## Instant Foodie: Predicting Expert Ratings From Grassroots

Chenhao Tan, Ed H. Chi, David Huffaker, Gueorgi Kossinets, Alexander J. Smola Cornell University & Google





## A World of Ratings

SERVICE

29

SERVICE

28

SERVICE

26

SERVICE

26

SERVICE

22

COST

\$111

COST

\$107

COST

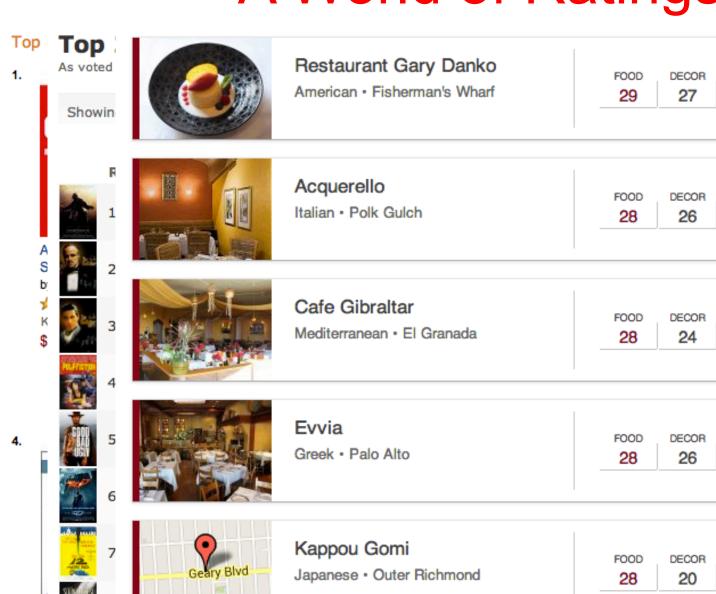
\$45

COST

\$56

COST

\$44



## Average Ratings Are Important

A one-star increase in Yelp ratings leads to 5-9% increase in revenue. [Luca 2011]



THE PROBLEM WITH AVERAGING STAR RATINGS But there are problems ...

# How do we collect a large number of reliable ratings to get good average ratings?

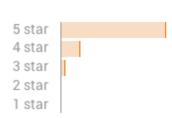
#### Ask "Grassroots"

A Large number of ratings for different items

- Self-selection bias
  - What to buy, limited experiences
  - What to rate (brag-and-moan [Hu et al. 2006])
- Variance in motivation to submit ratings, the understanding of ratings, tastes, etc
- Deception [Ott et al. 2012]







## Ask "Experts"

- A smaller coverage
- Mitigating self-selection bias
  - An extensive set of items experienced
  - A predetermined set of items to rate
- Repeated surveys at regular intervals reduces the variance (e.g. Michelin Guide, Zagat Survey)



FOOD	DECOR	SERVICE	COST
29	27	29	\$111

## Zagat

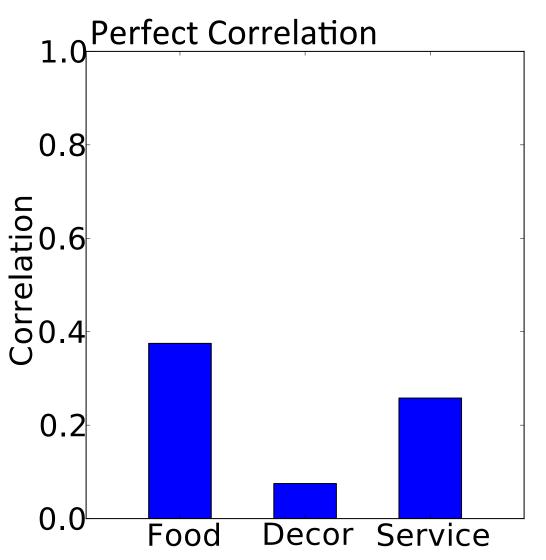




- Zagat restaurant guides were named as "a necessity second only to a valid credit card" by the New York Times
- Zagat ratings are in three dimensions for restaurants, food, décor, service
- Zagat repeatedly sends surveys on a predetermined set of restaurants to frequent users

How do "grassroots" Google Place ratings correlate with "expert" Zagat ratings?

## Correlation Between Google Place Ratings and Zagat Ratings



Little correlation without learning

Correlation is particularly bad in décor

## Bridge Two Popular Approaches

#### Ask "Grassroots"

A Large number of ratings

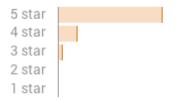
- Self-selection bias
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#### Ask "Experts"

A smaller coverage

Self-selection bias is mitigated Repeated surveys at regular intervals reduces the variance (e.g. Michelin Guide, Zagat Survey)









#### **Preview**

- We can generate an instant foodie by predicting "expert" Zagat ratings from "grassroots" Google Place ratings
- We find that users with more experiences are harsher
- We can answer questions such as what is the Gary Danko of New York?

#### Related Work

- Collaborative filtering
  - Matrix factorization [Koren and Bell 2011, Weimer et al. 2008, Yu et al 2009, ...]
    - We build on this framework
  - Transferring information between domains [Li et al. 2009, Pan et al. 2010, Zhang et al. 2010]
    - We are trying to transfer information between different approaches to collecting ratings
- Crowdsourced Labeling

[Raykar et al. 2010, Dekel and Shamir 2009, Whitehill et al. 2009, Rasch 60, Dawid and Skene 1979, Heckman 1979]

### Task

- Training data:
  - All the "grassroots" GooglePlace ratings

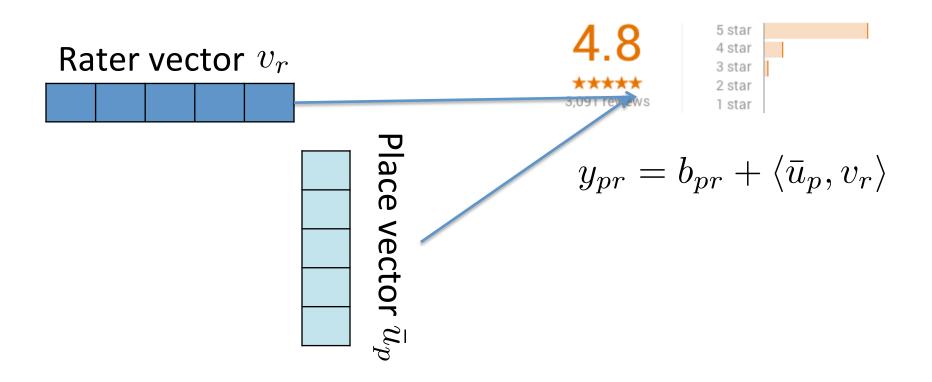


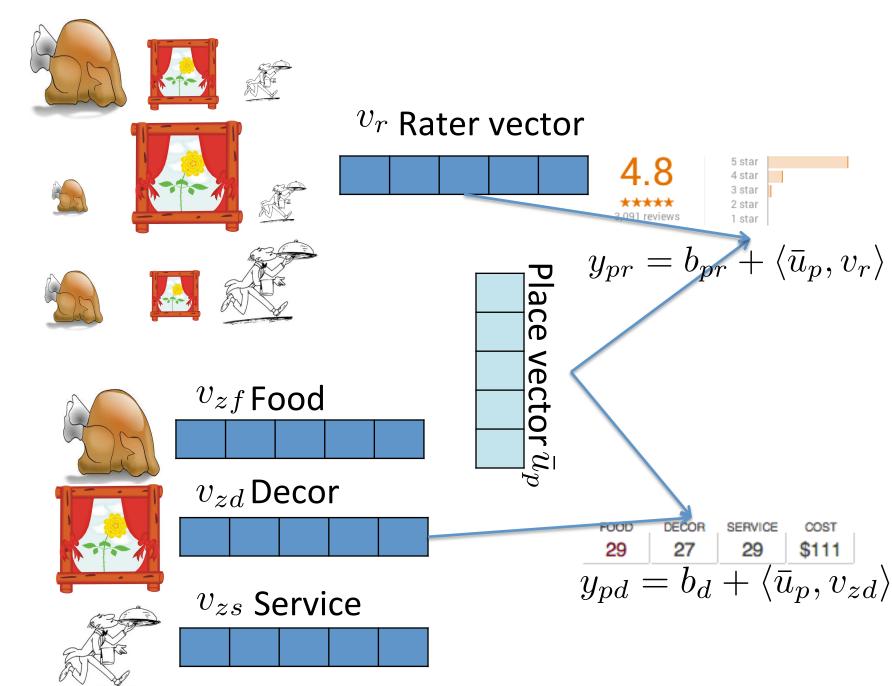
- Part of the "expert" Zagat ratings to provide some supervision
- Testing data:
  - Rest of the "expert" Zagat ratings

FOOD	DECOR	SERVICE	COST
28	28	29	\$101

## Approach Framework

Matrix Factorization





### Formulation

- Each place vector decomposes into different factors
  - Place itself, city, category, price level

$$\bar{u}_p = u_p + u_{\text{city}} + u_{\text{cat}} + u_{\$}$$

Objective Function

$$\sum_{(p,r)\in GP} \frac{1}{2} (y_{pr} - s_{pr})^2 + \sum_{p\in Z} \sum_{i\in\{f,d,s\}} \frac{1}{2} (y_{pi} - s_{pi})^2$$

+ constant + regularization

#### Data

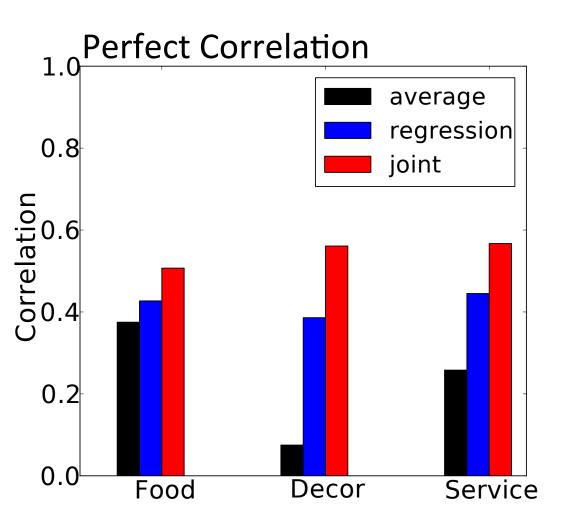
- 2M "grassroots" Google place ratings
  - One-dimensional
- 30K "expert" Zagat ratings
  - Three-dimensional (food, décor, service)

## **Experiment Setup**

- Baseline
  - Average transformation
  - Linear regression without joint optimization

- Evaluation Measure
  - Root mean squared error (RMSE)
  - Pearson Correlation

## **Correlation Comparison**

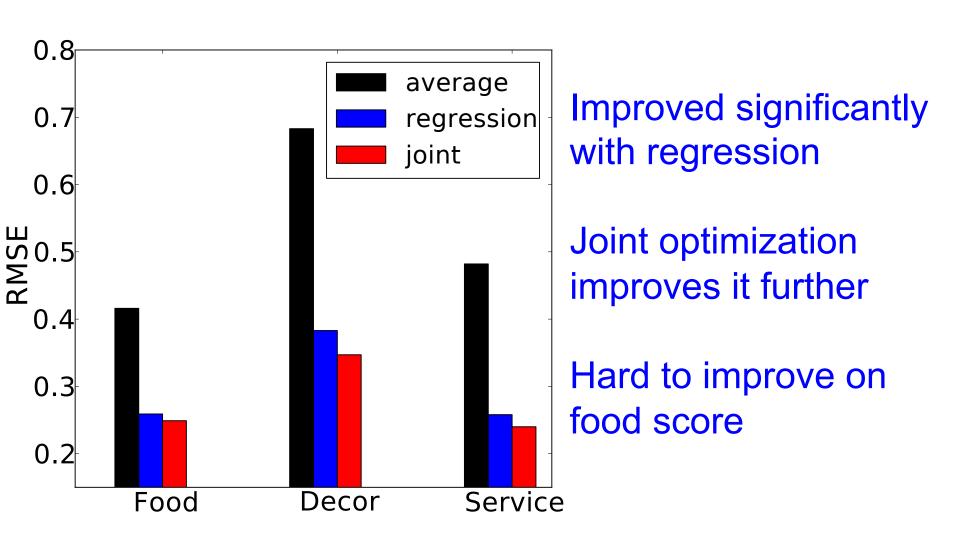


Improved significantly with regression

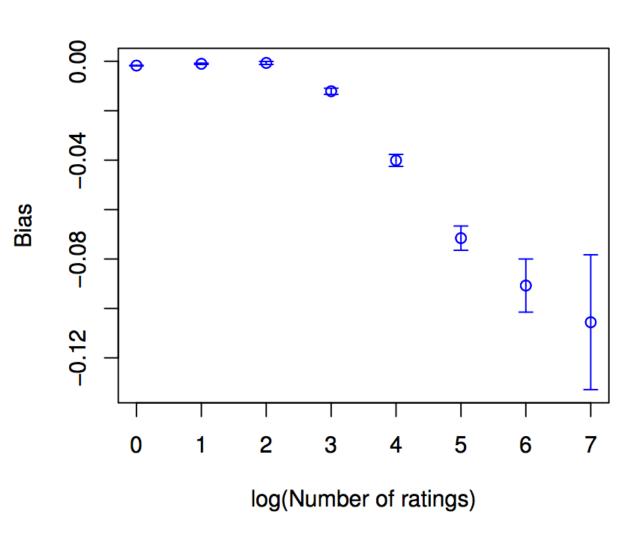
Joint optimization improves it further

The improvement in décor is especially significant

## RMSE Comparison



## User Bias vs. Experience



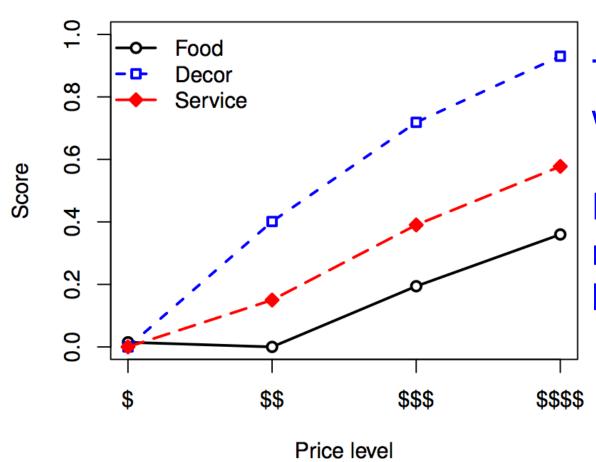
Users who give more ratings are more discerning

#### Place Vector

- Remember that each place vector decomposes into different factors
  - Place itself, city, category, price level  $\bar{u}_p = u_p + u_{\rm city} + u_{\rm cat} + u_{\$}$
- We can get food, décor, service score for different price levels by

$$\langle u_{\$}, v_{zf} \rangle, \langle u_{\$}, v_{zd} \rangle, \langle u_{\$}, v_{zs} \rangle$$

## Rating vs. Price



The ratings increase with price levels

For food, there is not much difference between \$ and \$\$

#### **Most Similar Place**

What is the Gary Danko of New York, Chicago?

FOOD DECOR SERVICE COST 29 27 29 \$111

**New York** 

Chicago

#### Jean Georges Restaurant

FOOD	DECOR	SERVICE	COST
28	27	28	\$153

#### Cafe Boulud

FOOD	DECOR	SERVICE	COST
27	24	26	\$82

#### **Annisa**

FOOD	DECOR	SERVICE	COST
27	24	26	\$87

#### Les Nomades

FOOD	DECOR	SERVICE	COST
28	26	28	\$126

#### Tru

FOOD	DECOR	SERVICE	COST
27	27	28	\$150

#### Spiaggia

FOOD	DECOR	SERVICE	COST
26	26	26	\$104

#### **Most Similar Place**

What is the Tartine Bakery & Café of New York, Chicago?

FOOD	DECOR	SERVICE	COST
27	15	16	\$16

#### **New York**

#### Chicago

#### Veniero's Pasticceria

FOOD	DECOR	SERVICE	COST
24	17	19	\$18

#### Amy's Bread Chelsea

FOOD	DECOR	SERVICE	COST
24	14	21	\$14

Mille-feuille Bakery Café

No Zagat

#### Lou Mitchell's

FOOD	DECOR	SERVICE	COST
24	14	20	\$17

#### **Starbucks**

No Zagat

Molly's Cupcakes

No Zagat

## Summary

- There is a gap between grassroots ratings and expert ratings
- It is possible to reconcile the two quite different approaches via joint optimization
- As users submit more ratings, they tend to become more discerning overall

Thank you & Questions?

Chenhao Tan
<a href="mailto:chenhao@cs.cornell.edu">chenhao@cs.cornell.edu</a>
www.cs.cornell.edu/~chenhao/