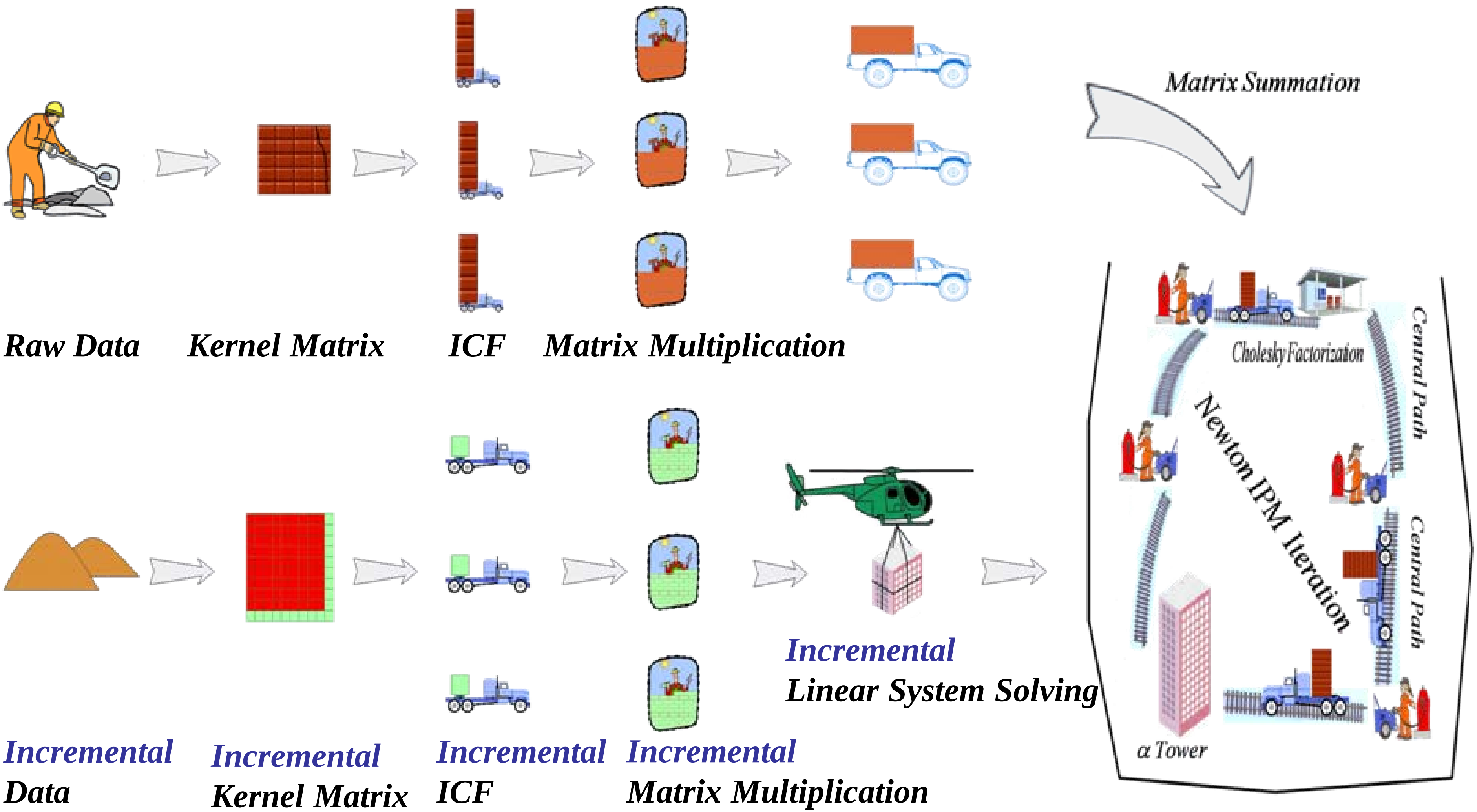
exact

approximate

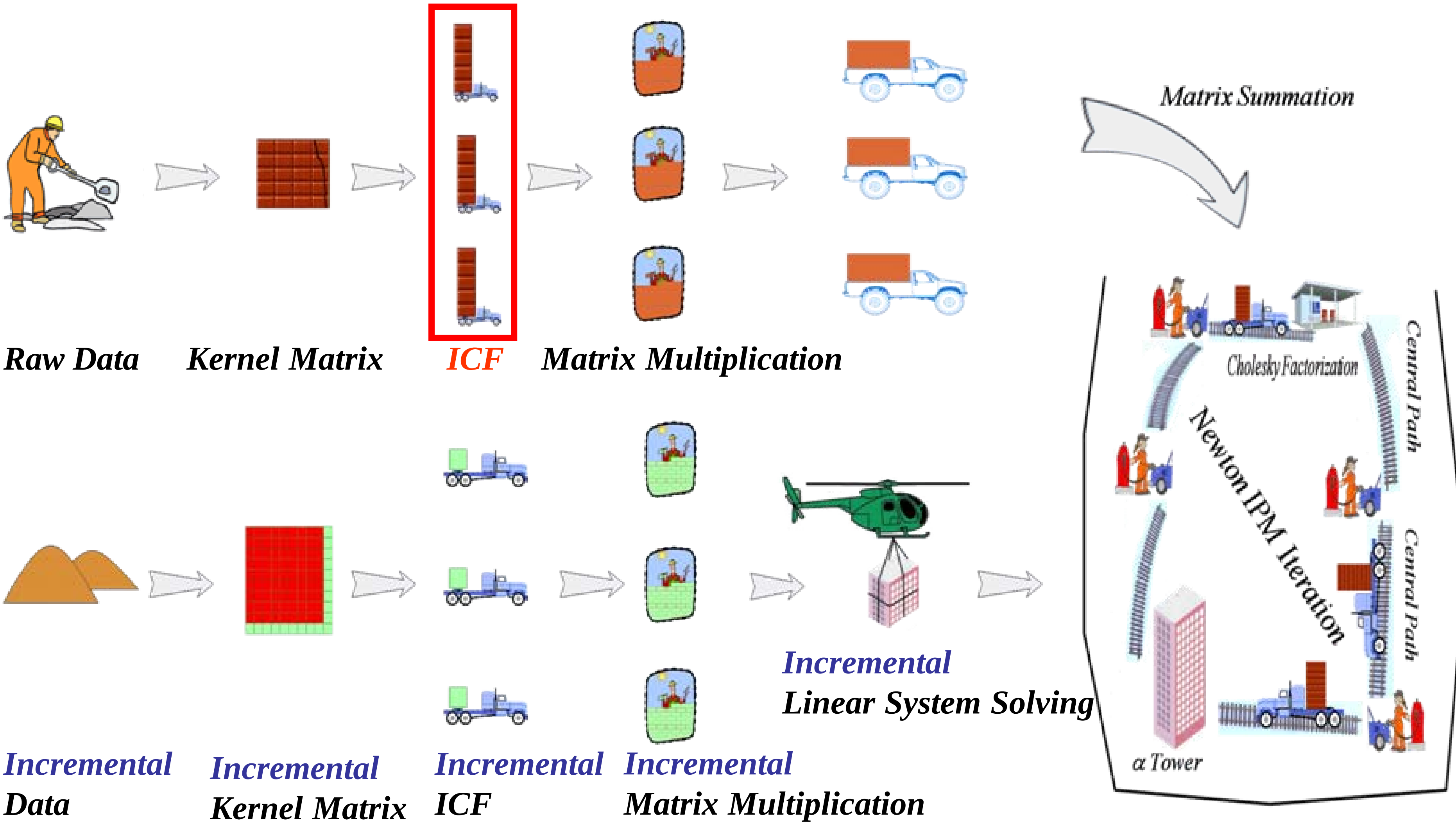
PSVM [E. Chang, et al, NIPS 07]

- Column-based ICF
  - Slower than row-based on single machine
  - Parallelizable on multiple machines
- Changing IPM computation order to achieve parallelization

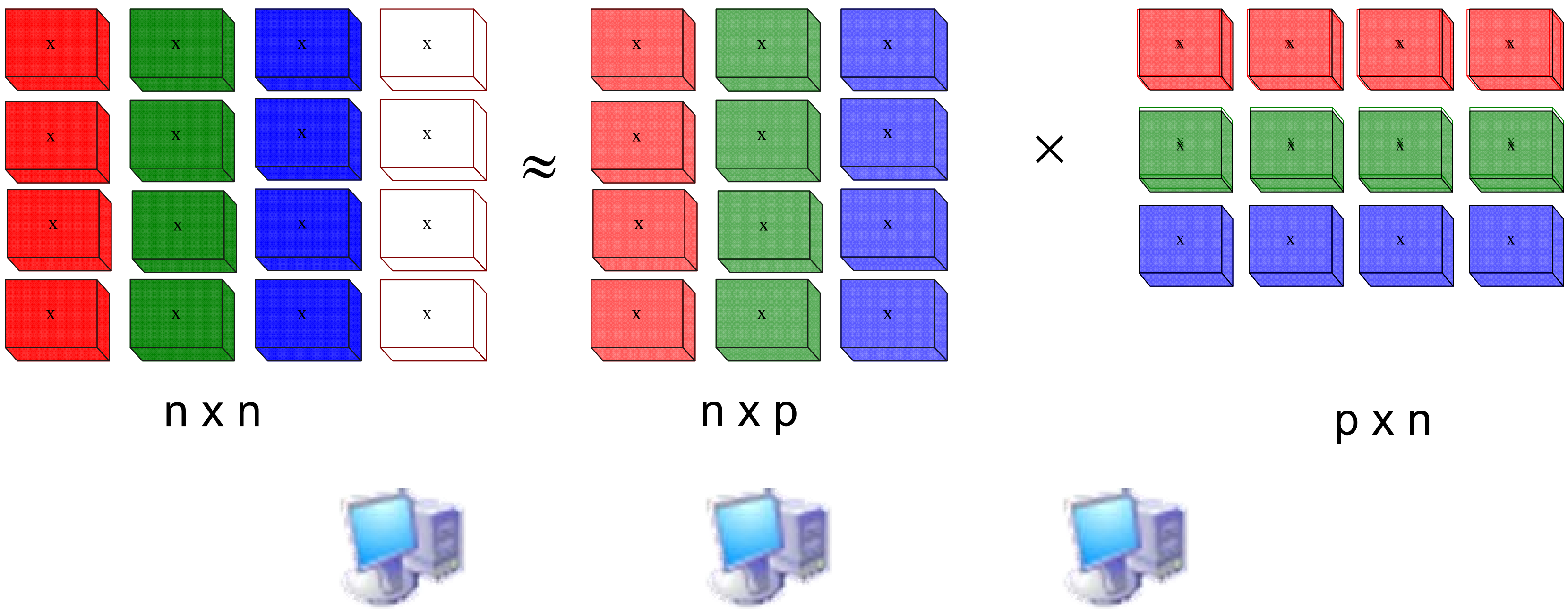
Parallelized and Incremental SVM



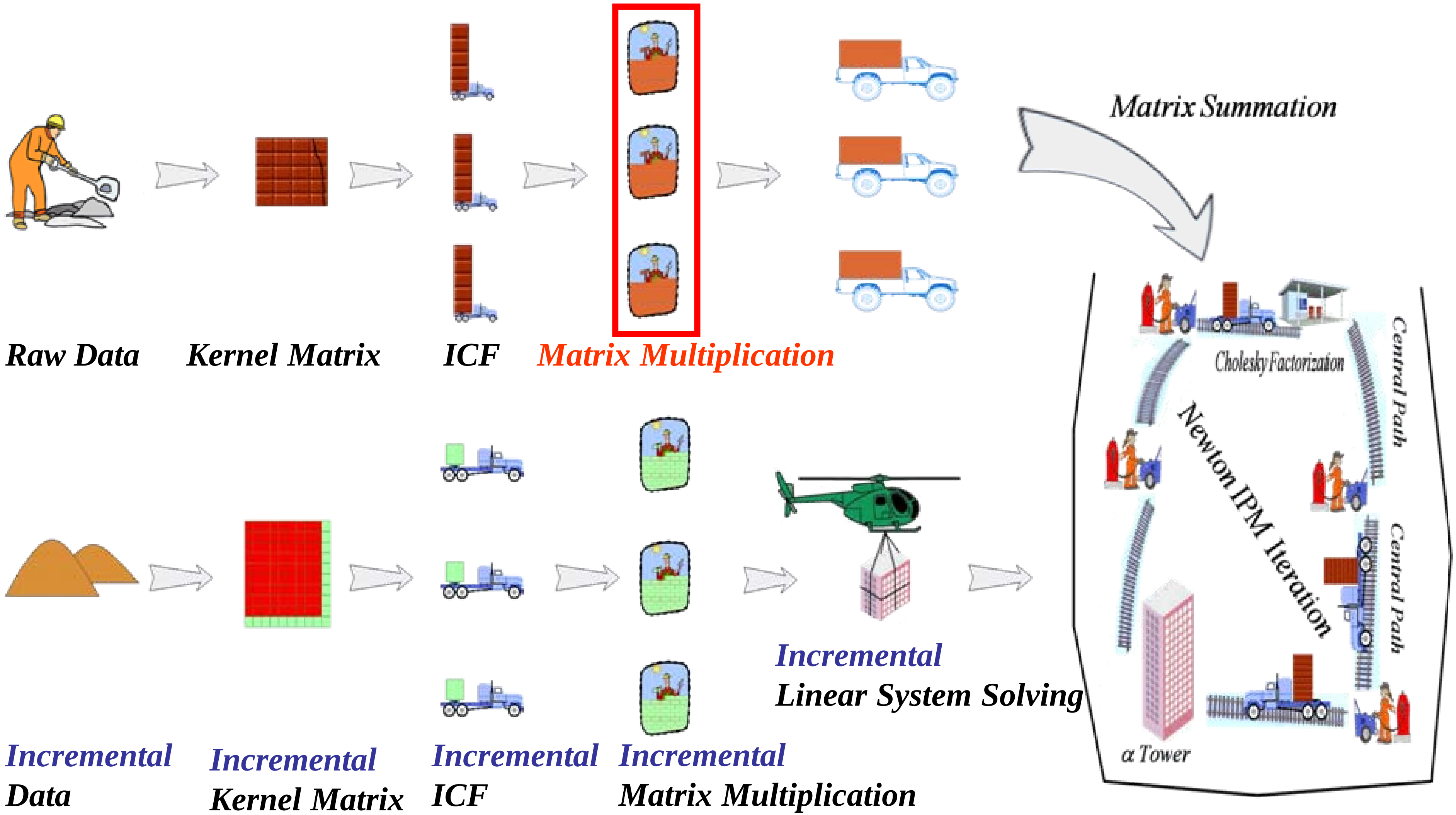
Parallelized and Incremental SVM



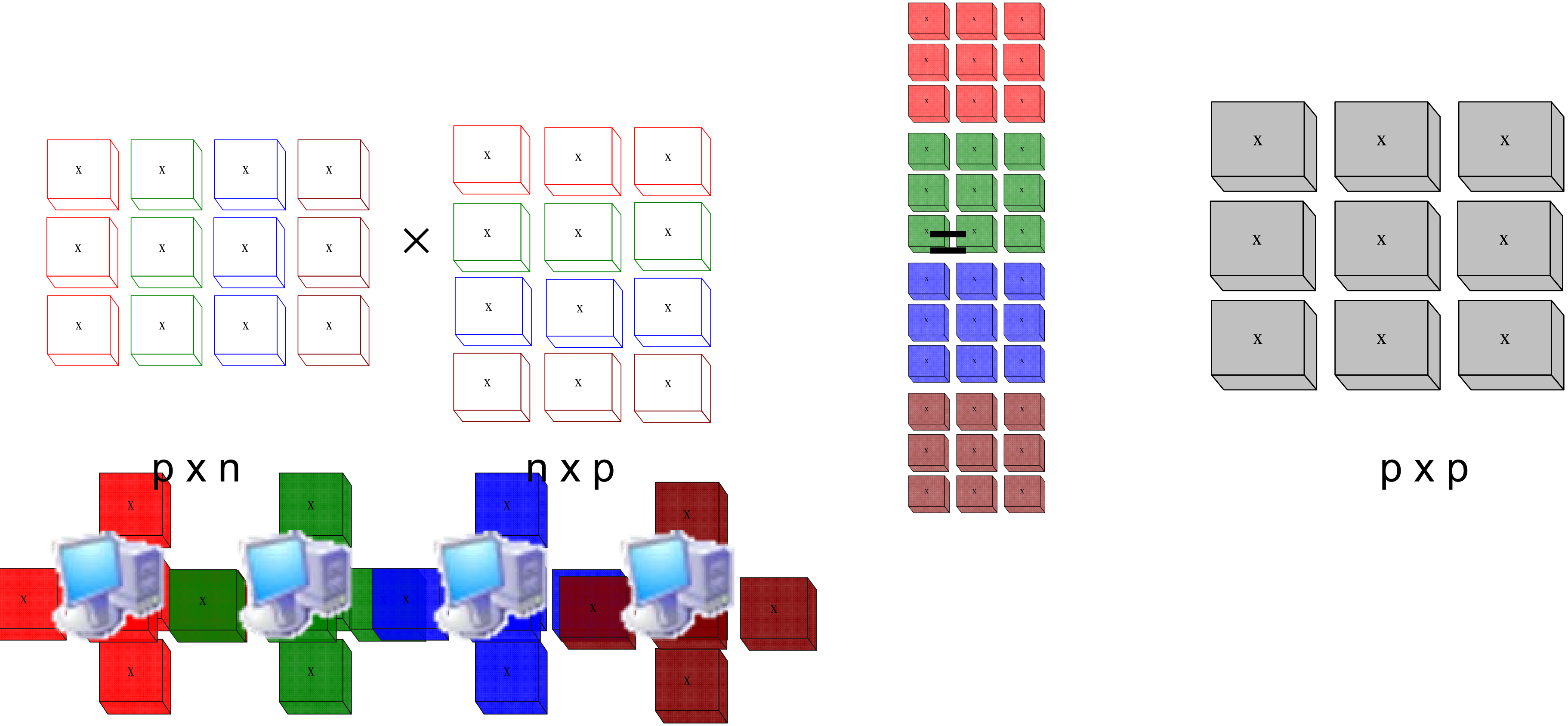
Incomplete Cholesky Factorization (ICF)



Parallelized and Incremental SVM



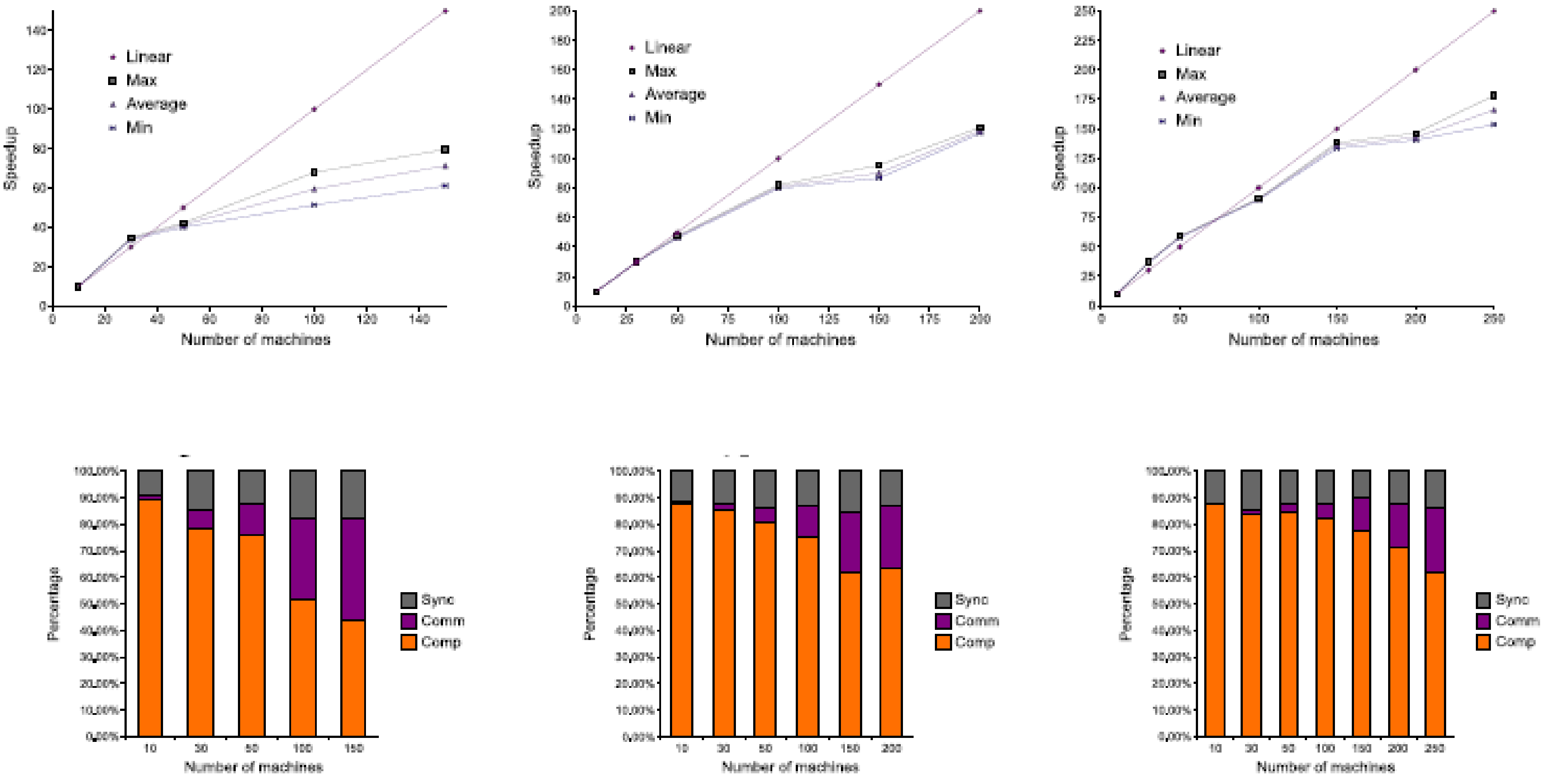
Matrix Product



Speedup

	Image (200k)			CoverType (500k)			RCV (800k)		
Machines	Time (s)		Speedup	Time (s)		Speedup	Time (s)		Speedup
10	1,958	(9)	10*	16,818	(442)	10*	45,135	(1373)	10*
30	572	(8)	34.2	5,591	(10)	30.1	12,289	(98)	36.7
50	473	(14)	41.4	3,598	(60)	46.8	7,695	(92)	58.7
100	330	(47)	59.4	2,082	(29)	80.8	4,992	(34)	90.4
150	274	(40)	71.4	1,865	(93)	90.2	3,313	(59)	136.3
200	294	(41)	66.7	1,416	(24)	118.7	3,163	(69)	142.7
250	397	(78)	49.4	1,405	(115)	119.7	2,719	(203)	166.0
500	814	(123)	24.1	1,655	(34)	101.6	2,671	(193)	169.0
LIBSVM	4,334	NA	NA	28,149	NA	NA	184,199	NA	NA

Overheads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Summary

- Have parallelized key subroutines for mining massive data sets
  - Spectral Clustering
  - Frequent Itemset Mining
  - Combinational Collaborative Filtering
    - with PLSA
    - with LDA
  - Support Vector Machines
- Relevant papers
  - http://infolab.stanford.edu/~echang/
- Open Source PSVM
  - http://code.google.com/p/psvm/

Concluding Remarks

- Google distributed computing infrastructure is cost effective
- Timeliness can be as good as real-time
  - E.g., timely recommendation
- An expensive and parallelizable algorithm can be a better choice than a fast but non-parallelizable one
  - Column-based ICF over row-based in PSVM
  - t-NN over Nystrom in Spectral Clustering
- Relevant Information critical
  - Information fusion of CCF
  - Sparsification of Spectral Clustering

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