Economic Recommendation with Surplus Maximization

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Outline

- Background and Motivation
- Problem Definition
- Total Surplus Maximization Framework
- Model Specification
  - E-commerce
  - P2P lending services
  - Online freelancing platforms
- Empirical Analysis Results
- Conclusions and Future Work

Human Activities from Offline to Online

- We are experiencing the historic moment of “Onlinization”
  - More and more human activities are moving from offline to online

Conduct socialing and make friends online by social networks

Work and make money online by online freelancing network services

Purchase online by E-commerce Websites

Manage asset properties online by, e.g., P2P Lending services

Web Applications as Economic System

- The Web is a whole Economic System for various human activities
  - Just as our offline physical world
- Involves interactions of two parties on some type of online services
  - Consumer – Online Services – Producer
  - E-commerce: Customers – Goods – Retailors
  - P2P lending: Lenders – Financial products (loan requests) – Borrowers
  - Online freelancing: Employees – Jobs – Employers
  - Social networks: You – Information (news/tweets/status) – Friends

Online Service Allocation

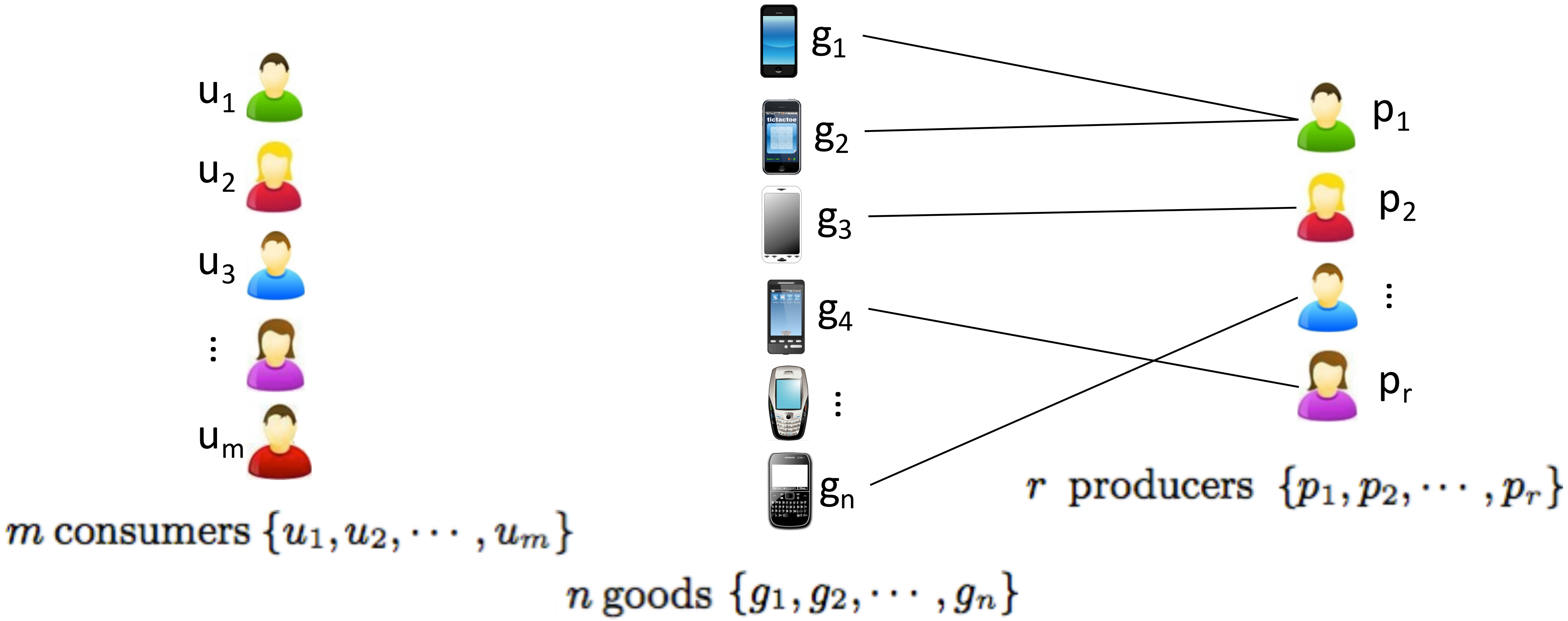
- Fundamental task: Online Service Allocation (OSA)
  - Assign online services (products, loans, jobs) from producers to consumers according to some principles
  - Mainly achieved by Recommender Systems
    - Consumers are granted by law to choose freely
    - Can only ‘recommend’ specific services from producer to consumer
- Existing methods
  - Usually aim at maximizing the benefits of one side
    - E.g., E-commerce: match user preference and boost user satisfaction
    - P2P lending services: recommend to maximize lender profits

Web Intelligence for Social Good

- May be problematic
  - A system should benefit both parties to be sustainable
- Web Intelligence for Social Good
  - Economists, philosophers, and sociologists devote their lives for a better off in human society of our physical world
  - We as computer scientists should also push the virtual online society towards a more fair, just and win-win world
- The concept of Social Surplus
  - To achieve this goal, we introduce the concept of social surplus as the metric for evaluating and optimizing online service allocations

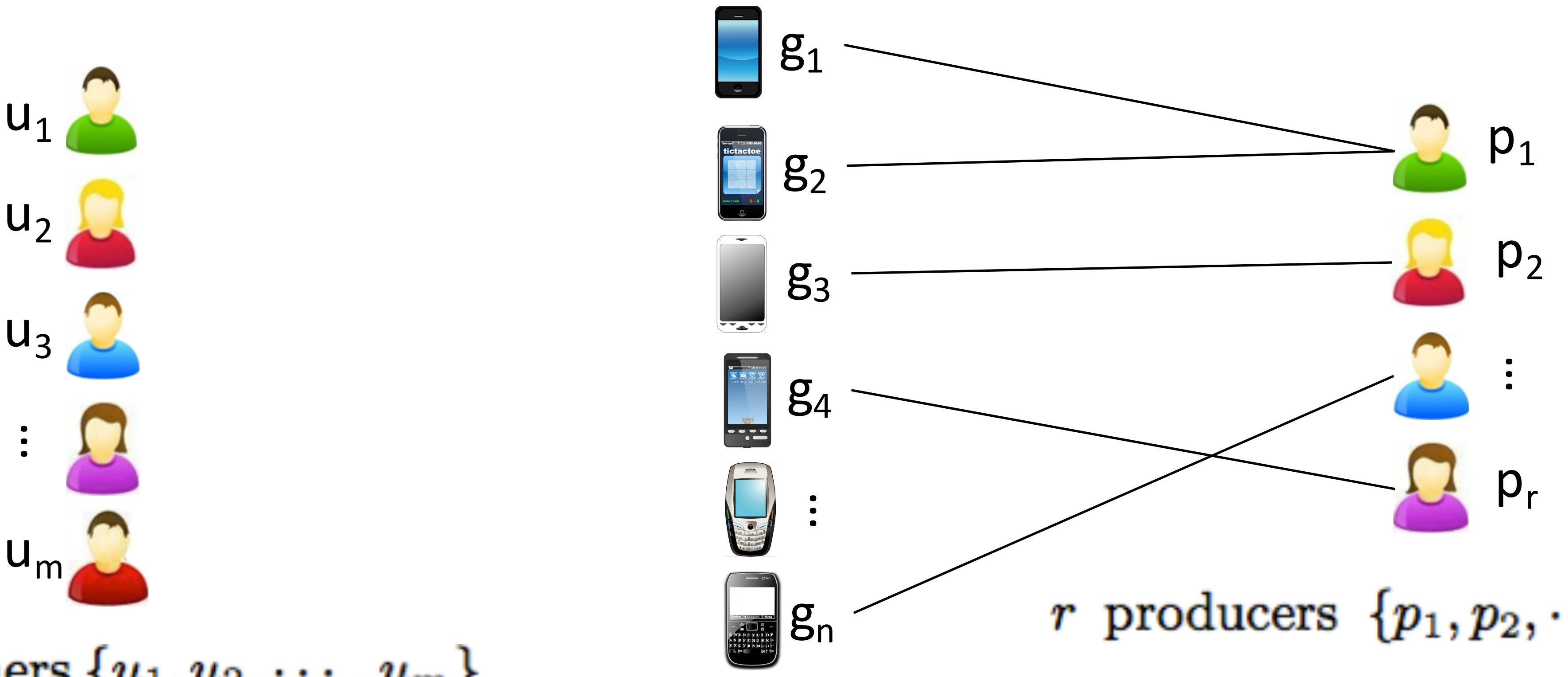
Problem Definition

- Consumers, Producers, and Goods



Problem Definition

- Service Quantity Vector



r producers $\{p_1, p_2, \cdots, p_r\}$

m consumers $\{u_1, u_2, \cdots, u_m\}$

n goods $\{g_1, g_2, \cdots, g_n\}$

$M = [M_1, M_2, \cdots, M_n]$

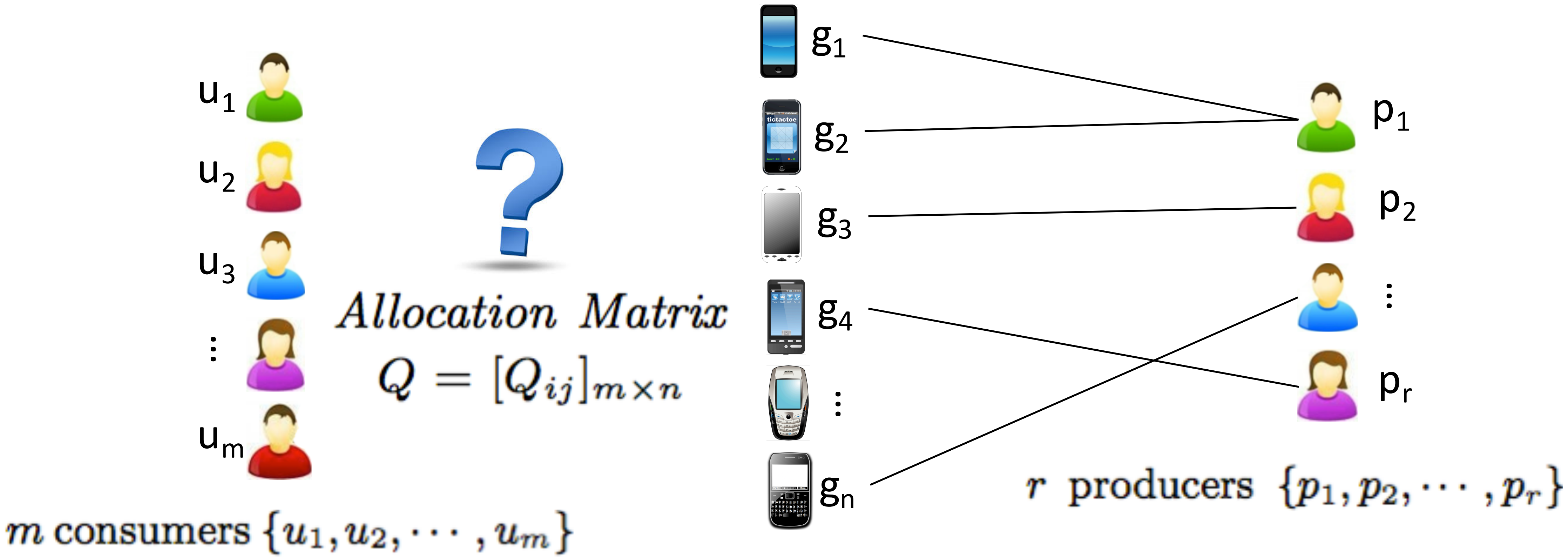
Mj = 1 for online freelancing

0<Mj<∞ for P2P loan

Mj= ∞ for E-commerce

Problem Definition

- Online Service Allocation (OSA)



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0<Mj<∞ for P2P loan

Mj= ∞ for E-commerce

Various Principles for OSA

- Various Principles for OSA
  - Maximize User Preference?
  - Maximize Provider Profit?
  - Maximize the Total Social Surplus for Social Good!
    - And fantastic things happen beyond expectation
    - Social good -> per user satisfaction + social better off

Basic Concepts: Utility and Surplus

- Utility
  - Basis of modern economics
  - Measures one's preference/satisfaction over some set of goods/services
  - Usually a function of quantity *q*: U(q)
  - Governed by the *Law of Diminishing Marginal Utility*
    - As a person increases the consumption of a product, there is a decline in the marginal utility that the person derives from consuming each additional unit.
    - Mathematically: $U(0)=0$ & $U'(q)>0$ & $U''(q)<0$
    - Consume the first slice of bread vs. Consuming the last slice when feeling full

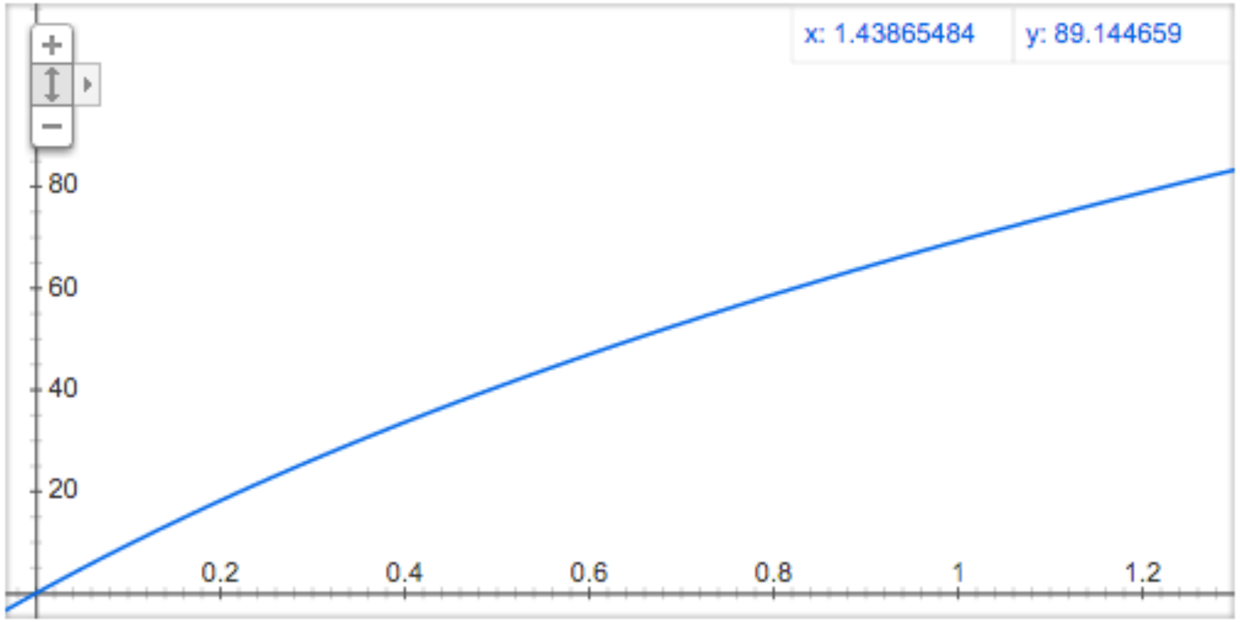
Basic Concept: Utility

- Utility – frequently used forms:
  - Economists introduced various functional forms for Utility
  - The KPR (log) Utility function

    King-Plosser-Rebelo (KPR) utility: $U(q) = a\ln(1+q)$

    - U(0)=0 & U'(q)>0 & U''(q)<0
- Personalized Utility
  - on Consumer to Good level

    $$U_{ij}(q) = a_{ij}\ln(1+q)$$
  - a_{ij} as parameter of curve lift



Basic Concept: Surplus

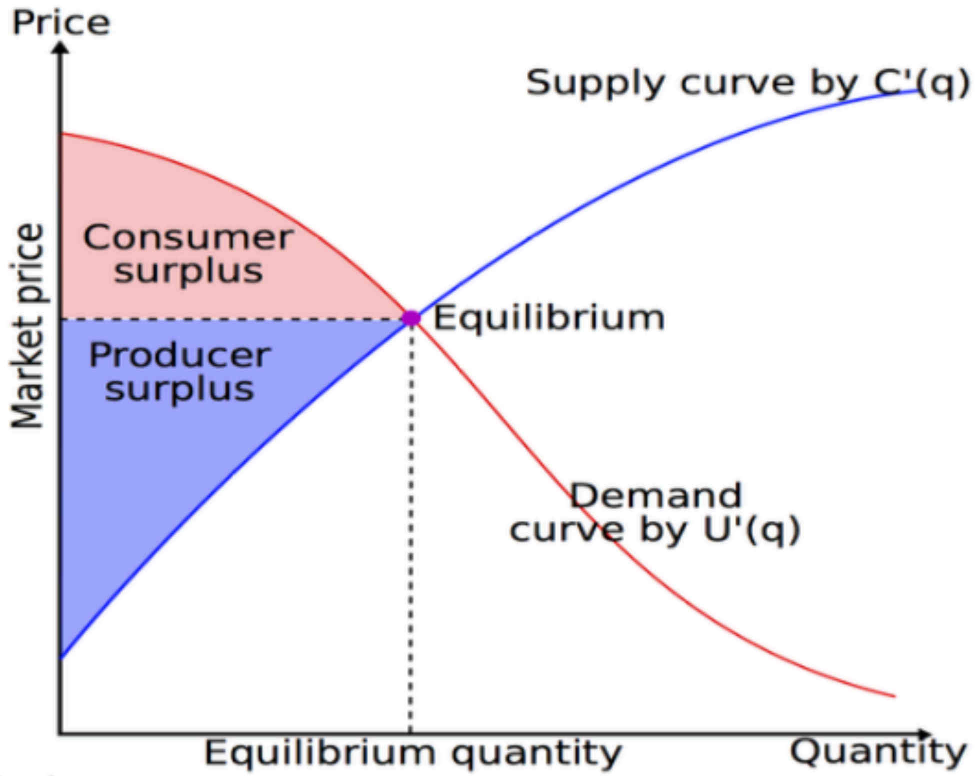
- Surplus
  - Surplus is the net benefit (in dollar terms) associated with buying or selling some good
  - Consumer Surplus (CS)
    - The amount of utility one experiences beyond the price that she pays

$$CS = \int_0^{q_c} \left(U'(q) - P\right) \mathrm{d}q = U(q_c) - Pq_c$$

  - Producer Surplus (PS)
    - The profit: one earns beyond the cost

$$PS = \int_0^{q_c} \left(P - C'(q)\right) \mathrm{d}q = Pq_c - C(q_c)$$

  - Total Surplus (TS) $TS = CS + PS = U(q_c) - C(q_c)$



Direct Total Surplus Maximization

- Direct Total Surplus Maximization (TSM)

$$\underset{Q}{\text{maximize}} \sum_i \sum_j \left(U_{ij}(Q_{ij}) - C_j(Q_{ij}) \right)$$

$$s.t.\ \mathbf{1}^T Q \leq M,\ Q_{ij} \in \mathbb{S}$$

  – **1** is a column vector of 1's
    - Sum of quantity for each product (column sum in Q) does not exceed maximal amount can be provided (by M)
  – S: The set of possible legal values for Q under given application
    - e.g., S=N for e-commerce, S={0,1} for online freelancing

Direct TSM – Drawbacks

- Drawbacks of Direct TSM
  - The Hypothesis of Rational Man may not always hold
  - Difficult to model the noisy data if we restrict Q to exact values

- Relax the Model
  - Relax Q_{ij} in Q to random variables for quantity distributions
  - E.g., $Q_{ij} \sim N(\mu_{ij}, \sigma_{ij})$, consumer u_i chooses good g_j on quantity μ_{ij} for the highest probability, but may also with other quantities.

Total Surplus Maximization – the Framework

- Maximize the expected total surplus
  - Our final framework for service allocation maximizes the following expected total surplus:

$$\underset{\Theta(Q)}{\text{maximize}} \sum_i \sum_j \boxed{\int (U_{ij}(Q_{ij}) - C_j(Q_{ij}))p(Q_{ij})\mathrm{d}Q_{ij}}$$

Expected total surplus for Each user-product pair

$$s.t.\ \mathbf{1}^T \int Qp(Q)\mathrm{d}Q \leq M,\ Q_{ij} \in \mathbb{S}$$

  - $p(Q_{ij})$ is the probabilistic density function of each quantity Q_{ij}
- Model Output
  - The model outputs the optimal density functions p(Q)
  - We take the expectation $\bar{Q} = \int Qp(Q)\mathrm{d}Q$ as the final allocation matrix to make recommendation decisions.

Model Specification in Different Applications

- Model Specification
  - Different choices of the parameters for different application scenarios
  - And also different methods for parameter estimation
- Model Specification in this work
  - E-commerce
  - P2P Lending
  - Online Freelancing

Application	$CS_{ij}(Q_{ij})$	$PS_{ij}(Q_{ij})$	$\mathbb{S}$	M	$p(Q_{ij})$	$\bar{Q}_{ij}$
E-commerce	$\hat{a}_{ij}\ln(1+Q_{ij})-P_jQ_{ij}$	$(P_j-c_j)Q_{ij}$	$\mathbb{N}$	$M_j=\infty$	$p(Q_{ij}=q)=\lambda_{ij}^q e^{-\lambda_{ij}}/q!$	λ_{ij}
P2P Loan	$(r_j-\hat{r})Q_{ij}$	$(r_j^{max}-r_j)Q_{ij}$	$\mathbb{R}_+$	$0<M_j<\infty$	$Q_{ij}\sim\mathcal{N}(\mu_{ij},\sigma_{ij})$	μ_{ij}
Freelancing	$h(\hat{r}_{ij})s_jQ_{ij}$	$h(\hat{r}_{kj})s_jQ_{ij}$	{0,1}	$M_j=1$	$p(Q_{ij}=1)=\alpha_{ij}, P(Q_{ij}=0)=1-\alpha_{ij}$	$I_{\alpha_{ij}=\max\{\alpha_{i'j}\}_{i'=1}^m}$

Model Specification – E-commerce

- Estimation of personalized utility $U_{ij}(q)$
  - U_{ij} (q) is subject to the *Law of Zero Surplus for the Last Unit*

$$\Delta CS_{ij}(q_{ij}) = CS_{ij}(q_{ij}) - CS_{ij}(q_{ij} - 1) \geq 0$$
$$\Delta CS_{ij}(q_{ij} + 1) = CS_{ij}(q_{ij} + 1) - CS_{ij}(q_{ij}) < 0$$

  - Where: $CS_{ij}(q_{ij}) = U_{ij}(q_{ij}) - P_j q_{ij}$ $\quad U_{ij}(q) = a_{ij} \ln(1 + q)$

- Then we need to estimate a_{ij}
  - Let $a_{ij} = \alpha + \beta_i + \gamma_j + \vec{x}_i^T \vec{y}_j$

Model Specification – E-commerce

- Estimation of Personalized Utility by Maximum Likelihood

$$\underset{\Theta}{\text{maximize}} \ \log p(D)$$
$$= \sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij} \log \left(\boxed{Pr(\Delta CS_{ij}(q_{ij}) \geq 0)} \boxed{Pr(\Delta CS_{ij}(q_{ij}+1) < 0)} \right)$$
$$-\lambda(\alpha^2 + \sum_{i=1}^{m}\beta_i^2 + \sum_{j=1}^{n}\gamma_j^2 + \sum_{i=1}^{m}\|\vec{x}_i\|_2^2 + \sum_{j=1}^{n}\|\vec{y}_j\|_2^2)$$
$$s.t.\ \vec{x}_i, \vec{y}_j \geq 0,\ \forall\, 1 \leq i \leq m,\ 1 \leq j \leq n$$

Sigmoid Probability $Pr(\Delta CS_{ij}(q_{ij}) \geq 0) = \dfrac{1}{1+\exp(-\Delta CS_{ij}(q_{ij}))}$ $Pr(\Delta CS_{ij}(q_{ij}+1) < 0) = 1 - Pr(\Delta CS_{ij}(q_{ij}+1) \geq 0)$

- Model learning with Gradient Descent
  - We have $U_{ij}(q) = \hat{a}_{ij} \ln(1+q) = (\alpha + \beta_i + \gamma_j + \vec{x}_i^T \vec{y}_j) \ln(1+q)$

Model Specification – E-commerce

- Cost function and quantity distribution
  - Constant per-product cost c_j, so the cost function is $C(q) = c_j q$
  - Let Q_{ij} in allocation matrix Q follow a Poisson distribution
    - Because Qij $\in$ N $p(Q_{ij} = q) = \lambda_{ij}^q e^{-\lambda_{ij}} / q!$
- Specification of TSM for E-commerce:

$$\underset{\Lambda}{\text{maximize}} \sum_i \sum_j \sum_{q=0}^{\infty} \frac{\lambda_{ij}^q e^{-\lambda_{ij}}}{q!} (\hat{a}_{ij} \ln(1+q) - c_j q) - \eta \sum_i \sum_j I_{ij} (\lambda_{ij} - q_{ij})^2$$

$$\underset{\Theta(Q)}{\text{maximize}} \sum_i \sum_j \int (U_{ij}(Q_{ij}) - C_j(Q_{ij})) p(Q_{ij}) \mathrm{d}Q_{ij}$$

  - Constraints are left out because $M_j = \infty$

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Expected total surplus under Poisson distribution

- Quantity regularizer to guide the model learning
- λ_{ij} is the quantity expectation under Poisson distribution
- Guide the model learning: predicted quantities do not bias too much from observed values in training set.

  - Constraints are left out because $M_j = \infty$

Model Specification – P2P Lending

- Consumer (Lender) and Producer (Borrower) Surplus
  - r_j: the actual interest rate of the j^{th} loan request
  - $\hat{r}$: the risk free interest rate (by saving the money in bank)
  - r_j^{max}: the maximum acceptable interest rate of the j^{th} loan request

$$CS_{ij}(Q_{ij}) = (r_j - \hat{r})Q_{ij}$$ For Lender i on loan j

Interest obtained from the loan – risk free interest (opportunity cost)

$$PS_{ij}(Q_{ij}) = (r_j^{max} - r_j)Q_{ij}$$ For borrower on loan j

The highest possible interest borrower would like to pay – actual interest he has to pay

$$TS_{ij}(Q_{ij}) = CS_{ij}(Q_{ij}) + PS_{ij}(Q_{ij}) = (r_j^{max} - \hat{r})Q_{ij}$$

Model Specification – P2P Lending

- Probabilistic Prior of Q_{ij}
  - Q_{ij} (the quantity of money) is a continuous variable: normal distribution

$$Q_{ij} \sim \mathcal{N}(\mu_{ij}, \sigma_{ij})$$

- OSA formalization for P2P

$$\underset{U,\Sigma}{\text{maximize}} \sum_i \sum_j \int \frac{(r_j^{max} - \hat{r})Q_{ij}}{\sqrt{2\pi}\sigma_{ij}} \exp\left(-\frac{(Q_{ij} - \mu_{ij})^2}{2\sigma_{ij}^2}\right) \mathrm{d}Q_{ij}$$

$$s.t.\ \mathbf{1}^T \int \frac{Q}{\sqrt{2\pi}\Sigma} \exp\left(-\frac{(Q - U)^2}{2\Sigma^2}\right) \mathrm{d}Q \leq M, Q_{ij} \in \mathbb{R}_+$$

Model Specification – P2P Lending

- Model Simplification

$$\underset{U,\Sigma}{\text{maximize}} \sum_i \sum_j \mu_{ij}(r_j^{max} - \hat{r})$$

$$s.t.\ \mathbf{1}^T U \leq M,\ \ \mu_{ij} \in \mathbb{R}_+$$

$$\bar{Q}_{ij} = \mu_{ij}$$

- Intuition
  - Allocate the investments in a greedy manner according to the per capita surplus $(r_j^{max} - \hat{r})$ of each loan request
  - An intuitional rule for investment in practice

Model Specification – Online Freelancing

- Utility and Cost
  - First predict employee-job $\hat{r}_{ij}$ and employer-job $\hat{r}_{kj}$ ratings through CF
  - Assumption: percentage surplus against price is proportional to sigmoid-normalized ratings
  - Qij $\in$ {0,1} because a job can be provided only once
    - can be viewed as an indicator of whether or not a job is assigned

$$\frac{U_{ij}(Q_{ij}) - s_j}{s_j} = h(\hat{r}_{ij})Q_{ij} = \left(\frac{2}{1+e^{-\hat{r}_{ij}}} - 1\right)Q_{ij} \quad \frac{s_j - C_j(Q_{ij})}{s_j} = h(\hat{r}_{kj})Q_{ij} = \left(\frac{2}{1+e^{-\hat{r}_{kj}}} - 1\right)Q_{ij}$$

- Representation of Surpluses

$$CS_{ij}(Q_{ij}) = U_{ij}(Q_{ij}) - s_j = h(\hat{r}_{ij})s_jQ_{ij}$$
$$PS_{ij}(Q_{ij}) = s_j - C_j(Q_{ij}) = h(\hat{r}_{kj})s_jQ_{ij}$$
$$TS_{ij}(Q_{ij}) = (h(\hat{r}_{ij}) + h(\hat{r}_{kj}))\, s_jQ_{ij}$$

Model Specification – Online Freelancing

- Probabilistic Prior of Q_{ij}
  - Q_{ij} is binary valued: Bernoulli distribution $A = [\alpha_{ij}]_{m \times n}$

$$p(Q_{ij} = 1) = \alpha_{ij}, P(Q_{ij} = 0) = 1 - \alpha_{ij}$$

- Quantity constraint:
  - M_j=1 because each job can by provided and only once
- Model Specification:

$$\underset{A}{\text{maximize}} \sum_i \sum_j \left(h(\hat{r}_{ij}) + h(\hat{r}_{kj})\right) s_j \alpha_{ij}$$

$$s.t.\ \mathbf{1}^T A \leq \mathbf{1},\ 0 \leq \alpha_{ij} \leq 1$$

Job assignment:

$$\bar{Q}_{ij} = \begin{cases} 1, & \text{if } \alpha_{ij} = \max\{\alpha_{i'j}\}_{i'=1}^{m} \\ 0, & \text{otherwise} \end{cases}$$

Empirical Analysis – E-commerce

- Dataset
  - Shop.com

#Consumers	#Products	#Transactions	Density	Train/Test
34,099	42,691	400,215	0.03%	75%/25%

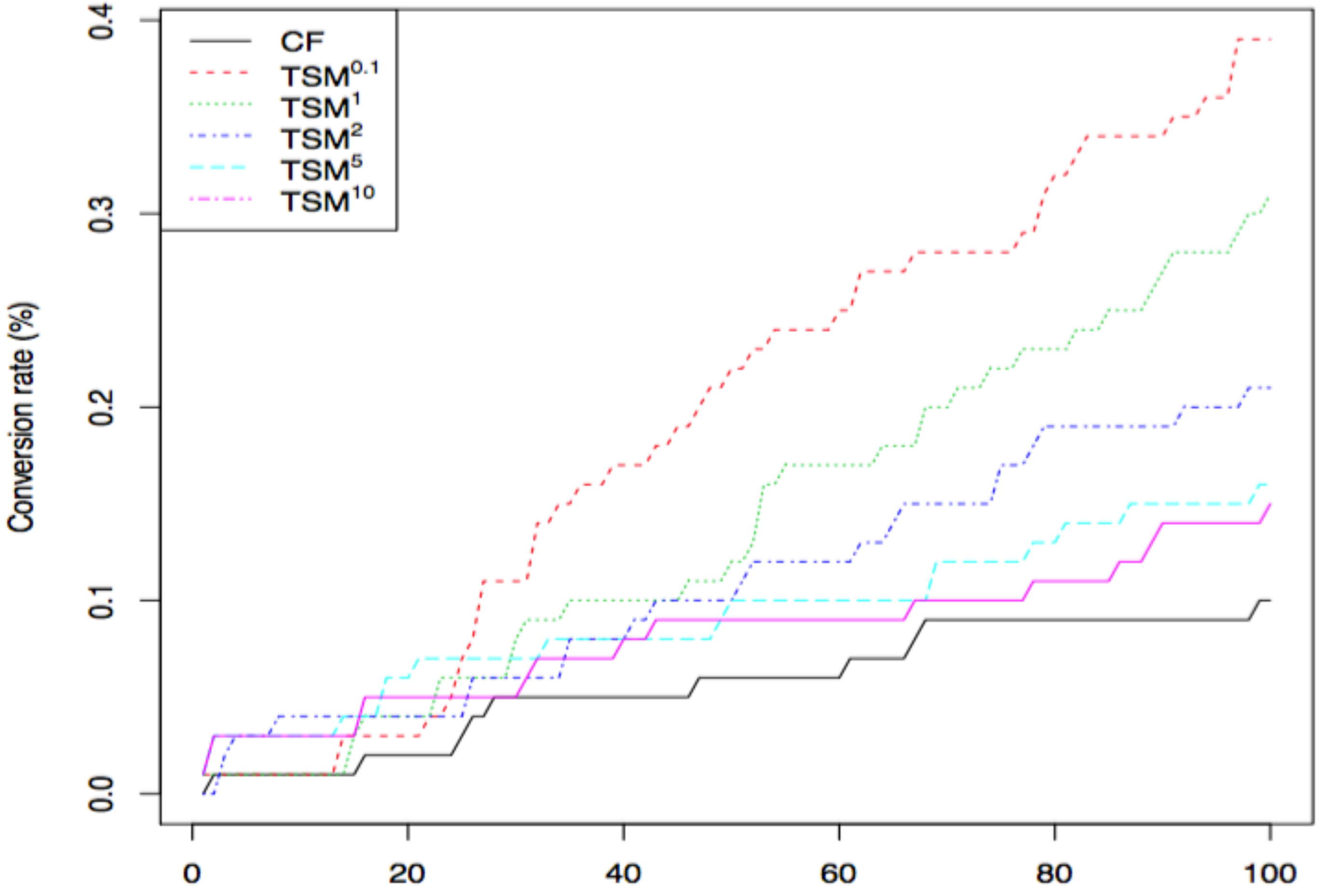
  - Each transection
    - Consumer and Product ID
    - Price of the product, and Purchasing quantity
  - Training and Testing set
    - For each consumer, randomly select 25% transactions as testing set

Empirical Analysis – E-commerce

- Experimental Setup
  - TSM gives estimated values of Q_{ij}
  - Product recommendation list of length N is provided to consumer u_i by ranking the products in descending order of Q_{ij}
  - Baseline method
    - Collaborative Filtering: $Q_{ij} = \alpha + \beta_i + \gamma_j + \vec{x}_i^T \vec{y}_j$
- Evaluation metrics
  - Conversion Rate @ N (CR@N)
    - For recommendation performance
  - Total Surplus @ N (TS@N) $TS@N = \frac{1}{M}\sum_{i=1}^{M}\sum_{j\in\Pi_{i,N}}\left(\hat{a}_{ij}\ln(1+\lambda_{ij}) - c_j\lambda_{ij}\right)$
    - For economic performance

Empirical Analysis – E-commerce

- Conversion Rate $\underset{\Lambda}{\text{maximize}} \sum_i \sum_j \sum_{q=0}^{\infty} \frac{\lambda_{ij}^q e^{-\lambda_{ij}}}{q!} (\hat{a}_{ij} \ln(1+q) - c_j q) - \boxed{\eta} \sum_i \sum_j I_{ij}(\lambda_{ij} - q_{ij})^2$
  - Under different η selections, constantly better than CF



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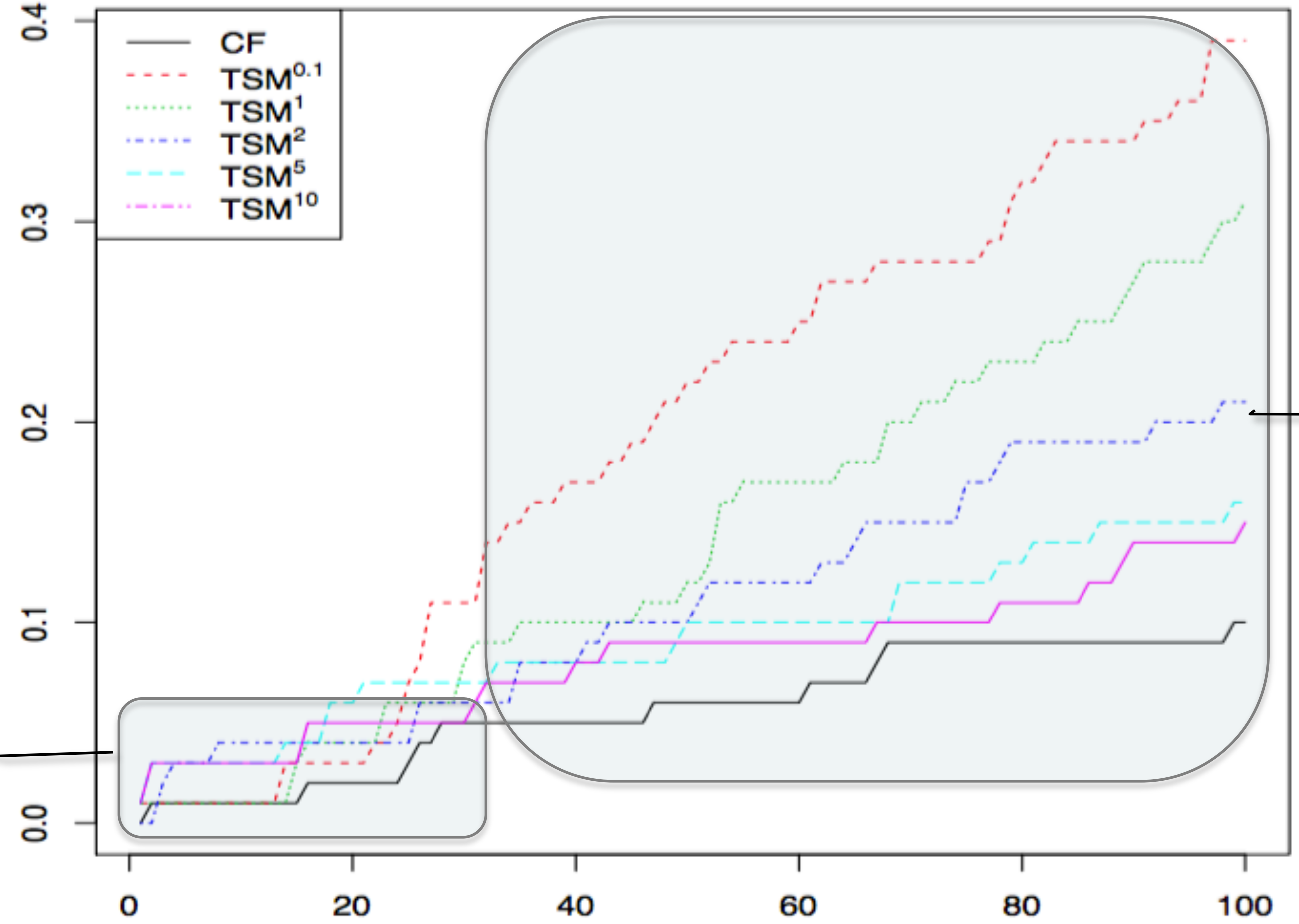
  - Under different η selections, constantly better than CF

Larger η's gain better conversion rate under short rec lists

We need strong quantity regularizers to guarantee quality of the top several recommendations

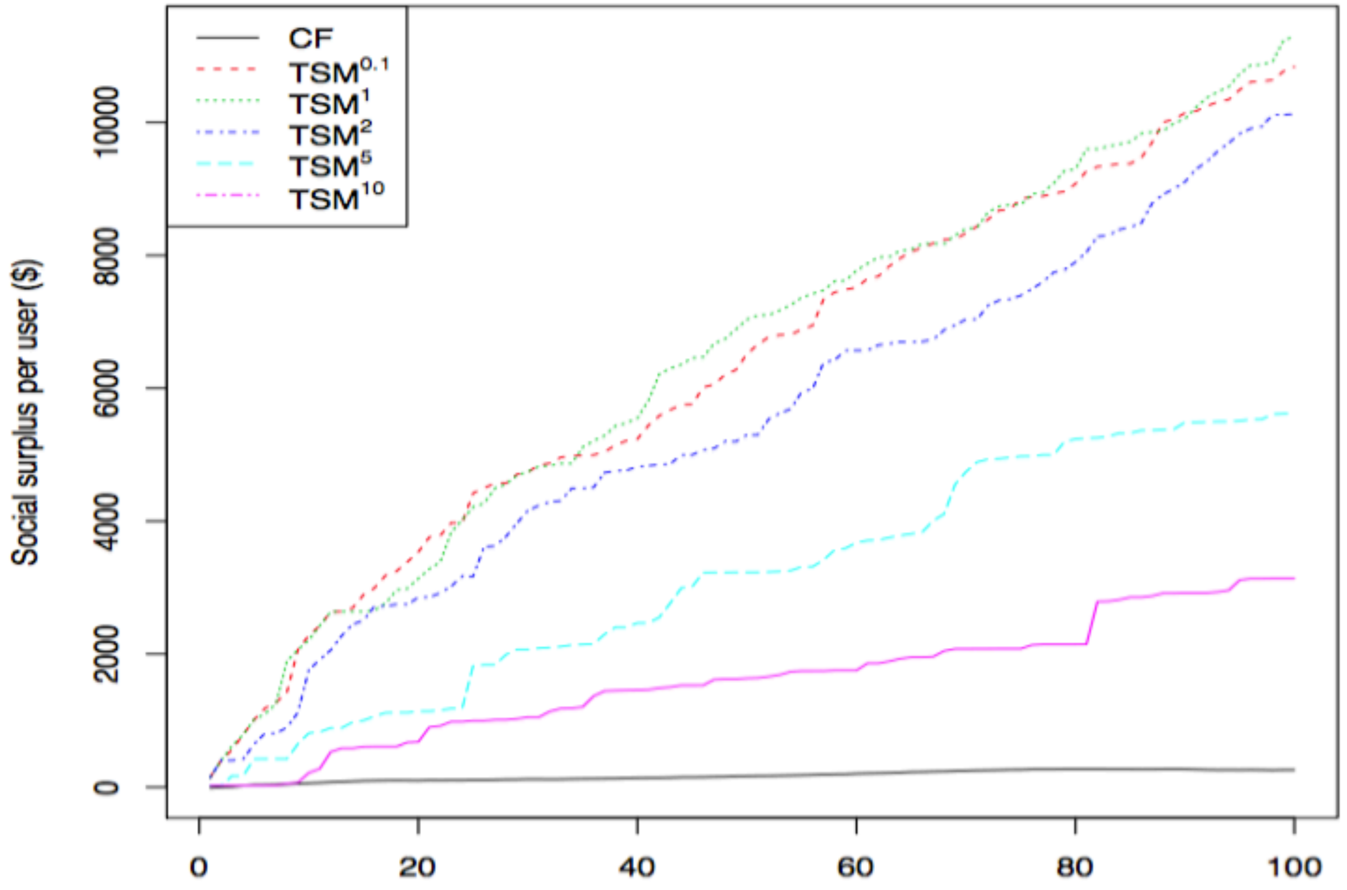


Smaller η's gain better conversion rate under long recommendation lists

Surplus component takes control of recommendation performance under long recommendations

Empirical Analysis – E-commerce

- Total Surplus $$\underset{\Lambda}{\text{maximize}} \sum_i \sum_j \sum_{q=0}^{\infty} \frac{\lambda_{ij}^q e^{-\lambda_{ij}}}{q!} (\hat{a}_{ij} \ln(1+q) - c_j q) - \boxed{\eta} \sum_i \sum_j I_{ij} (\lambda_{ij} - q_{ij})^2$$
  - Constantly better than CF under different η selections



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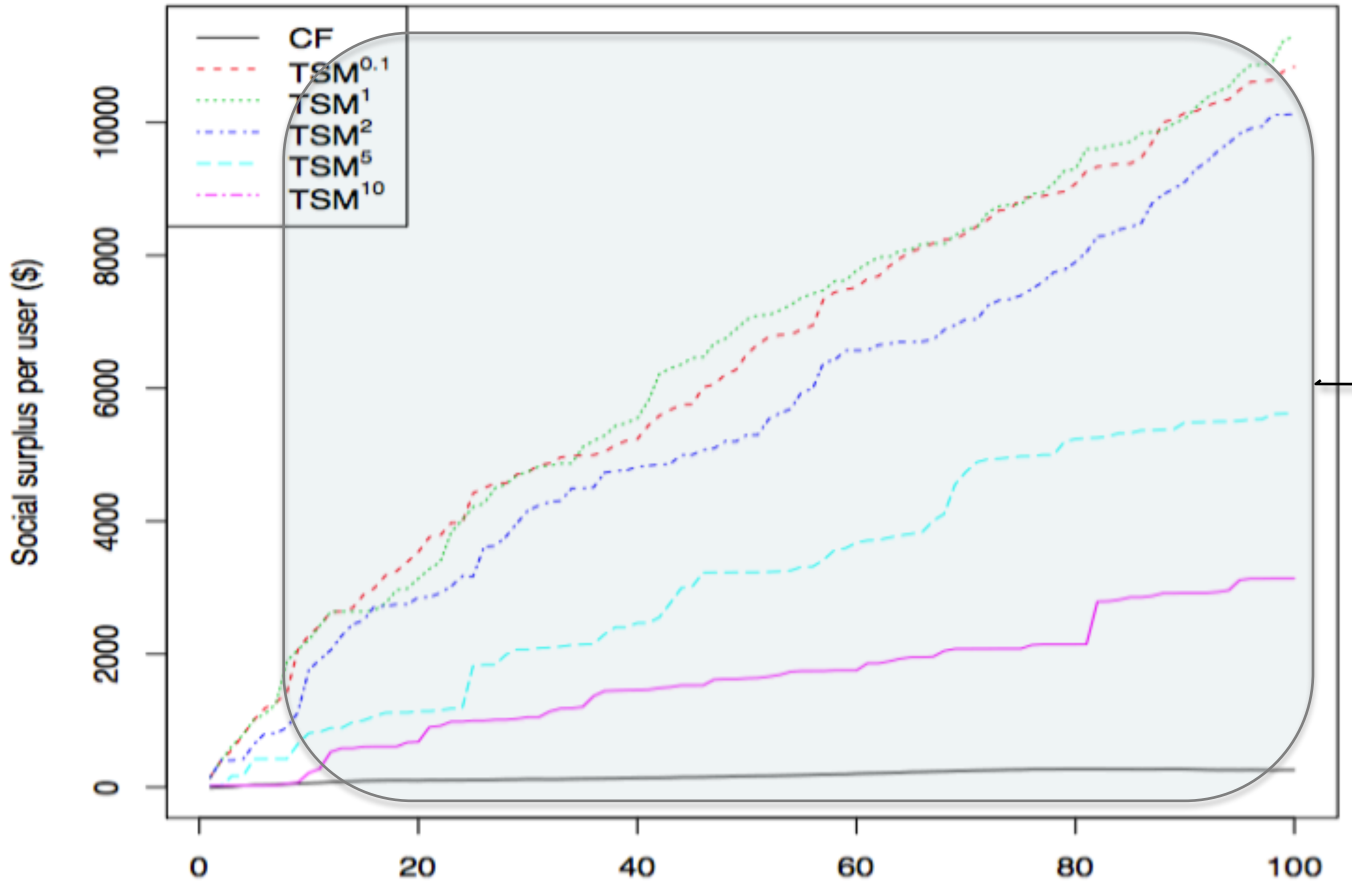

Smaller η's gain better total surplus

Not surprising because the total surplus component by nature tries to maximize total surplus

Empirical Analysis – E-commerce

- Details

Table 3: Evaluation on Conversion Rate (CR@N) and Total Surplus (TS@N) for Top-N recommendation, where TSM^* stands for our TSM approach with regularization coefficient $\eta = *$ in Eq.(16).

N	5					10					20				
Method	CF	$TSM^{0.1}$	TSM^1	TSM^5	TSM^{10}	CF	$TSM^{0.1}$	TSM^1	TSM^5	TSM^{10}	CF	$TSM^{0.1}$	TSM^1	TSM^5	TSM^{10}
CR (%)	0.10	0.10	0.10	**0.30**	**0.30**	0.10	0.10	0.10	**0.30**	**0.30**	0.20	0.30	0.40	**0.60**	0.50
TS ($)	33.05	**1009.45**	**1009.45**	422.01	24.48	57.89	**2278.36**	2208.50	807.56	213.45	98.09	**2892.03**	3135.35	1137.89	676.65

- Conclusion
  - Higher conversion rate (recommendation performance)
  - Higher total surplus (social good)
  - The TSM framework improves recommendation experience of users
    - Although we maximize the benefits of both sides jointly
  - Benefits social good at the same time

Empirical Analysis – P2P Lending

- Prosper Dataset
  - November 9th 2005 to May 8th 2009 (automatic bidding afterwards)
  - Statistics

#Listings	#Lenders	#Biddings	TotalAmount
46,680	49,631	1,814,503	$157,845,684
MinimumRate	MaximumRate	AverageRate	Amount/Listing
0.0001	0.4975	0.1662	$3,381.44

- Evaluation
  - Total Surplus (TS) $TS_{P2P} = \sum_i \sum_j Q_{ij}(r_j^{max} - \hat{r})$

Empirical Analysis – P2P Lending

- Evaluation Protocol
  - Compare the Total Surplus between our allocation and the actual allocation

	TS($)	TS/Listing($)	TS/capita($)
Actual	25,174,131	539.29	0.1595
TSM	33,838,364	724.90	0.2144

    - 34.42% higher total and per listing/capita surplus
    - From $0.16 per capita to $0.21 per capita
  - An exciting improvement in capital efficiency and social good

Empirical Analysis – Online Freelancing

- Dataset
  - ZBJ freelancing platform dataset (http://zbj.com)
    - A Chinese online marketing web applications

#Employers	#Freelancers	#Jobs	AverageSalary
40,228	46,856	296,453	¥21.68/hr

#Employer Ratings	#Freelancer Ratings	Average Employer Rating	Average Freelancer Rating
276,103	241,638	2.336	2.405

- Baseline
  - Construct the freelancer-job rating matrix and conduct CF
    - Hold out 25% ratings for testing $\hat{r}_{ij} = \alpha + \beta_i + \gamma_j + \vec{x}_i^T \vec{y}_j$
  - Assign a job to the freelancer with the highest predicted rating

Empirical Analysis – Online Freelancing

- Evaluation metrics
  - Conversion Rate (% of properly assigned jobs)
  - Total Surplus $TS_{Fr} = \sum_i \sum_j \left(h(\hat{r}_{ij}) + h(\hat{r}_{kj})\right) s_j Q_{ij}$
- Results under different # of factorization factors *K*
  - CR@K

K	5	10	20	30	40	50
CF(%)	0.165	0.216	0.244	0.258	0.262	0.266
TSM(%)	0.384	0.421	0.453	0.486	0.507	0.512

  - TS@K

K	5	10	20	30	ActualAllocation
CF(¥)	1.562m	1.758m	1.824m	1.860m	2,593,618
TSM(¥)	3.235m	3.862m	4.270m	4.336m	

  - Better CR and TS than CF, and better TS even than the actual allocation
    - ￥73.13/job for TSM when K=30, only ￥31.37/job for CF and ￥43.74/job for actual
    - Better market efficiency

Conclusions

- Conclusions
  - Web as online economic system with interaction of producers and consumers
  - Promote Web Intelligence for Social Good by direct social good metric maximization, for a better off of the whole online system
  - Propose a Total Surplus Maximization (TSM) framework
  - This framework can be specified to various real-world applications
  - Results show that by maximizing the total surplus, we can benefit user experience and social good at the same time

Future Work - More

- A new angle to view the Web
  - From a consumer-producer perspective of view
  - And maximizing the total surplus for a better off of the Web
- Other model specifications beyond EC, P2P, freelancing
  - Social networks, crowdsourcing, Uber, Airbnb, etc.
- Other possible directions beyond Economic Recommendation
  - Economic IR from a cooperative social good perspective
  - Dynamic pricing for social good maximization in E-commerce, driving services (Uber), Rental services (Airbnb), etc.

Thanks!

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