The Moving Target of Mobile User Modeling

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The World As We Know It!

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The Year of the "Mobile AD"?

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SOCIAL NETWORKING

Facebook CTO Says Mobile is the Focus. What About Tablets? Zuckerberg: The iPad is Not Mobile

By Todd Ogasawara on January 26, 2011 2:43 AM

Kim-Mai Cutler, Inside Facebook, reports:

Facebook CTO Bret Taylor: "Mobile is the primary focus for our platform this year."

My question is: What does Facebook consider a mobile device? After all, Facebook's founder and CEO was widely quoted last year as saying:

Mark Zuckerberg: iPad Is 'Not Mobile'

This response was a response to a question about why Facebook's iPhone app had not been tuned for use on the iPad. There's definitely a desire on the part of iPad users for a Facebook app. *Friendly Facebook for iPad*, for example, is currently #2 in the Top Free iPad Apps list. Twitter's official iPad app, by comparison, is at #29 on the same list.

So, will Facebook's mobile focus be limited to smartphones and ignore tablets?

Sunday Feb 6 2011
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Facebook to increase its mobile focus

By Tim Bradshaw, Digital Media Correspondent
Published: September 23 2010 10:16 | Last updated: September 23 2010 10:16

Facebook is planning to increase its focus on mobile phones as a platform for growth, its founder said on Wednesday.

In an **interview with Techcrunch**, chief executive Mark Zuckerberg said that the social networking company would not look to manufacture its own hardware or operating system, but would work closely with a wide range of partners to embed Facebook features into mobile phones.

That could include making Facebook's own customised version of Google's Android software for smartphones, he said, adding that the company was in discussions with third parties about "deep integration" and collaborative marketing.

But he sought to play down reports that Facebook would **challenge Apple or Google head-on**.

"Our goal is to have Facebook be everywhere and everything be social rather than a specific device," Mr Zuckerberg told Techcrunch. "The web is only at one and a half billion people whereas everyone is going to have a phone and all the phones are going to be smartphones ... Our goal [on mobile] is breadth not depth."

Making access to Facebook easier on hand-held devices will be crucial for adding users in emerging markets, where the mobile internet is "leapfrogging" web access on desktop PCs.

EDITOR'S CHOICE

Facebook founder's wealth rises 245% - Sep-23

E-commerce takes liking to Facebook's button - Sep-21

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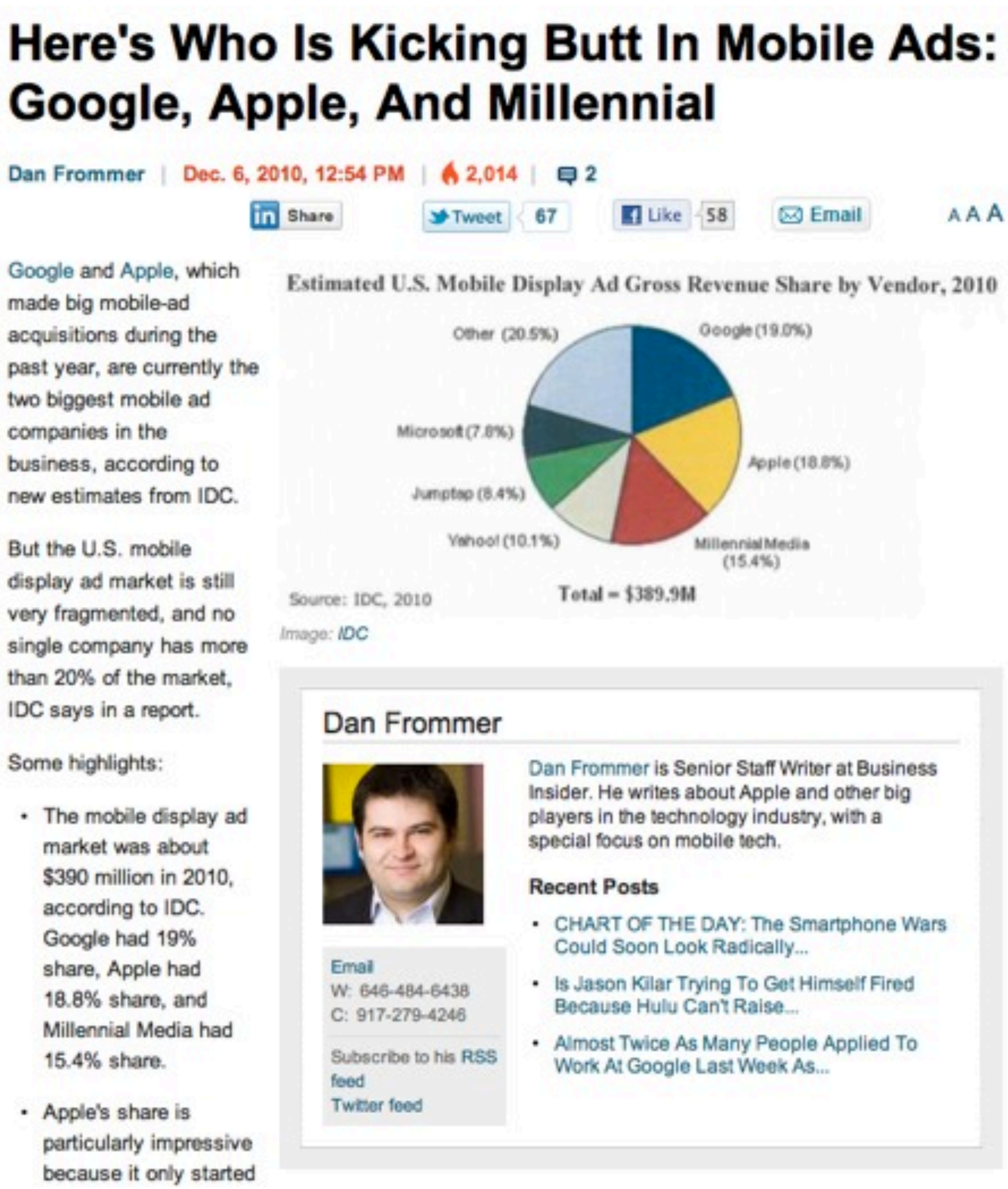
Facebook's 'value' soars - Aug-24

Interactive: Facebook's privacy policy - Sep-23

Mobile Users by Country

Rank	Country or region	Number of mobile phones	Population	% of population	Last updated
—	World	5,000,000,001	6,896,700,000	72.6	2010[1]
1	China	841,900,000	1,342,050,000	62.8	Jan 2011 [2] [3] [4] [5]
2	India	729,569,763	1,193,420,000	61.38	Nov. 2010[6]
3	United States	285,610,580	311,977,000	91.0	Dec. 2009[7][8]
4	Russia	213,900,000	141,940,000	147.3	Jun. 2010[9][10]
5	Brazil	202,940,000	190,732,694	106.4	Dec. 2010 [11]
6	Indonesia	168,264,000	229,965,000	73.1	May. 2009[12]
7	Pakistan	111,219,897	168,500,500	66.10	Dec.2010[13]
8	Japan	107,490,000	127,530,000	84.1	Mar. 2009[14]
9	Germany	107,000,000	81,882,342	130.1	2009[15]
10	Mexico	88,797,186	111,212,000	79.8	Sep.2010[16]
11	Italy	88,580,000	60,090,400	147.4	Dec.2008[17]
12	Philippines	78,000,000	92,226,600	73.6	January 2010[18]
13	Nigeria	76,000,000	144,339,000	50.3	Dec. 2009[19]
14	United Kingdom	75,750,000	61,612,300	122.9	Dec. 2008[20]
15	Turkey	66,000,000	71,517,100	92.2	2009[21]
16	Bangladesh	65,142,000	162,221,000	40.2	Sep. 2010[22]
17	France	58,730,000	65,073,842	90.2	Dec. 2008[23]
18	Thailand	56,170,908	65,001,021	81.0	2009[*citation needed*]
19	Ukraine	54,377,000	46,143,700	117.9	April. 2009[24]
20	Iran	52,000,000	75,078,000	69.3	2010[25][26]

The Mobile AD Pie



Here's Who Is Kicking Butt In Mobile Ads: Google, Apple, And Millennial

Dan Frommer | Dec. 6, 2010, 12:54 PM | 2,014 | 2

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Google and Apple, which made big mobile-ad acquisitions during the past year, are currently the two biggest mobile ad companies in the business, according to new estimates from IDC.

But the U.S. mobile display ad market is still very fragmented, and no single company has more than 20% of the market, IDC says in a report.

Some highlights:

- The mobile display ad market was about $390 million in 2010, according to IDC. Google had 19% share, Apple had 18.8% share, and Millennial Media had 15.4% share.
- Apple's share is particularly impressive because it only started

Image: IDC

Dan Frommer

Dan Frommer is Senior Staff Writer at Business Insider. He writes about Apple and other big players in the technology industry, with a special focus on mobile tech.

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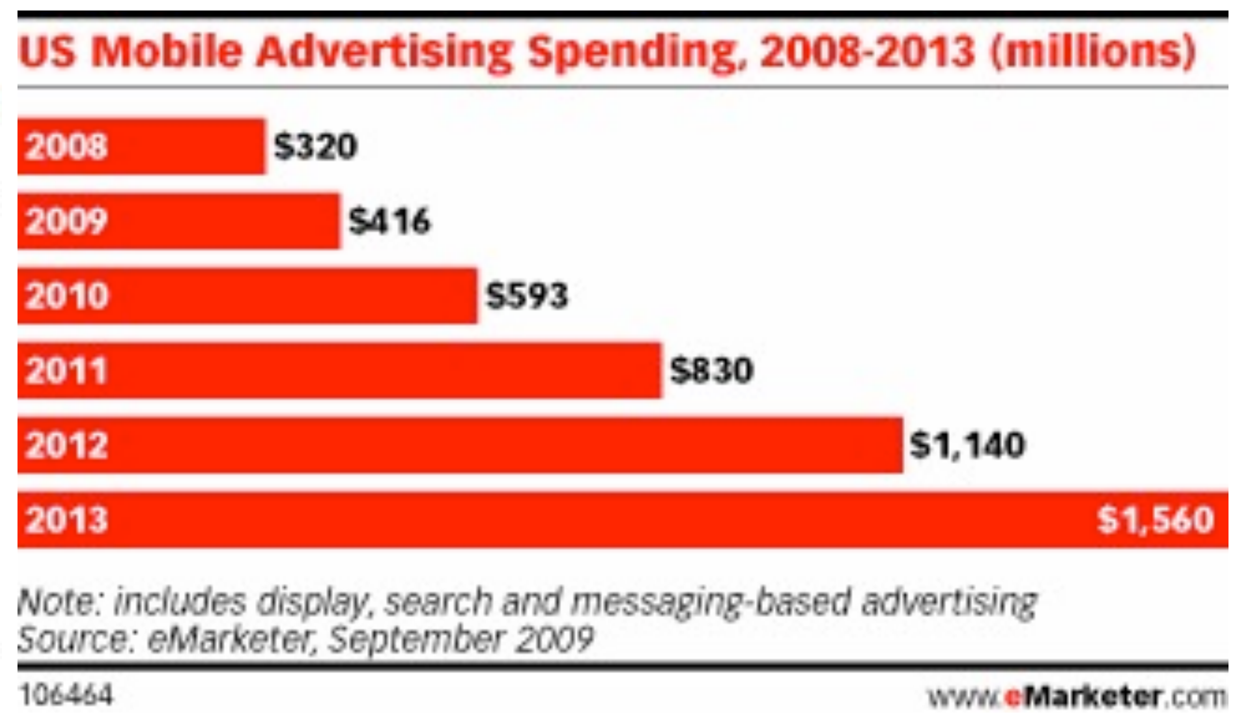

1 B euro in 2008
8.7 B euro in 2014
43% growth annually

The Mobile AD War

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Apple 2.0

Mac news from outside the reality distortion field

Apple is grabbing mobile ad share from Google, Yahoo, Microsoft and Nokia

Posted by Philip Elmer-DeWitt
September 27, 2010 5:45 AM

Smaller rivals like Jumptap and Millennial Media are also gaining, according to IDC

U.S. only. Source: IDC via Bloomberg Businessweek

The pie chart at right is somewhat premature, given that it is IDC's best guess -- via *Bloomberg Businessweek* -- of what the $500 million U.S. mobile advertising market will look three months from now.

But it's an indication of how the winds have shifted. Apple (AAPL), which had 0% share of the market before it bought Quattro Wireless in January and launched iAd in June, will end the year at 21%, according to IDC.

Where did that share come from? Chiefly from Google (GOOG), Yahoo (YHOO), Microsoft (MSFT) and Nokia (NOK), according to the *Businessweek* piece.

IDC's before-and-after numbers for the biggest losers below the fold.

	Dec. 2009	Dec. 2010
Google	27%	21%
Yahoo	12%	9%
Microsoft	10%	7%
Nokia	5%	2%

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Apple-Google Mobile Advertising War Fuels Innovation

Posted on 18 January 2010

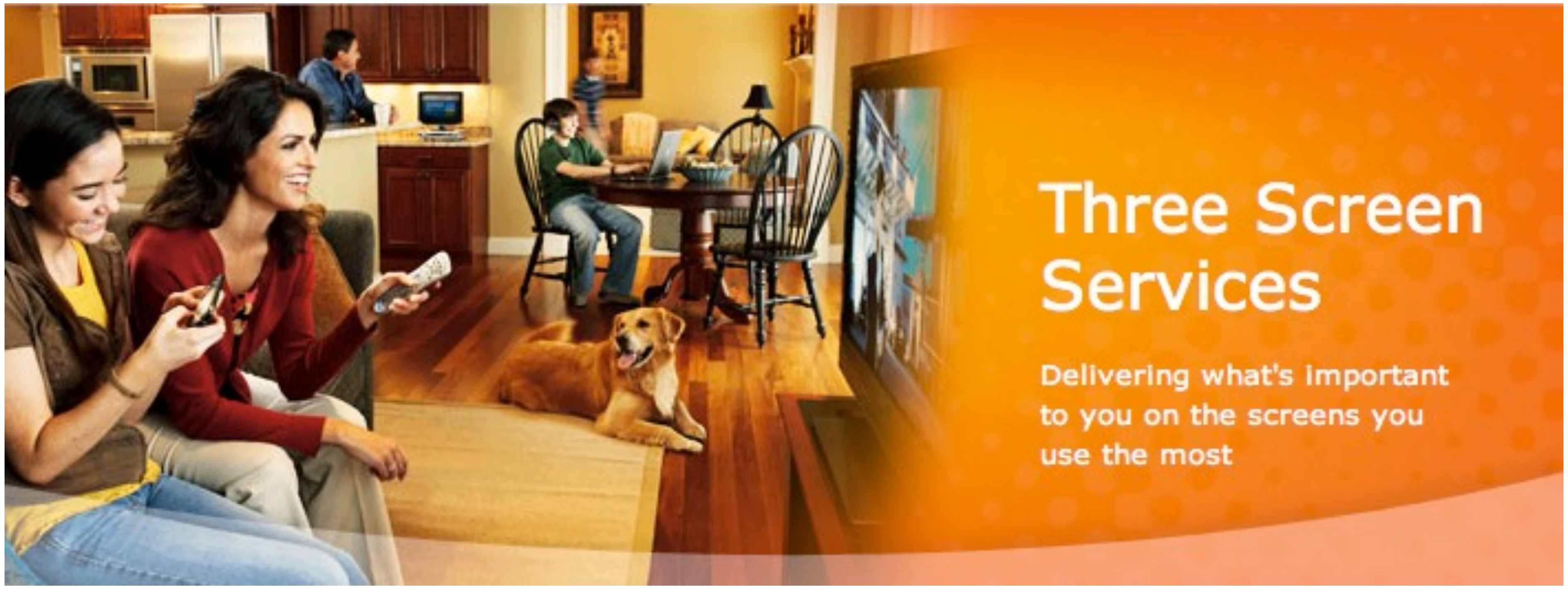
Steve Jobs wants to give mobile advertising an iTunes-worthy extreme makeover. Apple's CEO has revolutionized a lot of industries, so why not add mobile advertising to the list? According to a source familiar with his thinking, Jobs thinks "mobile ads suck" and that "improving the situation will make Apple even harder to beat," according to **BusinessWeek**.

Wanting to revolutionize mobile advertising is one thing, but can Apple really get to the core of what's wrong with the market today, all while bucking off Google's mobile ad dominance aspirations? Google's charging ahead with AdMob (well, that is, if the **FTC ever approves their $750M acquisition**) and Apple's off and running with their $275M mobile ad acquisition Quattro Wireless. If anything can give the mobile advertising industry a well-needed kick in its pants, it's a heated innovation battle between two of the most innovative companies in the world.

There are a few factors on Apple's side for the time being, but Google and their Android-based phones are catching up. For Apple's iPhone and iTouch devices, developers have already created more than 125,000 mobile applications... seven times as many that exist on Android.

Google => AdMob
Apple => Quattro

The Three Screens of Digital Lifestyle



TV	PC	Wireless Device
U-verse DVR	Internet Wi-fi	Mobile

What Does AT&T Offer?

- AT&T Mobility with 95.5 million mobile subscribers (Dec. 2010)
- AT&T U-verse reaches more than 27 million living units (Dec. 2010)
- AT&T Wi-Fi with 23,000 U.S. hotspots and more than 125,000 global hotspots (Dec. 2010)
- AT&T Interactive with YellowPages.com, Buzz.com, etc.

Phone connection graph, Call-through-rate (CTR)

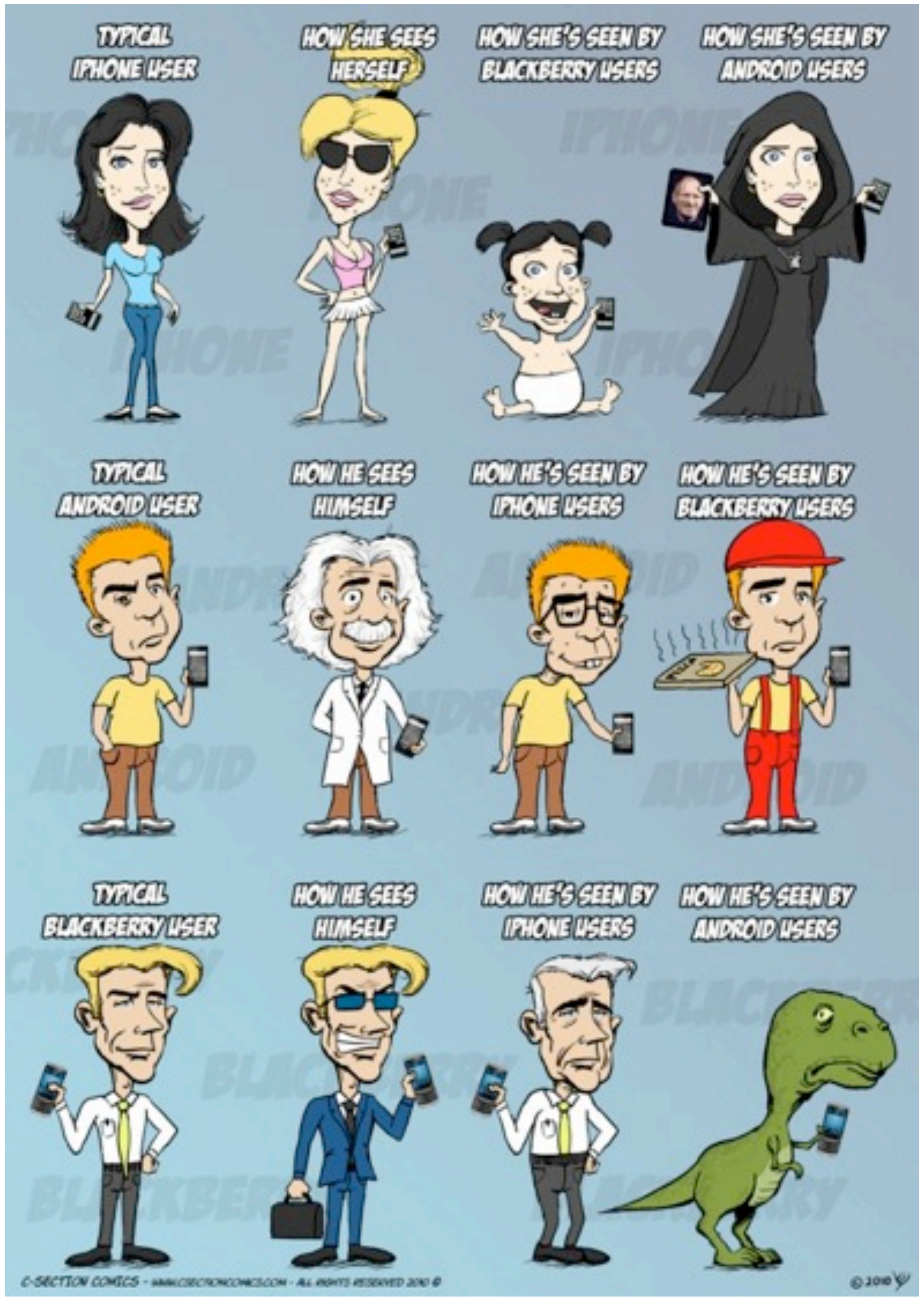
What to Model in User Modeling

- Intention - why
- Behavior - what
- Performance - how good
- Knowledge - how much
- Competence - how to act upon

What to Model

	TV	PC	Wireless
• Intention (action, goal, plan, etc.) • Behavior • Performance • Knowledge • Competence	• Aggregated media viewing habits	• Commercial search intentions • Network optimization	• Individual location-based information • User's locative intentions • Learning personal/family/business similarity

Difficulties in Mobile User Modeling



- What you see and what other see in you is different
- What you see and what we see in you is also different

http://www.intomobile.com/2010/11/04/how-iphone-android-and-blackberry-users-see-each-other/

Issues in Mobile User Modeling

- Missing value, error handling, accuracy, etc.
- Entity disambiguation
- Making inferences
- Scalability issues
- Algorithm efficiency

Potential Applications

- Personalization and adaptation
- Recommendation
- Learning to rank
- Intelligent analytics
- Target marketing

Multi-task Feature Selection

	Same Task	**Different Tasks**
Homogeneous Database (same features)	Regular Learning	**Multi-task Learning**
Heterogeneous Database (different features)	Structured Output Learning	Transfer Learning

Online Learning for Multi-Task Feature Selection

work with Haiqin Yang

- Why Multi-Task Feature Selection?
  - Related tasks contain helpful information
  - Redundant/irrelevant features exist
- Gene selection from microarray data in related diseases
  - Distinguish healthy from unhealthy genes for different diseases with few samples and large variables
- Text categorization from documents in multiple related categories
  - Detecting spams from persons with similar interests
  - Automatic classifying related web page categories

Previous Work

- A generalized L_1-norm single-task regularization (Argyriou et al., 2008)
- Mixed norms of L_1, L_2, and L_∞ norms (Obozinski et al., 2009)
- Nesterov's method on MTFS (Liu et al., 2009)
- $L_{0,0}$-regularization based on MIC (Dhillon et al., 2009)

Problems and Contributions

- Problems
  - Features among tasks are often redundant or irrelevant
  - Data come in sequence
  - Data are large in volume
- Contributions
  - First online learning framework for MTFS
  - Easy implementation
  - Efficient in both time complexity and memory requirement
  - Find important features and important tasks that dominate features
  - Easily extended to nonlinear models

Multi-Task Feature Selection Models

Data: i.i.d. observations: $\mathcal{D} = \bigcup_{q=1}^{Q} \mathcal{D}_q$

Model: $f_q(\mathbf{x}) = \mathbf{w}^{q\top}\mathbf{x}, \quad q = 1, \ldots, Q$

$\mathcal{D}_q = \{\mathbf{z}_i^q = (\mathbf{x}_i^q, y_i^q)\}_{i=1}^{N_q}$ sampled from $\mathcal{P}_q$, $q = 1, \ldots, Q$

$\mathbf{x} \in \mathbb{R}^d$–input variable, $y \in \mathbb{R}$–response

Objective: $\min\limits_{\mathbf{W}} \ \sum_{q=1}^{Q} \frac{1}{N_q} \sum_{i=1}^{N_q} \ell^q(\mathbf{W}_{\bullet q}, \mathbf{z}_i^q) + \Omega_\lambda(\mathbf{W})$

$\mathbf{W} = \left(\mathbf{w}^1, \mathbf{w}^2, \ldots, \mathbf{w}^Q\right) = (\mathbf{W}_{\bullet 1}, \ldots, \mathbf{W}_{\bullet Q}) = \left(\mathbf{W}_{1\bullet}^\top, \ldots, \mathbf{W}_{d\bullet}^\top\right)^\top$

Multi-Task Feature Selection Models

Regularization

$$\textbf{iMTFS:} \quad \Omega_\lambda(\mathbf{W}) = \lambda \sum_{q=1}^{Q} \left\| \mathbf{W}_{\bullet q} \right\|_1 = \lambda \sum_{j=1}^{d} \left\| \mathbf{W}_{j\bullet}^\top \right\|_1$$

$$\textbf{aMTFS:} \quad \Omega_\lambda(\mathbf{W}) = \lambda \sum_{j=1}^{d} \left\| \mathbf{W}_{j\bullet}^\top \right\|_2$$

$$\textbf{MTFTS:} \quad \Omega_{\lambda,\mathbf{r}} = \lambda \sum_{j=1}^{d} \left(r_j \left\| \mathbf{W}_{j\bullet}^\top \right\|_1 + \left\| \mathbf{W}_{j\bullet}^\top \right\|_2 \right)$$

$$\begin{array}{ccc} \textbf{iMTFS} & \textbf{aMTFS} & \textbf{MTFTS} \\ \begin{pmatrix} x & 0 & 0 & x & x \\ 0 & x & x & x & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x & 0 & x & x & x \end{pmatrix}, & \begin{pmatrix} x & x & x & x & x \\ 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x & x & x & x & x \end{pmatrix}, & \begin{pmatrix} x & 0 & x & x & 0 \\ 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & x & 0 & x & x \end{pmatrix} \end{array}$$

Online Learning Algorithm

Initialization: $\mathbf{W}_1 = \mathbf{W}_0,\ \bar{\mathbf{G}}_0 = \mathbf{0}$
for $t = 1, 2, 3, \ldots$

1. Compute the subgradient on $\mathbf{W}_t$, $\mathbf{G}_t \in \partial\, l_t$
2. Update the average subgradient $\bar{\mathbf{G}}_t$:
   $$\bar{\mathbf{G}}_t = \frac{t-1}{t}\bar{\mathbf{G}}_{t-1} + \frac{1}{t}\mathbf{G}_t$$
3. Calculate the next iteration $\mathbf{W}_{t+1}$:
   $$\mathbf{W}_{t+1} = \arg\min_{\mathbf{W}} \Upsilon(\mathbf{W}) \triangleq \left\{\bar{\mathbf{G}}_t^\top \mathbf{W} + \Omega_\lambda(\mathbf{W}) + \frac{\gamma}{\sqrt{t}} h(\mathbf{W})\right\}$$

end for

- **W**: Matrix
- Original formulation is in linear case; it can be extended to non-linear case easily
- Motivated by the success of dual averaging method (Xiao, 2009; Yang et al., 2010)

Updating Rules for Online MTFS

Define: $h(\mathbf{W}) = \frac{1}{2}\|\mathbf{W}\|_F^2$

- **iMTFS**: For $i = 1, \ldots, d$ and $q = 1, \ldots, Q$,

$$(W_{i,q})_{t+1} = -\frac{\sqrt{t}}{\gamma}\left[|(\bar{G}_{i,q})_t| - \lambda\right]_+ \cdot \text{sign}\,((\bar{G}_{i,q})_t).$$

- **aMTFS**: For $j = 1, \ldots, d$,

$$(\mathbf{W}_{j\bullet})_{t+1} = -\frac{\sqrt{t}}{\gamma}\left[1 - \frac{\lambda}{\|(\bar{\mathbf{G}}_{j\bullet})_t\|_2}\right]_+ \cdot (\bar{\mathbf{G}}_{j\bullet})_t.$$

- **MTFTS**: For $j = 1, \ldots, d$,

$$(\mathbf{W}_{j\bullet})_{t+1} = -\frac{\sqrt{t}}{\gamma}\left[1 - \frac{\lambda}{\|(\bar{\mathbf{U}}_{j\bullet})_t\|_2}\right]_+ \cdot (\bar{\mathbf{U}}_{j\bullet})_t,$$

  where the q-th element of $(\bar{\mathbf{U}}_{j\bullet})_t$ is calculated by

$$(\bar{U}_{j,q})_t = \left[|(\bar{G}_{j,q})_t| - \lambda r_j\right]_+ \cdot \text{sign}\,((\bar{G}_{j,q})_t),\ \ q = 1, \ldots, Q.$$

Efficiency: $\mathcal{O}(d \times Q)$ in memory cost and time complexity

Theoretical Results

- Average regret for MTFS

$$\bar{R}_T(\mathbf{w}) := \frac{1}{Q}\sum_{q=1}^{Q}\frac{1}{T}\sum_{t=1}^{T}(\Omega_\lambda(\mathbf{W}_t) + l_t(\mathbf{W}_t)) - S_T(\mathbf{W})$$

- Theoretical bounds

$$\bar{R}_T \sim \mathcal{O}(1/\sqrt{T})$$

Experimental Setup

- Data
  - School data
  - Computer survey data for conjoint analysis
- Comparison algorithms
  - iMTFS (individual MTFS)
  - aMTFS (across MTFS)
  - DA-iMTFS (dual average)
  - DA-aMTFS (dual average)
  - DA-MTFTS (dual average)
- Platform
  - PC with 2.13 GHz dual-core CPU
  - Batch-mode algorithms: Matlab
  - Online-mode algorithms: Matlab

School Data

- Description
  - Objective-Predict examination scores
  - Data: Exam scores of 15,362 students from 139 secondary schools in London during the years 1985, 1986, and 1987, Q=139
  - Features: Year of the exam (YR), 4 school-specific and 3 student-specific features, d=27
- Setup
  - Evaluation: Explained variance (R^2) $1 - \frac{SS_{\text{err}}}{SS_{\text{tol}}}$, the larger the better
  - Loss: Square loss
  - Parameters setting: Cross validation (hierarchical search and grid search)

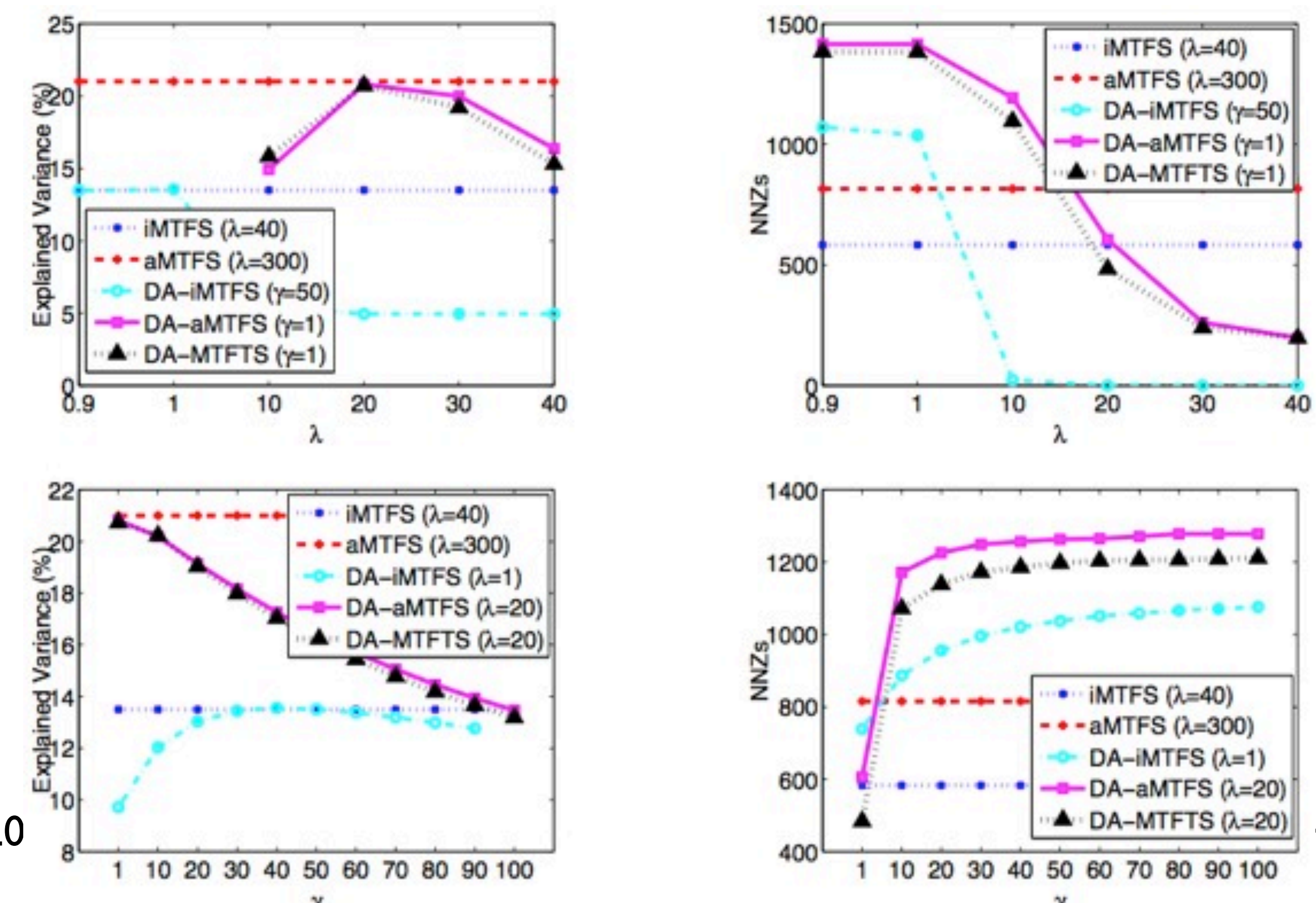
School Data Results

- Learning multiple tasks simultaneously can gain over 50% improvement than learning the task individually
- Online learning algorithms attain (nearly) the same accuracies as batch-trained algorithms
- DA-MTFTS attains the same accuracy as DA-aMTFS with fewer NNZs

Method	Explained Variance	NNZs	Parameters
aMTFS	**21.0**±1.7	815.5±100.6	$\lambda = 300$
iMTFS	13.5±1.8	583.0±16.6	$\lambda = 40$
DA-aMTFS	**20.8**±1.8	605.8±180.3	$\lambda = 20, \gamma = 1$, ep=120
DA-MTFTS	**20.8**±1.9	483.7±130.7	$\lambda = 20, \gamma = 1$, ep=120
DA-iMTFS	13.5±1.8	1037.1±21.4	$\lambda = 1, \gamma = 50$, ep=120

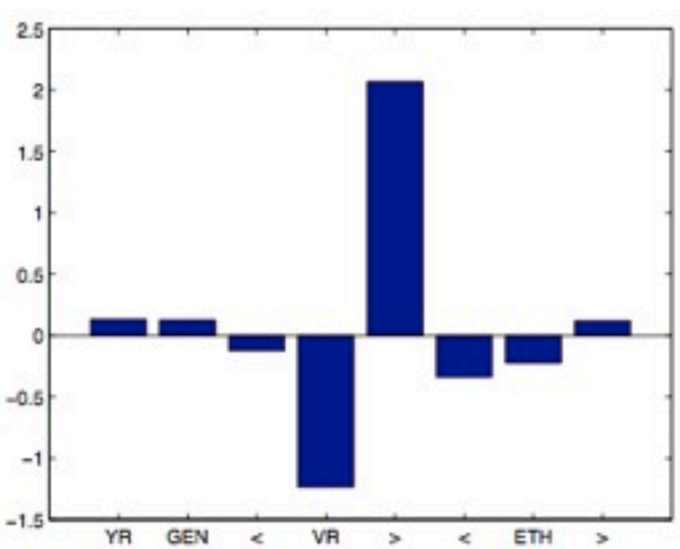
Effect of λ and γ

- Results
  - NNZs decreases as λ increases
  - NNZs increases as γ increases
  - Fewer NNZs in DA-MTFTS than DA-aMTFS

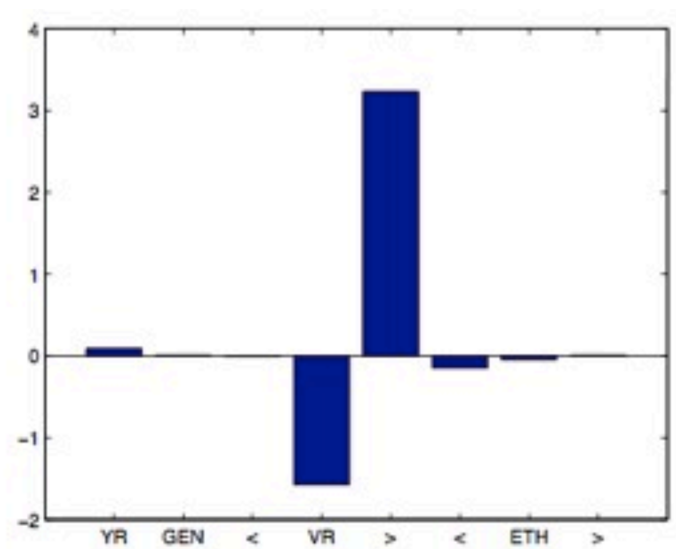


Learned Features

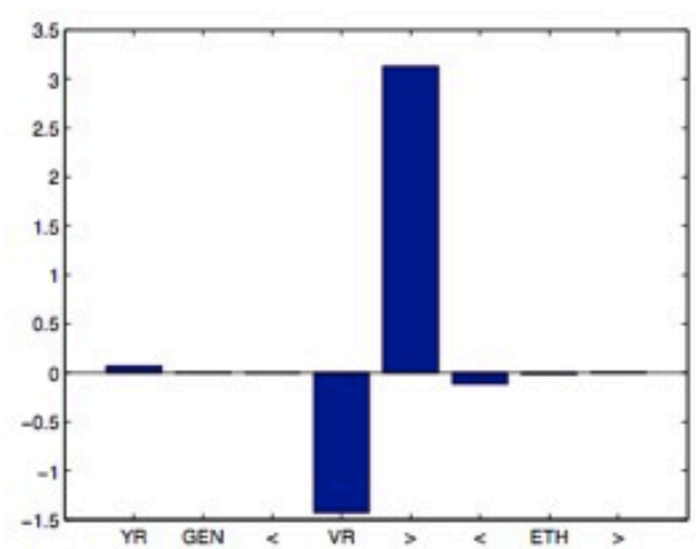
- Results
  - Features learned from the online algorithms are consistent to those learned from the batch-trained algorithm
  - Predicted exam score depends strongly on the students' verbal reasoning (VR) test band
  - Next influence is the ethnic background and year admission



aMTFS



DA-aMTFS



DA-MTFTS

Conjoint Analysis

- Description
  - Objective: Predict rating by estimating respondents' partworths vectors
  - Data: Ratings on personal computers of 180 students for 20 different PC, $Q = 180$
  - Features: Telephone hot line (TE), amount of memory (RAM), screen size (SC), CPU speed (CPU), hard disk (HD), CDROM/multimedia (CD), cache (CA), color (CO), availability (AV), warranty (WA), software (SW), guarantee (GU) and price (PR); $d = 14$
- Setup
  - Evaluation: Root mean square errors (RMSEs)
  - Loss: Square loss
  - Parameters setting: Cross validation (hierarchical and grid search)

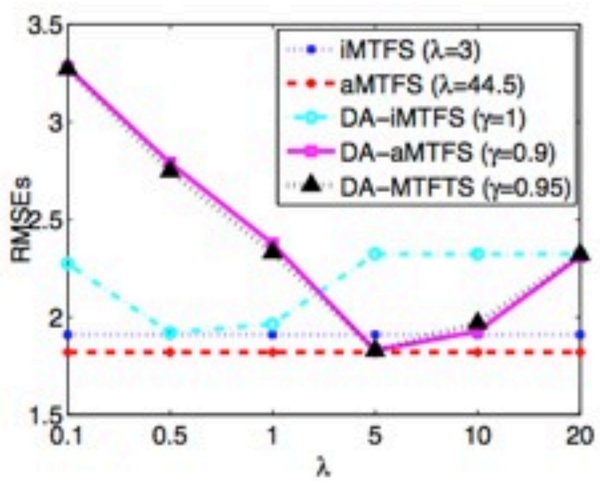
Conjoint Analysis Results

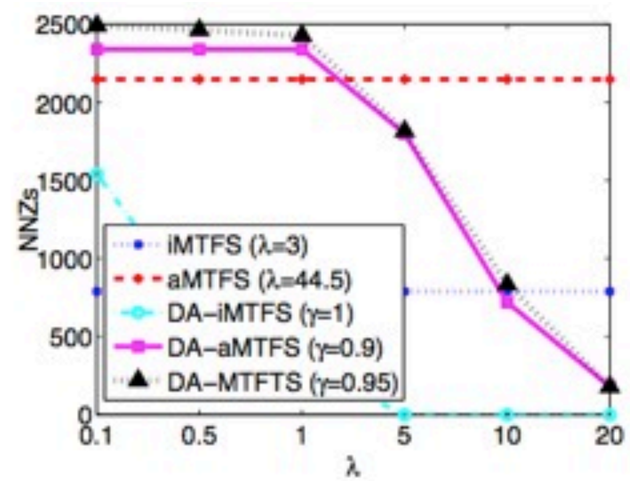
- Accuracy
  - Learning partworths vectors across respondents can help to improve the performance
  - Online learning algorithms attain nearly the same accuracies as batch-trained algorithms

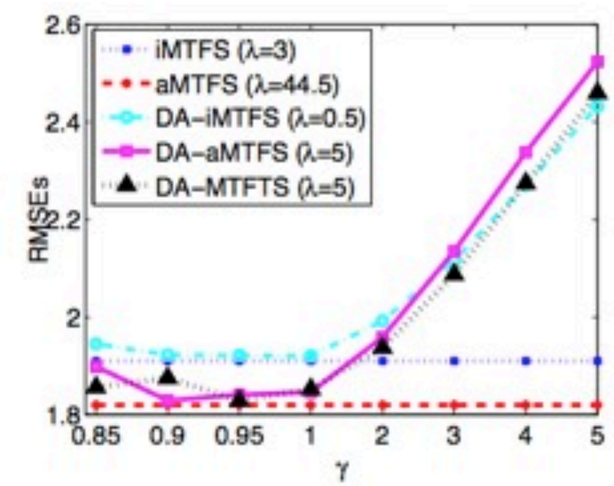
Method	RMSEs	NNZs	Parameters
aMTFS	**1.82**	2148	$\lambda = 44.5$
iMTFS	1.91	789	$\lambda = 3$
DA-aMTFS	**1.83**	1800	$\lambda = 5, \gamma = 0.9$, ep=20
DA-MTFTS	**1.83**	1816	$\lambda = 5, \gamma = 0.95$, ep=20
DA-iMTFS	1.92	662	$\lambda = 0.5, \gamma = 1.0$, ep=20

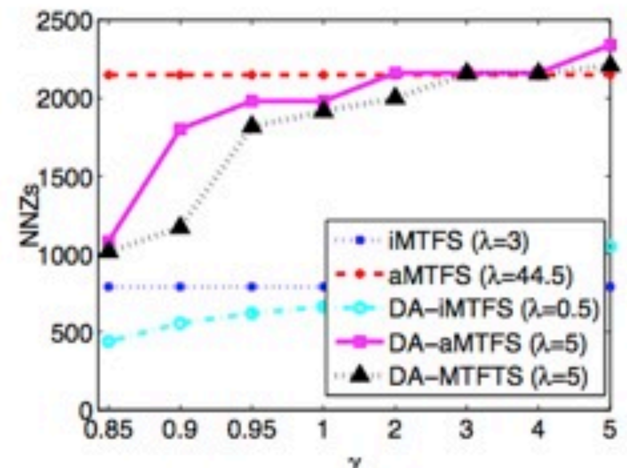
Effect of λ and γ

- Results
  - NNZs decreases as λ increases
  - NNZs increases as γ increases
  - Fewer NNZs in DA-MTFTS than DA-aMTFS



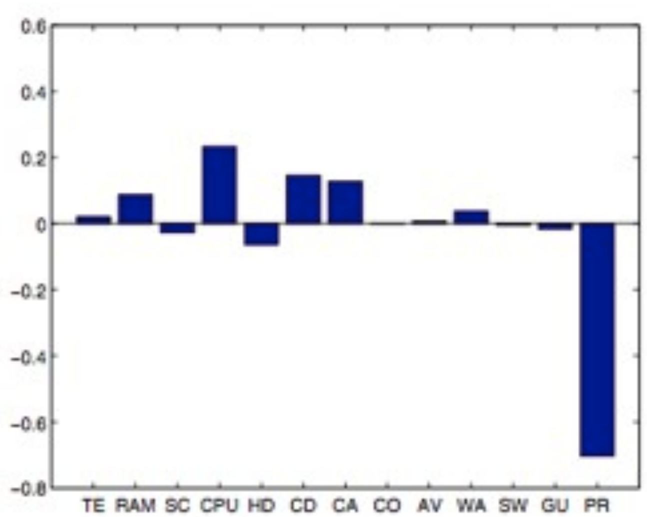




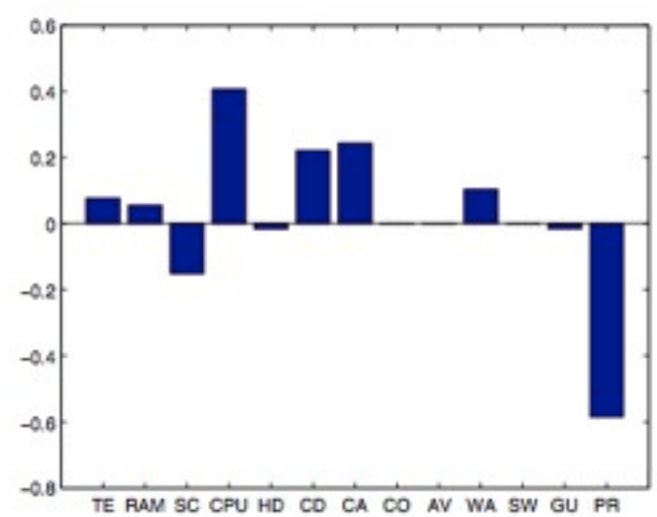


Learned Features

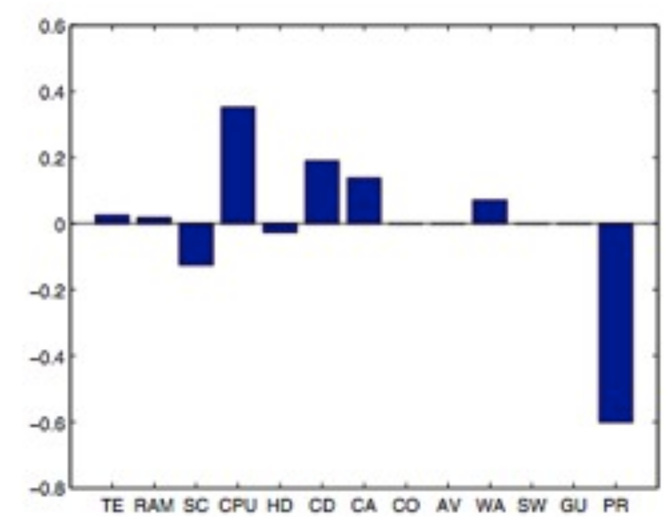
- Results
  - Features learned from the online algorithms are consistent to those learned from the batch-trained algorithm
  - Ratings are strongly negative to the price and positive to the RAM, the CPU speed, CDROM, and cache



aMTFS



DA-aMTFS



DA-MTFTS

Time Cost

- School Data
  - aMTFTS: 1.30s
  - DA-MTFTS: 0.99s
- Conjoint Analysis
  - aMTFTS: 0.162s
  - DA-aMTFS: 0.115s

Summary

- Mobile user modeling is a challenging and interesting problem!
- A novel online learning algorithm framework for multi-task feature selection
- Apply this framework for several multi-task feature selection models
- Experimental results demonstrate its efficiency and effectiveness

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- Wei Wang (M.Phil.)
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- Connie Yuen (Ph.D.)
- Xin Xin (Ph.D.)
- Chao Zhou (Ph.D.)
- Yi Zhu (Ph.D.)

On-Going Research

Machine Learning

- Smooth Optimization for Effective Multiple Kernel Learning (AAAI'10)
- Online Learning for Multi-Task Feature Selection (CIKM'10)
- Simple and Efficient Multiple Kernel Learning By Group Lasso (ICML'10)
- Online Learning for Group Lasso (ICML'10)
- Heavy-Tailed Symmetric Stochastic Neighbor Embedding (NIPS'09)
- Adaptive Regularization for Transductive Support Vector Machine (NIPS'09)
- Direct Zero-norm Optimization for Feature Selection (ICDM'08)
- Semi-supervised Learning from General Unlabeled Data (ICDM'08)
- Learning with Consistency between Inductive Functions and Kernels (NIPS'08)
- An Extended Level Method for Efficient Multiple Kernel Learning (NIPS'08)
- Semi-supervised Text Categorization by Active Search (CIKM'08)
- Transductive Support Vector Machine (NIPS'07)
- Global and local learning (ICML'04, JMLR'04)

On-Going Research

Web Intelligence/Information Retrieval

- Routing Questions to Appropriate Answerers in Community Question Answering Services (CIKM'10)
- Diversifying Query Suggestion Results (AAAI'10)
- A Generalized Co-HITS Algorithm and Its Application to Bipartite Graphs (KDD'09)
- Entropy-biased Models for Query Representation on the Click Graph (SIGIR'09)
- Effective Latent Space Graph-based Re-ranking Model with Global Consistency (WSDM'09)
- Formal Models for Expert Finding on DBLP Bibliography Data (ICDM'08)
- Learning Latent Semantic Relations from Query Logs for Query Suggestion (CIKM'08)
- RATE: a Review of Reviewers in a Manuscript Review Process (WI'08)
- MatchSim: link-based web page similarity measurements (WI'07)
- Diffusion rank: Ranking web pages based on heat diffusion equations (SIGIR'07)
- Web text classification (WWW'07)

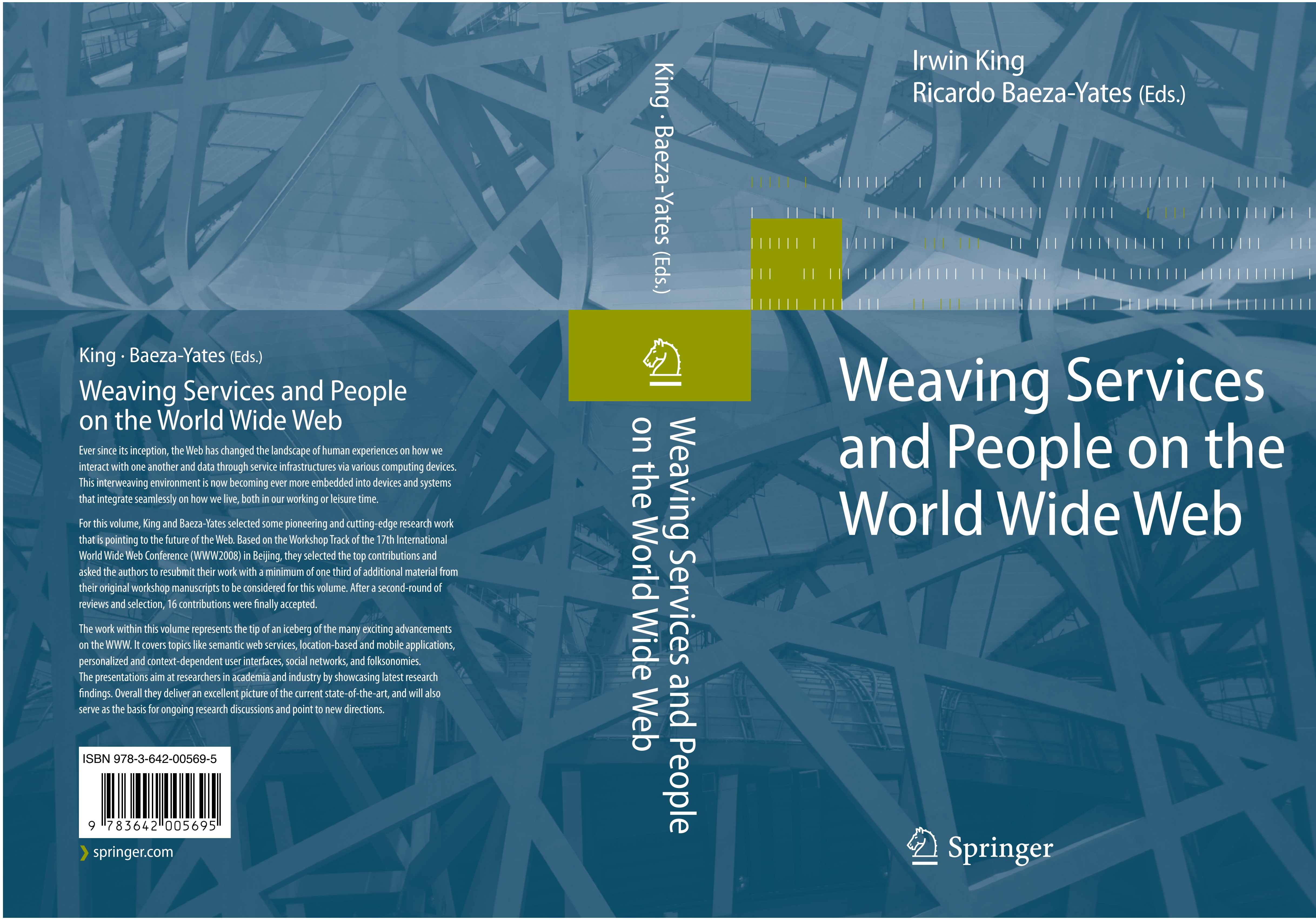
On-Going Research

Recommender Systems/Collaborative Filtering

- Recommender Systems with Social Regularization (WSDM'11)
- CMAP: Effective Fusion of Quality and Relevance for Multi-criteria Recommendation (WSDM'11)
- UserRec: A User Recommendation Framework in Social Tagging Systems (AAAI'10)
- Learning to Recommend with Social Trust Ensemble (SIGIR'09)
- Semi-Nonnegative Matrix Factorization with Global Statistical Consistency in Collaborative Filtering (CIKM'09)
- Recommender system: accurate recommendation based on sparse matrix (SIGIR'07)
- SoRec: Social Recommendation Using Probabilistic Matrix Factorization (CIKM'08)

Human Computation

- Collection of User Judgments on Spoken Dialog System with Crowdsourcing (SLT'10)
- A Survey of Human Computation Systems (SCA'09)
- Mathematical Modeling of Social Games (SIAG'09)
- An Analytical Study of Puzzle Selection Strategies for the ESP Game (WI'08)
- An Analytical Approach to Optimizing The Utility of ESP Games (WI'08)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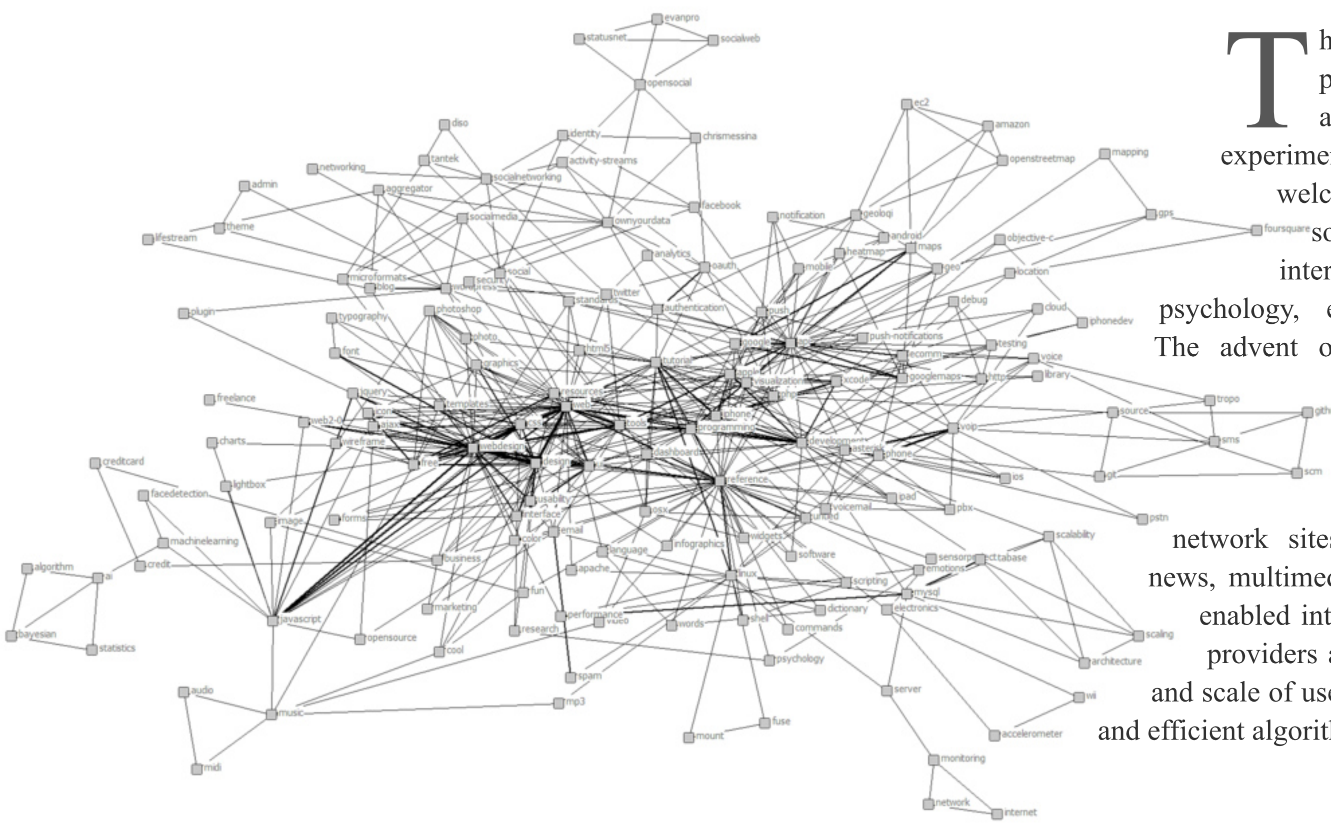

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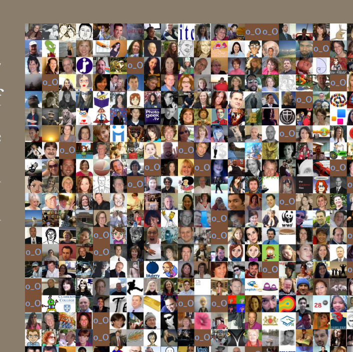

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