Large-scale Data Mining Tutorial

Edward Chang

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Hongjie Bai

KeyPapers

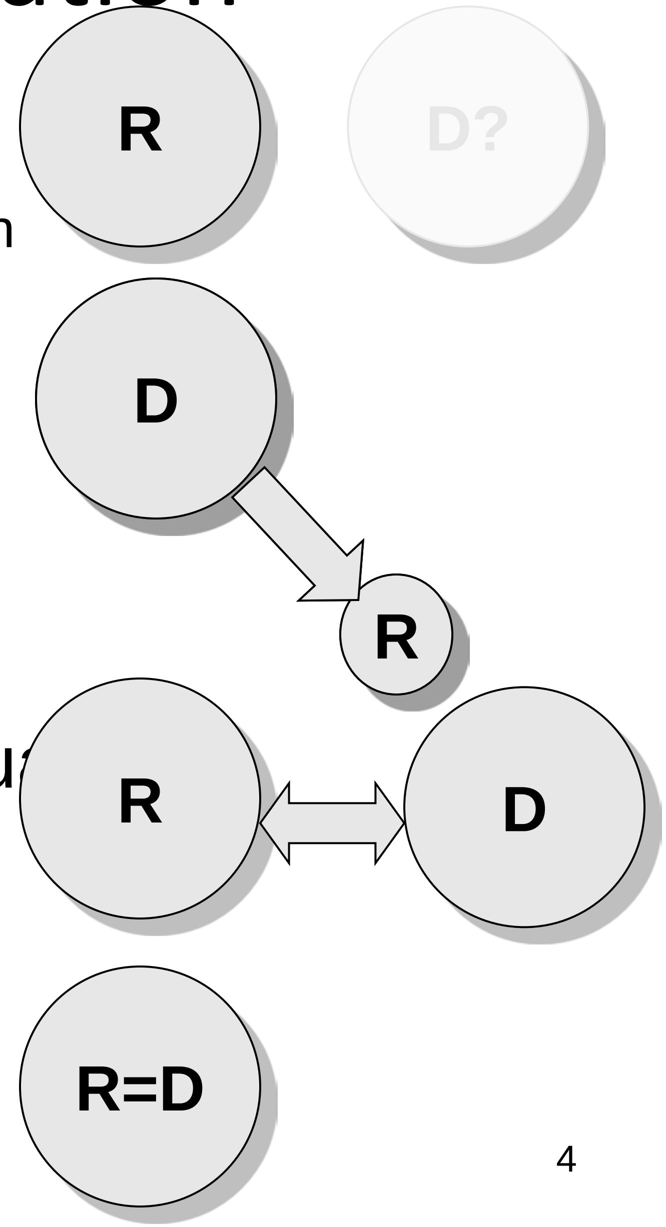
- **AdHeat (Social Ads)**:
  - AdHeat: An Influence-based Diffusion Model for Propagating Hints to Match Ads, H.J. Bao and E. Y. Chang, WWW 2010 (best paper candidate), April 2010.
  - Parallel Spectral Clustering in Distributed Systems, W.-Y. Chen, Y. Song, H. Bai, Chih-Jen Lin, and E. Y. Chang, IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2010.
- **UserRank**:
  - Confucius and its Intelligent Disciples, Search + Social, X. Si, E. Y. Chang, Z. Gyongyi, and M.Sun, VLDB, September 2010 .
  - Topic-dependent User Rank, X. Si, Z. Gyongyi, E. Y. Chang, and M.S. Sun, Google Technical Report.
- **Large-scale Collaborative Filtering**:
  - PLDA+: Parallel Latent Dirichlet Allocation with Data Placement and Pipeline Processing, ACM Transactions on Intelligent Systems and Technology (accepted).
  - Collaborative Filtering for Orkut Communities: Discovery of User Latent Behavior, W.-Y. Chen, J. Chu, Y. Wang, and E. Y. Chang, WWW 2009: 681-690.
  - Combinational Collaborative Filtering for Personalized Community Recommendation, W.-Y. Chen, D. Zhang, and E. Y. Chang, KDD 2008: 115-123.
  - Parallel SVMs, E. Y. Chang, et al., NIPS 2007.

Collaborators

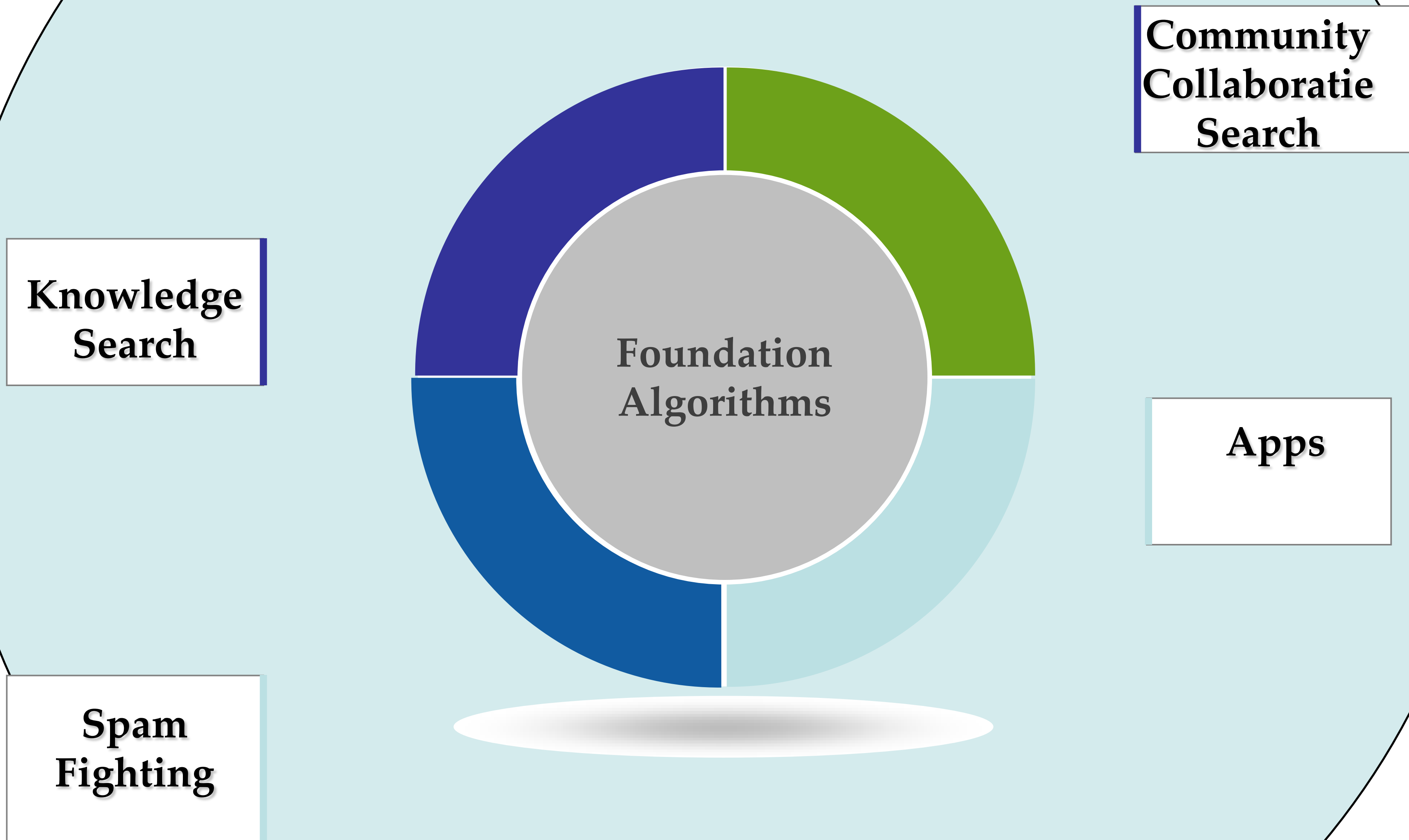
- Prof. Chih-Jen Lin (NTU)
- Hongjie Bai (Google)
- Hongji Bao (Google)
- Wen-Yen Chen (UCSB)
- Jon Chu (MIT)
- Haoyuan Li (PKU)
- Zhiyuan Liu (Tsinghua)
- Yangqiu Song (Tsinghua)
- Matt Stanton (CMU)
- Xiance Si (Tsinghua)
- Yi Wang (Google)
- Dong Zhang (Google)
- Kaihua Zhu (Google)

Models of Innovation

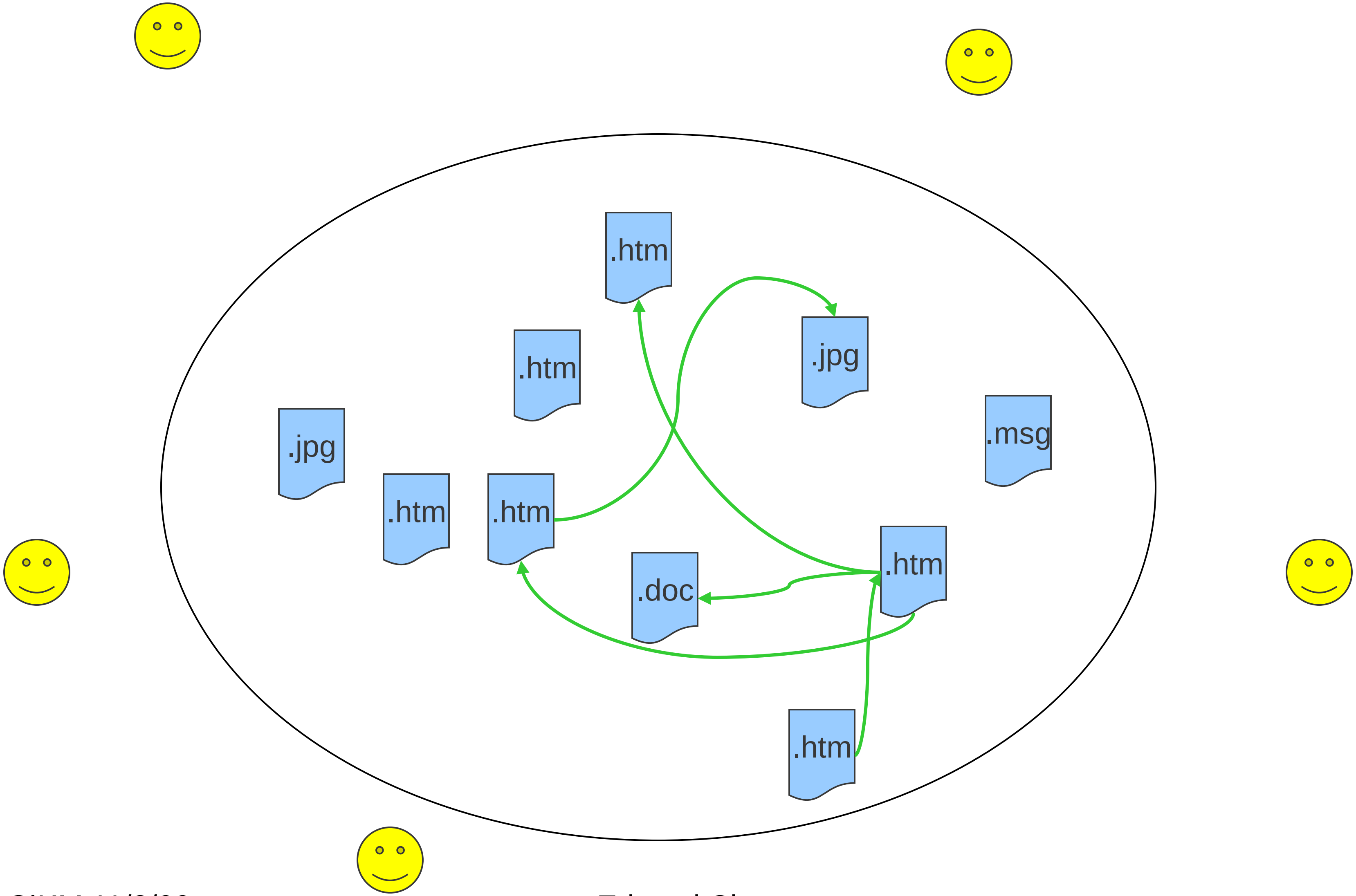
- Ivory tower
  - Only consider theory but not application
- Build it and they will come
  - Scientists drives product development
- “Research for sale”
  - Research funded by:
    - product groups or customers
- Research & development as equa
  - Research “sells” innovation;
  - Product “requests” innovation
- Google-style innovation



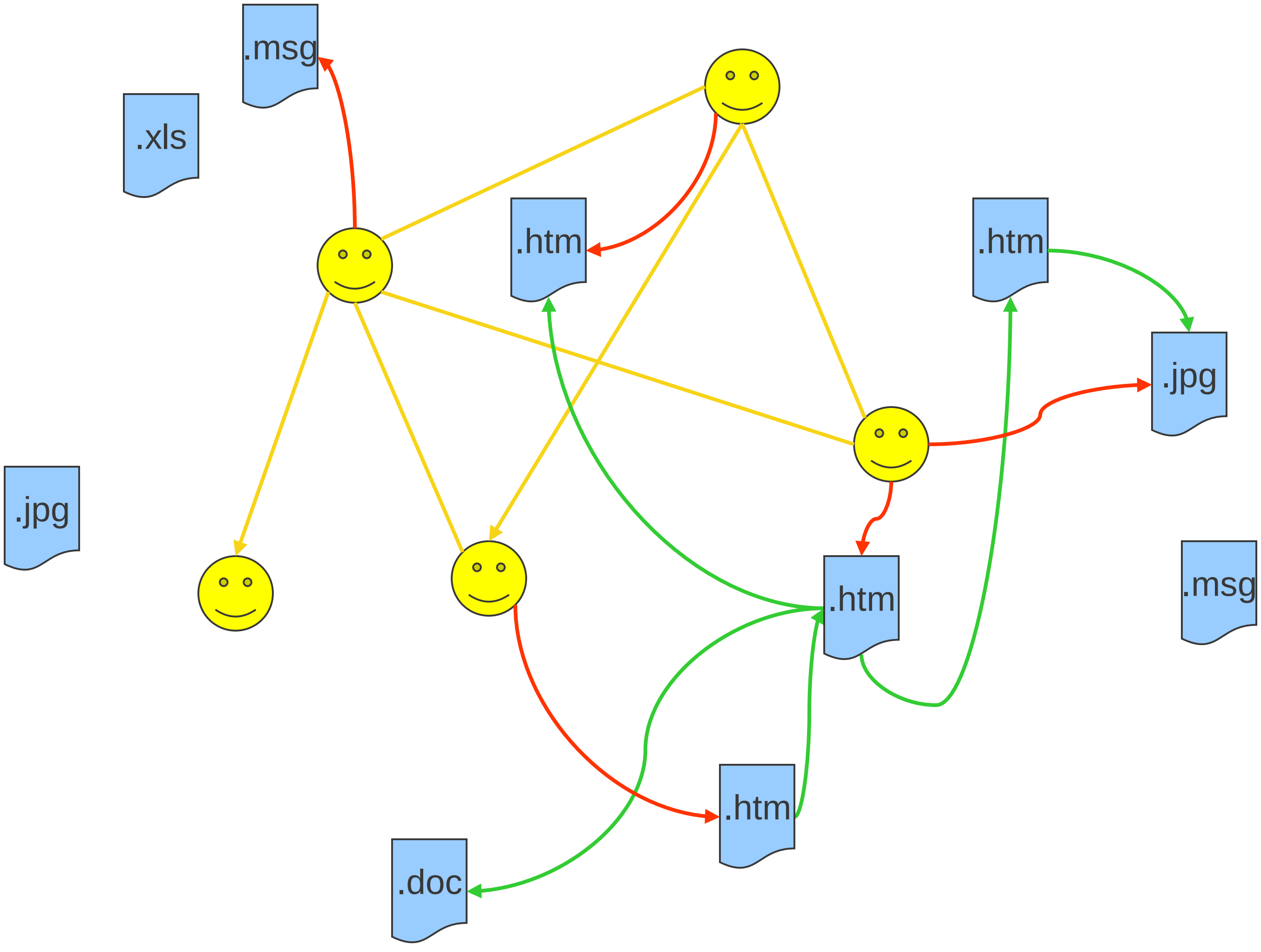
Project Summary



Web 1.0

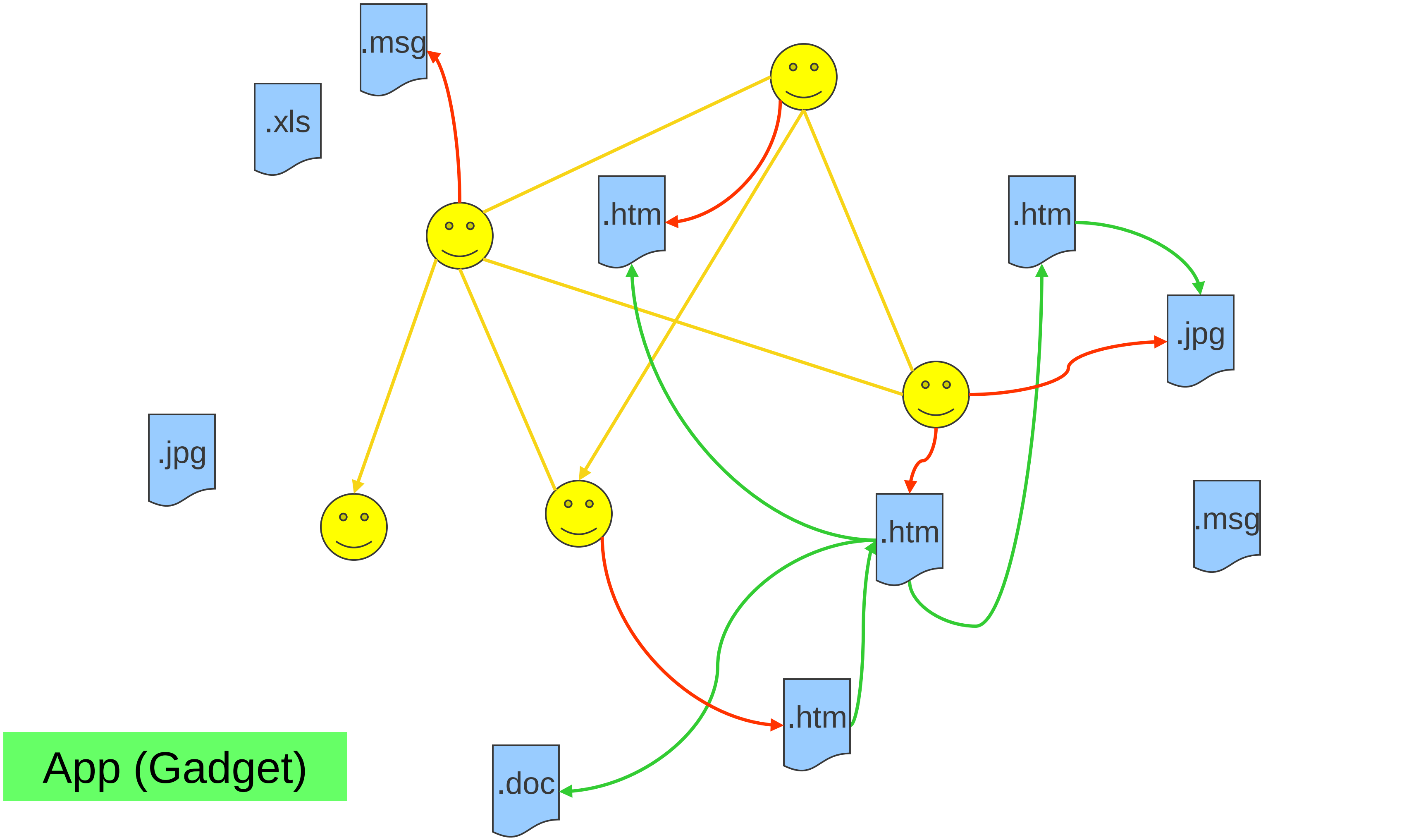


Web 2.0 --- Web with People



+ Social Platforms

App (Gadget)




天涯来吧 - 我的朋友圈 - Mozilla Firefox
File Edit View History Bookmarks Tools Help
http://laiba.tianya.cn/laiba/FlashFriends
Google
Google.com - In...
google gadget -...
OpenSocial Plat...
Fensi Dashboard
天涯来吧 - 我...
Darren Huang - ...
Google.com - C...
我的主页
资料
朋友
来吧
帖子
影集
日记
礼物
New!
评价
留言簿
我的朋友圈 | 我的朋友
上一步 |
回到自己
永远来吧
易绍
机械舞
汤汤汤圆
暗香浮月
开复
沉网
武汉牛牛
水星cici
梦侠人
无聊最寂寞
邀请朋友加入来吧
邮件
*
发送邀请
我要群发邀请»
看看我的朋友在哪
Transferring data from laiba.tianya.cn...
start
3 Firefox
C:\Docum...
Document...
2 Micros...
Google R...
EN
10:04 PM


天涯来吧 - 我的朋友圈 - Mozilla Firefox
File Edit View History Bookmarks Tools Help
http://laiba.tianya.cn/laiba/FlashFriends
Google
Google.com - In...
google gadget -...
Google.com
Fensi Dashboard
天涯来吧 - 我...
Darren Huang - ...
Google.com - C...
我的主页 资料 朋友 来吧 帖子 影集 日记 礼物 New! 评价 留言簿
我的朋友圈 | 我的朋友
上一步
回到自己
永远来吧
机械舞
暗香浮月
水星cici
梦侠人
无聊最寂寞
永远来吧 (离线)
我的好友
批量上传照片吧!
男 37岁 北京
夜幕诱惑,诱的就是你!... [08-1-3]
这有没GOOGLE公司的伙... [07-8-20]
白领的家庭聚会 [07-12-30]
白领的家庭聚会 [07-12-30]
白领的家庭聚会 [07-12-30]
移除好友
邀请朋友加入来吧
邮件
发送邀请
我要群发邀请»
看看我的朋友在哪
Transferring data from laiba.tianya.cn...
start
3 Firefox
C:\Docum...
Document...
2 Micros...
Google R...
EN
10:12 PM

Open Social APIs

1

Profiles (who I am)

2

Friends (who I know)

Open Social

3

Activities (what I do)

4

Stuff (what I have)


Mozilla Firefox
File Edit View History Bookmarks Tools Help
我的主页
资料
朋友
来吧
帖子
影集
日记
礼物 New!
评价
留言簿
我的朋友圈 | 我的朋友
上一步
回到自己
cxwangyi
DogCaptain
NelsonYao
bornde
eyuchang
calla_qu
cyr_215
2dowhat
Mindy_xiaomi...
80x86
YitengZhang
Google
邀请朋友加入来吧
邮件
姓名
发送邀请
我要群发邀请»
看看我的朋友在哪
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2 Windows Explorer
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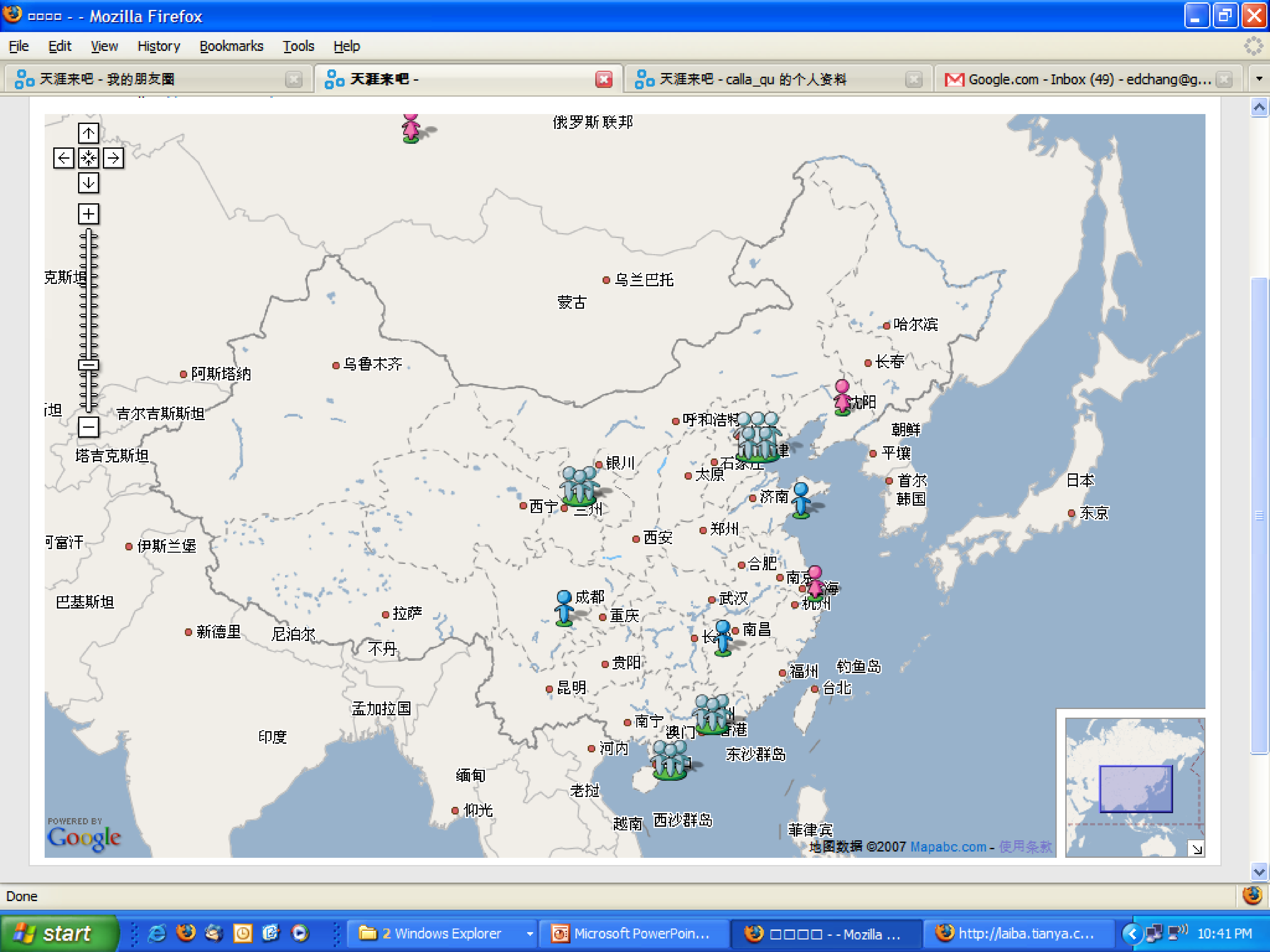
Mozilla Firefox
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天涯来吧 - 我的朋友圈
天涯来吧 -
天涯来吧 - calla_qu 的个人资料
Google.com - Inbox (49) - edchang@g...
俄罗斯联邦
乌兰巴托
蒙古
哈尔滨
长春
阿斯塔纳
乌鲁木齐
吉尔吉斯斯坦
塔吉克斯坦
朝鲜
平壤
银川
太原
首尔
韩国
日本
东京
济南
西宁
郑州
西安
伊斯兰堡
合肥
巴基斯坦
成都
武汉
拉萨
重庆
南昌
新德里
尼泊尔
不丹
贵阳
福州
钓鱼岛
台北
昆明
孟加拉国
南宁
澳门
印度
河内
东沙群岛
缅甸
老挝
仰光
越南
西沙群岛
菲律宾
POWERED BY Google
地图数据 ©2007 Mapabc.com - 使用条款
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2 Windows Explorer
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- - Mozilla ...
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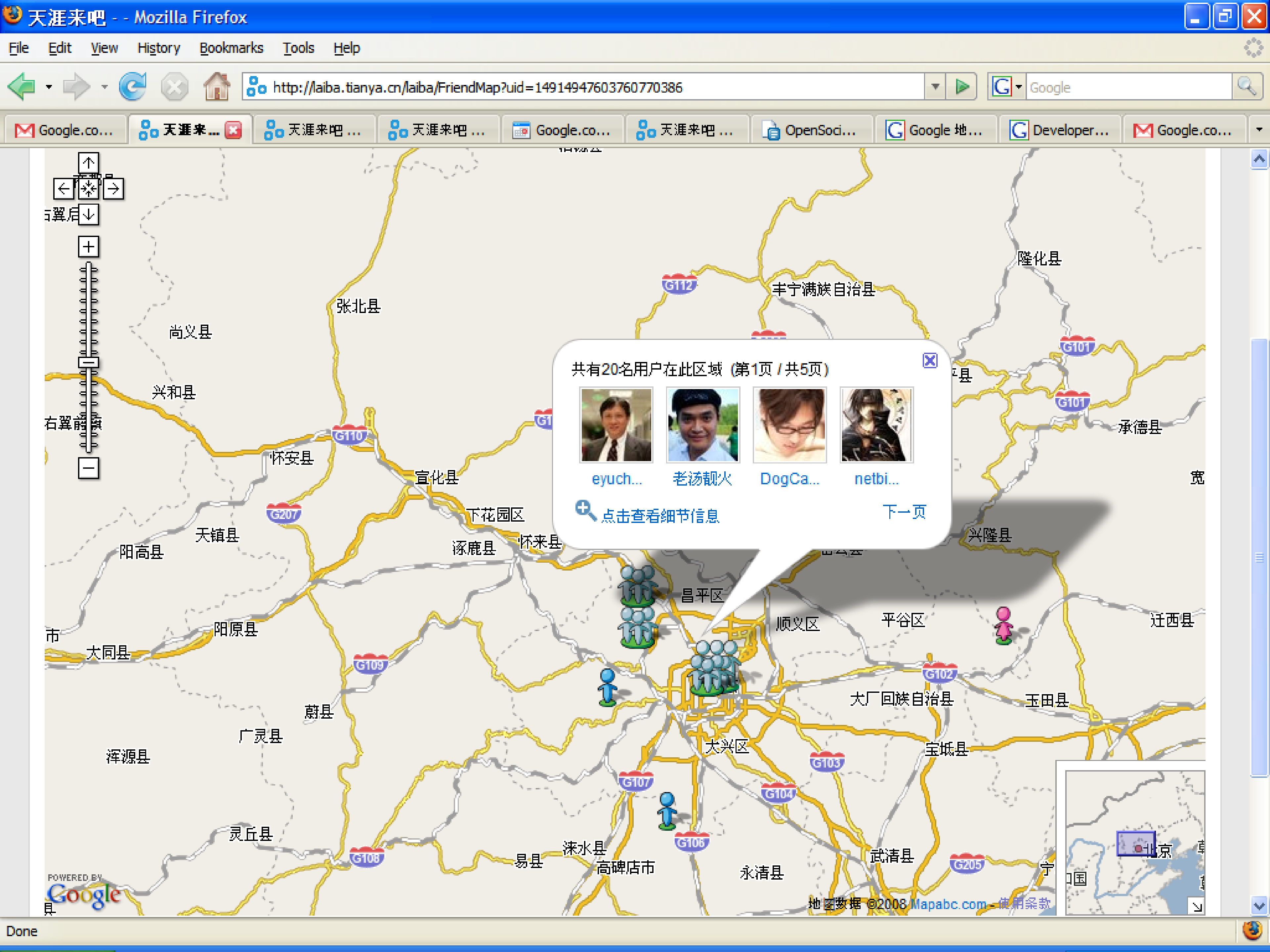

天涯来吧 - - Mozilla Firefox
File Edit View History Bookmarks Tools Help
http://laiba.tianya.cn/laiba/FriendMap?uid=14914947603760770386
Google
Google.co...
天涯来...
天涯来吧 ...
天涯来吧 ...
Google.co...
天涯来吧 ...
OpenSoci...
Google 地...
Developer...
Google.co...
共有20名用户在此区域（第1页 / 共5页）
eyuch...
老汤靓火
DogCa...
netbi...
点击查看细节信息
下一页
张北县
尚义县
兴和县
怀安县
宣化县
下花园区
涿鹿县
怀来县
天镇县
阳高县
阳原县
大同县
蔚县
广灵县
浑源县
灵丘县
易县
涞水县
高碑店市
永清县
武清县
宝坻县
玉田县
大厂回族自治县
大兴区
昌平区
顺义区
平谷区
迁西县
兴隆县
承德县
隆化县
丰宁满族自治县
G112
G101
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G207
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G103
G104
G107
G106
G108
G205
地图数据 ©2008 Mapabc.com - 使用条款
POWERED BY Google
Done


Facebook | Home - Mozilla Firefox
File Edit View History Bookmarks Tools Help
http://www.facebook.com/home.php?ref=logo
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Google.com Mail - I...
Google.com - Cale...
Flare | Demos
Google
Facebook | Home
Dart Search Notific...
facebook
Home Profile Friends Inbox
Edward Chang Settings Logout
Search
News Feed
UCSB
Status Updates
Photos
Links
More
Create
What's on your mind?
Share
Activities
Bo Zhang http://www.optrip.com
BETA
OpTrip - Plan a Trip
Source: www.optrip.com
Yesterday at 5:02pm · Comment · Like · Share
Tom Wang at 9:28pm June 1
are u working there? btw, I can't connect to it.
Write a comment...
Ling Ling Wed - dinner at BJ's to meet up some old friends from Beijing; funny thing was everyone thought BJ's was a Peking duck restaurant!
Thur - salsa @ Alberto's in MV. Thanks Wing for coming and Stephen was visiting from NYC.
Sat - BBQ @ Lynn and Jeff's new crib in SOMA and we also watched UP in 3D IMAX :)
Sun - reunion brunch with International staffing at Stanford mall and also did shopping there with Dandan.
Requests
See All
6 friend requests
1 how will you die? request
1 best friend request
41 other requests
Suggestions
See All
Chunlei Niu
You and Chunlei both worked at Google.
Add as Friend
Sponsored
Recommendations
Ads
Learn how to connect your business to real customers through Facebook Ads.
Highlights
Last week of May
by Ling Ling
Random...
by Rosalind Chang
TouchGraph Photos
Applications
Applications
Chat (1)
Done
start
4 Windows Explorer
2 Firefox
2 Microsoft Office ...
4 Microsoft Office ...
9:02 AM

Facebook | Kaihua Zhu's Photos - Mobile Uploads - Mozilla Firefox

File Edit View History Bookmarks Tools Help

http://www.facebook.com/photo.php?pid=2038339&id=553855783&ref=nf

Google.com Mail - I... | Google.com - Cale... | Flare | Demos | Google | Facebook | Kaih... | Dart Search Notific...

facebook Home Profile Friends Inbox Edward Chang Settings Logout Search

Kaihua Zhu's Photos - Mobile Uploads

Photo 3 of 5 | Back to Album | Kaihua's Photos | Kaihua's Profile Previous Next

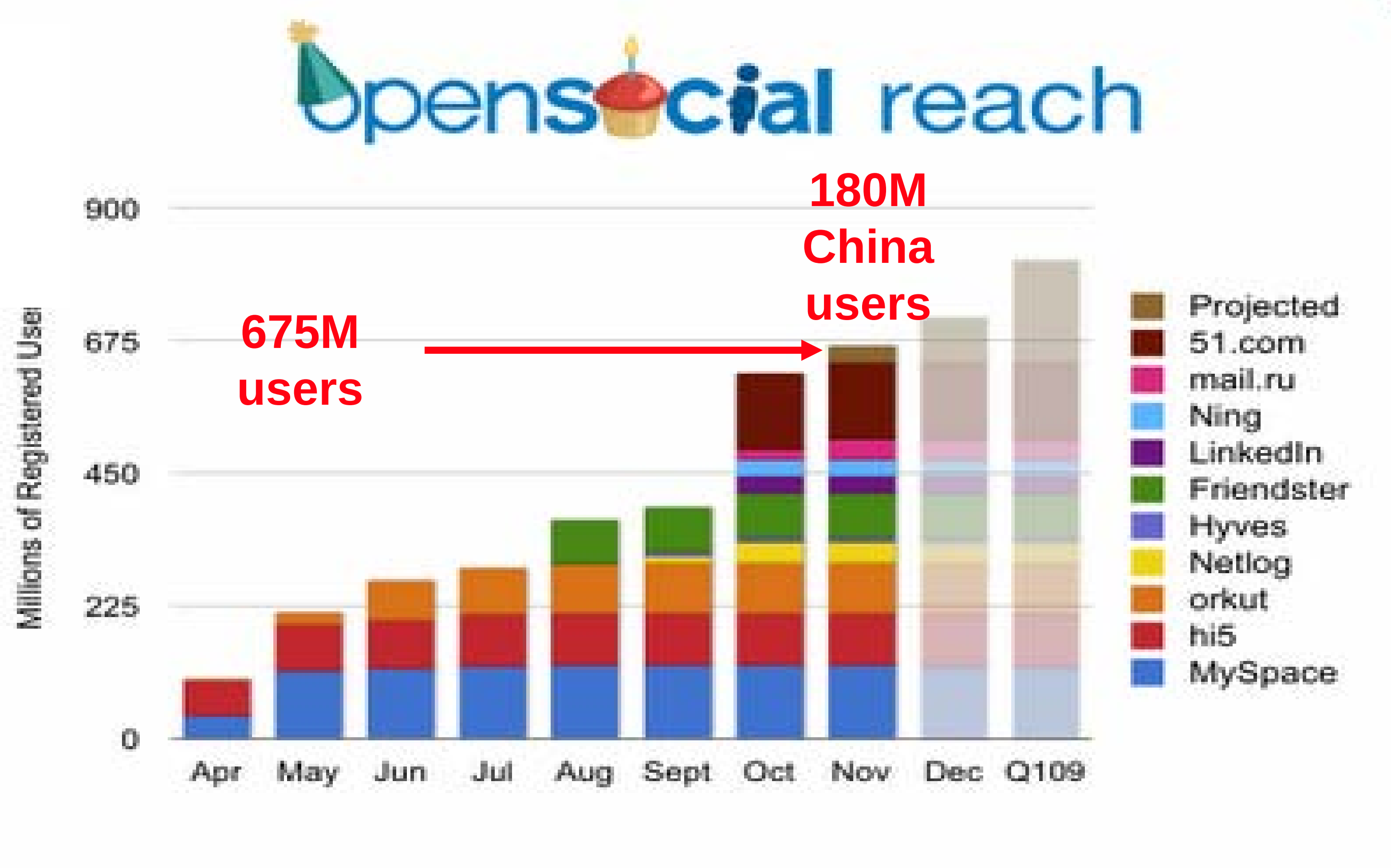
Applications Chat (0)

Done

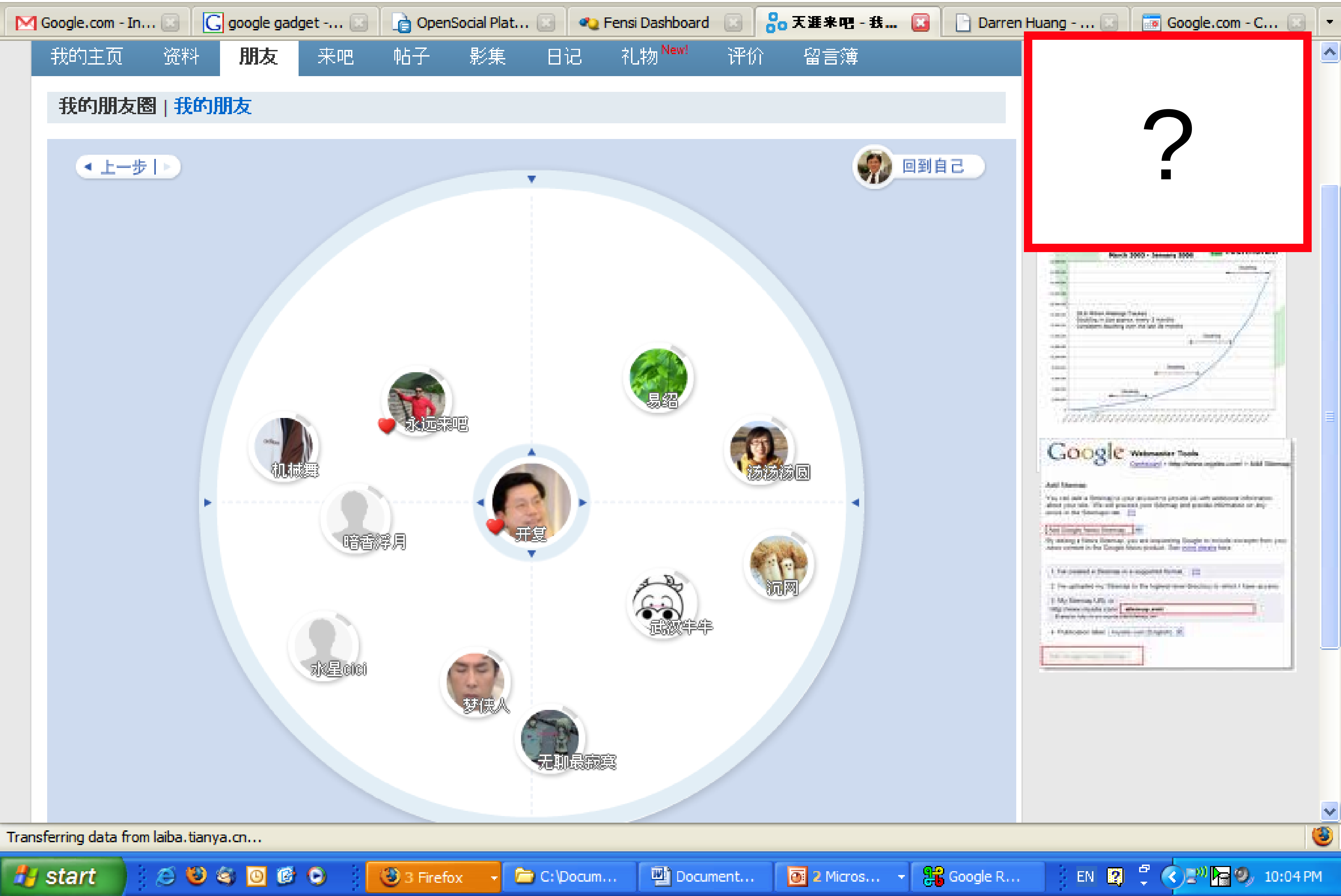
start 4 Windows Explorer 2 Firefox 2 Microsoft Office ... 4 Microsoft Office ... 8:59 AM


orkut
LinkedIn
hi5
salesforce.com
OpenSocial

Open Social in China



Kill Apps



Google.com - In...
google gadget -...
OpenSocial Plat...
Fensi Dashboard
天涯来吧 - 我...
Darren Huang - ...
Google.com - C...
我的主页 资料 朋友 来吧 帖子 影集 日记 礼物 New! 评价 留言簿
我的朋友圈 | 我的朋友
上一步
回到自己
永远来吧
易绍
机械舞
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无聊最寂寞
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Transferring data from laiba.tianya.cn...
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C:\Docum...
Document...
2 Micros...
Google R...
EN
10:04 PM

Killer Apps

- Monetization!
  - Social ads
- Knowledge Search (Q & A)
  - Improving search quality
  - Capturing user intent


秦始皇 - Google 搜索 - Mozilla Firefox
File Edit View History Bookmarks Tools Help
http://www.google.cn/search?hl=zh-CN&q=秦始皇&btnG=Google+搜索&meta=&aq=f&oq=
Google.com M... Google.com - ... Flare | Demos 天涯问答 秦始皇 - Goo... Google.com M... Google.com M...
网页 图片 视频 地图 资讯 财经 博客 更多 ▼ 登录
秦始皇
Google 搜索
高级搜索 | 使用偏好
所有网页 中文网页 简体中文网页 中国的网页
网页 搜索百宝箱...
约有 3,590,000 项符合 秦始皇 的查询结果，以下是第1-10 项 （搜索用时 0.05 秒）
秦始皇_百度百科
秦始皇（公元前259—前210年），中国第一个封建王朝——秦王朝的始皇帝。后人称之为"千古一帝"。 姓嬴，名政，秦庄襄王之子，出生于赵国首都邯郸（今河北省邯郸市）， ...
baike.baidu.com/view/2389.htm - 75k - 网页快照 - 类似网页
《秦始皇》官网网站
秦始皇游戏：封王进爵，争当乱世英雄，装备打造，绝世神兵与日逐光，热血战争，开疆扩土誓夺天下。 光宇游戏：是中国五大百万在线级玩家游戏平台之一，集休闲、即时、 ...
qin.gyyx.cn/ - 8k - 网页快照 - 类似网页
秦始皇新手卡,非秦始皇官网,秦始皇推广人,秦始皇ol推广员填tg1700
本站是秦始皇官网合作推广人,注册秦始皇填写秦始皇推广人tg1700可获得秦始皇至尊奖励只要注册时填写可在收费后获得奖励,本站主要介绍秦始皇ol新闻及资料,非秦始皇官网.
www.1300h.com/ - 30k - 网页快照 - 类似网页
"秦始皇"的视频搜索结果
揭密秦始皇陵千古真相（下）
8 分钟
you.video.sina.com.cn
秦始皇陵墓春节被盗
3 分 29 秒
v.ku6.com
秦始皇-维基百科，自由的百科全书
秦始皇（前259年－前210年），是中國戰國末期秦國君主及秦朝第一任皇帝，全稱秦始皇帝，
赞助商链接
Google视频- 秦始皇
热门视频搜索，及时快速网络更新
众多热门视频，最新流行尽在掌握!
video.google.cn
在此查留言 »
Done
start
4 Windows Explorer
2 Firefox
2 Microsoft Office ...
HAAS
1:13 PM

Query: *What are must-see attractions at Yellowstone*

What are must-see attractions at Yellowstone - Google Search - Mozilla Firefox

Who is the First Emperor... | Google.com Mail - Inbox ... | Program (RUGS'08) | What are must-see at... | Seeing the opportunity f...

Google

What are must-see attractions at Yellowstone [Search] Advanced Search Preferences

Web Results **1** - **10** of about **12,000** for **What are must-see attractions at Yellowstone**. (**0.18** seconds)

Three Must See Attractions at Yellowstone National Park « The View ...
Jan 15, 2008 ... Smith presents Three **Must See Attractions at Yellowstone** National Park posted at The View West. Interested in **Yellowstone** National Park? ...
theviewwest.com/2008/01/15/three-**must-see-attractions-at-yellowstone**-national-park/ - 26k - Cached - Similar pages

Three Must See Attractions At Yellowstone National Park
Jan 15, 2008 ... Three **Must See Attractions At Yellowstone** National Park.
ezinearticles.com/?Three-**Must-See-Attractions-At-Yellowstone**-National-Park&id=929265 - 47k - Cached - Similar pages

Yellowstone National Park: Top Ten Attractions
YELLOWSTONE NATIONAL PARK by **Yellowstone** Net. Top 10 Things to See in YNP What are the "**Must See**" **attractions** to view in **Yellowstone**? Start here! ...
www.**yellowstone**.net/topten.htm - 16k - Cached - Similar pages

Yellowstone Must-see Attractions
Yellowstone's Must-See Attractions. The locations of all sites listed below are shown on the map that you receive as you enter the park. ...
www.geocities.com/dmonteit/**must_see**.html - 8k - Cached - Similar pages

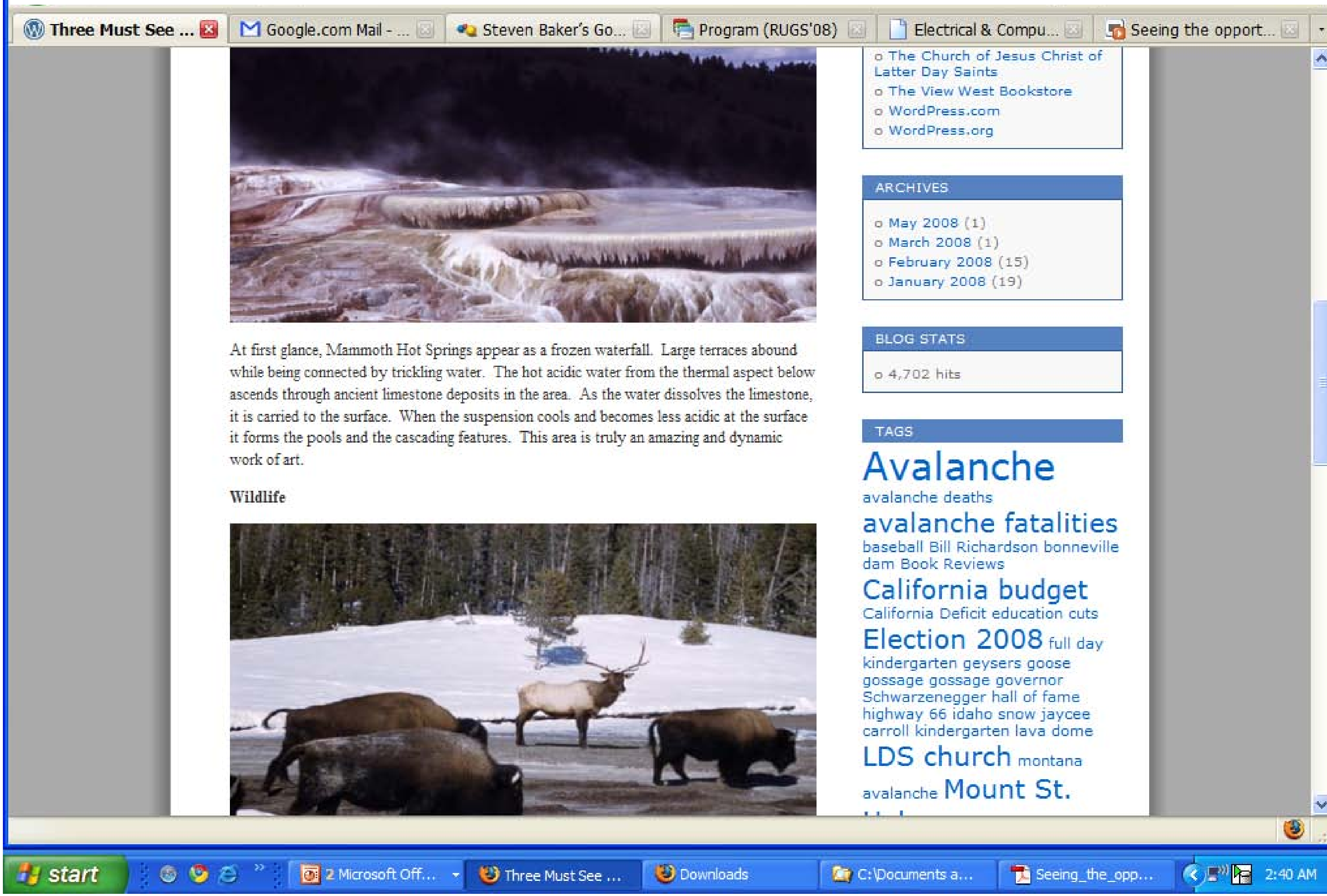
> **What to See in Yellowstone**
> **Must-See Attractions** -- Text Only Version · Upper Geyser Basin and Old Faithful · Grand Canyon of the **Yellowstone** · Fountain Paint Pots Trail · Wildlife ...
> www.geocities.com/dmonteit/whattosee.html - 10k - Cached - Similar pages
> More results from www.geocities.com »

Must See in Yellowstone National Park

start | 2 Microsoft Off... | What are must-s... | Downloads | C:\Documents a... | Seeing_the_opp... | 3:15 AM

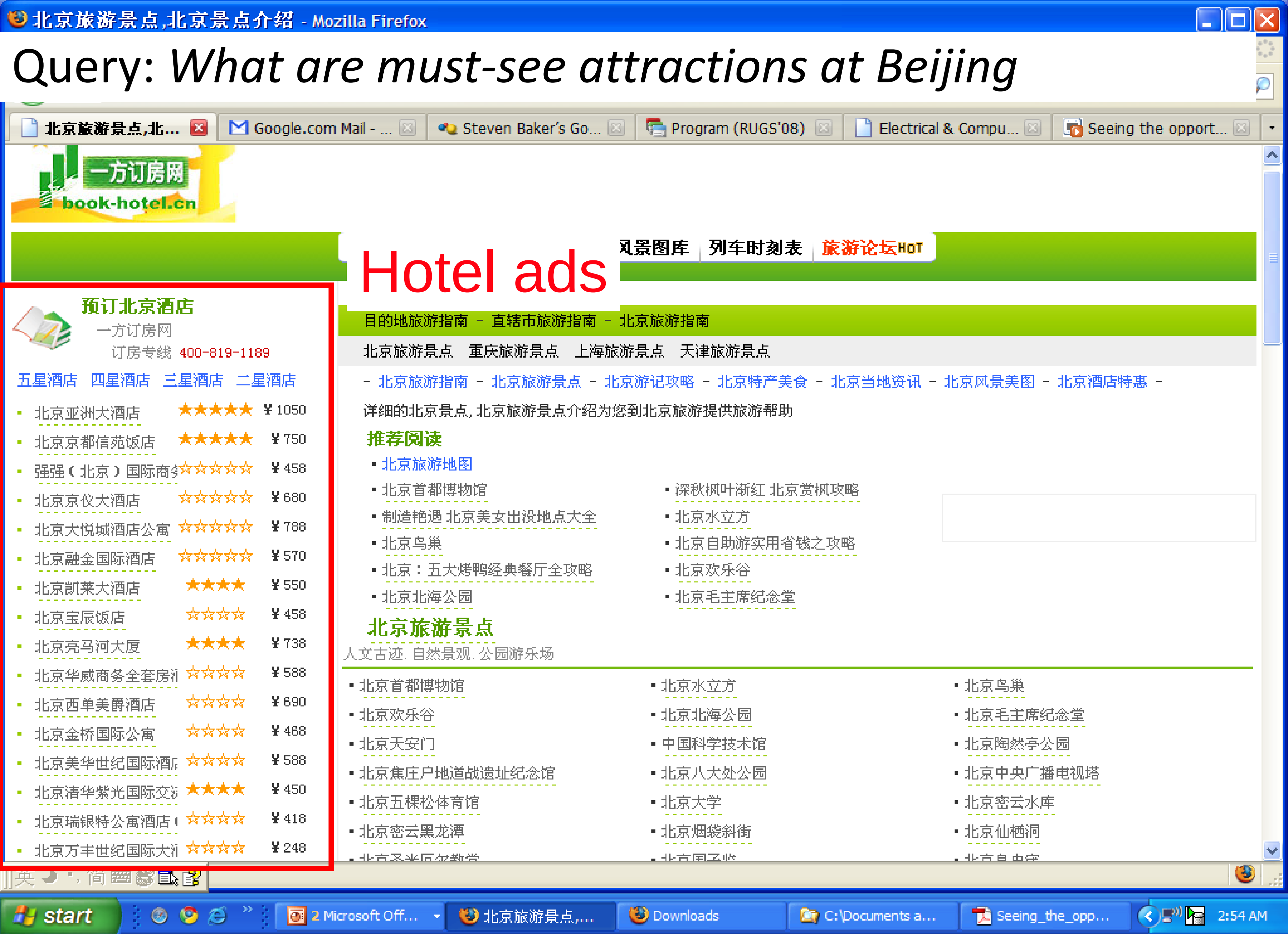
Three Must See Attractions at Yellowstone National Park « The View West - Mozilla Firefox

Query: *What are must-see attractions at Yellowstone*



Query: *What are must-see attractions at Yosemite*

Query: *What are must-see attractions at Beijing*



谁是姚明 - Google 搜索 - Mozilla Firefox

File Edit View History Bookmarks Tools Help

http://www.google.cn/search?hl=zh-CN&q=谁是姚明&btnG=Google+搜索&meta=&aq=f&oq

Google

Most Visited | Helpdesk | Presentations (Fensi ...

谁是姚明 - Google 搜索 | GOOG: 390.43 +1.69 (0.43%) - ... | Google.com - Calendar

Google

谁是姚明

Who is Yao Ming

高级搜索 | 使用偏好

所有网页

网页 约有 **7,730,000** 项符合 **谁是姚明** 的查询结果，以下是第**1-10** 项 （搜索用时 **0.27** 秒）

谁是姚明的相关焦点

谁把开拓者推给火箭队？ 姚明：要解决绕前防守 - 9小时前

比赛结束之后，姚明在更衣室接受了媒体采访，他表示，火箭队要想在季后赛中走得更远，就必须解决一个问题，“破绕前”。“我想这个问题，一直是处理不好，打破对方的绕前 ...

搜狐 - 1913 篇相关文章 »

对话魔兽：姚明最难防守我要成第二位黑人总统 - 搜狐 - 22 篇相关文章 »

郭晶晶凭何压张怡宁 谁是下一任广告天后(图) - 央视国际 - 25 篇相关文章 »

姚明官方Flash 谁是姚明？ -姚明官方网站

“我对姚明最欣赏的地方就是他对待比赛的那种谦虚和热情共存的态度，在如今的联盟中，具有这些优点的球员已经看不到了。” ——杰夫-范甘迪，火箭队主帅 ...

yaoming.sports.sohu.com/20071208/n253876711.shtml - 16k - 网页快照 - 类似网页

谁是火箭最该走的人呢？_姚明之家_篮坛风云_新浪论坛_新浪网

2009年4月5日 ... 谁是火箭最该走的人呢？_姚明之家_篮坛风云_新浪论坛_新浪网.

sports.sina.com.cn/bbs/2009/0405/114144169.html - 140k - 网页快照 - 类似网页

赛季评分：姚明钻石引领高分猜猜谁是唯一10分？_姚明-火箭_体坛周报-体坛网

在常规赛结束的时候，还是让我们看看现在和这个赛季曾经的火箭球员的表现，给他们的赛季表现打一个分吧。

rockets.basketball.titan24.com/09-04-16/210058.html - 30k - 网页快照 - 类似网页

火箭球迷热论大前锋人选到底谁是姚明左膀右臂

MrButtocks最后认为诺瓦克应该充当第一替补大前锋，因为从04－05赛季就可以看出三分球对

Done

start | 4 Microsoft Office ... | 谁是姚明 - Google ... | Downloads | Google - Mozilla Fire... | 9:50 AM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春秋中文社区# K# C#]# K0 h- b# f1 }5 Q! m8]姚明和王治郅还能打出6年前那样的数据吗?
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网友调查：您认为火箭队中谁是姚明的最佳替补-搜狐体育
网友调查：您认为火箭队中谁是姚明的最佳替补. 2009年04月11日13:02 [我来说两句] [字号：
大 中 小]. 来源：搜狐体育. 搜狐体育讯 ...
sports.sohu.com/20090411/n263328639.shtml - 128k - 网页快照 - 类似网页
谁是火炬手？姚明和刘翔的得票数一直领先_YNET.com北青网
谁是火炬手？姚明和刘翔的得票数一直领先. 来源：体育新报(2007/09/07 13:56)◇字号：［大
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谁是NBA第四中国秀？姚明不忍朱芳雨来火箭受罪. 2005年04月26日16:31:59 来源：篮球先
锋报. 【字号大 中 小】 【我要打印】 【我要纠错】 ...
Q&A Yao Ming
Discuss Yao Ming
相关服务：
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到天涯来吧讨论谁是姚明
Gooooooooooogle
1 2 3 4 5 6 7 8 9 10 下一页
Done

天涯问答 - Mozilla Firefox
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GOOG: 390.43 +1.69 (0.43%) - ...
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Google 谷歌 技术提供
搜索引擎里找不到想要的答案？让天涯社区成千上万的专家高手来帮助你！
已有3,634,299个匿名用户已经在此提问，平均每个问题收到第一个答案时间不超过3分钟
让天涯问答专家帮助你答疑解惑
您可以匿名提问。要获得更多精彩知识，请 登录 或者 注册
提问的标题：
谁是姚明
Who is Yao Ming
详细描述：
（选填）
提问形式：
还不是天涯用户，使用匿名提问
已经是天涯注册用户，使用天涯ID登录后提问
发表提问
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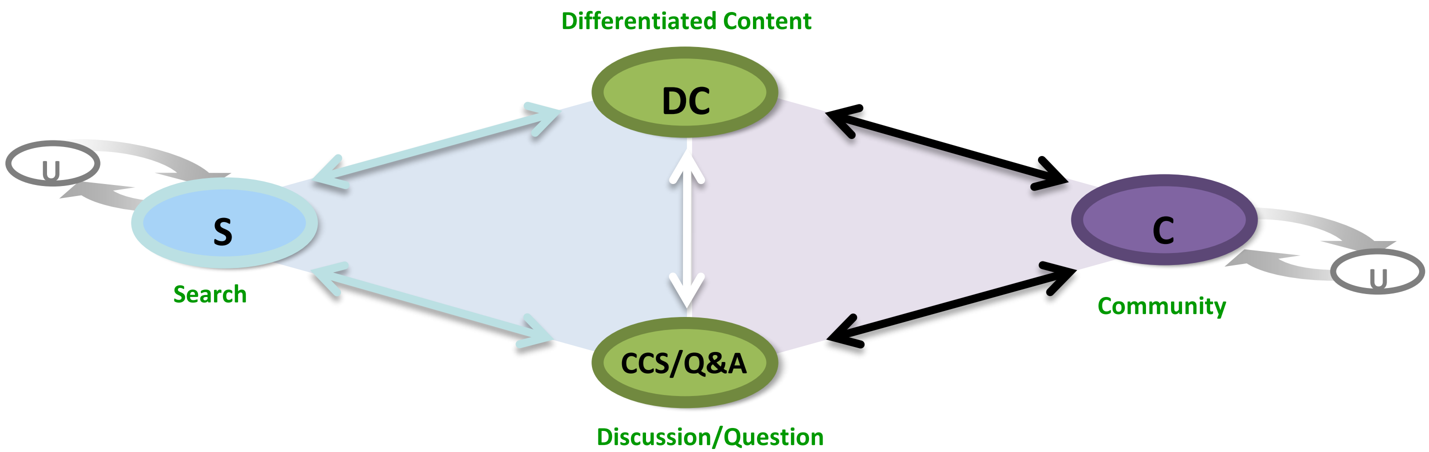
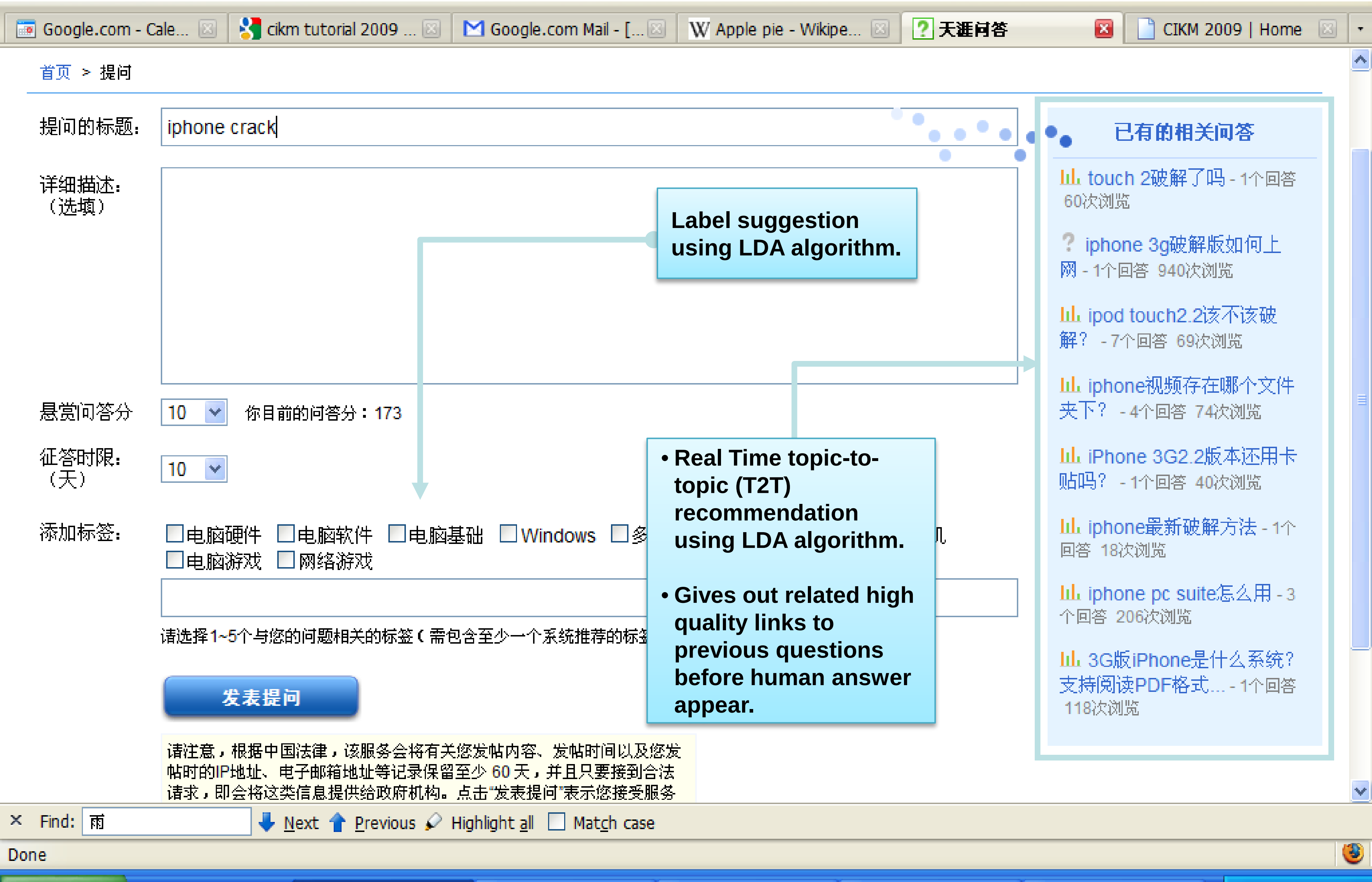
谁是第一个成为NBA状元秀的中国球员？ - 10个回答 1470次浏览
Done

Synergy between Search & Community



- Trigger a discussion/question session during search
- Provide labels to a post (semi-automatically)
- Given a post, find similar posts (automatically)
- Evaluate quality of a post, relevance and originality
- Evaluate user credentials in a topic sensitive way
- Routing questions to experts
- Provide most relevant, high-quality content for Search to index

Knowledge Search Uses Data Mining



Large-scale Challenges

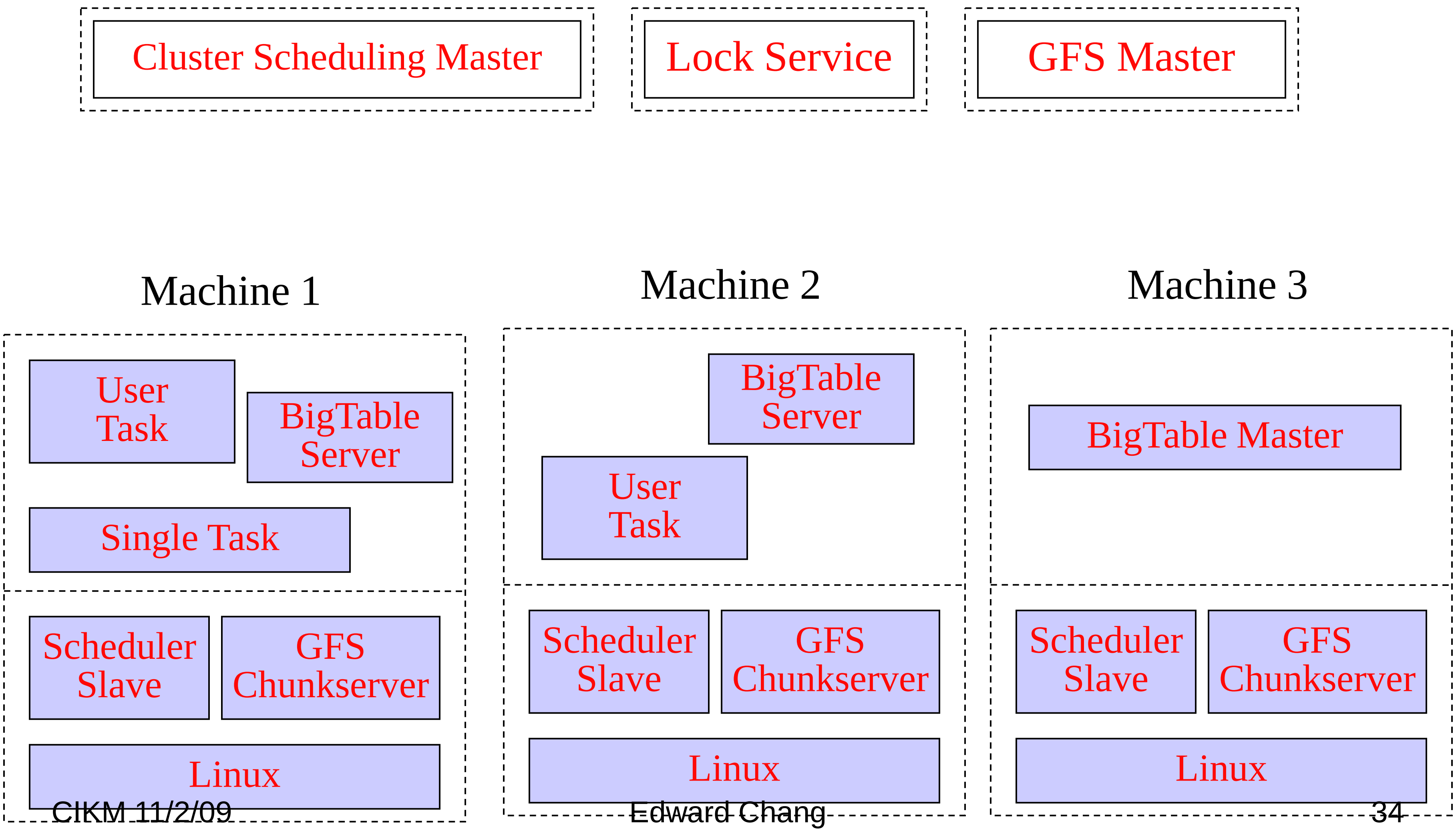
- Heterogeneous data
- Voluminous data
- Cost constraint
- Large number of distributed processors
- Large number of disks

Google Data Centers

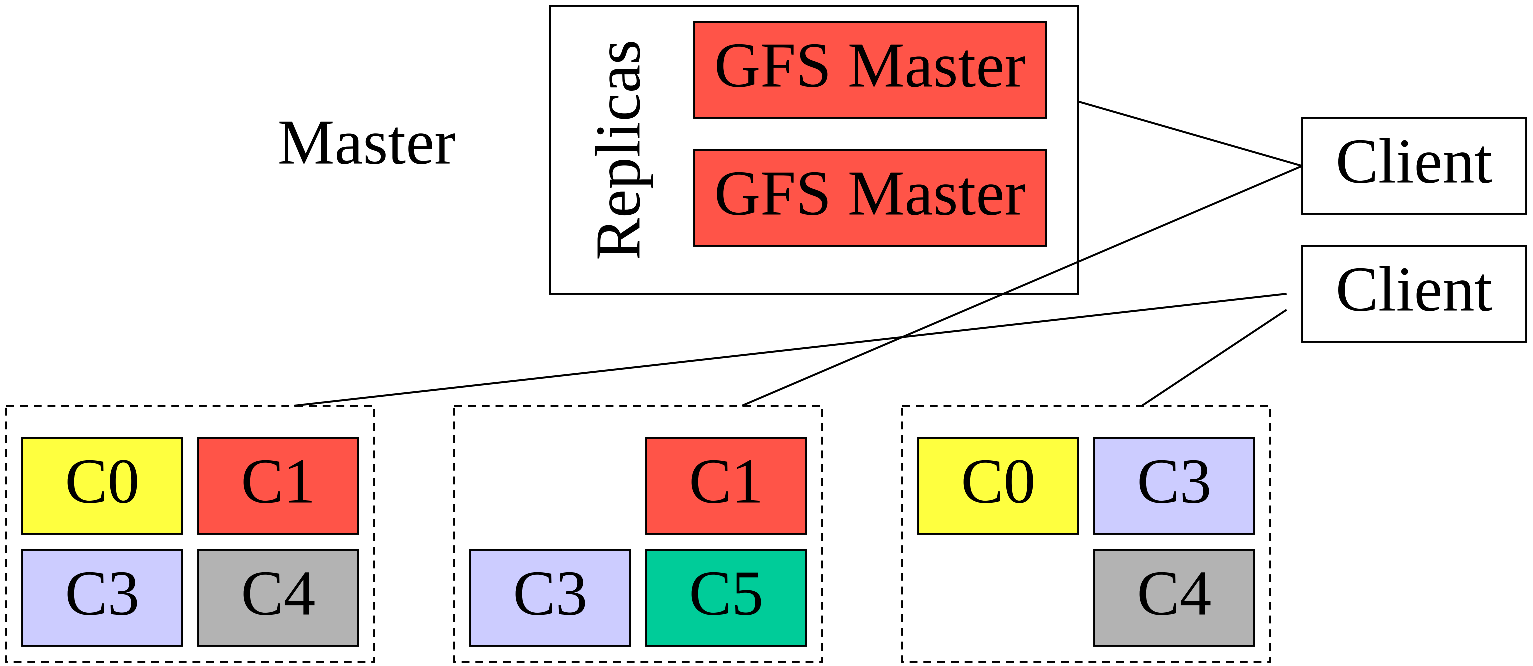
Building Blocks

- Google File System
- Big Table
- Distributed Lock
- MapReduce
- Scheduler

Typical Cluster



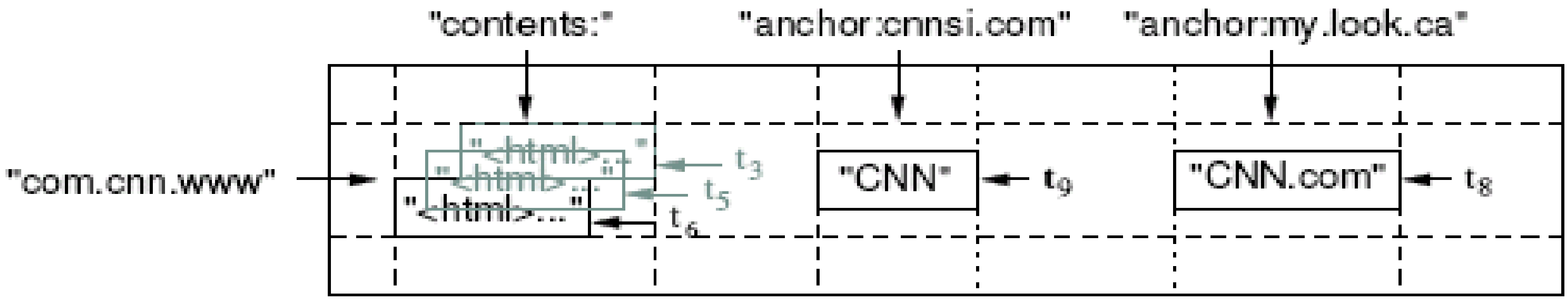
Google File System (GFS)



- Master manages metadata
- Data transfers happen directly between clients/chunkservers
- Files broken into chunks (typically 64 MB)
- Chunks triplicated across three machines for safety
- See SOSP^03 paper at http://labs.google.com/papers/gfs.html

Memory Data Model

- <Row, Column, Timestamp> triple for key - lookup, insert, and delete API

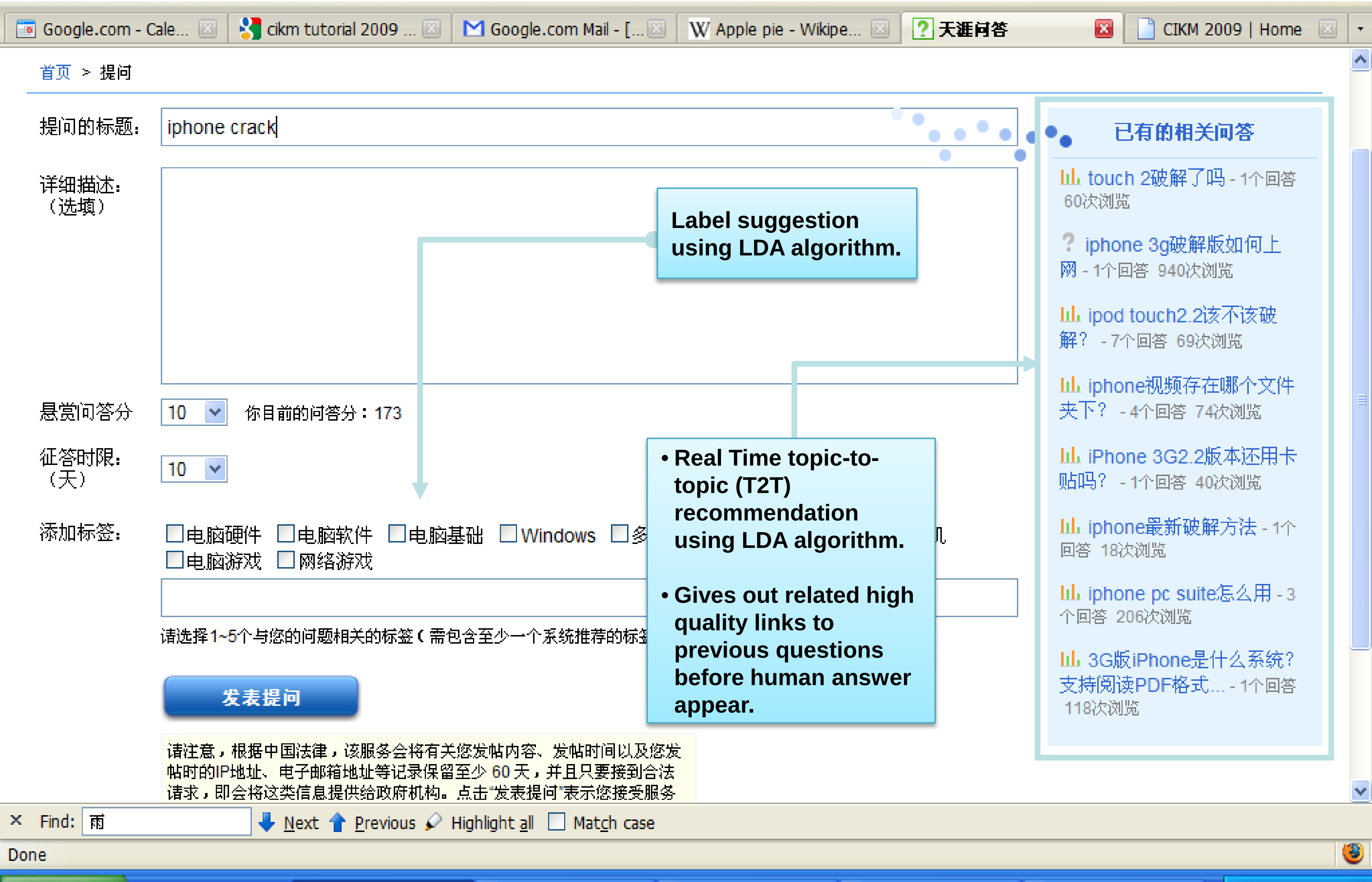


- Example
  - Row: a Web Page
  - Columns: various aspects of the page
  - Time stamps: time when a column was fetched

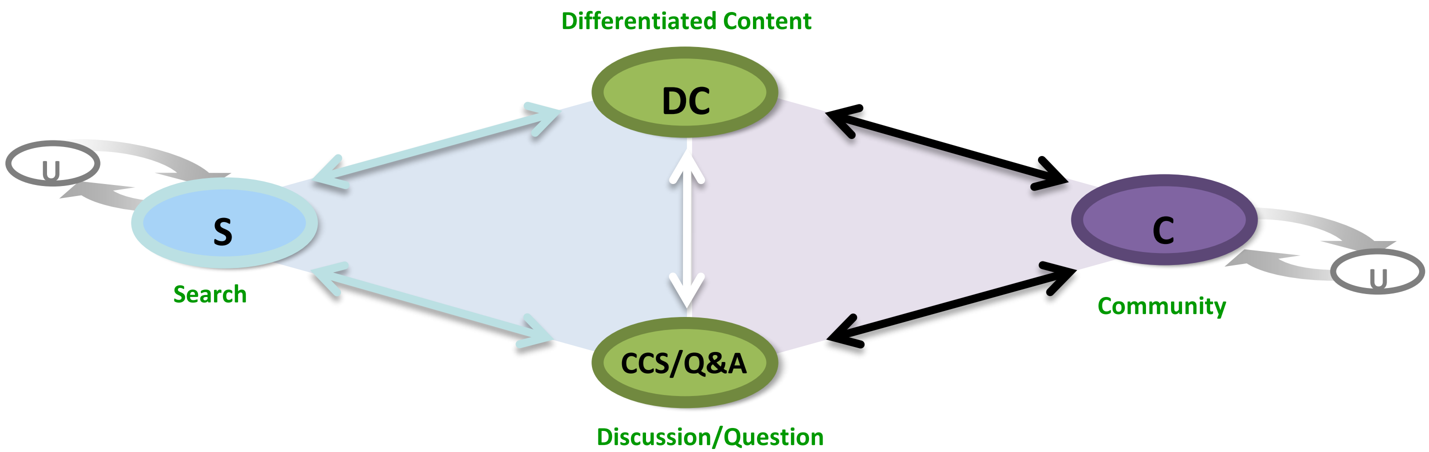
Large-scale Data Mining

- Motivating Applications
  - Confucius
- Confucius' Disciples
  - Frequent Itemset Mining [ACM RS 08]
  - Latent Dirichlet Allocation [WWW 09, AAIM 09]
  - Clustering [ECML 08]
  - Support Vector Machines [NIPS 07]
- Distributed Computing Perspectives

Q&A Uses Machine Learning



Confucius: Google Q&A



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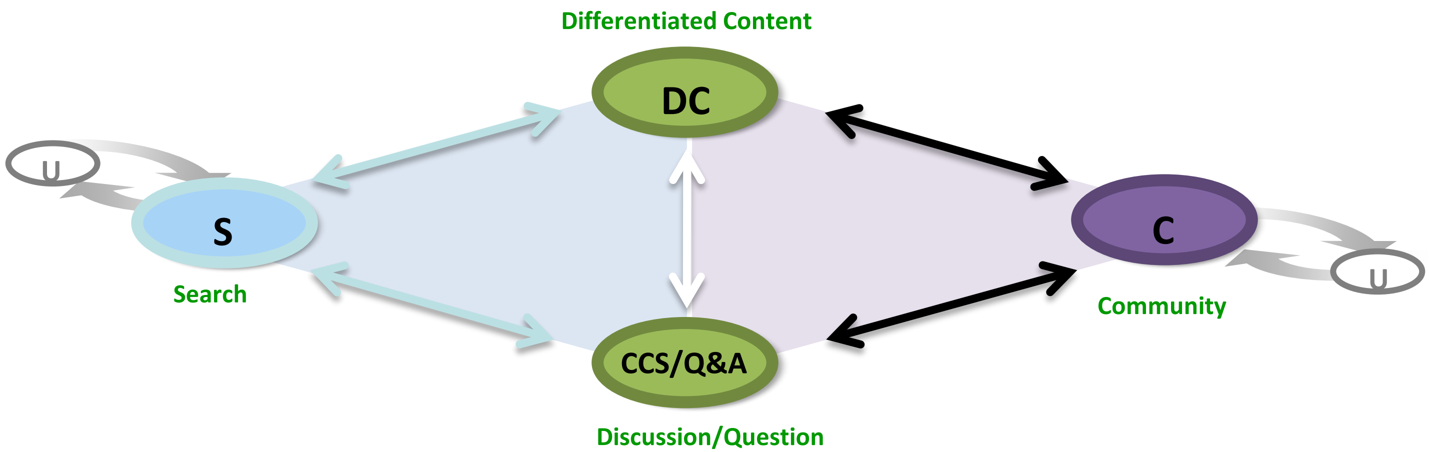
Confucius: Google Q&A



- ❑ Trigger a discussion/question session during search
- ❑ Provide labels to a post (semi-automatically)
- ❑ Given a post, find similar posts (automatically)
- ❑ Evaluate quality of a post, relevance and originality
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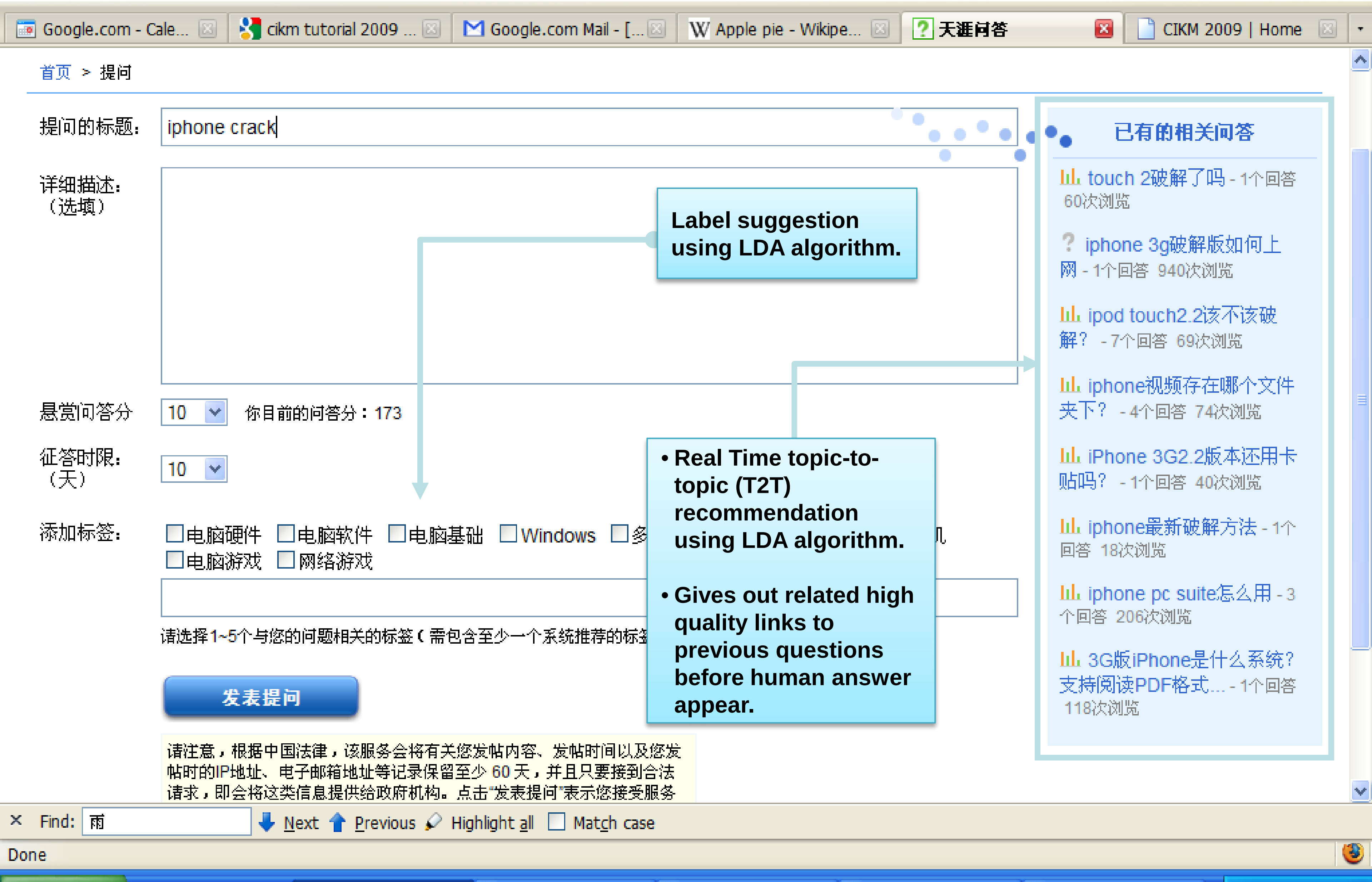
Q&A Uses Machine Learning



Collaborative Filtering

Based on *membership* so far,
and *memberships* of others

↓

Predict further *membership*

Labels/Qs

Questions

		1	1	1						
	1		1	1		1		1		1
					1		1			1
	1		1		1	1				
		1								
						1	1			
			1					1		
1	1									
	1								1	
1										1
	1	1	1	1	1					

Outline

- Motivating Applications
  - Confucius
- Parallel Algorithms
  - Frequent Itemset Mining [ACM RS 08]
  - Latent Dirichlet Allocation [WWW 09, AAIM 09]
  - Clustering [ECML 08]
  - Support Vector Machines [NIPS 07]
- Distributed Computing Perspectives

FIM-based Recommendation

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*} → CDB *A*

  {*A, B*}, {*B, C*} → CDB *B*

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*
- Dedup 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 in order of *f*, *c*, *a*, *b*, *m*, *p*
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 }
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 }

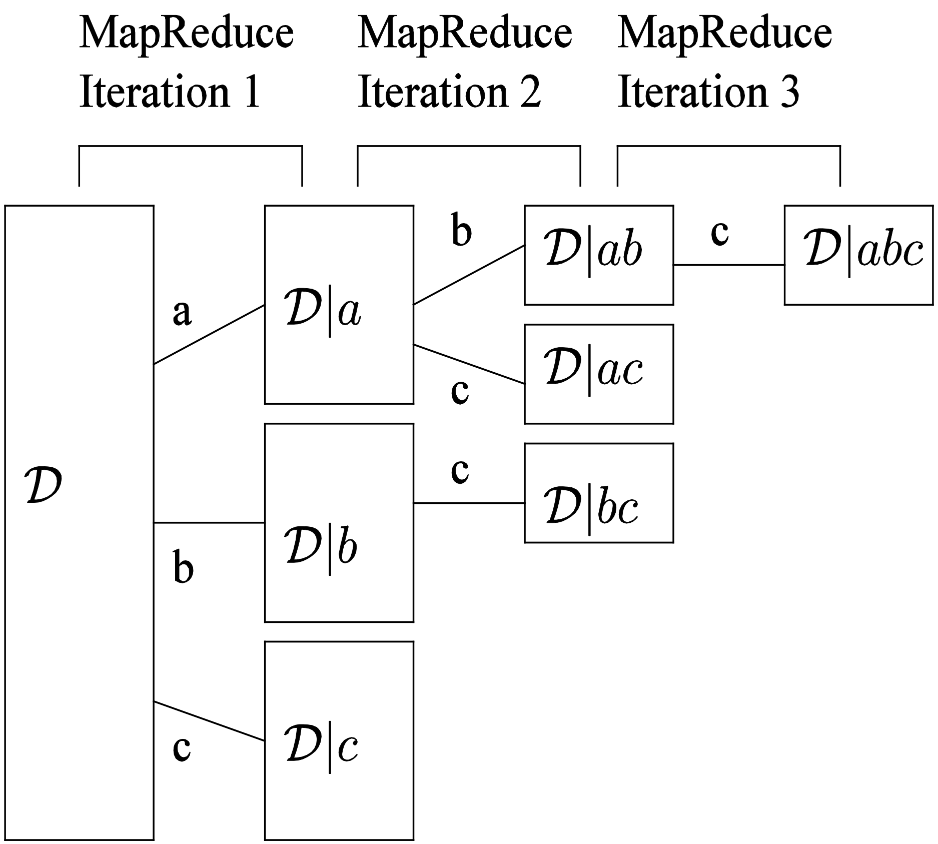
Example of Projection of a database into CDBs.
Left: sorted transactions;
Right: conditional databases of frequent items

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 }
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

Recursive Projections [H. Li, et al. ACM RS 08]



- Recursive projection form a search tree
- Each node is a CDB
- Using the order of items to prevent duplicated CDBs.
- 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.

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

p:{fcam/fcam/cb} p:3, pc:3

Reduce inputs (conditional databases) key: value	Reduce outputs (patterns and supports) key: value
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

Collaborative Filtering

Based on *membership* so far,
and *memberships* of others

↓

Predict further *membership*

Labels/Related Qs

Questions

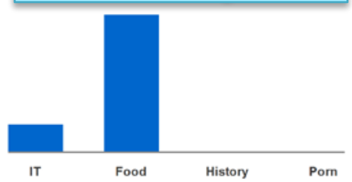
		1	1	1						
	1		1	1		1		1		1
					1		1			1
	1		1		1	1				
		1								
						1	1			
			1					1		
1	1									
	1								1	
1										1
	1	1	1	1	1					

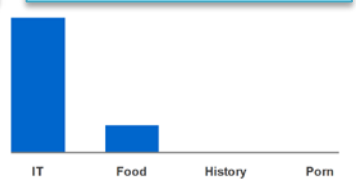
Distributed Latent Dirichlet Allocation (LDA)

- Search
  - Construct a latent layer for better for semantic matching
- Example:
  - iPhone crack
  - Apple pie

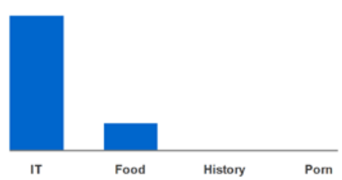
Documents	1 recipe pastry for a 9 inch double crust 9 apples, 2/1 cup, brown sugar	How to install apps on Apple mobile phones?

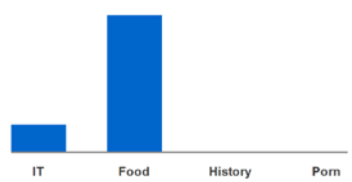
Topic Distribution





Topic Distribution





User quries: **iPhone crack** | **Apple pie**

Users/Music/Ads/Question

Users/Music/Ads/Answers

?	?	1	3	1	?	?	?	?	?	?
?	2	?	1	2	?	1	?	3	?	1
?	?	?	?	?	1		5			1
	5		3		1	1				
		1								
						1	4			
			2					1		
1	2									
	1								5	
1										1
	1	4	1	3	6					

- Other Collaborative Filtering Apps
  - Recommend Users → Users
  - Recommend Music → Users
  - Recommend Ads → Users
  - Recommend Answers → Q
- Predict the ? In the light-blue cells

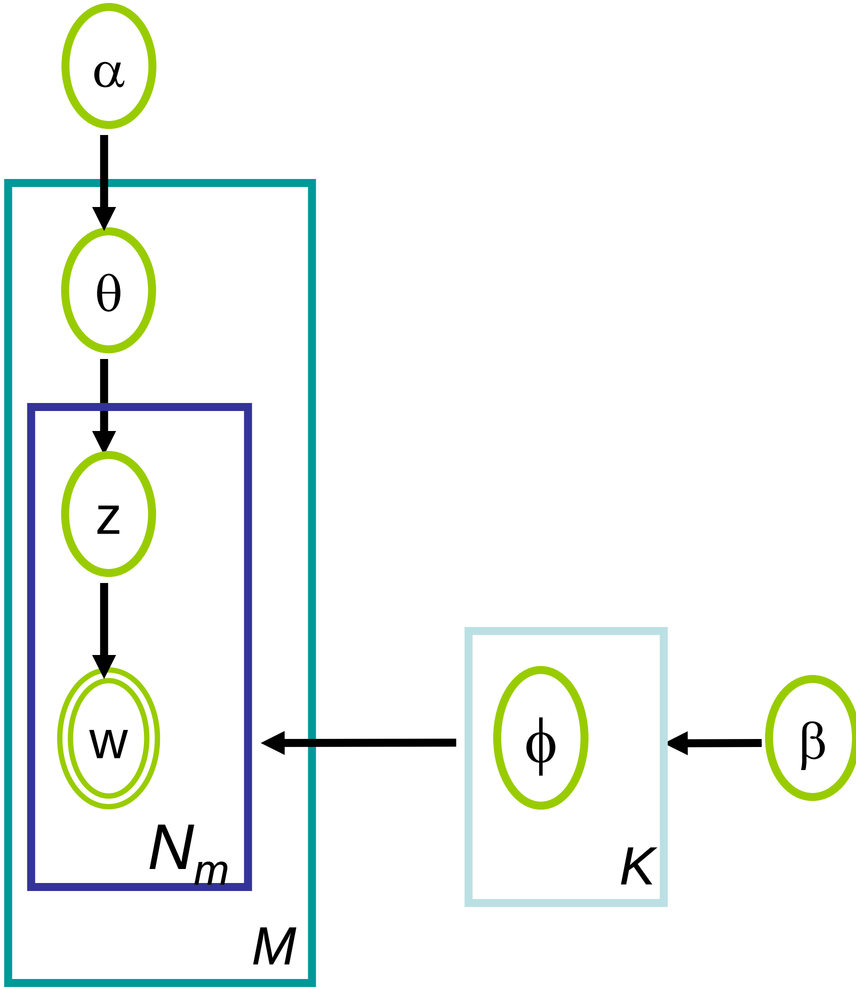
Documents, Topics, Words

- A document consists of a number of topics
  - A document is a probabilistic mixture of topics
- Each topic generates a number of words
  - A topic is a distribution over words
  - The probability of the i^{th} word in a document

$$P(w_i) = \sum_{j=1}^{T} P(w_i | z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation [M. Jordan 04]

- α: uniform Dirichlet ϕ prior for per document d topic distribution (corpus level parameter)
- β: uniform Dirichlet ϕ prior for per topic z word distribution (corpus level parameter)
- θ_d is the topic distribution of document d (document level)
- z_{dj} the topic if the j^{th} word in d, w_{dj} the specific word (word level)



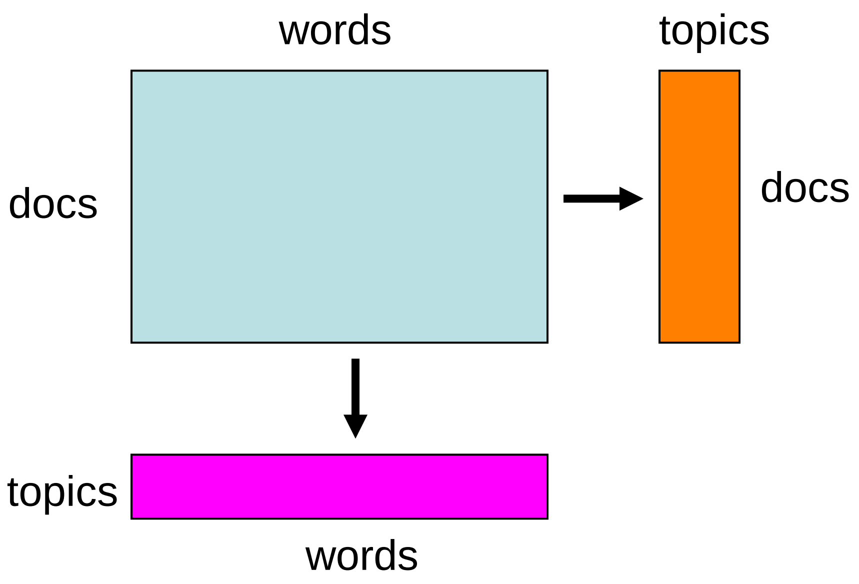
LDA Gibbs Sampling: Inputs And Outputs

Inputs:

1. training data: documents as bags of words
2. parameter: the number of topics

Outputs:

1. model parameters: a co-occurrence matrix of topics and words.
2. **by-product**: a co-occurrence matrix of topics and documents.



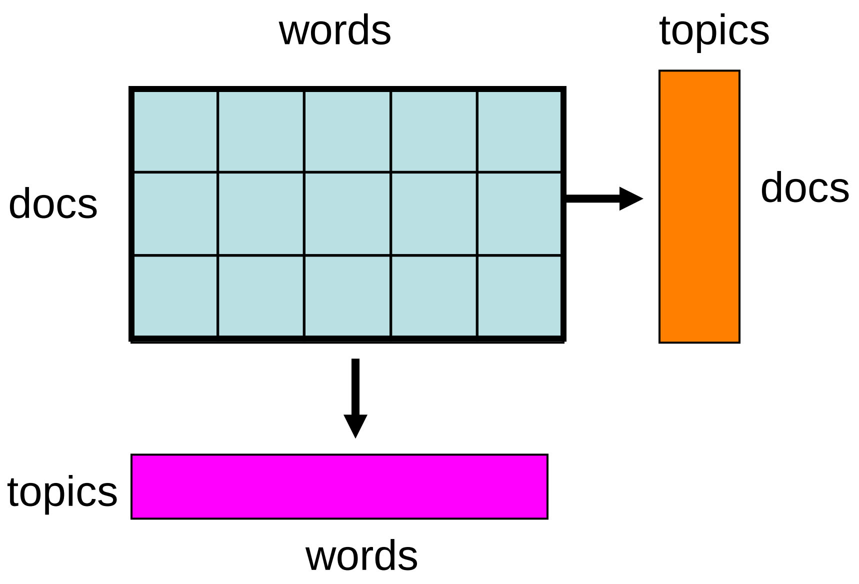
Parallel Gibbs Sampling [aaim 09]

Inputs:

1. training data: documents as bags of words
2. parameter: the number of topics

Outputs:

1. model parameters: a co-occurrence matrix of topics and words.
2. by-product: a co-occurrence matrix of topics and documents.



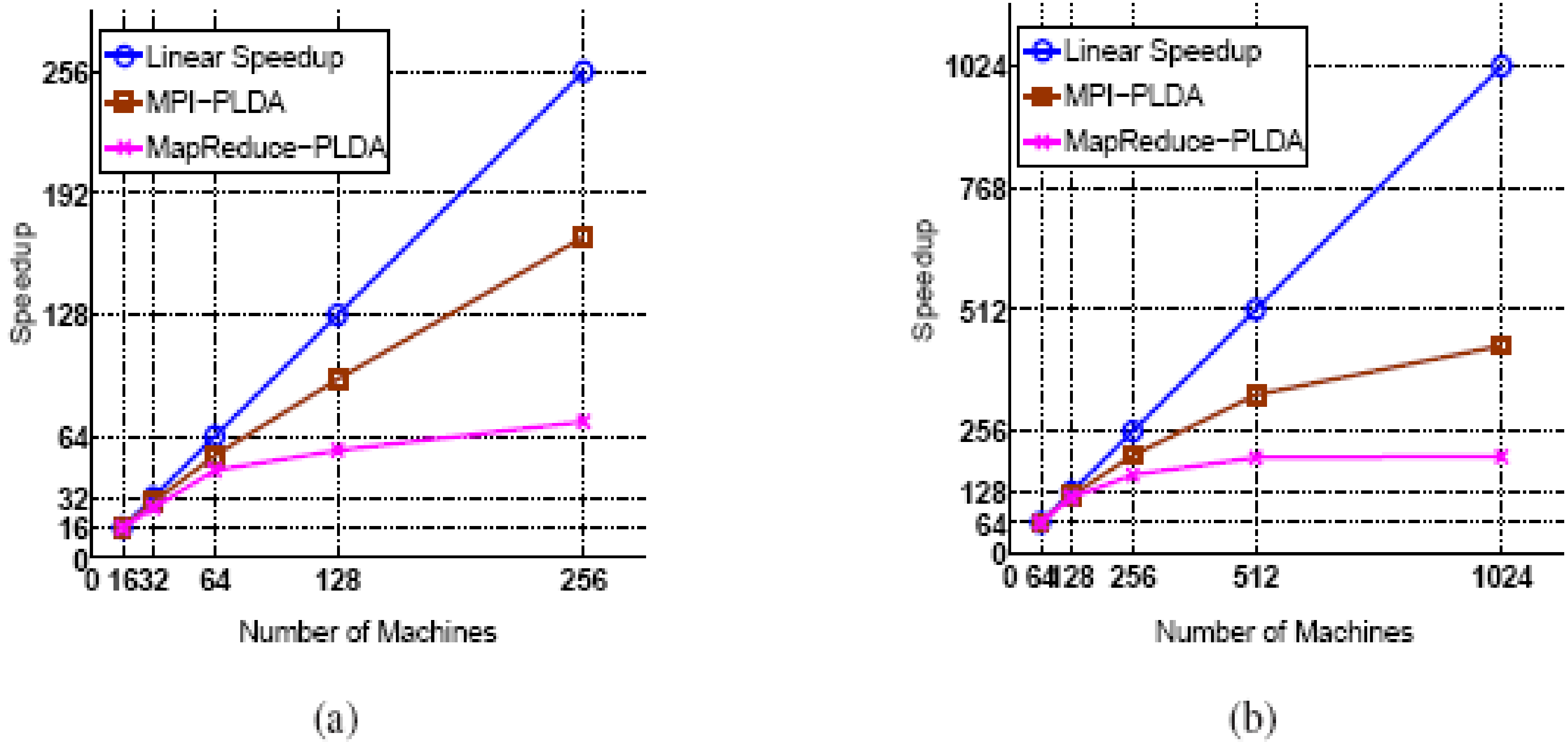


Fig. 4: The speedup of (a) Wikipedia: $K = 500$, $V = 20000$, $D = 2,122,618$, TotalWordOccurrences $= 447,004,756$, iterations $= 20$, $\alpha = 0.1$, $\beta = 0.1$. (b) Forum Dataset: $K = 500$, $V = 50000$, $D = 2,450,379$, TotalWordOccurrences $= 3,223,704,976$, iterations $= 10$, $\alpha = 0.1$, $\beta = 0.1$.

Table 6: Speedup Performance of MPI-PLDA and MapReduce-PLDA

# Machines	MPI-PLDA		MapReduce-PLDA	
	Running Time	*Speedup*	*Running Time*	*Speedup*
16	11940s	16	12022s	16
32	6468s	30	7288s	26
64	3546s	54	4165s	46
128	2030s	94	3395s	57
256	1130s	169	2680s	72

(a) Widipedia dataset (Runtime of 20 iterations)

# Machines	MPI-PLDA		MapReduce-PLDA	
	Running Time	*Speedup*	*Running Time*	*Speedup*
64	9012s	64	10612s	64
128	4792s	120	5817s	117
256	2811s	205	4132s	164
512	1735s	332	3390s	200
1024	1323s	436	3349s	203

(b) Forum dataset (Runtime of 10 iterations)

Outline

- Motivating Applications
  - Confucius
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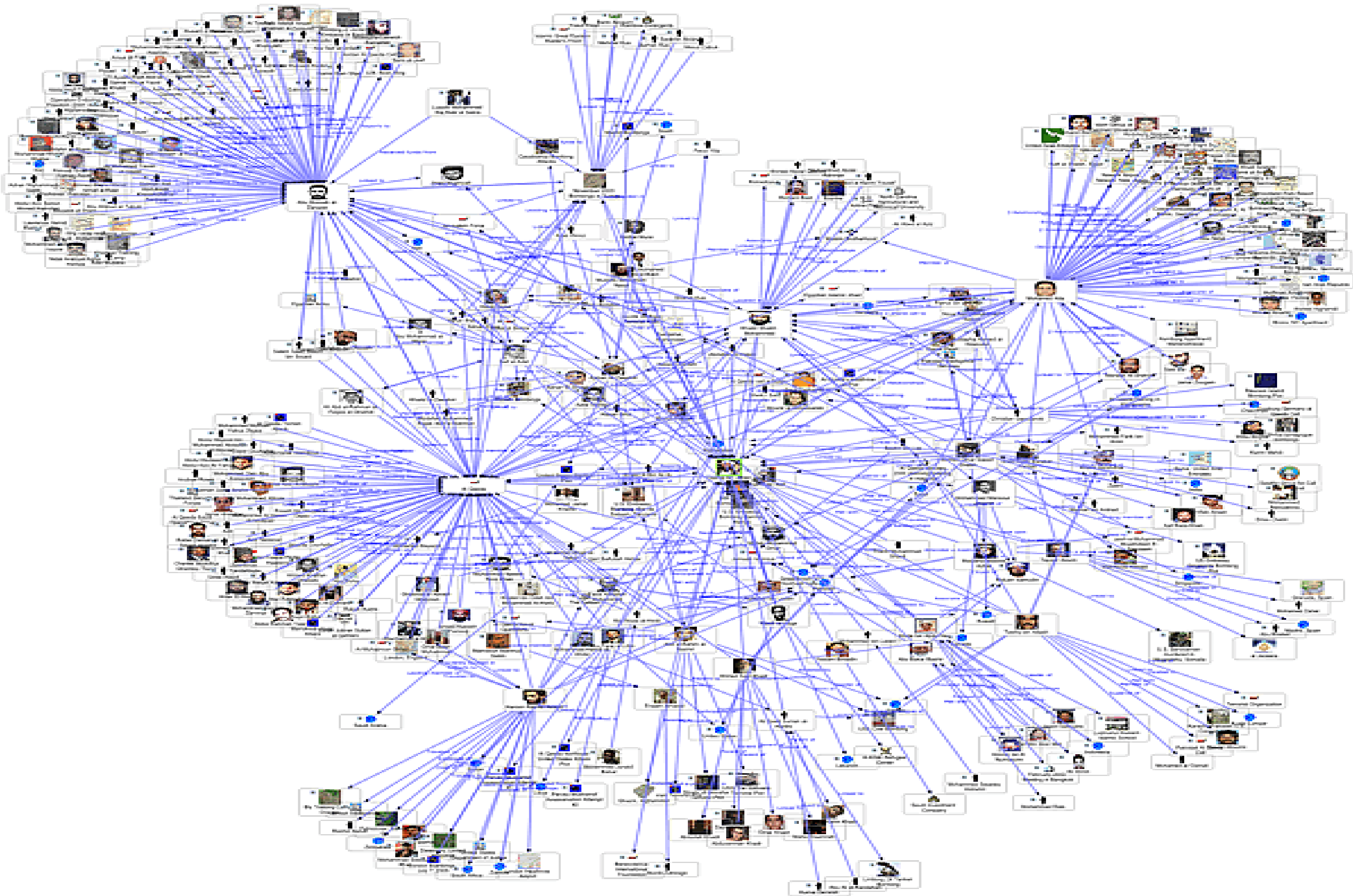
Social Networks

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礼物
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留言簿
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上一步
回到自己
永远来吧
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汤汤汤圆
暗香浮月
开复
沉冈
武汉牛牛
水星cici
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邀请朋友加入来吧
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Darren Huang - ...
Google.com - C...
我的主页 资料 朋友 来吧 帖子 影集 日记 礼物 New! 评价 留言簿
我的朋友圈 | 我的朋友
上一步 |
回到自己
永远来吧 (离线)
我的好友
批量上传照片吧!
男 37岁 北京
夜幕诱惑,诱的就是你!... [08-1-3]
这有没GOOGLE公司的伙... [07-8-20]
白领的家庭聚会 [07-12-30]
白领的家庭聚会 [07-12-30]
白领的家庭聚会 [07-12-30]
移除好友
永远来吧
机械舞
暗香浮月
水星cici
梦侠人
无聊最寂寞
邀请朋友加入来吧
邮件 *
发送邀请
我要群发邀请»
看看我的朋友在哪
Transferring data from laiba.tianya.cn...
start
3 Firefox
C:\Docum...
Document...
2 Micros...
Google R...
EN
10:12 PM

Task: Targeting Experts

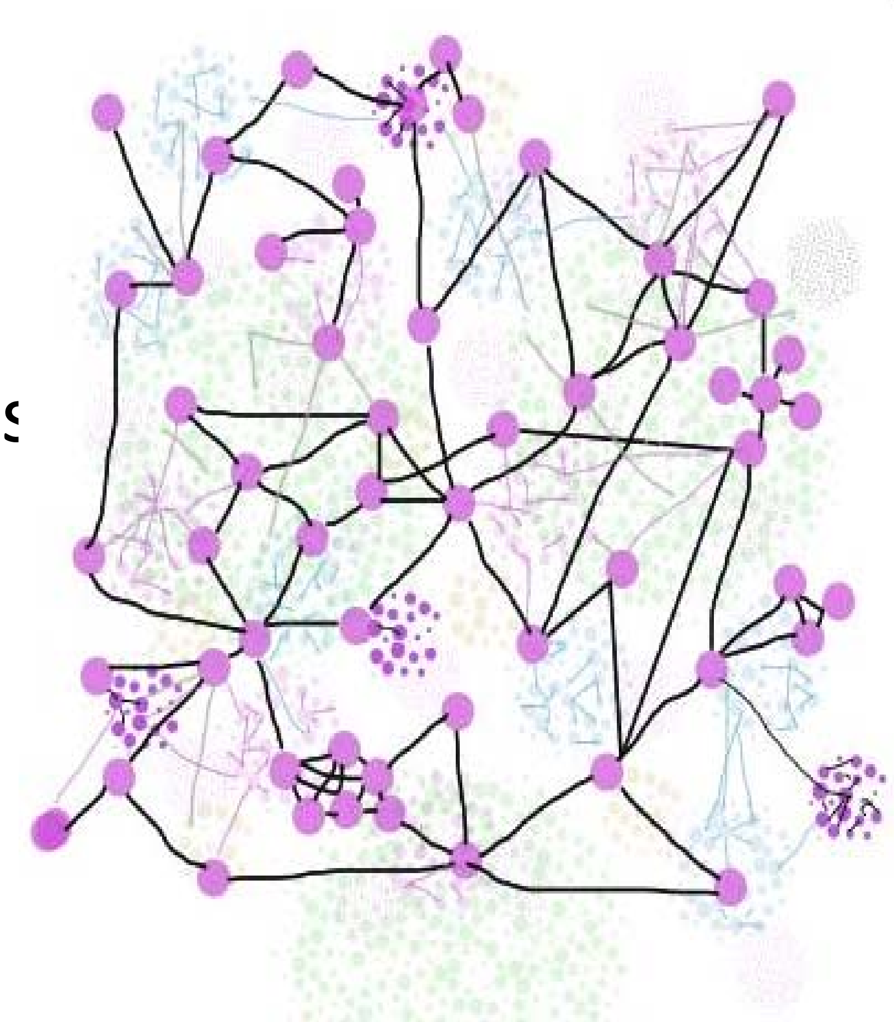
Users

Questions

Mining Profiles, Friends & Activities for Relevance

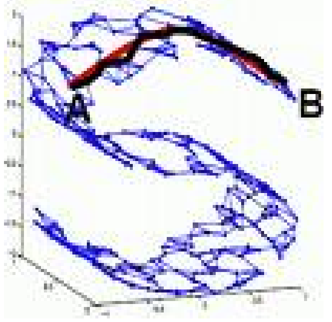
Consider also User *Influence*

- Advertisers consider users who are
  - Relevant
  - *Influential*
- SNS Influence Analysis
  - Centrality
  - Credential
  - Activeness
  - etc.



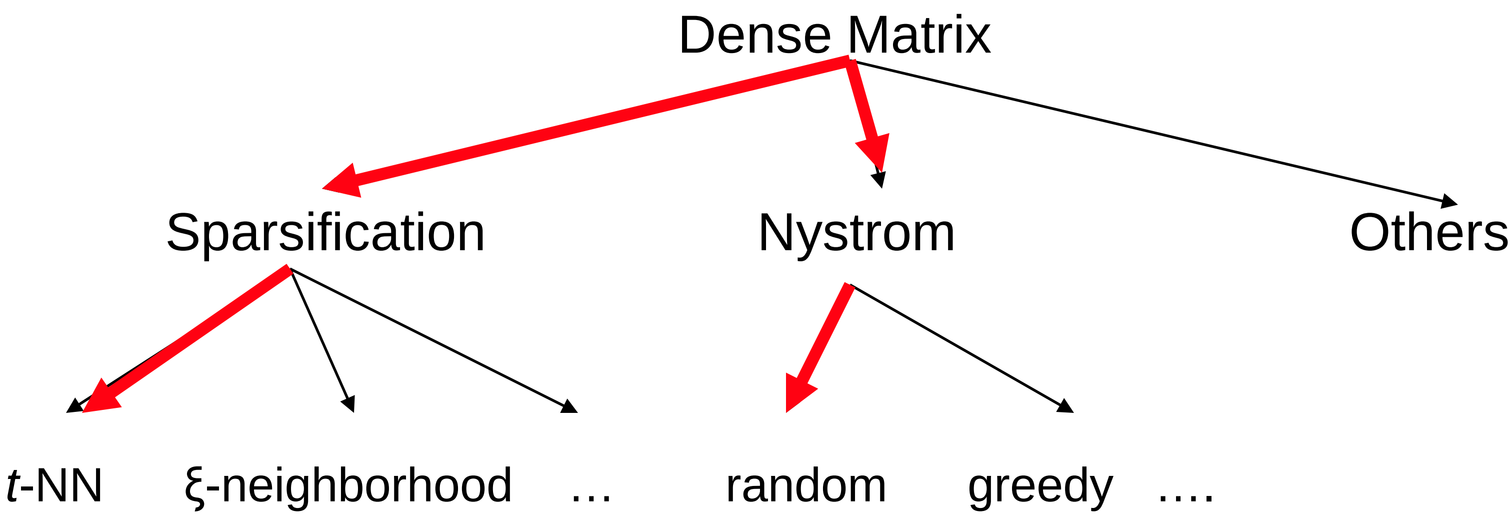
Spectral Clustering [A. Ng, M. Jordan]

- 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
    - e.g., using Geodisc distance
  - 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 in Laplacian form

$R = A + A^{-1/2} B B^T A^{-1/2};$

$R = U \Sigma U^T$

- *k*-means

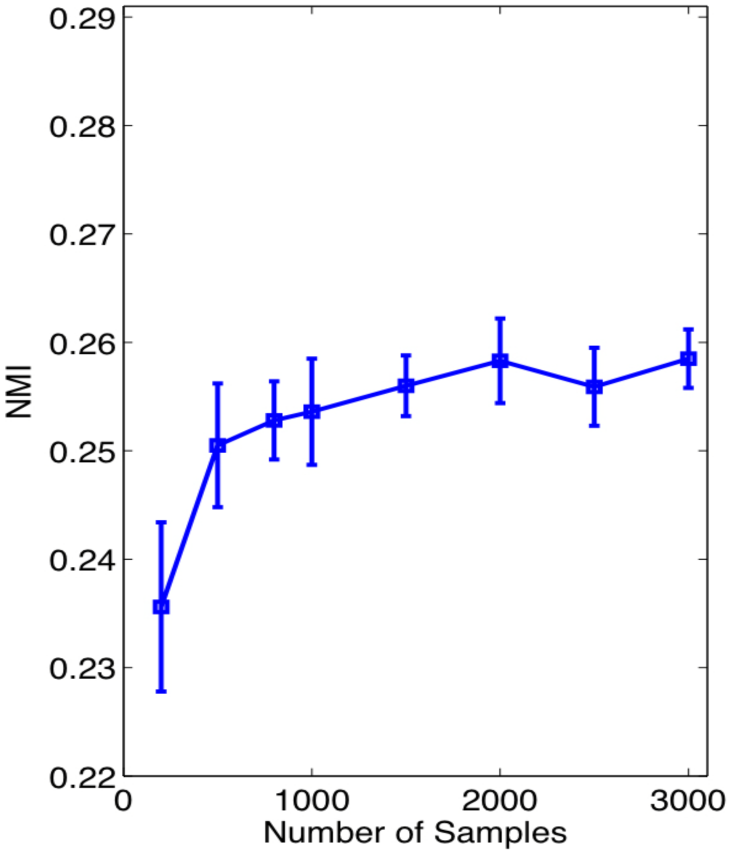
Empirical Study [song, et al., ecml 08]

- 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)

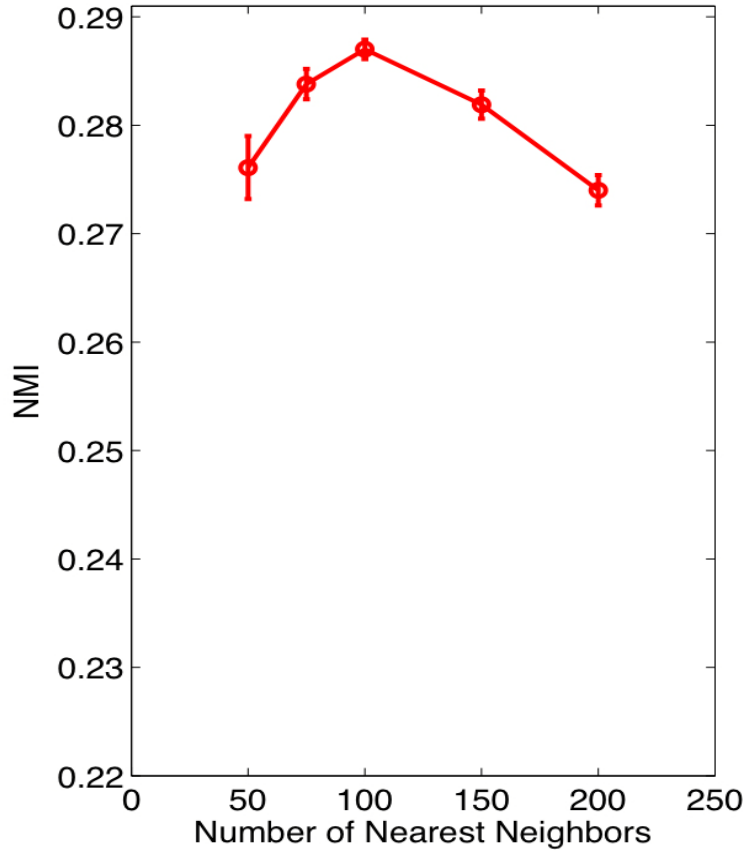
$$NMI(CAT;CLS) = \frac{I(CAT;CLS)}{\sqrt{H(CAT)H(CLS)}}$$

  - Scalability

NMI Comparison (on RCV1)



Nystrom method



Sparse matrix approximation

Sparsification vs. Sampling

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

Speedup Test on *637,137* Photos

- K = 1000 clusters

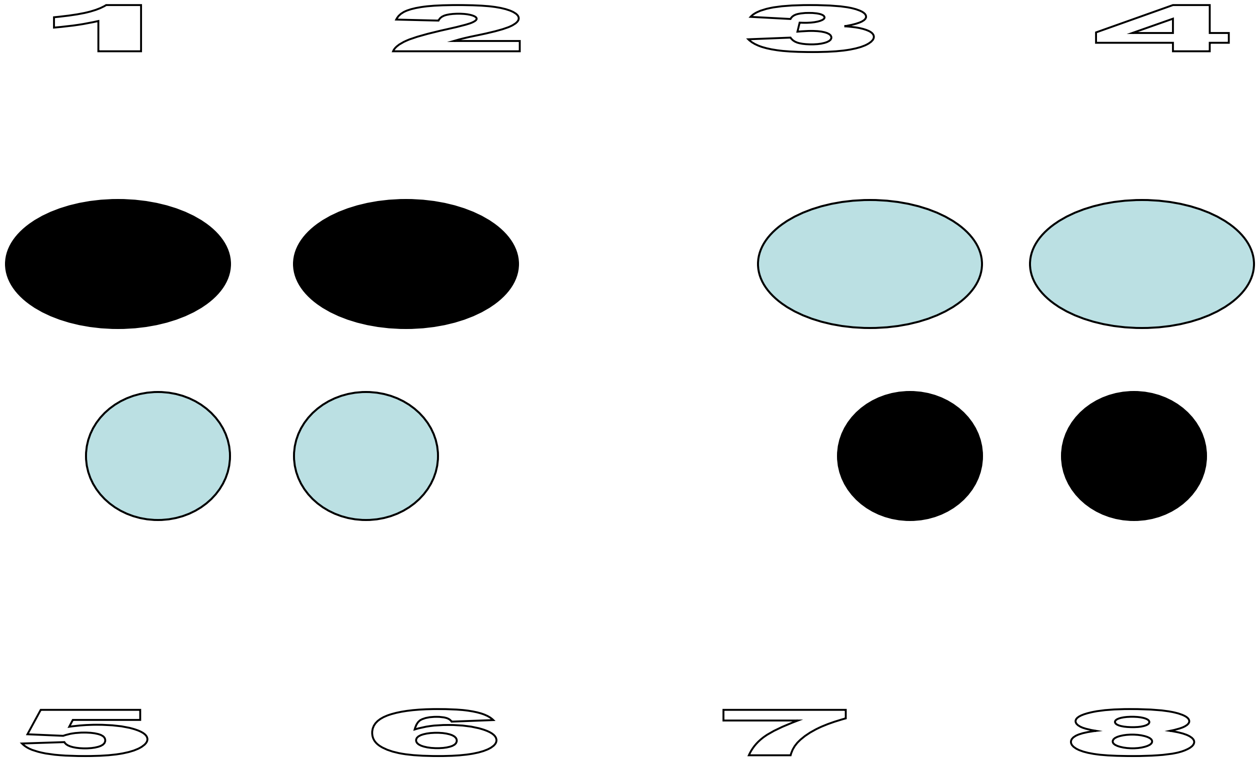
	Eigensolver		k-means	
Machines	Time (sec.)	Speedup	Time (sec.)	Speedup
1	—	—	—	—
2	8.074×10^4	2.00	3.609×10^4	2.00
4	4.427×10^4	3.65	1.806×10^4	4.00
8	2.184×10^4	7.39	8.469×10^3	8.52
16	9.867×10^3	16.37	4.620×10^3	15.62
32	4.886×10^3	33.05	2.021×10^3	35.72
64	4.067×10^3	39.71	1.433×10^3	50.37
128	3.471×10^3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

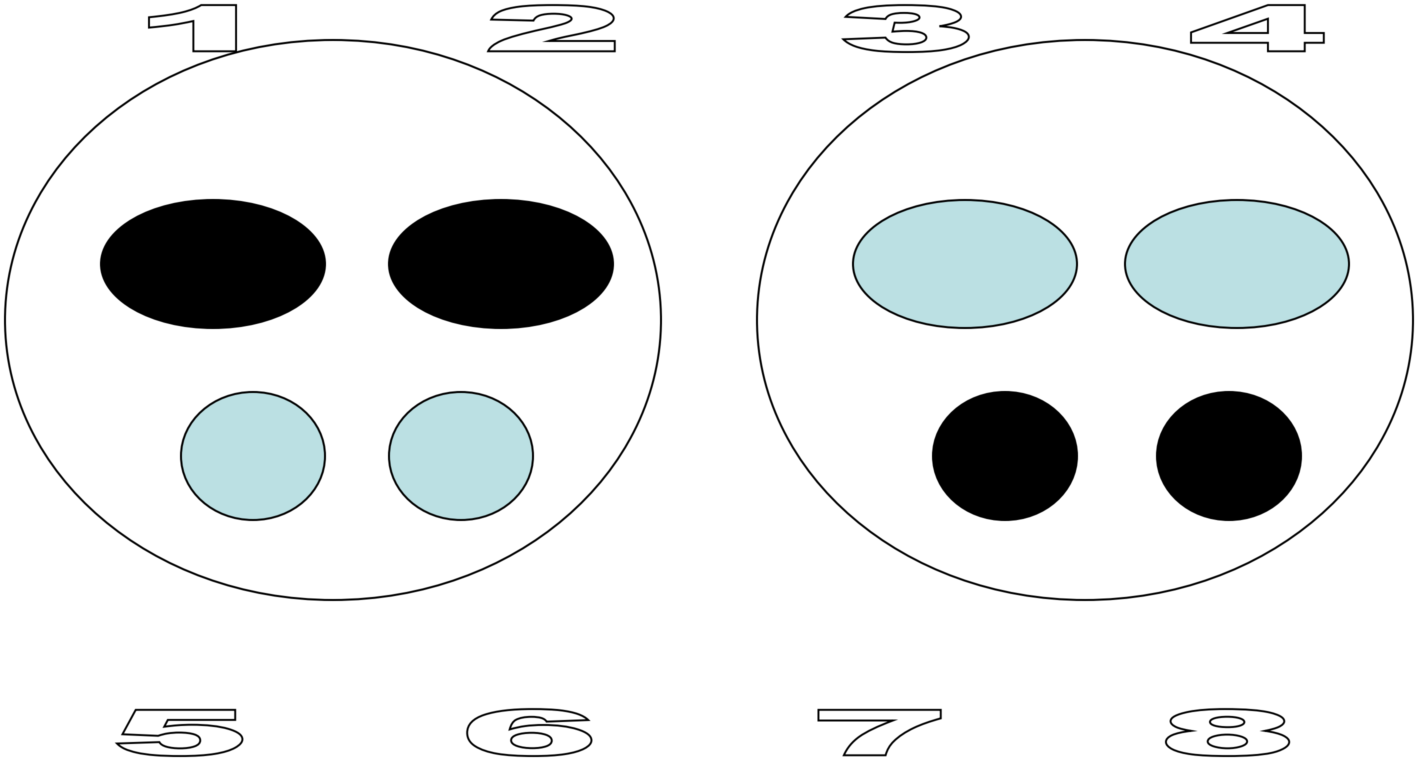
Outline

- Motivating Applications
- Key Subroutines
  - Frequent Itemset Mining [ACM RS 08]
  - Latent Dirichlet Allocation [WWW 09, AAIM 09]
  - Clustering [ECML 08]
  - UserRank [Google TR 09]
  - Support Vector Machines [NIPS 07]
- Distributed Computing Perspectives

Distance Function?



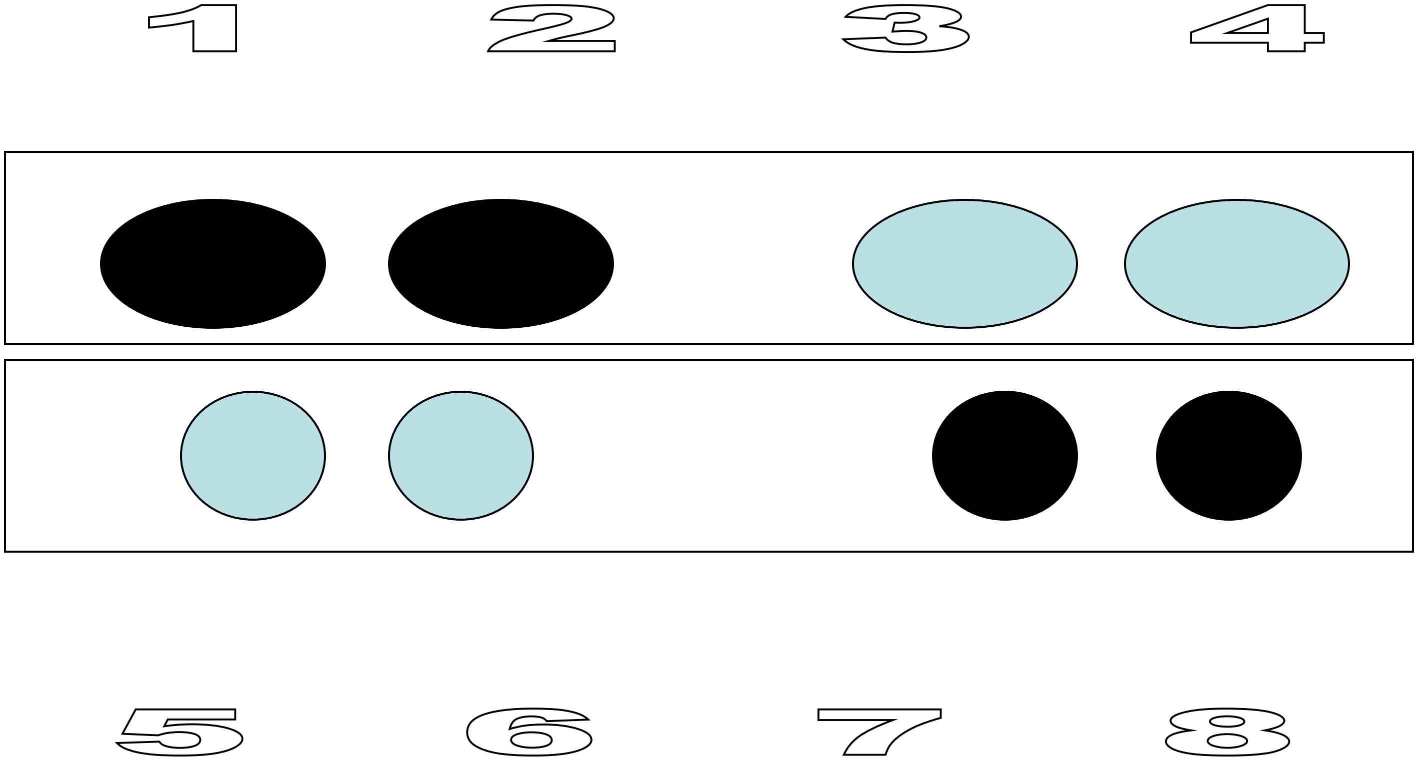
Group by Proximity



Group by Proximity

	x1	x2	x3	x4	x5	x6	x7	x8
x1	1	.7	.4	.3	.7	.6	.2	.1
X2		1	.4	.3	.6	.7	.3	.2
X3			1	.7	.3	.4	.7	.6
x4				1	.1	.2	.6	.7
x5					1	.7	.3	.2
x6						1	.6	.4
x7							1	.7
X8								1

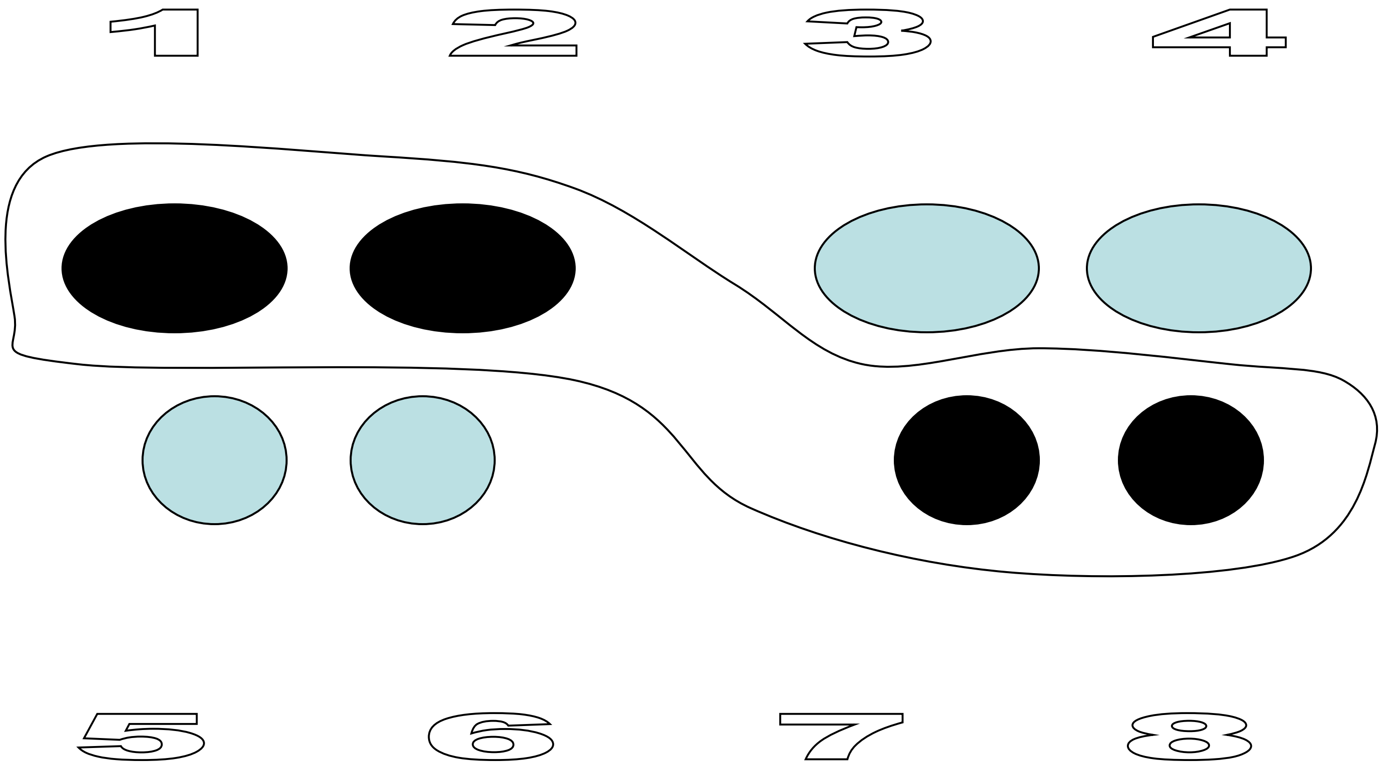
Group by Shape



Group by Shape

	x1	x2	x3	x4	x5	x6	x7	x8
x1	1	.7	.7	.7	.2	.2	.2	.2
X2		1	.7	.7	.2	.2	.2	.2
X3			1	.7	.2	.2	.2	.2
x4				1	.2	.2	.2	.2
x5					1	.7	.7	.7
x6						1	.7	.7
x7							1	.7
X8								1

Group by Color



Group by Color

	x1	x2	x3	x4	x5	x6	x7	x8
x1	1	.7	.3	.3	.3	.2	.2	.7
X2		1	.3	.3	.3	.3	.7	.7
X3			1	.7	.7	.7	.3	.3
x4				1	.7	.7	.3	.3
x5					1	.7	.3	.3
x6						1	.3	.3
x7							1	.7
X8								1

Naïve Alignment Rules

- Increasing the scores of similar pairs
- Decreasing the scores of dissimilar pairs
- $S_{ij} > D_{ij}$

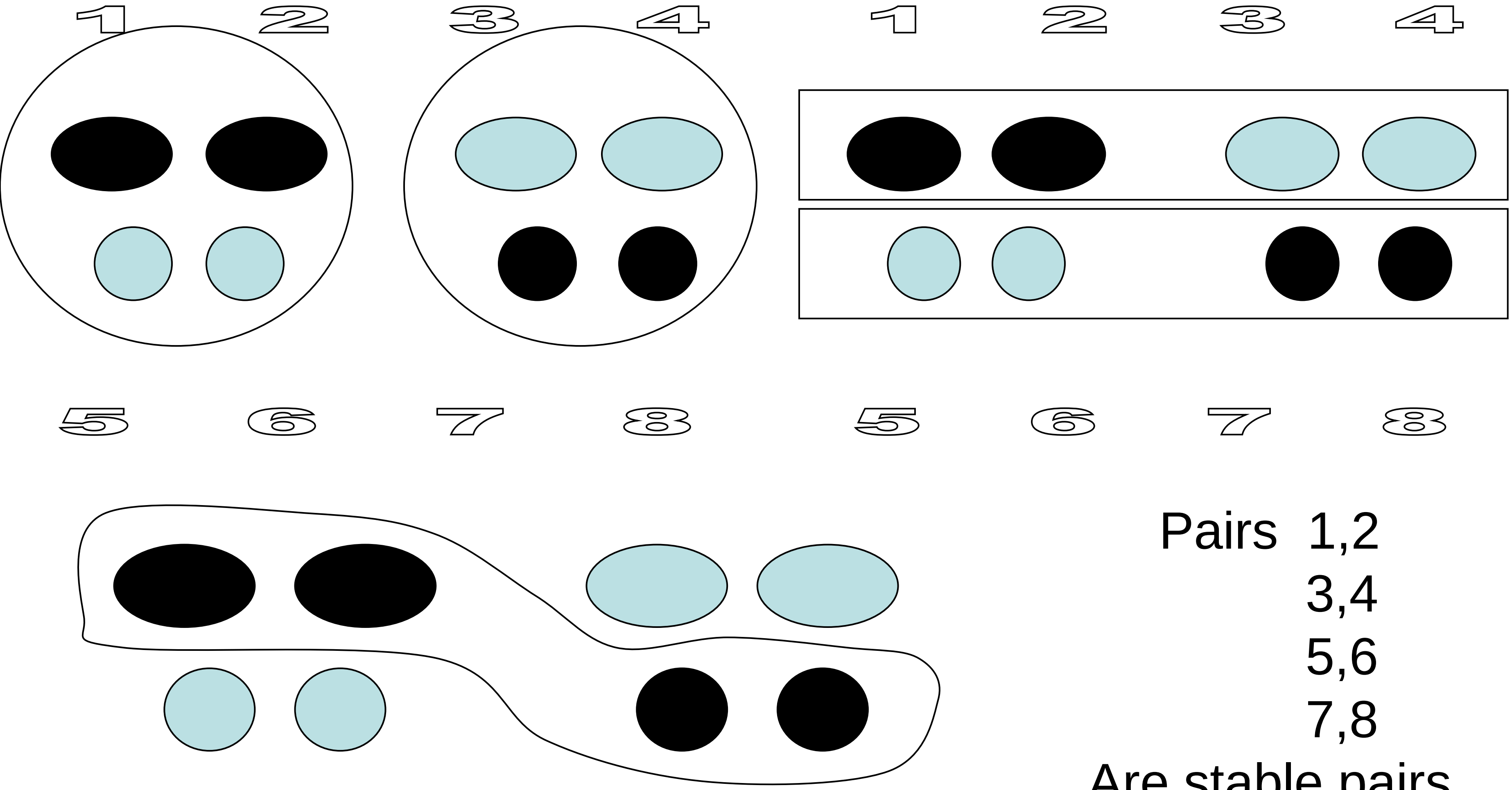
Our Work [ACM KDD 2005, ACM MM 05]

- kij = β_1 kij if (xi, xj) $\in$ D
- kij = β_2 kij + (1 - β_2) if (xi, xj) $\in$ S
- $0 \le \beta_1 \beta_2 \le 1$

- Theorem #1 The resulting matrix is psd
- Theorem #2 The resulting matrix is better aligned with the ideal kernel

ULP --- Unified Learning Paradigm [KDD 05]

- Unsupervised Method
  - Clustering
  - Multi-version Clustering
- Supervised
- Active Learning
- Reinforcement Learning



Pairs 1,2
3,4
5,6
7,8
Are stable pairs

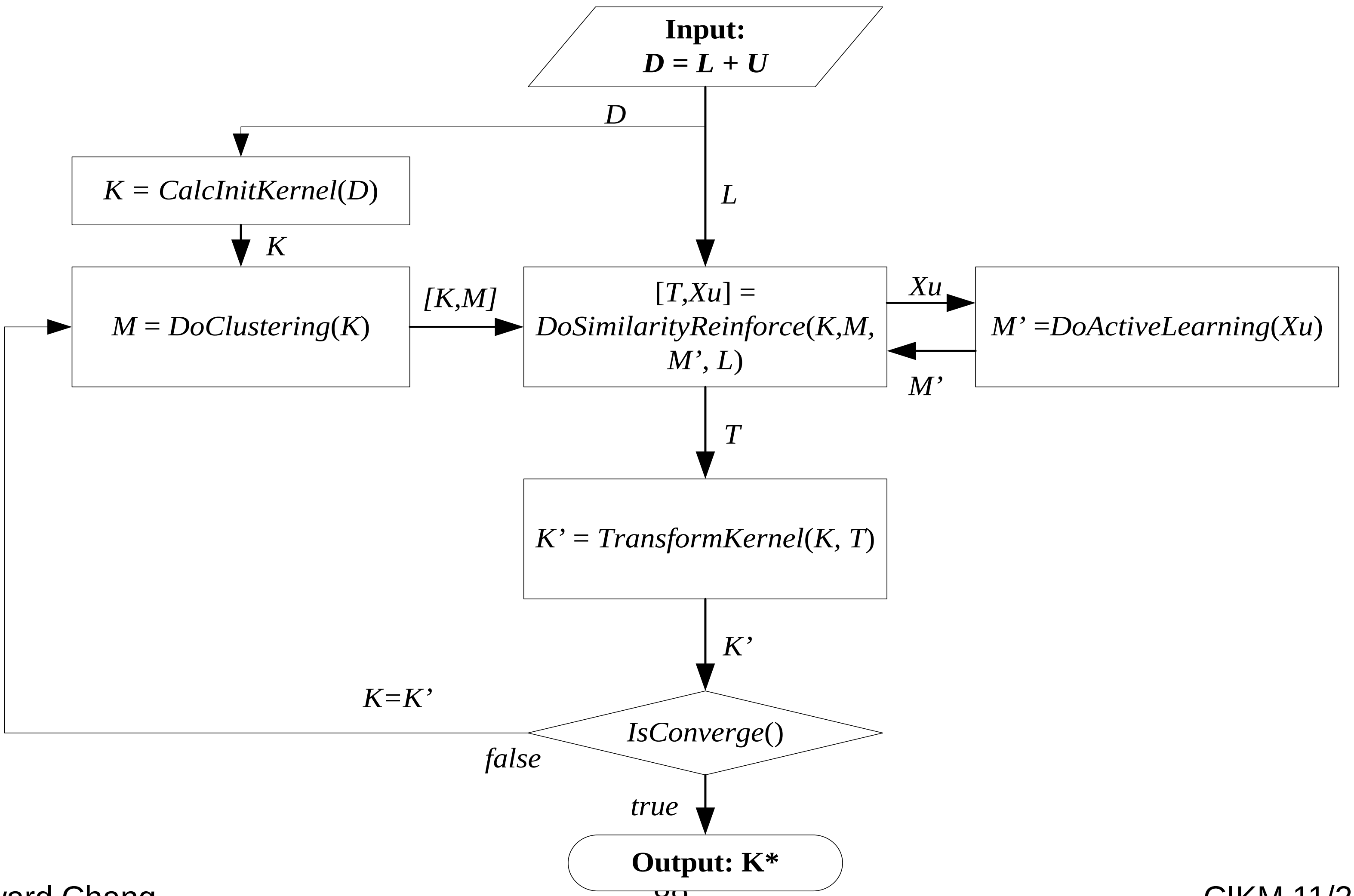
ULP: Unified Learning Paradigm

Stable Pairs	x1	x2	x3	x4	x5	x6	x7	x8
x1	1	.7	.3	.3	.3	.2	.2	.7
X2		1	.3	.3	[illegible]	.3	.7	.7
X3			1	.7	[illegible]	[illegible]	.3	.3
x4				1	.7	.7	.3	.3
x5					1	.7	.3	.3
x7							1	.7
X8								1

ULP

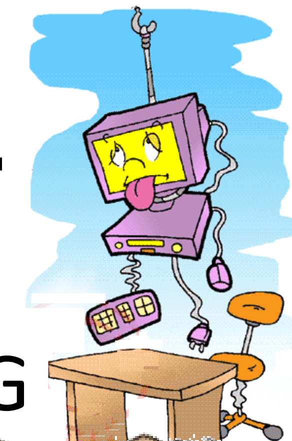
- Stable Pairs (green circles)
  - Found via shot-gun clustering
- Selected Uncertain Pairs (red circles)
  - Identified via the maximum information or fastest convergence rule
- Propagation (green arrow)

ULP [EITC 05]


Input:
D = L + U
D
L
K = CalcInitKernel(D)
K
M = DoClustering(K)
[K,M]
[T,Xu] =
DoSimilarityReinforce(K,M,
M', L)
Xu
M'
M' =DoActiveLearning(Xu)
T
K' = TransformKernel(K, T)
K'
K=K'
IsConverge()
false
true
Output: K*

SVM Bottlenecks

Time consuming – 1M dataset, 8 days



Memory consuming – 1M dataset, 10G

Matrix Factorization Alternatives

exact

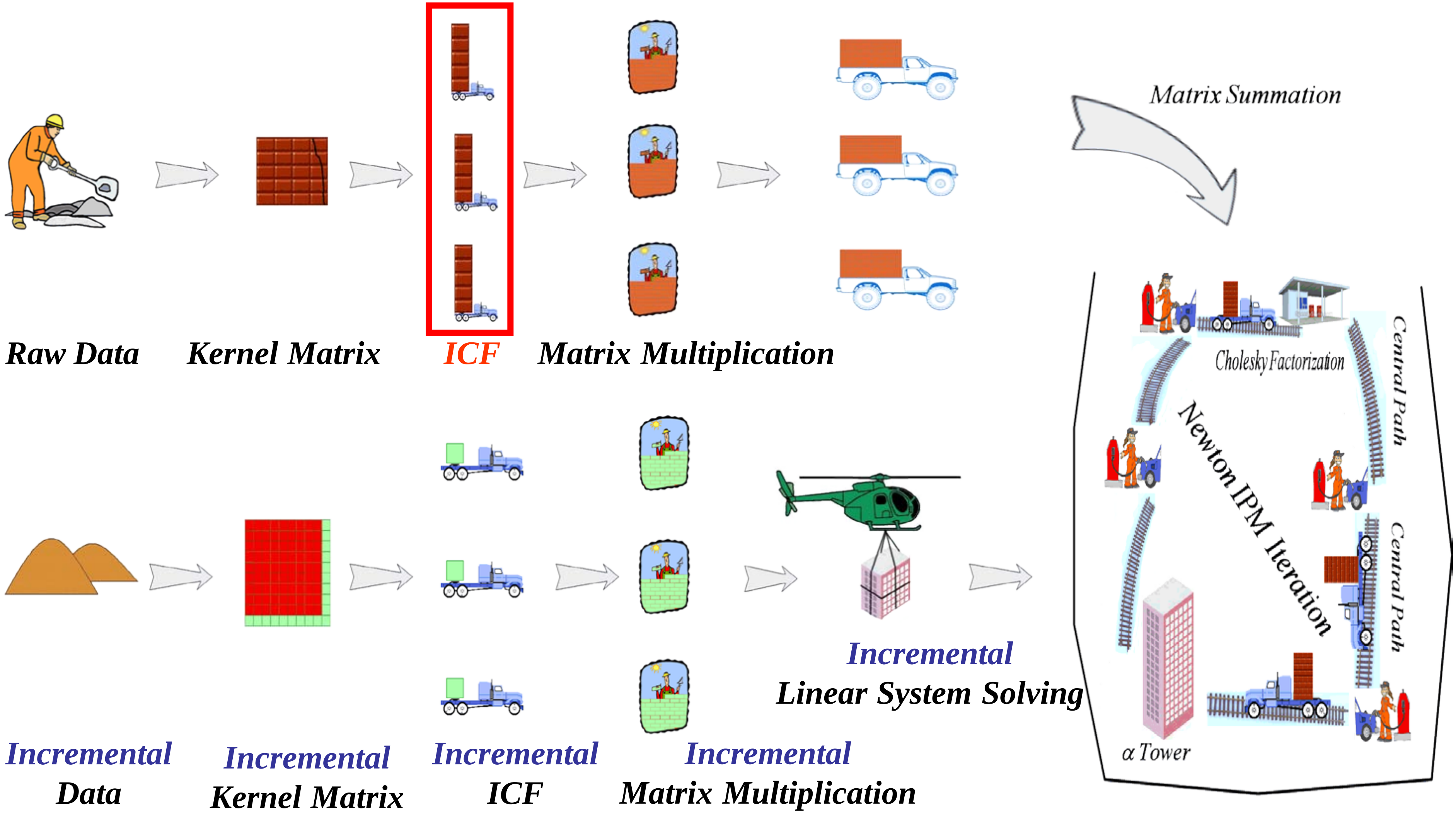
Factorization	Cost
QR	$O(\frac{4}{3}n^3)$
LU	$O(\frac{2}{3}n^3)$
Cholesky	$O(\frac{1}{3}n^3 + 2n^2)$
LDL^T	$O(\frac{1}{3}n^3)$
Incomplete Cholesky	$O(p^2 n)$
Kronecker	$O(2n^2)$

approximate

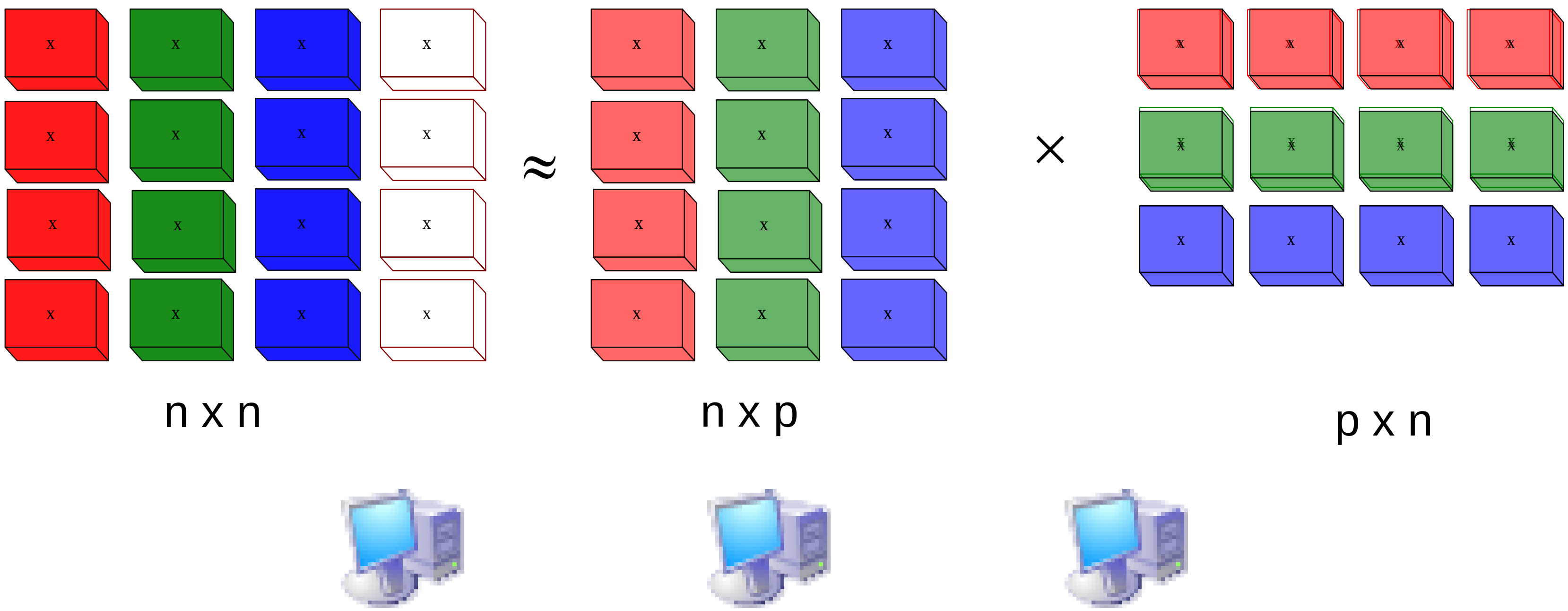
PSVM [E. Chang, et al, NIPS 07]

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

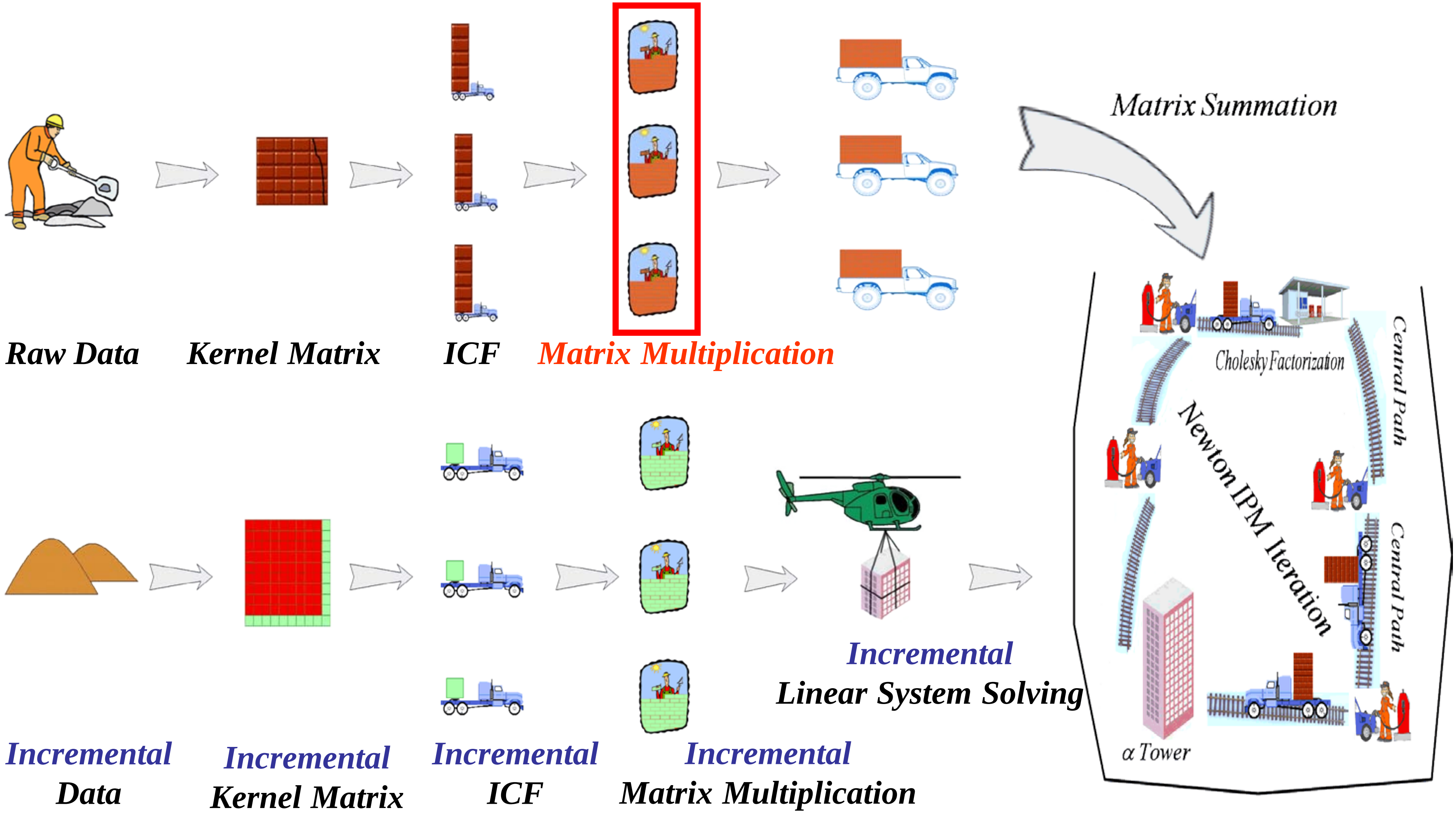
Parallelized and Incremental SVM



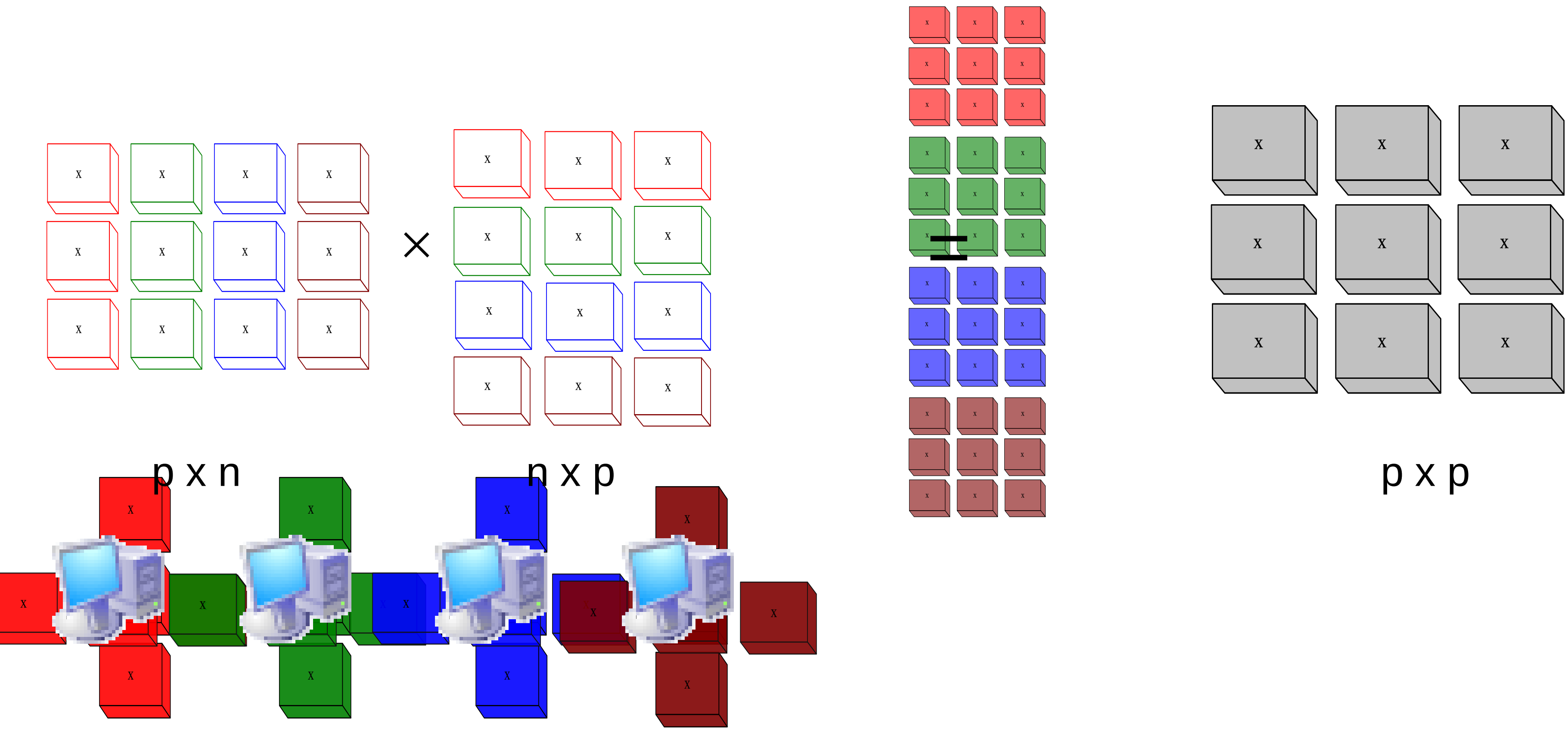
Incomplete Cholesky Factorization (ICF)



Parallelized and Incremental SVM



Matrix Product



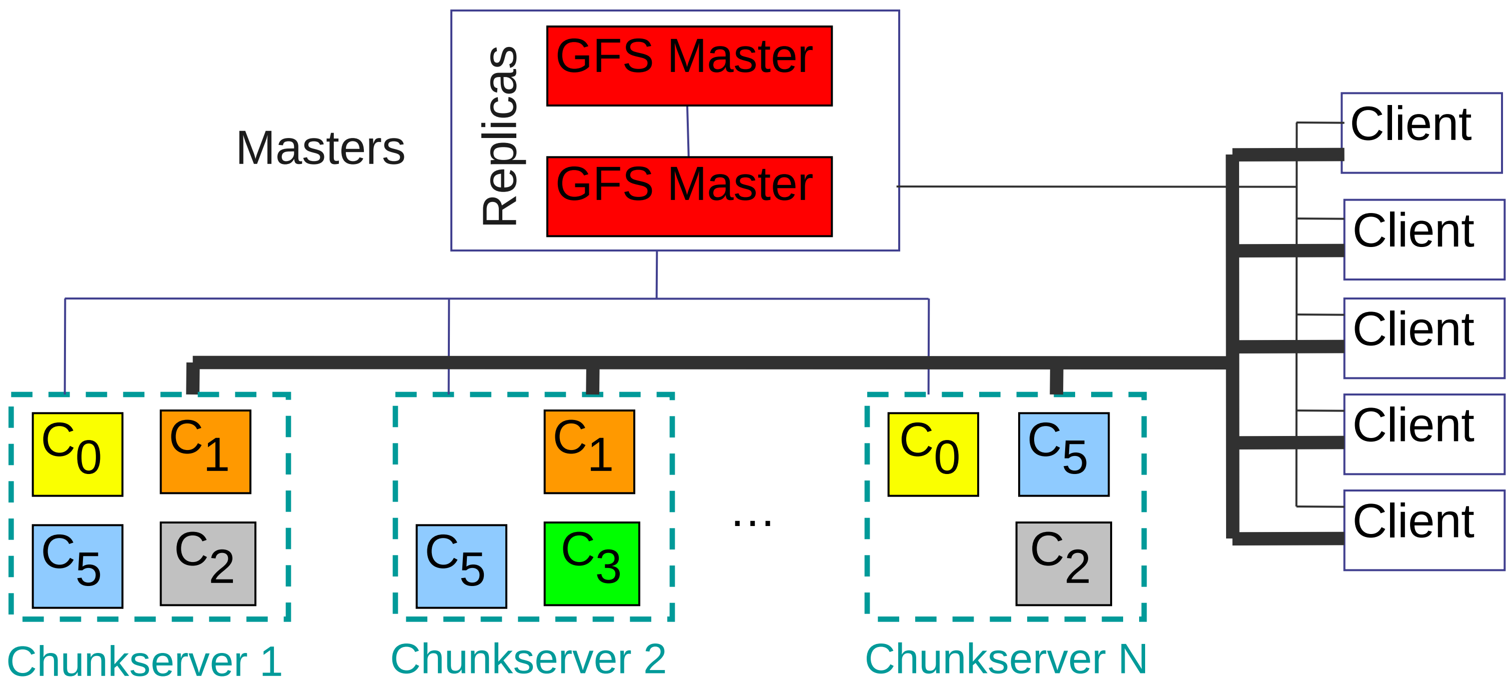
Speedup

	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

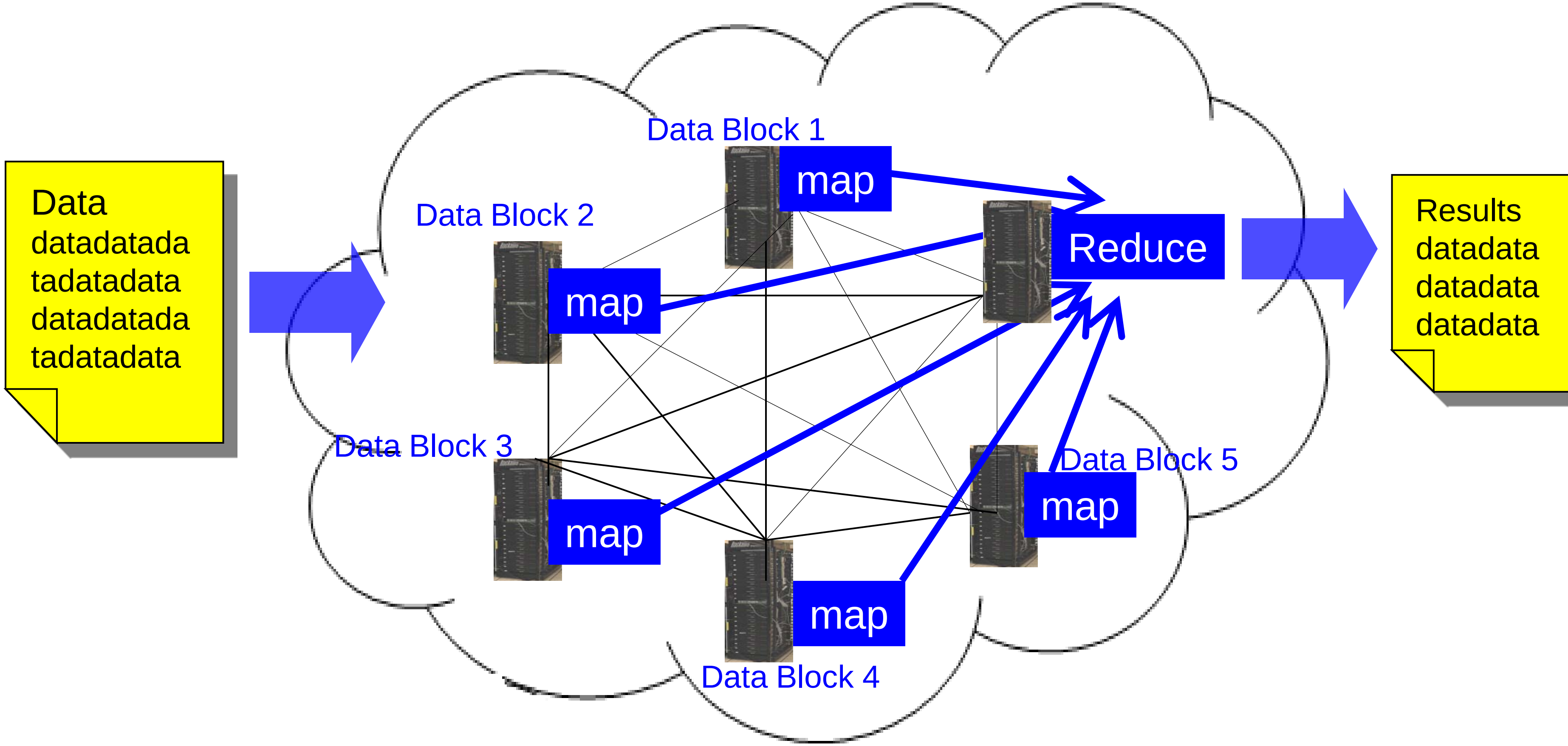
Outline

- Motivating Applications
  - Confucius
- Parallel Algorithms
  - Frequent Itemset Mining [ACM RS 08]
  - Latent Dirichlet Allocation [WWW 09, AAIM 09]
  - Clustering [ECML 08]
  - Support Vector Machines [NIPS 07]
- Distributed Computing Perspectives

Massive data storage
Distributed File Systems



MapReduce


Data
datadatada
tadatadata
datadatada
tadatadata
Data Block 1
map
Data Block 2
map
Reduce
Data Block 3
map
map
Data Block 4
Data Block 5
map
Results
datadata
datadata
datadata
datadata

Comparison between Parallel Computing Frameworks

	MapReduce	Project B	MPI
GFS/IO and task rescheduling overhead between iterations	Yes	No +1	No +1
Flexibility of computation model	AllReduce only +0.5	? +1	Flexible +1
Efficient AllReduce	Yes +1	Yes +1	Yes +1
Recover from faults between iterations	Yes +1	Yes +1	Apps
Recover from faults within each iteration	Yes +1	Yes +1	Apps
Final Score for scalable machine learning	3.5	5	5

Concluding Remarks

- Search + Social
- Increasing quantity and complexity of data demands scalable solutions
- Have parallelized key subroutines for mining massive data sets
  - Spectral Clustering [ECML 08]
  - Frequent Itemset Mining [ACM RS 08]
  - PLSA [KDD 08]
  - LDA [WWW 09, AAIM 09]
  - UserRank [Google TR 09]
  - Support Vector Machines [NIPS 07]
- Relevant papers
  - http://infolab.stanford.edu/~echang/
- Open Source PSVM, PLDA
  - http://code.google.com/p/psvm/
  - http://code.google.com/p/plda/

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