Food Recommenders

A Data Science Perspective

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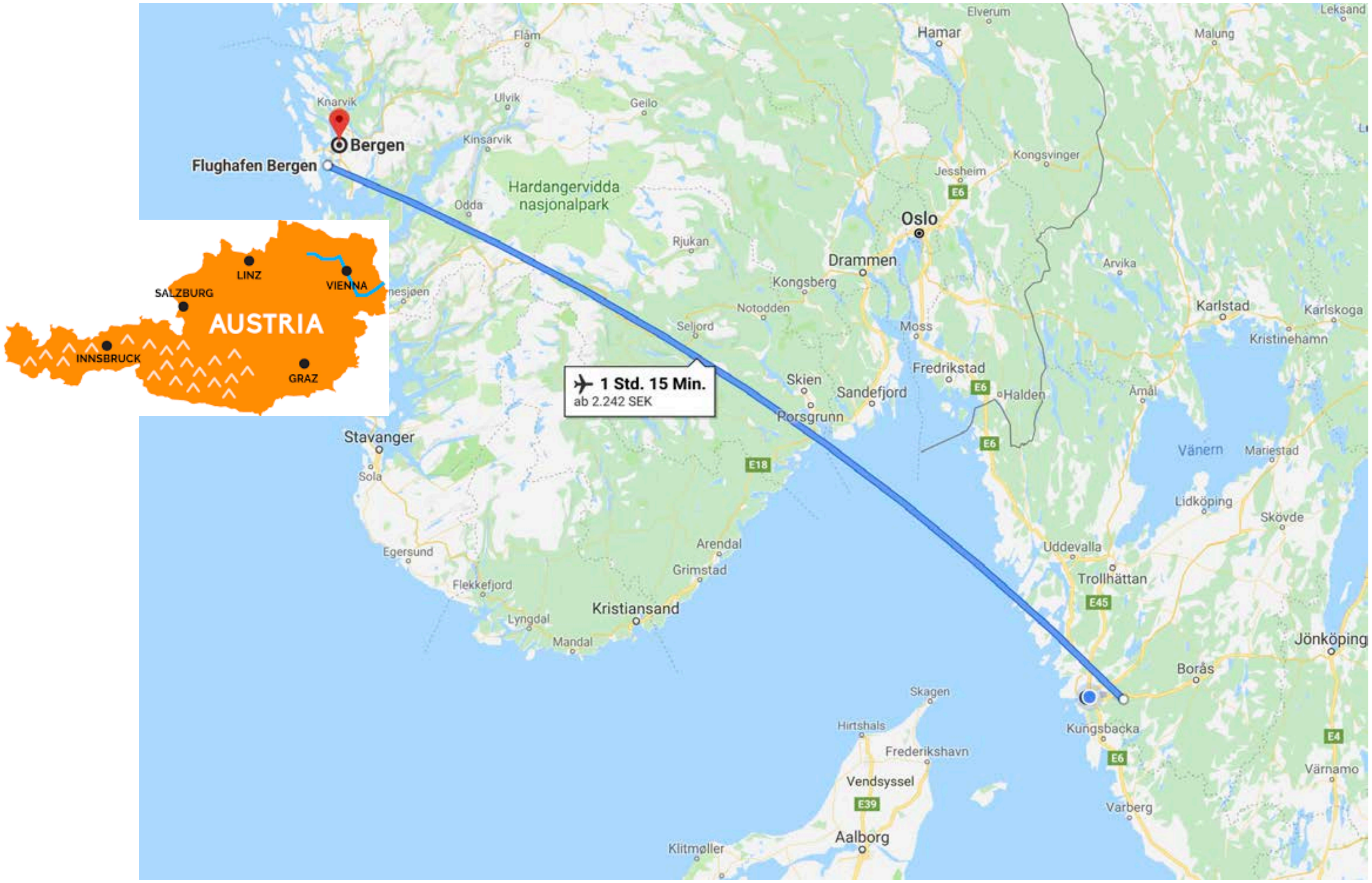
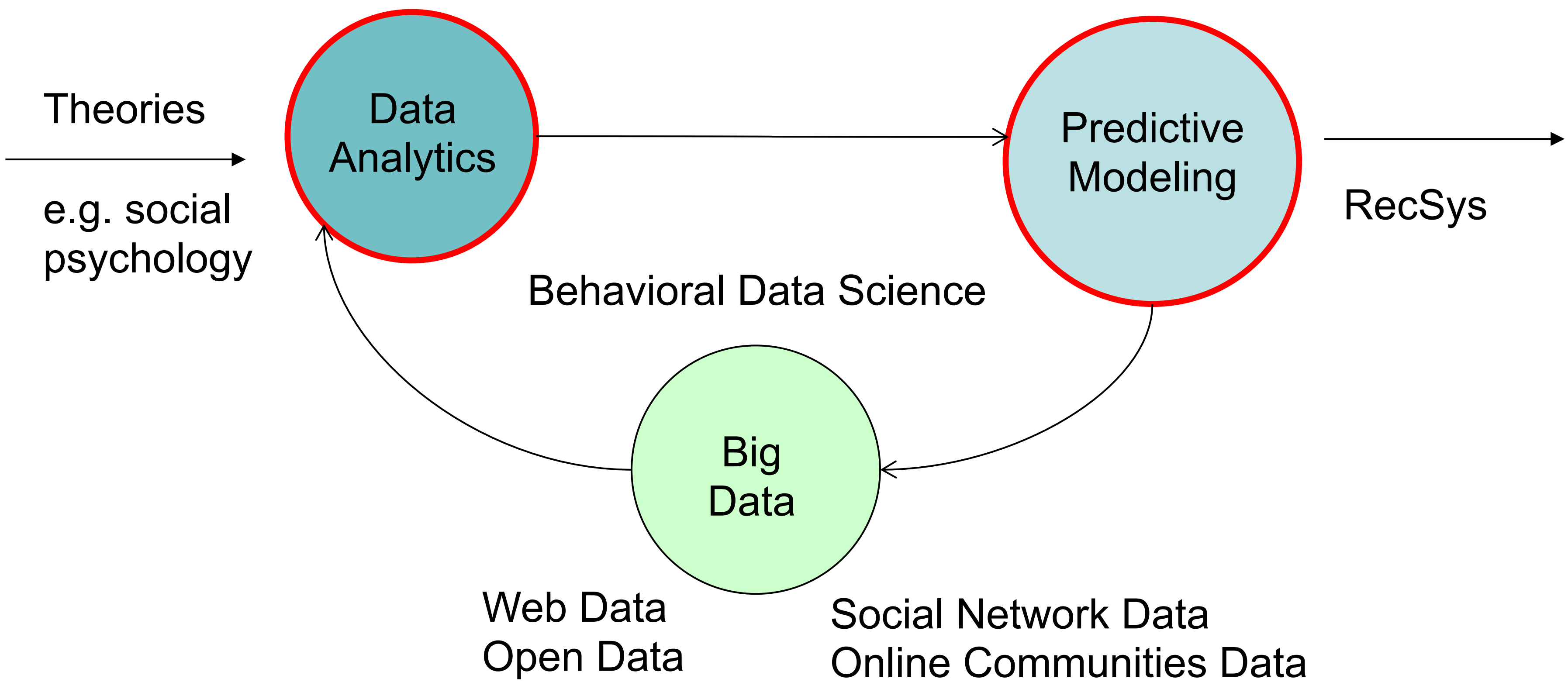
University of Bergen

Where do I come from?



Research Focus

Understand how people behave



Agenda

1. Motivation
2. DS: Healthiness of Online Food
3. RS: State-of-the-art & Health-aware Food RecSys
4. DS: Linking Online to Offline
5. DS: Predicting Item Popularity (Factor Analysis)
6. DS/RS: Factors & Food RecSys
7. RS: Altering Food Choice with RecSys
8. RS: Recommending Similar Foods
9. RS: Collaborative Filtering vs Content-Based
10. The Future & Conclusions

Part 1: Motivation

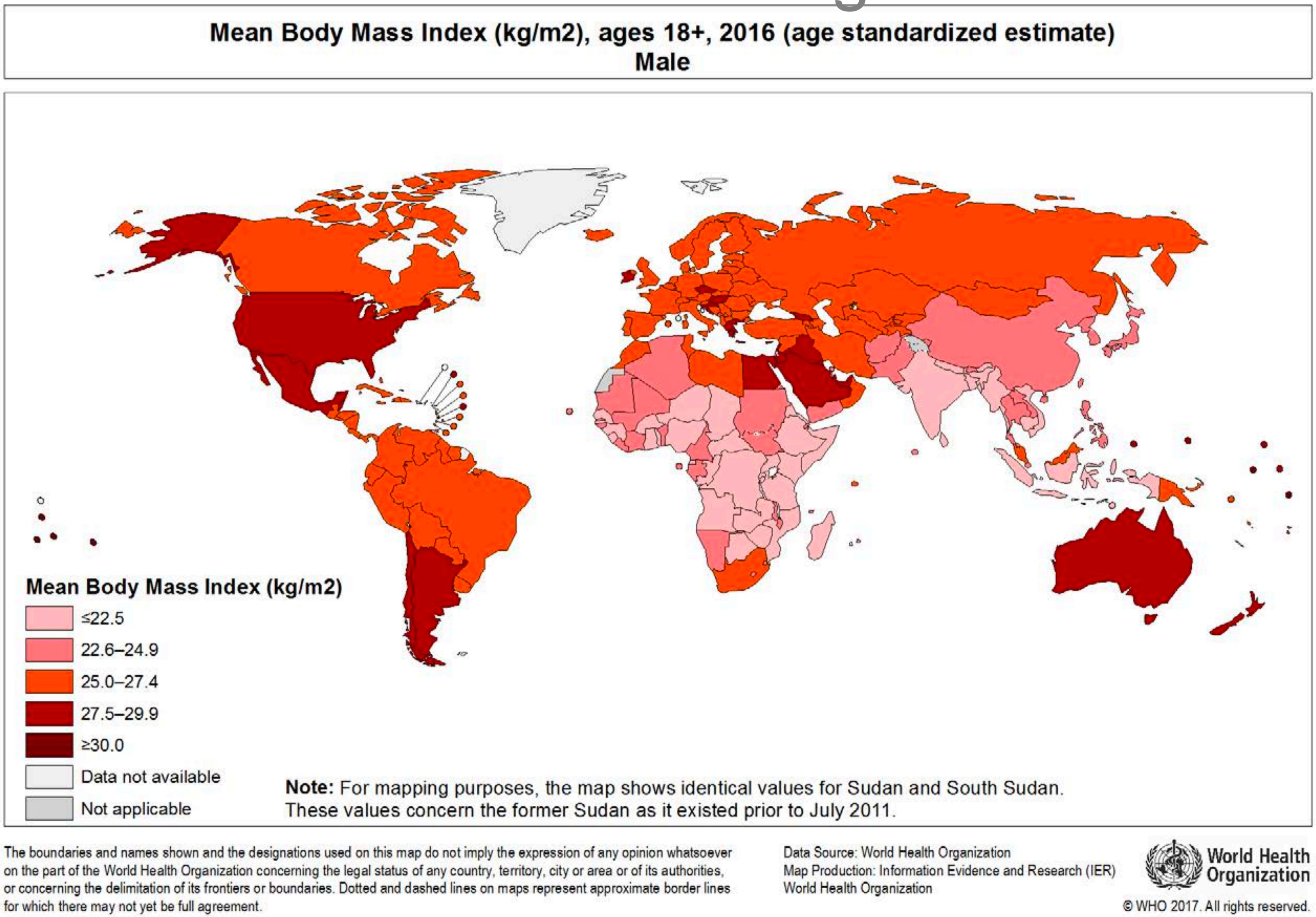
Why is research into Food Recsys Important?

Why is that important?

- Food is one the main concepts that **shapes how good we feel** and **how healthy we are**

- According to the WHO, if common lifestyle risk factors, among others diet-related ones, were eliminated, **around 80% of cases of heart disease, strokes and type 2 diabetes, and 40% of cancers, could be avoided** (European Comission Recommendation C(2010) 2587 final, 2010).

Health is decreasing World Wide

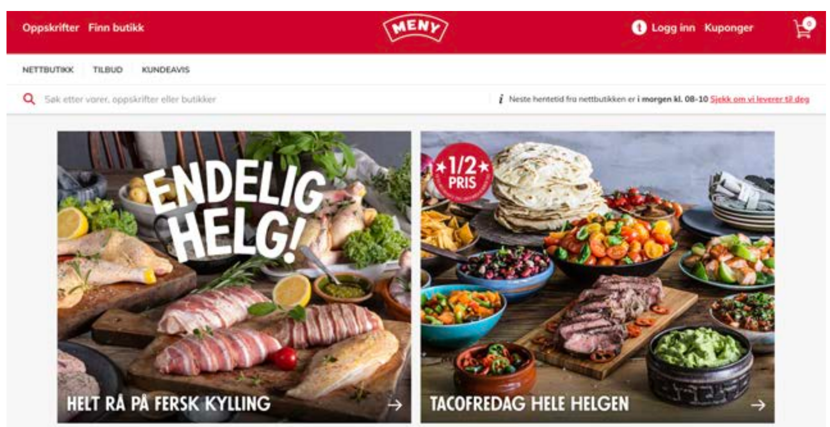


The approaches I am discussing today are all online food recommender approaches!

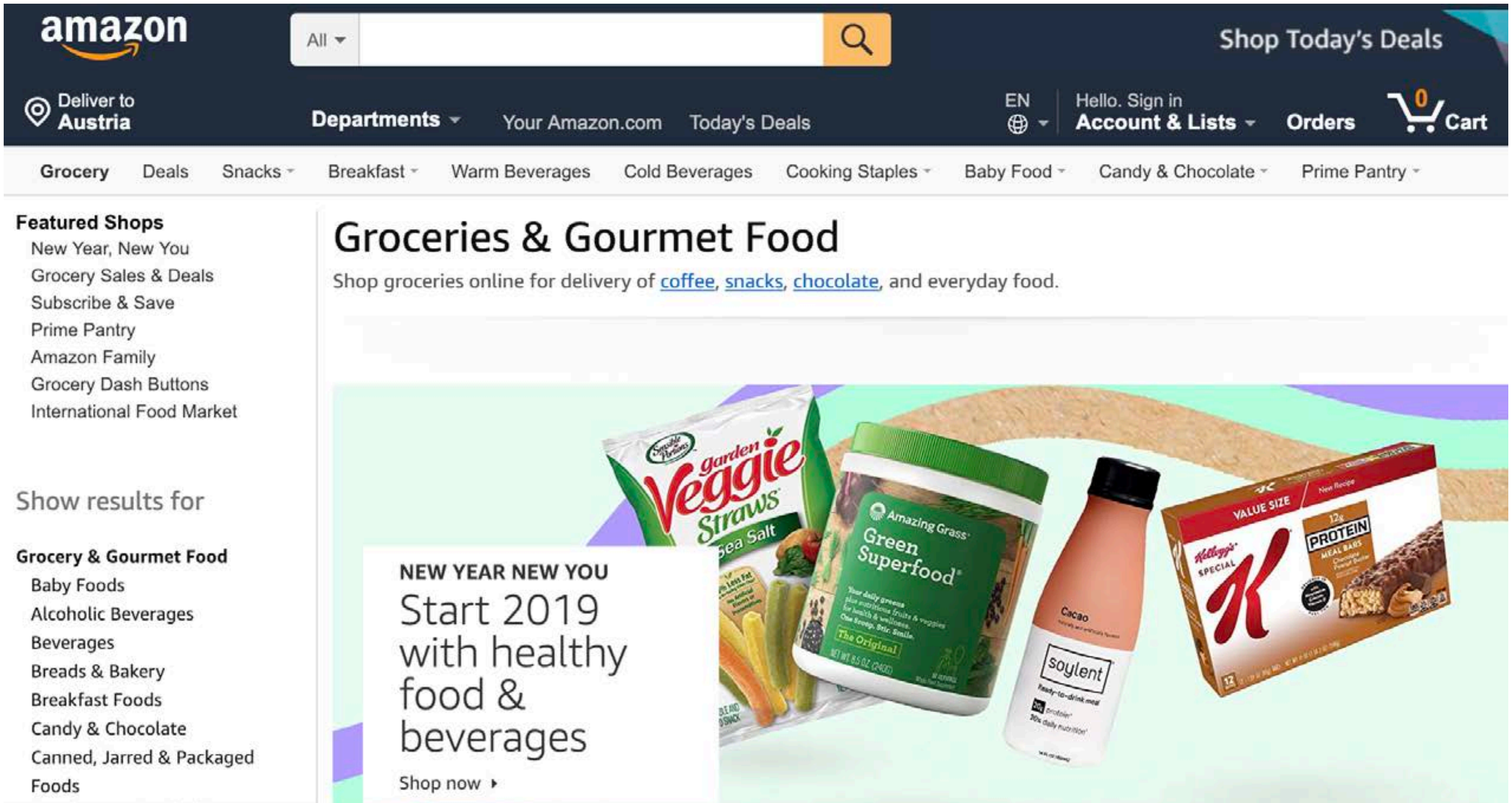
Why Online?

Most food interactions nowadays online

According to recent market research over 50%



Amazon

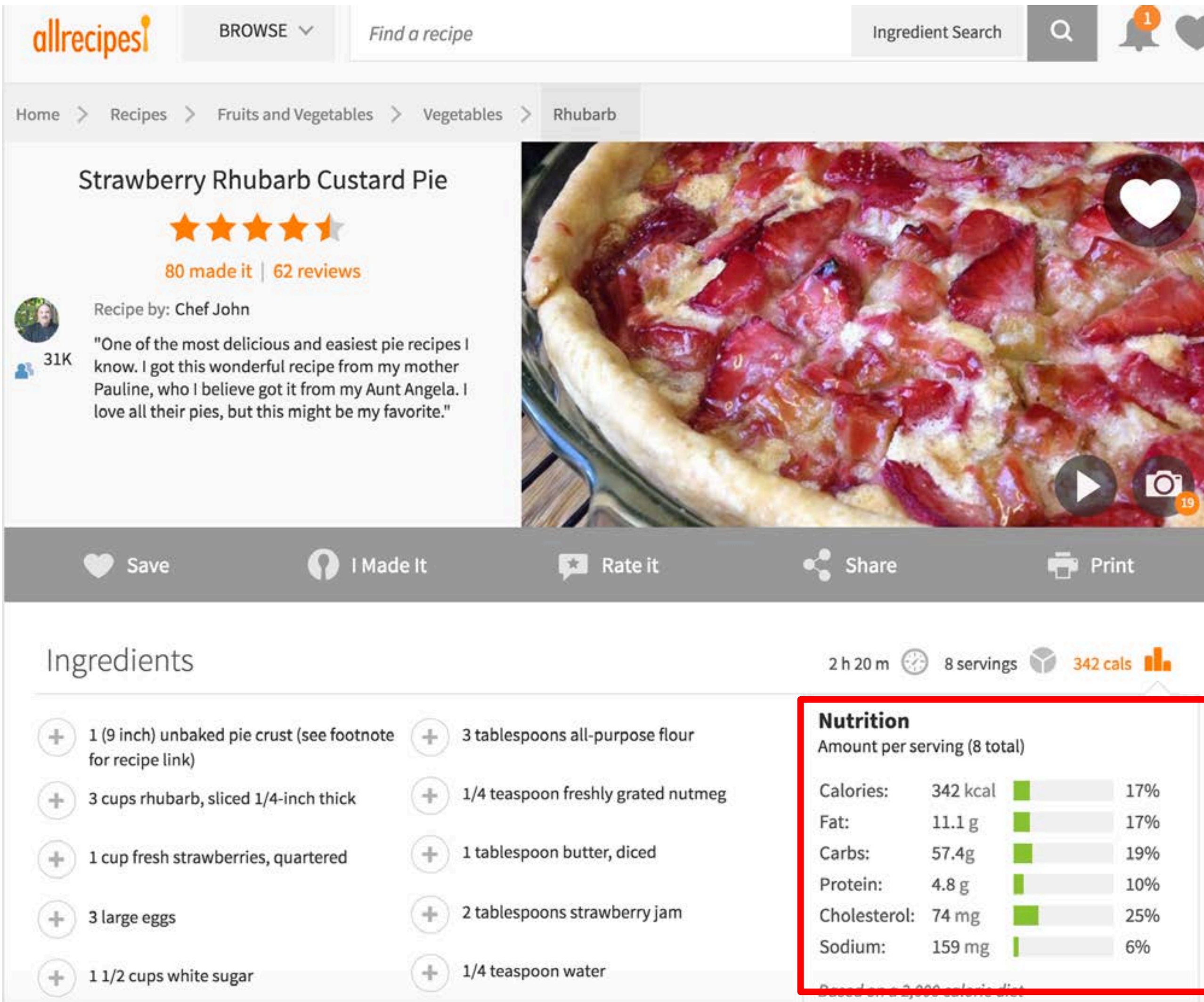


amazon
All
Shop Today's Deals
Deliver to Austria
Departments
Your Amazon.com
Today's Deals
EN
Hello. Sign in
Account & Lists
Orders
0 Cart
Grocery
Deals
Snacks
Breakfast
Warm Beverages
Cold Beverages
Cooking Staples
Baby Food
Candy & Chocolate
Prime Pantry
Featured Shops
New Year, New You
Grocery Sales & Deals
Subscribe & Save
Prime Pantry
Amazon Family
Grocery Dash Buttons
International Food Market
Show results for
Grocery & Gourmet Food
Baby Foods
Alcoholic Beverages
Beverages
Breads & Bakery
Breakfast Foods
Candy & Chocolate
Canned, Jarred & Packaged Foods
Groceries & Gourmet Food
Shop groceries online for delivery of coffee, snacks, chocolate, and everyday food.
NEW YEAR NEW YOU
Start 2019 with healthy food & beverages
Shop now

Part 2:
Healthiness of Online Food (Recipes)

RQ: How healthy are online food items (recipes) actually?

http://allrecipes.com



Basic statistics:

- 60,983 recipes
- 1,032,226 ratings
- 17,190,534 bookmarks

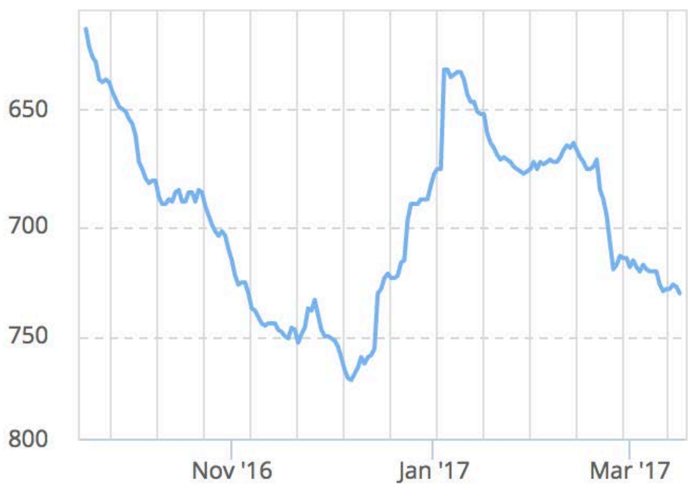
Nutrition Facts

Allrecipes.com popularity

How popular is allrecipes.com?

Alexa Traffic Ranks

How is this site ranked relative to other sites?



Global Rank

730 ▼ 2

Rank in United States

217

Country	Percent of Visitors	Rank in Country
United States	69.6%	217
Canada	8.0%	219
United Kingdom	2.5%	1,375
Germany	2.0%	2,017
India	1.3%	4,349

According to Alexa.com

How can we determine the healthiness of online recipes?

Trattner, C. Elsweiler, D. and Simon, H. **Estimating the Healthiness of Internet Recipes: A Cross-Sectional Study.** Frontiers in Public Health, 2017.

Trattner, C. and Elsweiler, D. **Investigating the Healthiness of Internet-Sourced Recipes: Implications for Meal Planning and Recommender Systems.** In Proceedings of the World Wide Web Conference (WWW), 2017.

Determining the healthiness of recipes

What the colours mean:

RED means **HIGH**
*indicating that the food is **high** in fat, sugars or salt*

It's fine to eat this food occasionally or as a treat, but think about how often you choose it and how much of it you eat.

AMBER means **MEDIUM**
*making it an **OK** choice*

Although going for green is even better!

GREEN means it's **LOW**

Which makes it a healthier choice.

FSA food health criteria

Determining the healthiness of recipes

WHO food health criteria

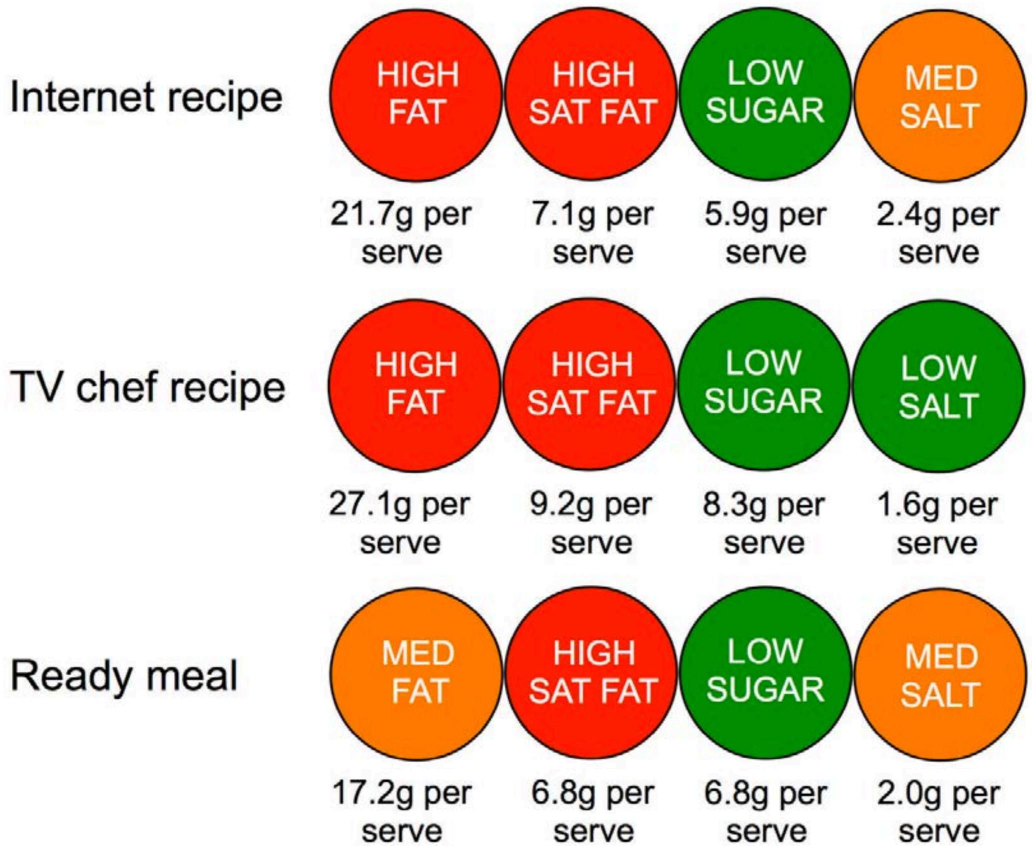
Ranges of population nutrient intake goals

Dietary factor	Goal (% of total energy, unless otherwise stated)
Total fat	15–30%
Saturated fatty acids	<10%
Polyunsaturated fatty acids (PUFAs)	6–10%
n-6 Polyunsaturated fatty acids (PUFAs)	5–8%
n-3 Polyunsaturated fatty acids (PUFAs)	1–2%
Trans fatty acids	<1%
Monounsaturated fatty acids (MUFAs)	By difference[a]
Total carbohydrate	55–75%[b]
Free sugars[c]	<10%
Protein	10–15%[d]
Cholesterol	<300 mg per day
Sodium chloride (sodium)[e]	<5 g per day (<2 g per day)
Fruits and vegetables	≥400 g per day
Total dietary fibre	From foods[f]
Non-starch polysaccharides (NSP)	From foods[f]

Who. Diet, nutrition and the prevention of chronic diseases. World Health Organ TechRep Ser, 916(i-viii), 2003.

Results

Online food is unhealthy ☹



Allrecipes

e.g. Tesco

Trattner, C. Elsweiler, D. and Simon, H. Estimating the Healthiness of Internet Recipes: A Cross-Sectional Study. Frontiers in Public Health, 2017.

Online food (recipes) is unhealthy ☹

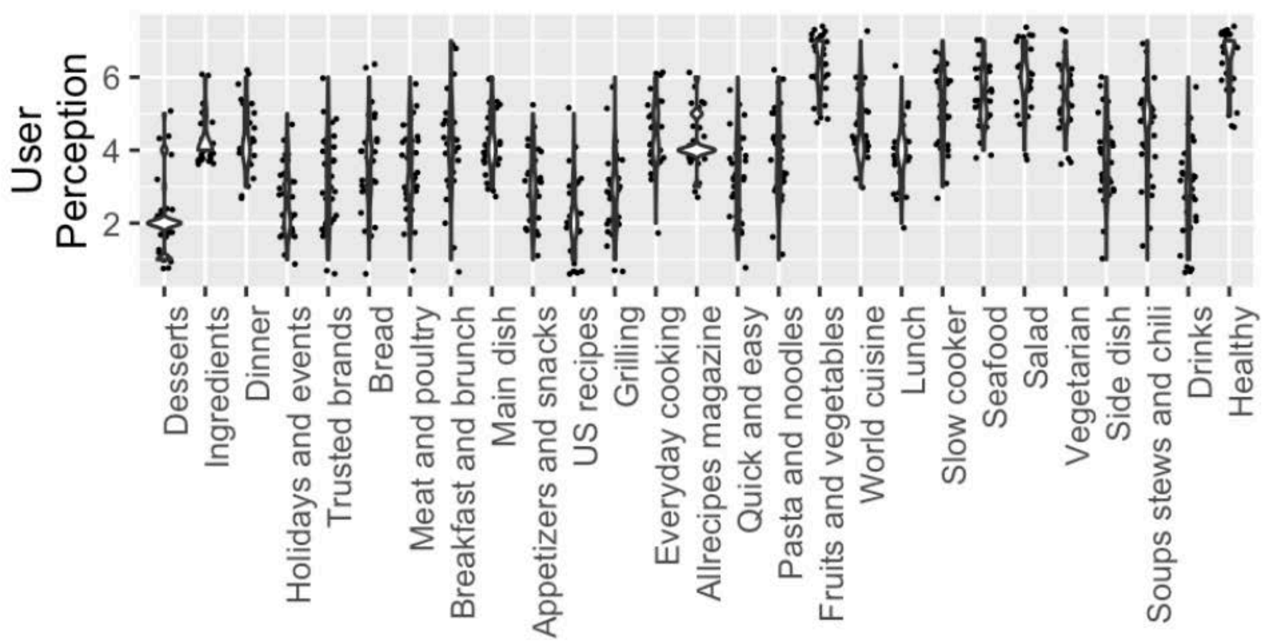
FSA criteria	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Fat	26.6g	25.8g	25.8g	25.1g	20.9g	23.5g	24.6g	26.6g	26.1g	23.3g	23.5g	25.1g	22.8g	23.1g	22.4g	21.7g
Saturated Fat	10g	9.8g	8.9g	9.3g	7.9g	8g	8.4g	9.2g	8.4g	7.7g	7.8g	9.2g	8g	8.3g	8g	7.1g
Sugar	5g	5.7g	5.4g	6.1g	5g	5.1g	6.4g	6g	5.3g	6.1g	5.6g	5.7g	5.4g	5.9g	5.5g	5.9g
Salt	2.1g	2.1g	2.1g	1.9g	2g	2.1g	2.1g	2.2g	2.2g	2g	2.1g	2.3g	2.3g	2.4g	2.2g	2.4g

Online food is unhealthy ☹

Category	n	Energy (kCal)	Fat (grams)	Sat. Fat (grams)	Sugar (grams)	Sodium (grams)	WHO score	FSA score‡
			FSA front of package label				Health scores	
Desserts	11,317↑	331.48↑	16.27 ↑	7.27 ↑	27.92 ↑	0.21 ↓	1.61	9.64 (1)
Ingredients	2039	265.06↑	14.13 ↑	5.84 ↑	16.44 ↑	0.36 ↑	1.59	9.06 (2)
Dinner	1033↓	166.61	9.07	3.44	2.59 ↓	0.35	1.41	8.43 (3)
Holidays and events	11,185	218.42↑	11.33 ↑	4.52 ↑	12.62 ↑	0.28	1.87	8.38 (4)
Trusted brands	1744	200.45	10.06	4.08 ↑	8.73	0.32	1.83	8.2 (5)
Bread	2972	261.86↑	9.95	3.53	12.72 ↑	0.35 ↑	2.42	8.18 (6)
Meat and poultry	12,672↑	151.97	8.46	3.09	2.62	0.33	1.62	8.17 (7)
Breakfast and brunch	2167	188.8	9.26	3.56	7.82	0.28	2.11	8.09 (8)
Main dish	13,188↑	159.51	8.36	3.08	2.48 ↓	0.31	1.77	8.09 (9)
Appetizers and snacks	4162	226.67↑	15.73 ↑	5.79 ↑	4.8	0.44 ↑	1.82	8.08 (10)
US recipes	3556	185.89	9.76	3.52	8.3	0.36 ↑	1.92	8.08 (11)
Grilling	1682↓	156.72	8.74	2.77	4.83	0.54 ↑	1.64	8 (12)
Allrecipes magazine	842↓	190.79	10.08 ↑	3.84	9.27	0.33	2	7.94 (13)
Everyday cooking	22,657↑	187	9.69	3.71	8.66	0.28	2	7.97 (14)
Quick and easy	1955	167.82	8.65	3.23	2.39 ↓	0.32	1.83	7.86 (15)
Pasta and noodles	2692	186.21	8.62	3.28	2.79	0.27	2.31	7.82 (16)
Fruits and vegetables	19,574↑	171.44	8.7	3.25	9.06	0.24 ↓	2.15	7.76 (17)
World cuisine	7444	178.05	9.05	3.26	7.46	0.29	2.16	7.68 (18)
Lunch	693↓	158.36	9.1	2.78	3.11	0.32	2.07	7.63 (19)
Slow cooker	1283↓	121.26↓	5.66 ↓	2.17 ↓	3.67	0.3	1.89	7.6 (20)
Seafood	3237	157.6	8.94	3.05	1.79 ↓	0.32	1.9	7.46 (21)
Salad	3031	146.84	9	1.93 ↓	4.48	0.24	2.33	7.22 (22)
Vegetarian	4889	159.09	8.47	3.01	5.95	0.26	2.58	7.15 (23)
Side dish	4006	128.99↓	6.64 ↓	2.69	3.71	0.24	2.58	6.97 (24)
Soups stews and chili	3605	82.93↓	3.89 ↓	1.59 ↓	1.65 ↓	0.22 ↓	2.29	6.87 (25)
Drinks	1801	86.37↓	1.5 ↓	0.82 ↓	10.22 ↑	0.03 ↓	2.51	6.01 (26)
Healthy	3175	107.83↓	2.34 ↓	0.56 ↓	6.77	0.2 ↓	3.43	5.6 (27)
All recipes	58,263	204.87	10.58	4.10	10.55	.31	1.94	8.13

User perception

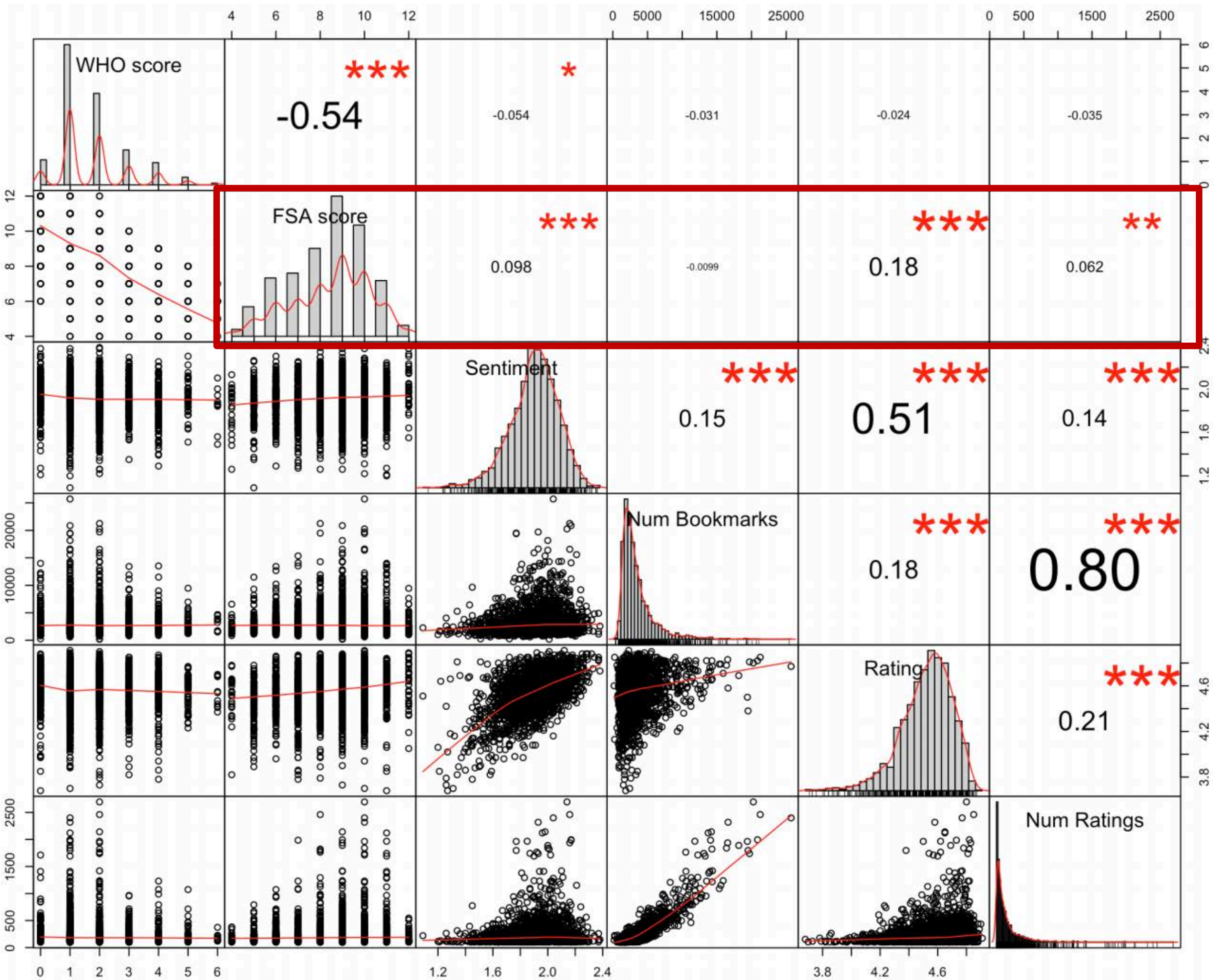
Results when asking users how healthy categories are on Allrecipes.com



(Kappa κ = .165, z = 42, p < .001)

With which types of recipes do user interact the most?

People seem to like unhealthy recipes



Part 3:
State-of-the-art & Health-aware Food RecSys

How healthy are recommendations produced by std. recommender systems algorithms in terms of health?

What is actually the current state-of-the-art in Food Recommenders?

Food Recommender Systems: Important Contributions, Challenges and Future Research Directions. Trattner, C. and Elsweiler, D. Collaborative Recommendations: Algorithms, Practical Challenges and Applications, World Scientific Publishing Co. Pte. Ltd., 2018

Author(s)	Algorithm(s)	Person-alized	RecSys Type(s)	Feedback	Context/ Content Feature(s)	Dietary Constrains	Target	Dataset
(Elsweiler, Trattner & Harvey, 2017)	Logistic Random Forrest Naive Bayes	no	Recipes	Ratings Binary	Title Image Ingredients Nutrition Pop. & Appr	no	Single User	Allrecipes
(Trattner & Elsweiler, 2017)	LDA WRMF AR SLIM BPR MostPop User- ItemKNN	yes/no	Recipes Meal Plans	Bookmarks Ratings Comments	WHO-FSA health score	no	Single User	Allrecipes
(Cheng, Rokicki & Herder, 2017)	BPR MostPop	yes/no	Recipes	Ratings	City Size	no	Single User	Kochbar
(Yang et al., 2017)	Learning to Rank	yes	Recipes	Binary	Image Embeddings	yes	Single User	Yummly
(Rokicki, Herder, Kuśmierczyk & Trattner, 2016)	UserKNN MostPop	yes/no	Recipes	Ratings	Gender	no	Single User	Kochbar
(Ge, Elahi, Fernaández-Tobías, Ricci & Massimo, 2015)	MF CB	yes	Recipes	Ratings Tags	Tags	no	Single User	Wellbeing Diet Book
(Elsweiler & Harvey, 2015)	SVD-Hybrid	yes	Meal Plans (Set of recipes)	Ratings	Ingredients	yes	Single User	Quizine
(Sano, Machino, Yada & Suzuki, 2015)	UserKNN SVD Hybrid NL-PCA	yes	Groceries	Purchases	Food Categories	no	Single User	Grocery store data
(Trevisiol, Chiarandini & Baeza-Yates, 2014)	UserKNN CB	yes	Menus (Set of dishes)	Binary	Text Sentiment	no	Single User	Yelp
(Elahi, Ge, Ricci, Massimo & Berkovsky, 2014)	MF	yes	Recipes	Ratings Tags	tags	no	Group of Users	Wellbeing Diet Book
(Harvey et al., 2013)	CB, CF Logistic Reg. SVD-Hybrid	yes	Recipes	Ratings	Ingredients etc.	no	Single User	Quizine
(Teng, Lin & Adamic, 2012)	SVM	no	Recipes	Ratings	Ingredients Nutrition Cook effort Cook methods	no	Single User	Allrecipes
(Kuo, Li, Shan & Lee, 2012)	Graph-based CB	yes	Menus (Set of recipes)	Tags	Ingredients	no	Single User	Food
(El-Dosuky, Rashad, Hamza & El-Bassiouny, 2012)	CB KB	yes	Food items	Query	tags	no	Single User	USDA
(Freyne, Berkovsky, Baghaei, Kimani & Smith, 2011)	CF	yes	Meal plans (Set of recipes)	Ratings	-	no	Single User	Wellbeing Diet Book
(Ueta, Iwakami & Ito, 2011)	KB	yes	Recipes	Query	tags	no	Single User	Cookpad
(van Pinxteren, Geleijnse & Kamsteeg, 2011)	CB	yes	Recipes	Cooked recipes	Recipe content features	no	Single User	Smulweb
(Freyne & Berkovsky, 2010)	UserKNN CB Hybrid	yes	Recipes	Ratings	Ingredients	no	Single User	Wellbeing Diet Book
	UserKNN							

Results: Recommender Experiment

	Mean (n =4791)									
							FSA front of package label			
	MAP@5	nDCG@5	WHO score	FSA score	Δ WHO	Δ FSA	Fat (g)	Sat. Fat (g)	Sugar (g)	Sodium (g)
LDA	**.0175**	**.0395**	1.554	9.110	-.137***	.498***	8.70	3.73	8.73	0.32
WRMF	.0160	.0365	1.496	9.114	-.196***	.503***	9.50	3.89	8.84	0.34
AR	.0149	.0343	1.550	9.206	-.141***	.595***	9.27	4.12	10.50	0.25
SLIM	.0143	.0326	1.643	8.907	-.048***	.295***	9.27	3.82	7.91	0.33
BPR	.0141	.0325	1.432	9.252	-.259***	.641***	8.69	3.82	7.83	0.29
MostPop	.0126	.0294	1.537	9.004	-.154***	.393***	9.02	3.94	10.01	0.23
UserKNN	.0100	.024	1.583	8.985	-.108***	.372***	8.96	3.73	7.98	0.31
ItemKNN	.0073	.0178	1.660	8.652	-.032***	.041***	8.59	3.51	6.03	0.31
Random	.0011	.0029	**1.750**	**8.486**	**.059******	**-.126******	8.74	3.49	5.71	0.30

*** p < .001

☹

$$\Delta = \text{train} - \text{pred}$$

Libray: LibRec
Eval: 10 fold-cross validation

Can we improve std. recommender systems in terms of health?

Re-ranking for health

Post-Filter scoring functions

$$score_{u,i,who} = score_{u,i} \cdot (who_i + 1) \qquad (1)$$
$$score_{u,i,fsa} = score_{u,i} \cdot (16 - fsa_i - 4 + 1) \qquad (2)$$

Linear combinations as discussed in Elsweiler et al. (2015) did not work ☹

D. Elsweiler, M. Harvey, B. Ludwig, and A. Said. Bringing the "healthy" into food recommenders. In Proc. of DRMS'15., pages 33–36.

Results: Recommender (2)

	Mean (n =4791)									
							FSA front of package label			
	MAP@5	nDCG@5	WHO score	FSA score	Δ WHO	Δ FSA	Fat (g)	Sat. Fat (g)	Sugar (g)	Sodium (g)
LDA	**.0175**	**.0395**	1.554	9.110	-.137***	.498***	8.70	3.73	8.73	0.32
WRMF	.0160	.0365	1.496	9.114	-.196***	.503***	9.50	3.89	8.84	0.34
AR	.0149	.0343	1.550	9.206	-.141***	.595***	9.27	4.12	10.50	0.25
SLIM	.0143	.0326	1.643	8.907	-.048***	.295***	9.27	3.82	7.91	0.33
BPR	.0141	.0325	1.432	9.252	-.259***	.641***	8.69	3.82	7.83	0.29
MostPop	.0126	.0294	1.537	9.004	-.154***	.393***	9.02	3.94	10.01	0.23
UserKNN	.0100	.024	1.583	8.985	-.108***	.372***	8.96	3.73	7.98	0.31
ItemKNN	.0073	.0178	1.660	8.652	-.032***	.041***	8.59	3.51	6.03	0.31
Random	.0011	.0029	**1.750**	**8.486**	**.059*****	**-.126*****	8.74	3.49	5.71	0.30
	FSA score post-filtered ($score_{u,i,fsa}$)									
LDA	**.0137**	**.0321**	2.170	7.323	.479***	-1.288***	6.51	2.42	4.03	0.29
WRMF	.0131	.0303	2.140	7.361	.449***	-1.250***	6.48	2.30	4.75	0.31
SLIM	.0109	.0248	2.384	7.008	.692***	-1.604***	6.20	2.56	2.59	0.24
AR	.0100	.0238	2.600	6.984	.909***	-1.627***	5.64	1.94	3.95	0.28
MostPop	.0096	.0228	2.542	7.334	.851***	-1.278***	5.37	2.02	2.46	0.24
BPR	.0086	.0205	2.783	6.722	1.092***	-1.889***	6.42	2.30	4.95	0.26
UserKNN	.0069	.0168	2.486	6.722	.795***	-1.891***	6.88	2.73	3.33	0.33
ItemKNN	.0044	.0109	2.703	6.124	1.012***	-2.488***	5.15	1.79	3.51	0.25
Random	.0009	.0022	**3.228**	**4.305**	**1.537*****	**-4.306*****	1.59	0.43	1.45	0.09

Note: $^{***}p < .001$

☹

☺

Note: similar results with bookmarks

Conclusions

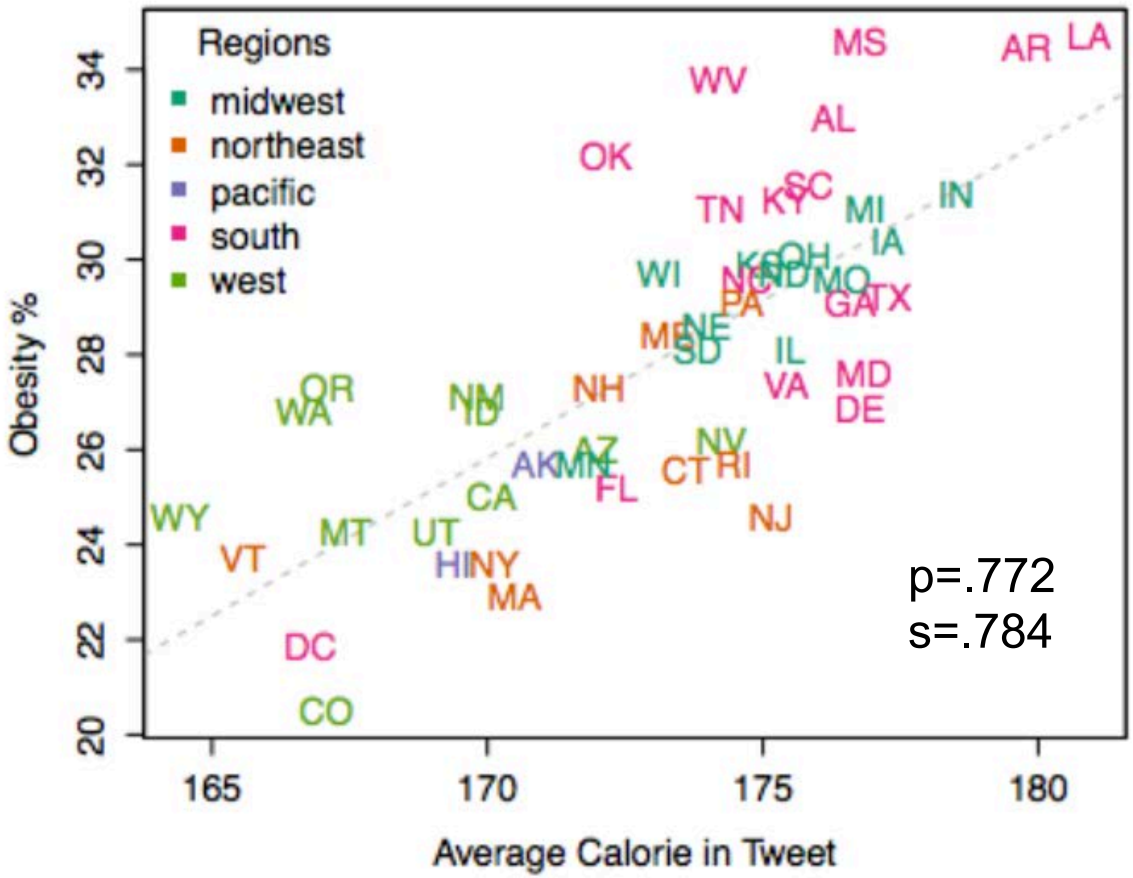
- Only a **small percentage** of Allrecipes.com recipes can be considered **healthy** according to WHO and FSA guidelines.
- **Users** are to some extent able to judge how healthy categories will be, but **often disagree**.
- Interaction data reveals that people are **most positive about the unhealthy recipes.**
- **Current state-of-the-art recommender algorithms in general produce unhealthy recommendations**.

Part 4:
Linking Online & Offline

Can we find a link between the online and offline world?

Abbar, S., Mejova, Y., & Weber, I. (2015). You tweet what you eat: Studying food consumption through twitter. ACM CHI 2015.

Correlation between food mentions on Twitter & Obese



- 50 million tweets
- Food related keywords

http://www.caloriecount.com/

Abbar, S., Mejova, Y., & Weber, I. (2015). You tweet what you eat: Studying food consumption through twitter. ACM CHI 2015.

…in RecSys, we typically use other types of signals…

Trattner, C., Parra, D. and Elsweiler, D. *Monitoring obesity prevalence in the United States through bookmarking activities in online food portals*. PLOS ONE 12(6), 2017.

Trattner, C. and Elsweiler, D. **What online data say about eating habits**. NATURE Sustainability, 2019.

Research Questions

- **RQ1.** To what extent do the nutritional properties of bookmarked recipes on Allrecipes.com correlate with obesity levels in the US?

- **RQ2.** To what extent can temporal or geographical factors help in explaining obesity patterns?

- **RQ3.** To what extent do nutrition factors explain the variance in obesity rates across the US?

Dataset

Dataset in detail

Table 1. Basic statistics of the Allrecipes.com dataset with at least 30 users per county.

Year	Num. Users	Num. Bookmarks	Num. Recipes	Num. Counties	Num. States
2004	1348	29,827	1491	25	13
2005	3185	63,512	2210	54	25
2006	7149	185,251	4964	99	36
2007	10,803	270,835	6850	135	40
2008	17,873	500,063	10,227	193	43
2009	21,644	625,661	12,077	225	47
2010	27,331	910,918	15,442	256	46
2011	29,004	933,521	15,351	266	47
2012	26,093	656,364	12,738	244	47

https://doi.org/10.1371/journal.pone.0179144.t001

Variables

Dependent Variable

- **Obesity prevalence** (state / county level)

Independent Variables

- Fat (of recipe)
- Saturated Fat (of recipe)
- Sugar (of recipe)
- Sodium (of recipe)
- *Healthiness (of recipe)*

Results

Trends over time

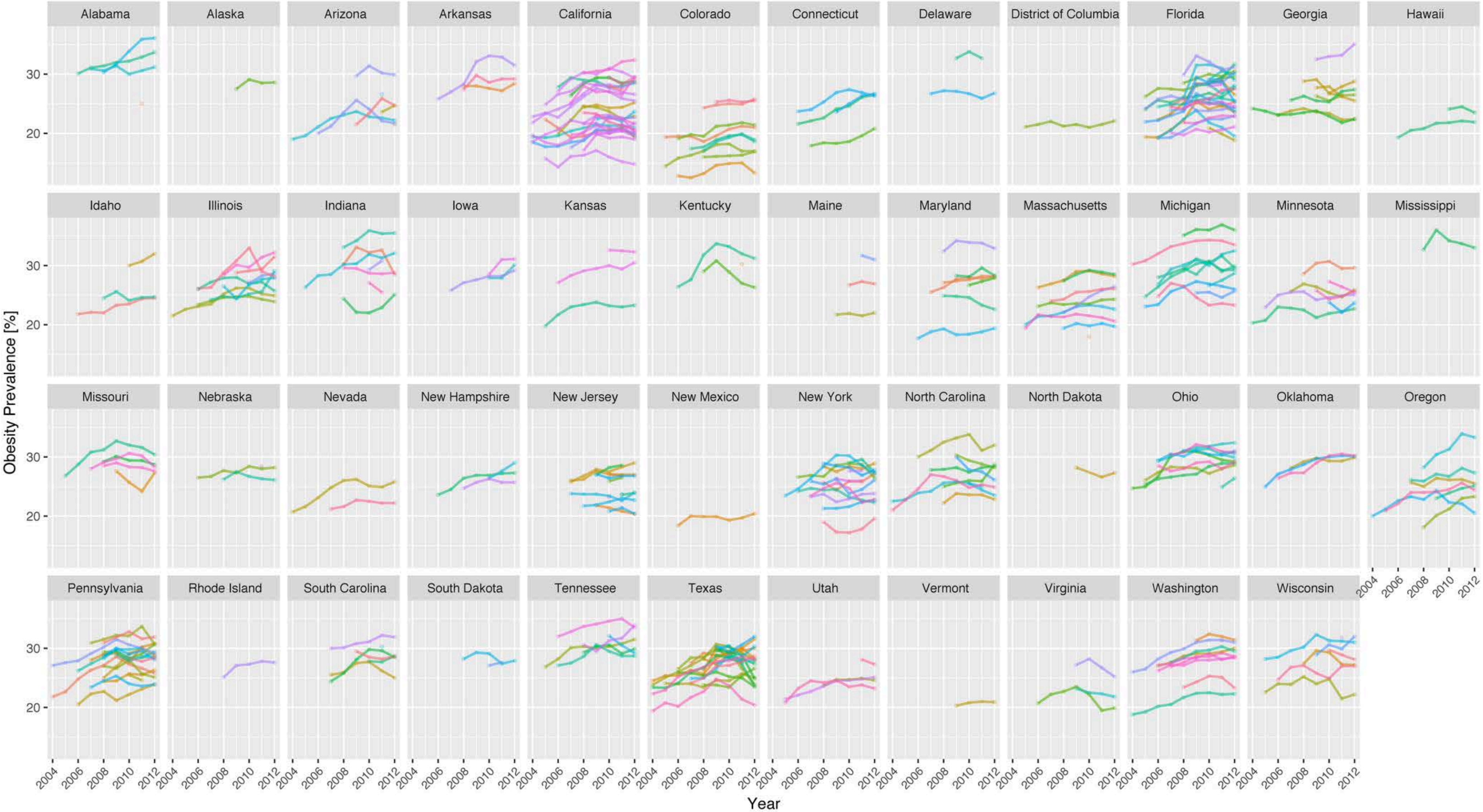


Fig 2. Trends of obesity prevalence levels as a function of time (2004–2012) for states and corresponding counties (presented as lines) in the US. We only report states and counties with at least 30 users bookmarking recipes in each of the counties for each year.

Trends over time (zoom in)

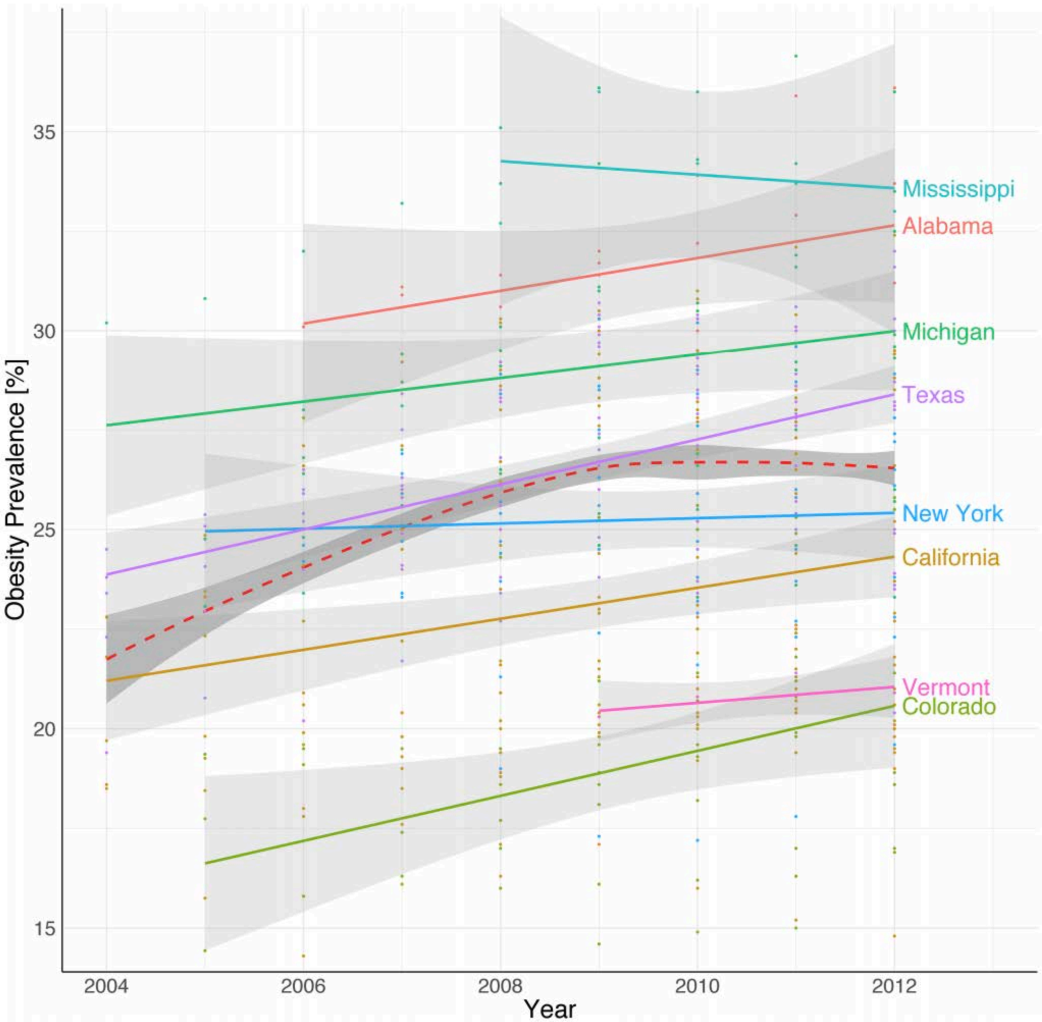


Fig 1. Linear trends of fat as a function of time (2004–2012) for selected states in the US. The plots show a variety of intercepts and trends (slopes) over time. The general aggregated trend is shown with a dashed line.

RQ1. To what extent do the nutritional properties of bookmarked recipes on Allrecipes.com correlate with obesity levels in the US?

County Level Correlations

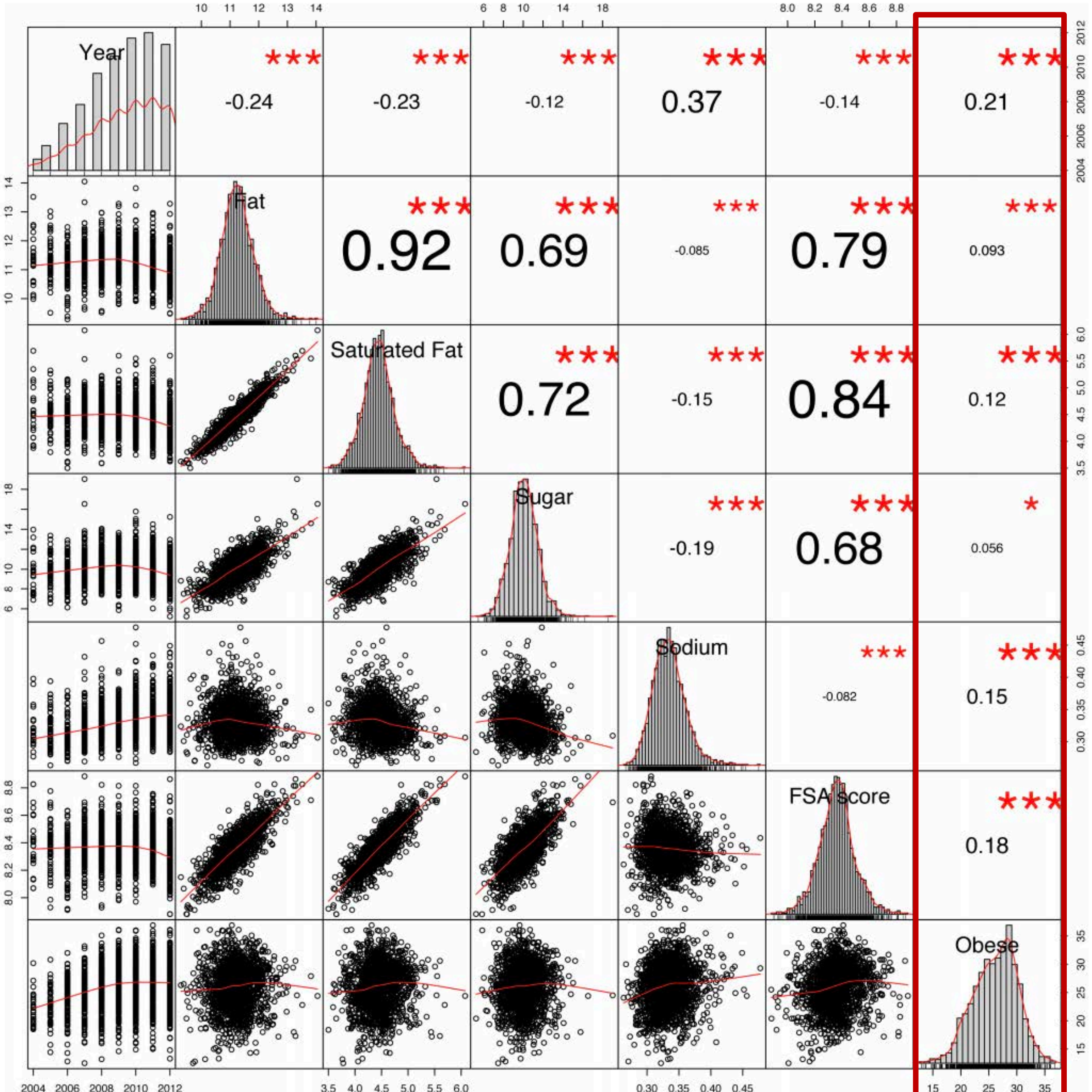


Fig 4. County-level correlations (spearman). Note: *** $p < 0.001$, * $p < 0.05$.

State Level Correlations

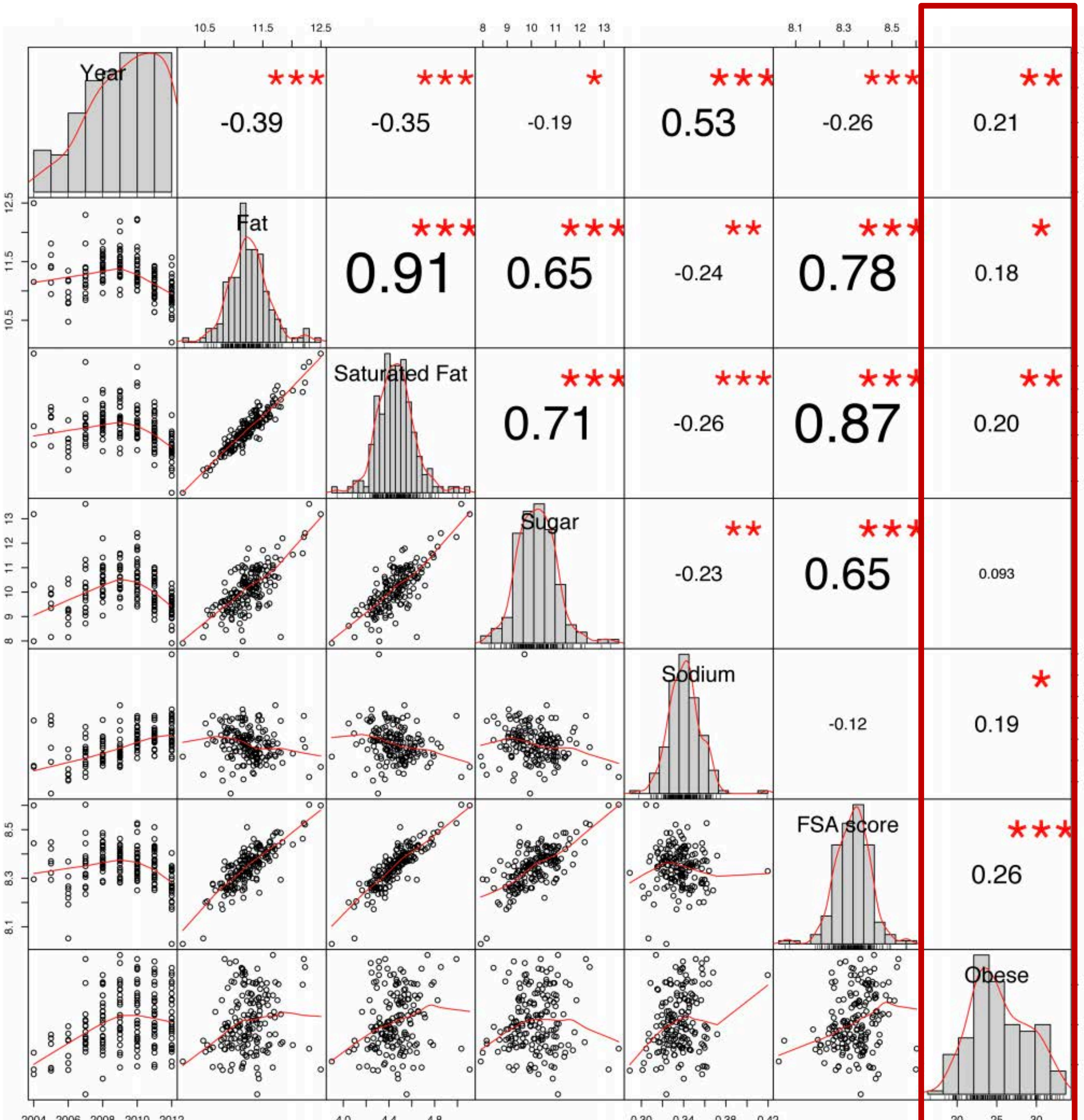


Fig 5. State-level correlations (spearman). Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

RQ2. To what extent can temporal or geographical factors help in explaining obesity patterns?

RQ3. To what extent do nutrition factors explain the variance in obesity rates across the US?

Table 2. Multilevel models for obesity. Models 3 and 4 incorporate a random intercept per county/state, a random slope for year, and fixed effects for the FSA score and Fat and Sugar. A likelihood ratio test shows significant differences between the models: Model 1 vs Model 2: $\chi^2(5) = 585.64$, $p < 0.001$; Model 2 vs Model 3: $\chi^2(1) = 23.91$, $p < 0.001$; Model 3 vs Model 4: $\chi^2(1) = 14.67$, $p < 0.001$. For the fixed effects, the number in parenthesis shows the standard error.

	Model 1	Model 2	Model 3	Model 4
Variance Components				
Var: county:State (Intercept)	8.90	9.01	8.84	9.02
Var: State (Intercept)	4.87	5.35	5.28	5.31
Var: Residual	1.79	0.97	0.96	0.94
Var: County:State Year		0.09	0.09	0.09
Cov: County:State (Intercept) Year		-0.28	-0.27	-0.28
Var: State Year		0.00	0.00	0.00
Cov: State (Intercept) Year		-0.04	-0.04	-0.04
Fixed Effects				
(Intercept)	26.56*** (0.39)	24.89*** (0.42)	14.27*** (2.20)	21.74*** (0.83)
Year		0.30*** (0.03)	0.31*** (0.03)	0.32*** (0.03)
FSA score			1.26*** (0.26)	
Fat/100g				0.19* (0.08)
Sugar/100g				0.08* (0.03)
AIC	6796.61	6226.47	6205.44	6200.72
BIC	6818.30	6275.28	6259.68	6260.38
Log Likelihood	-3394.31	-3104.23	-3092.72	-3089.36
Num. obs.	1675	1675	1675	1675
Num. groups: county:state	311	311	311	311
Num. groups: state	47	47	47	47
	Baseline	Baseline+ Time	Baseline+ Time + FSA	Baseline+ Time + Fat + Sugar

Note:
*** $p < 0.001$,
* $p < 0.05$

Conclusion

- **We demonstrate significant and meaningful** (i.e. sensibly interpretable) **relationships** between the nutritional properties of bookmarked recipes (sugar content, fat content and a combined FSA-score for recipes) and obesity incidence.

- The good fit achieved by our models suggests that combining interaction data, geographical data and temporal **data can be a useful in monitoring obesity incidence**.

Part 5:
Predicting Item Popularity

Why do people like the unhealthy recipes more?

Trattner, C., Moesslang, D. and Elsweiler, D. **On the Predictability of the Popularity of Online Recipes**. EPJ Data Science, 2018.

What makes a recipe actually to be chosen/popular?

...from the social psychology literature we know that there are several biases involved in when people cook or select food, e.g.

social & cultural factors, season, healthiness, visual appeal

Scheibehenne, B., Miesler, L., and Todd, P.M. (2007). Fast and frugal food choices: Uncovering individual decision heuristics. Appetite, 49, 578-589.

Predicting Recipe Popularity
=
Item Cold-Start Prediction

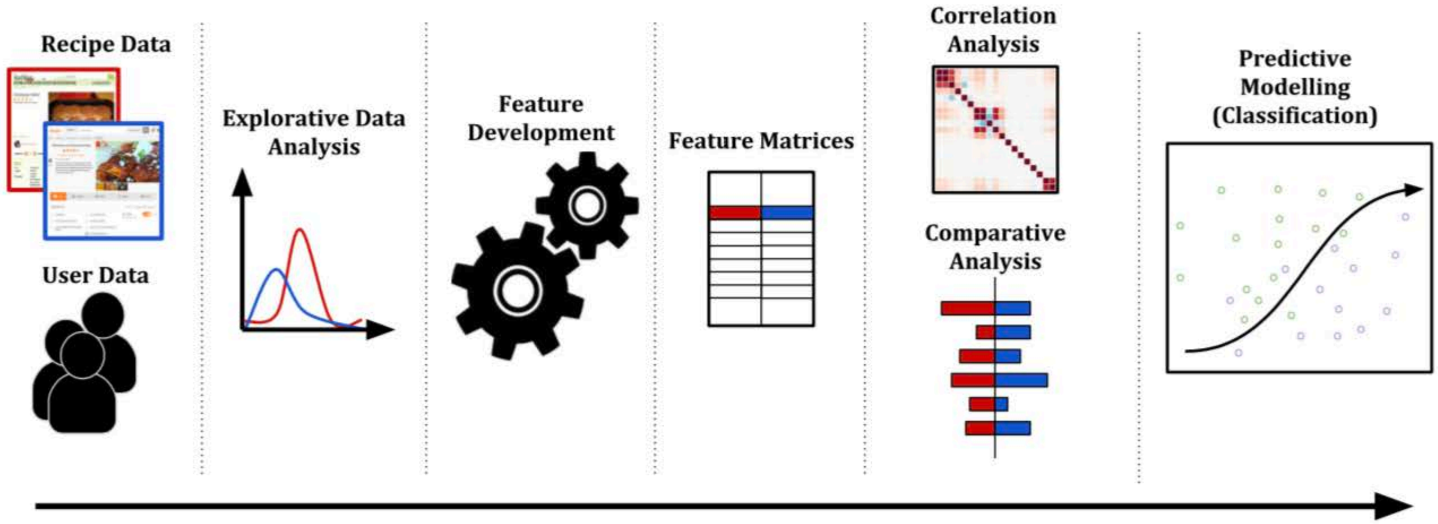


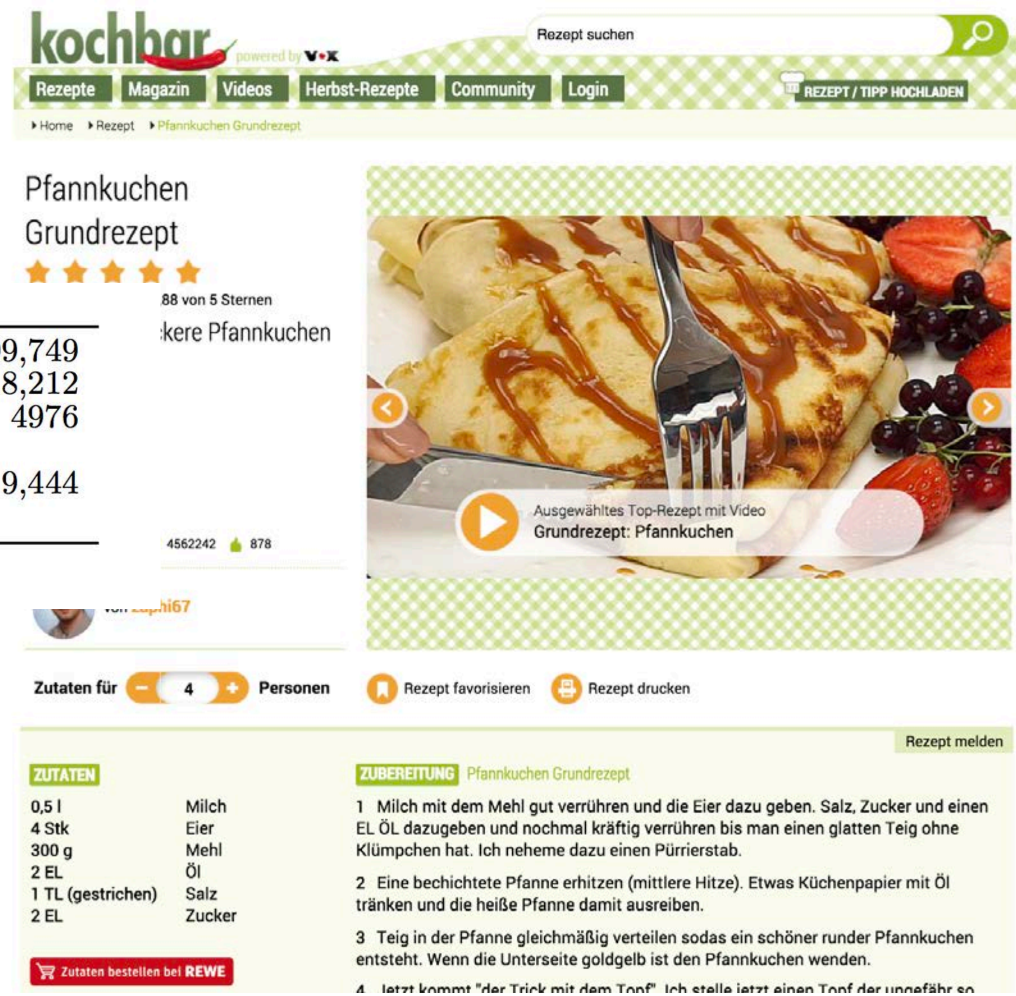
Figure 1.1: A schematic illustration of the approach to popularity prediction of online recipes

Datasets

- Allrecipes.com
- Kochbar.de

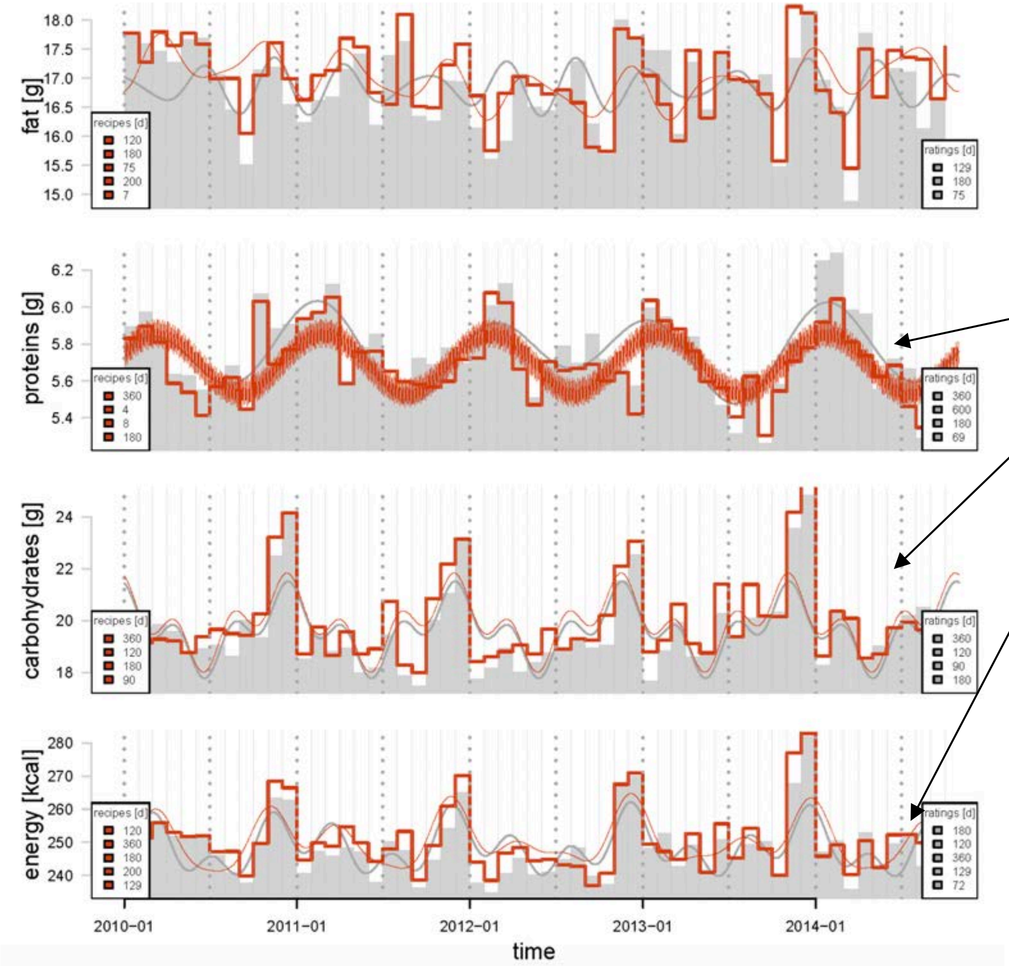
recipes	405,868	users	199,749
ratings	7,794,868	publishing users	18,212
recipes with at least 10 ratings	240,518	users with at least 10 recipes	4976
ingredients	1485	ratings users	19,444
categories	246		

Table 1: Overview of the dataset.



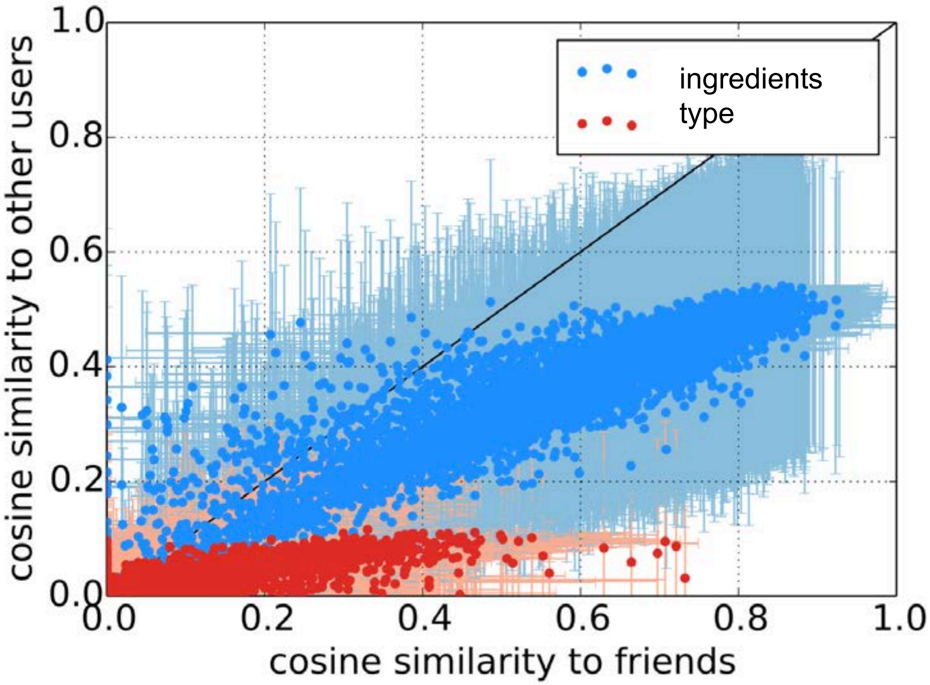
Factors

Temporality?

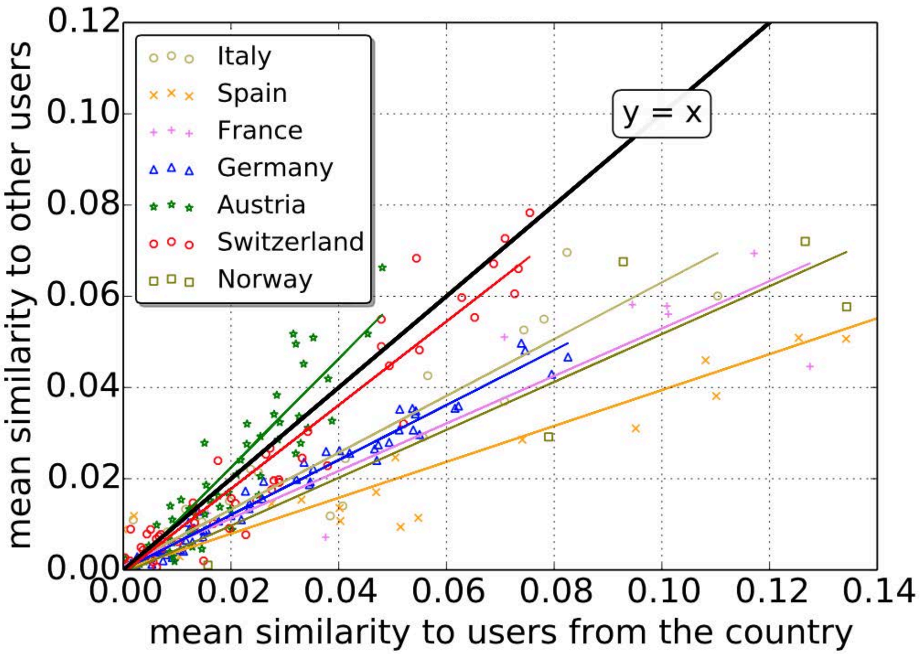


Clear temporal patterns emerge

Homophilie?



Location?



Visual Attractiveness?

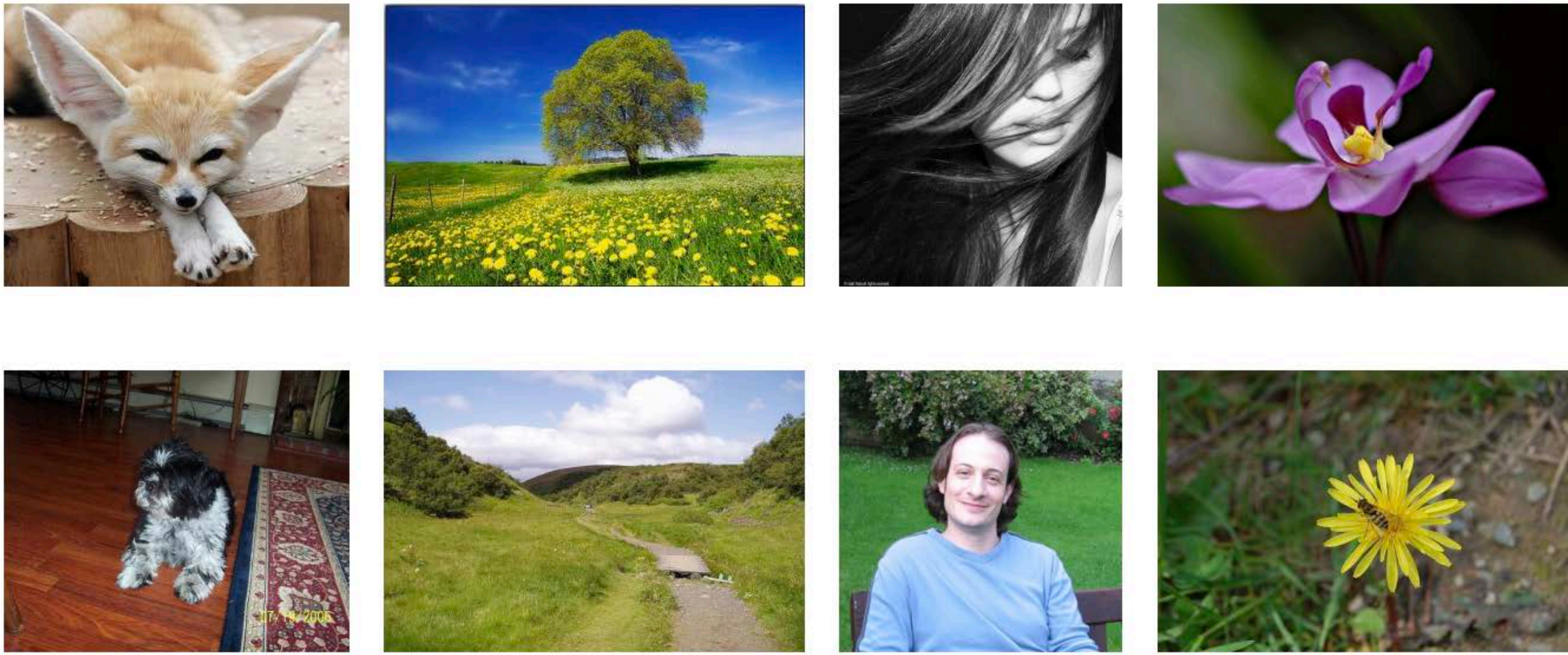


Figure 1: "Attractive" (upper row) vs. "Unattractive" (lower row) images: Each column represents the same semantic concept (animal, landscape, portrait, flower) but differences in appeal-related visual attributes.

San Pedro J, Siersdorfer S (2009) Ranking and classifying attractiveness of photos in folksonomies. In: Proceedings of the 18th international conference on world wide web. WWW '09. ACM, New York, pp 771–780

Other factors

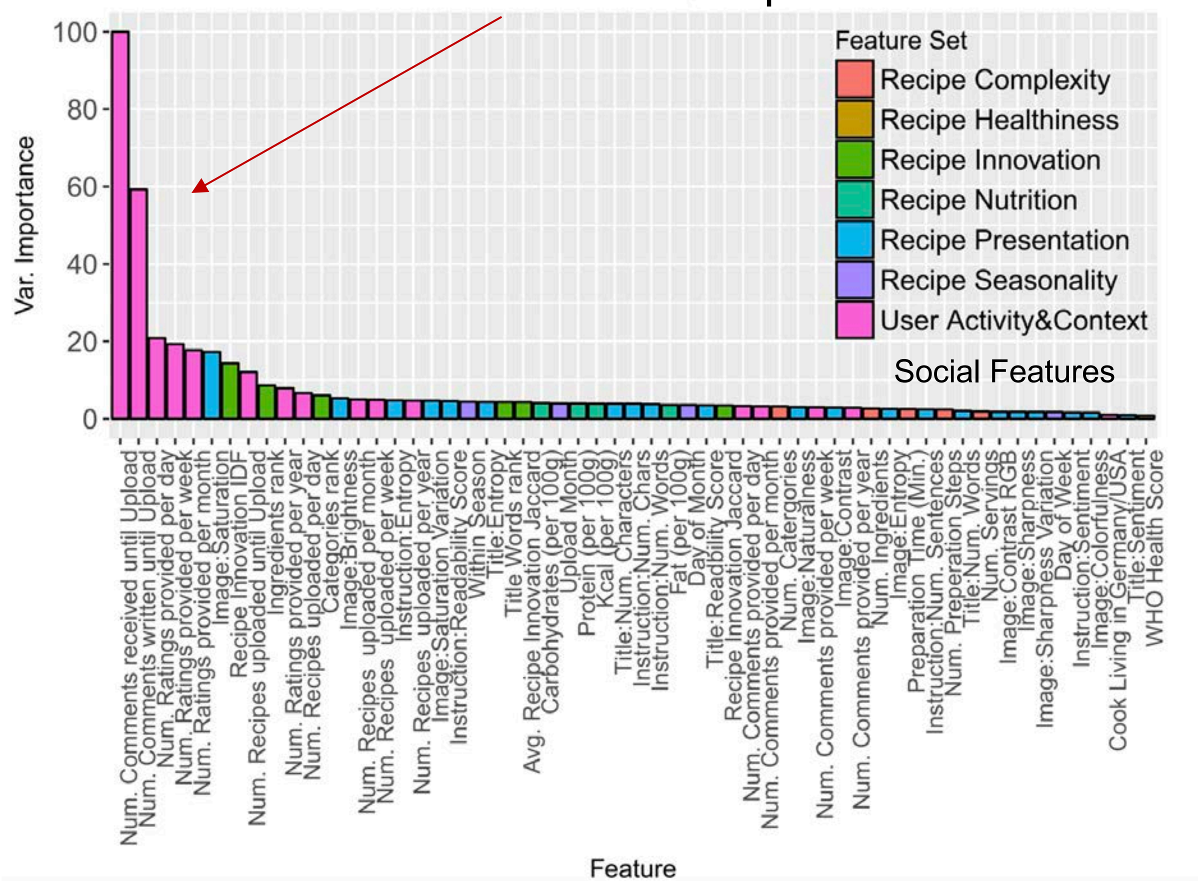
- Recipe complexity
  - Instruction: Num. Words
  - Instruction: Num. Sentences
  - Entropy
  - LIX
- Recipe innovation

$$recipe\_innovation\_IDF = \frac{1}{|I_r|} \sum_{i \in I_r} ing\_rareness_i$$

$$recipe\_innovation\_jaccard = 1 - \max_{r' \prec r} \frac{|\{i : i \in r \wedge i \in r'\}|}{|\{i : i \in r \vee i \in r'\}|},$$

Predicting popularity: Kochbar.de

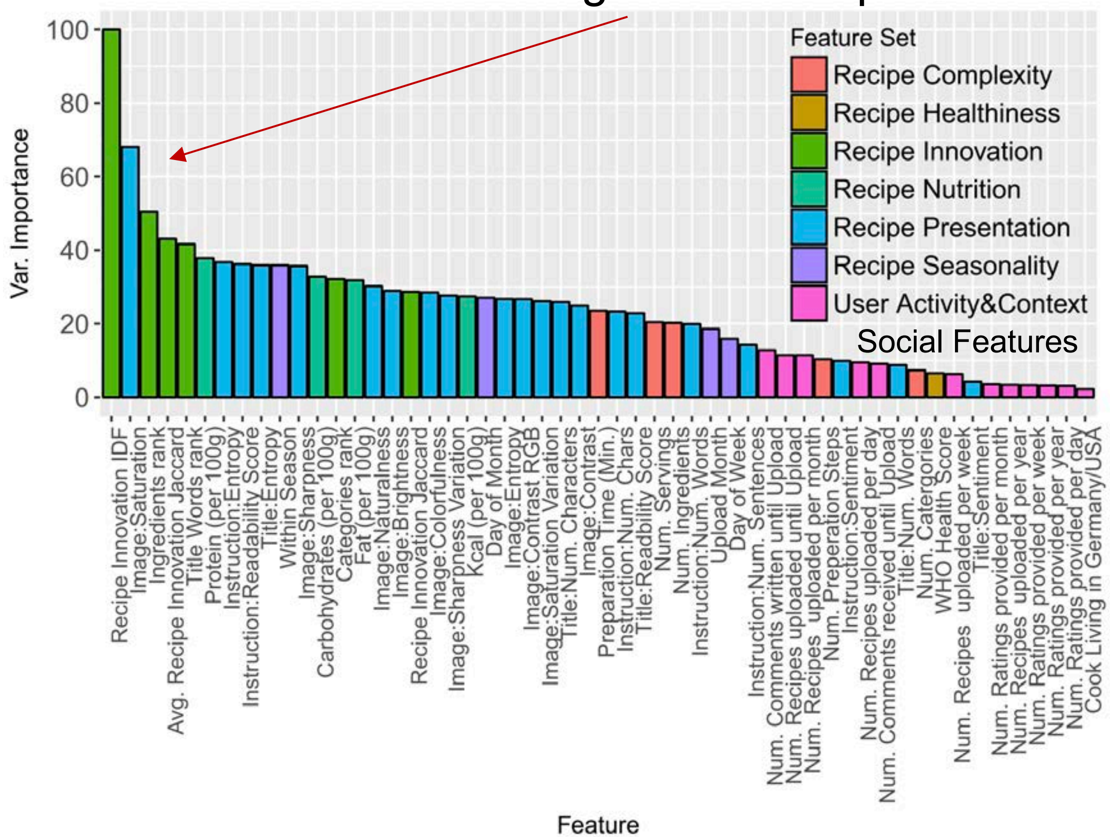
Social factors most important



Random Forrest:
90% accuracy

Predicting popularity: Allrecipes.com

Innovation & Image factors important



Random Forrest
70% accuracy

How about other food cultures?

Zhang, Q., Trattner, C., Elsweiler, D. and Ludwig, B. **Identifying Cross-Cultural Visual Food Tastes with Online Recipe Platforms**. In Proceedings of the 11th International AAAI conference on Web and Social Media (ICWSM), 2019.

China?

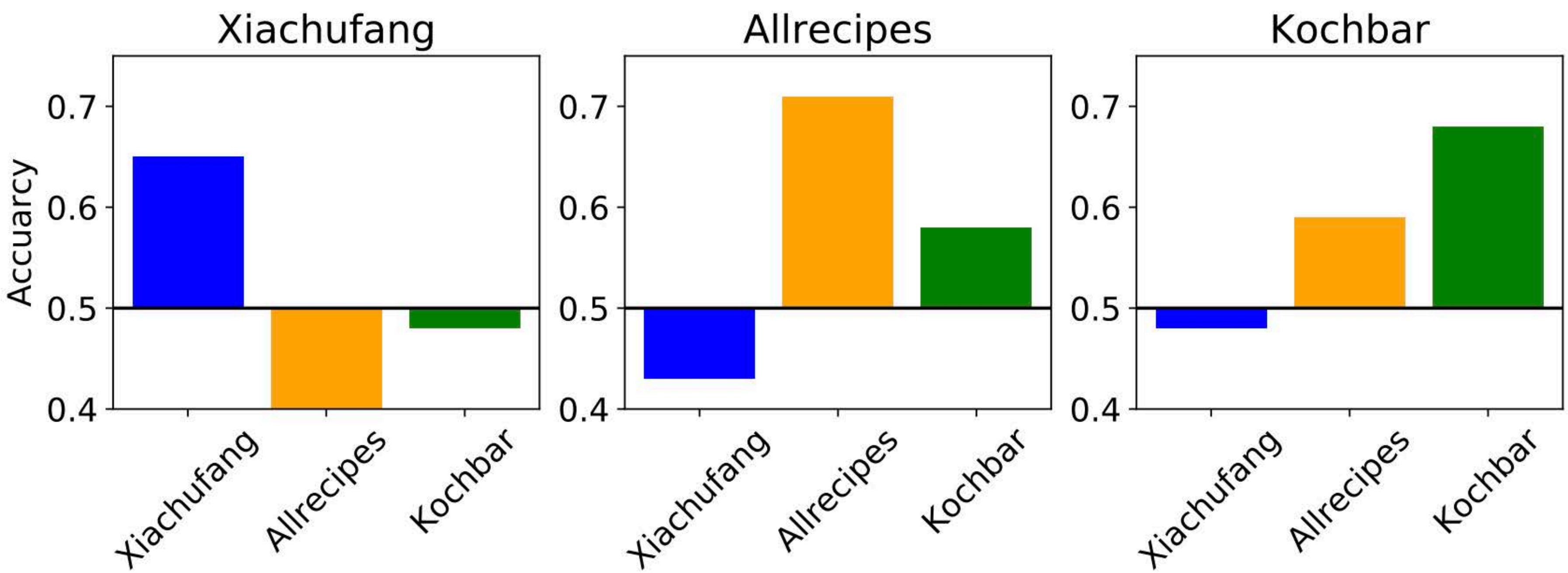
(a) *Xiachufang:* High (↑) prediction scores

(b) *Xiachufang:* Low (↓) prediction scores

(c) *Allrecipes:* High (↑) prediction scores

(d) *Allrecipes:* Low (↓) prediction scores

Cross-Country Prediction



Part 6:
Factors & Food RecSys

How would these features work in a recommendation scenario?

Trattner, C., Kusmierczyk, T. and Norvag, K. **Investigating and Predicting Online Food Recipe Upload Behavior**. Information Processing and Management. 2019.

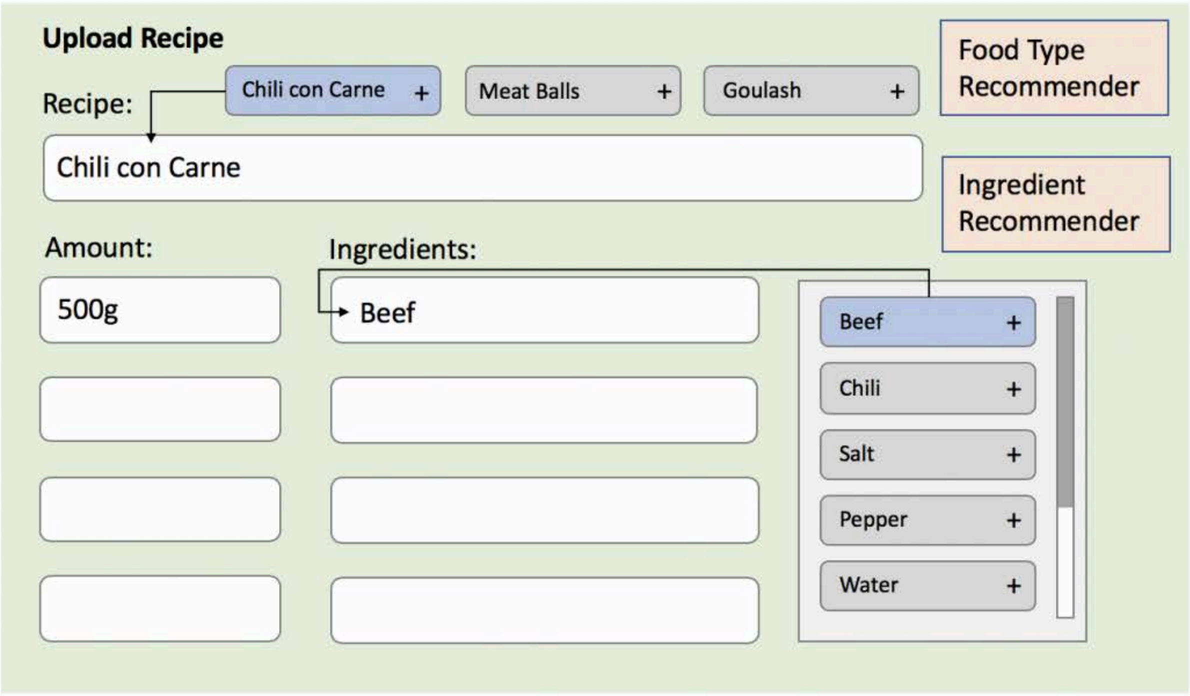
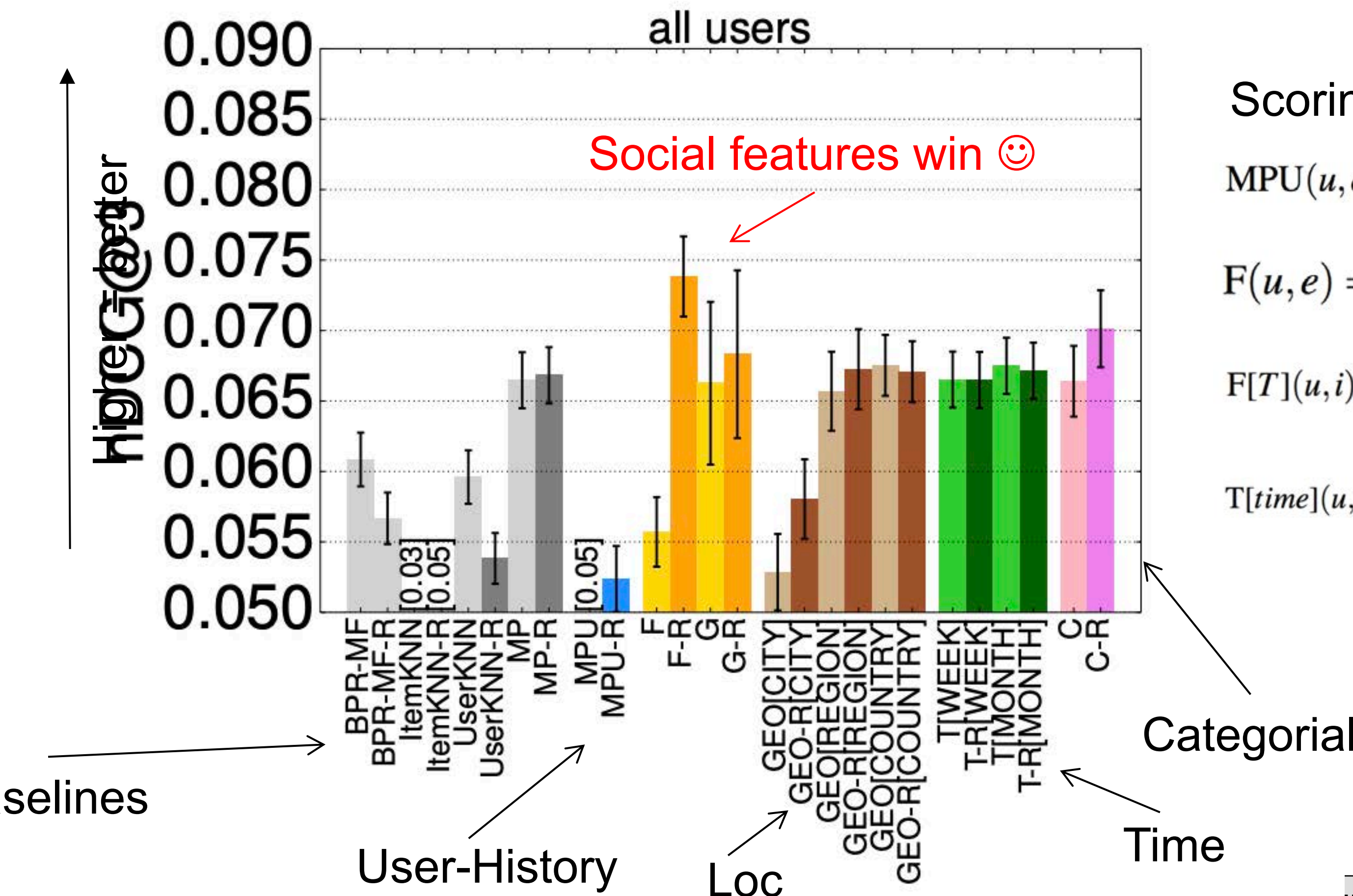


Figure 1: Example of an intelligent user interface that tries to support the user in the recipe upload process by recommending food type and corresponding ingredients to cook this meal.

Predicting the top-3 food of recipe a user would upload



Scoring functions:

$$\mathrm{MPU}(u,e) = \sum_{r \in U_u} [e \in r]$$

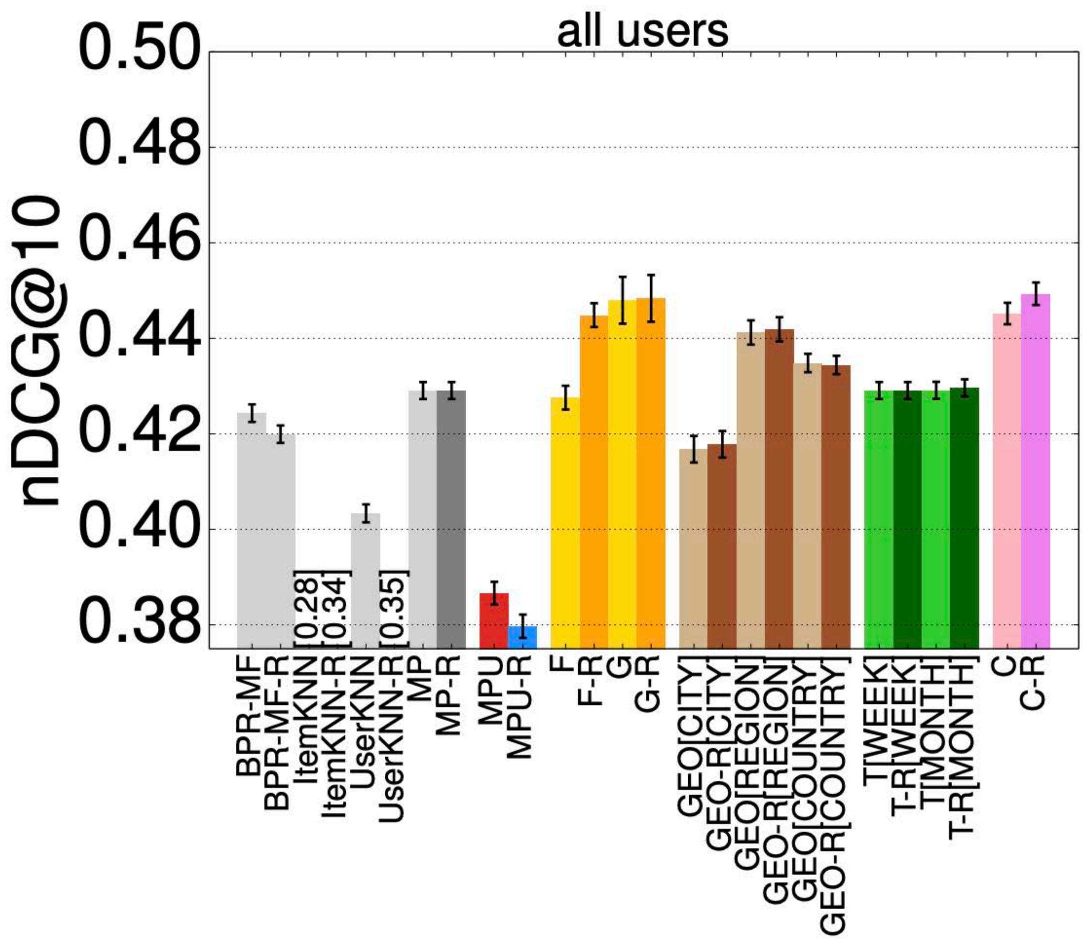
$$\mathrm{F}(u,e) = \sum_{f \in F_u} \sum_{r \in U_f} [e \in r]$$

$$\mathrm{F}[T](u,i) = \sum_{t \in T} \sum_{f \in F_u} \sum_{r \in U_f} w(t) \cdot [i \in r \wedge t \in r]$$

$$\mathrm{T}[time](u,e) = \sum_{u' \in \mathscr{U}} \sum_{r' \in U_{u'}} [tm(r') = tm(u) \wedge e \in r']$$

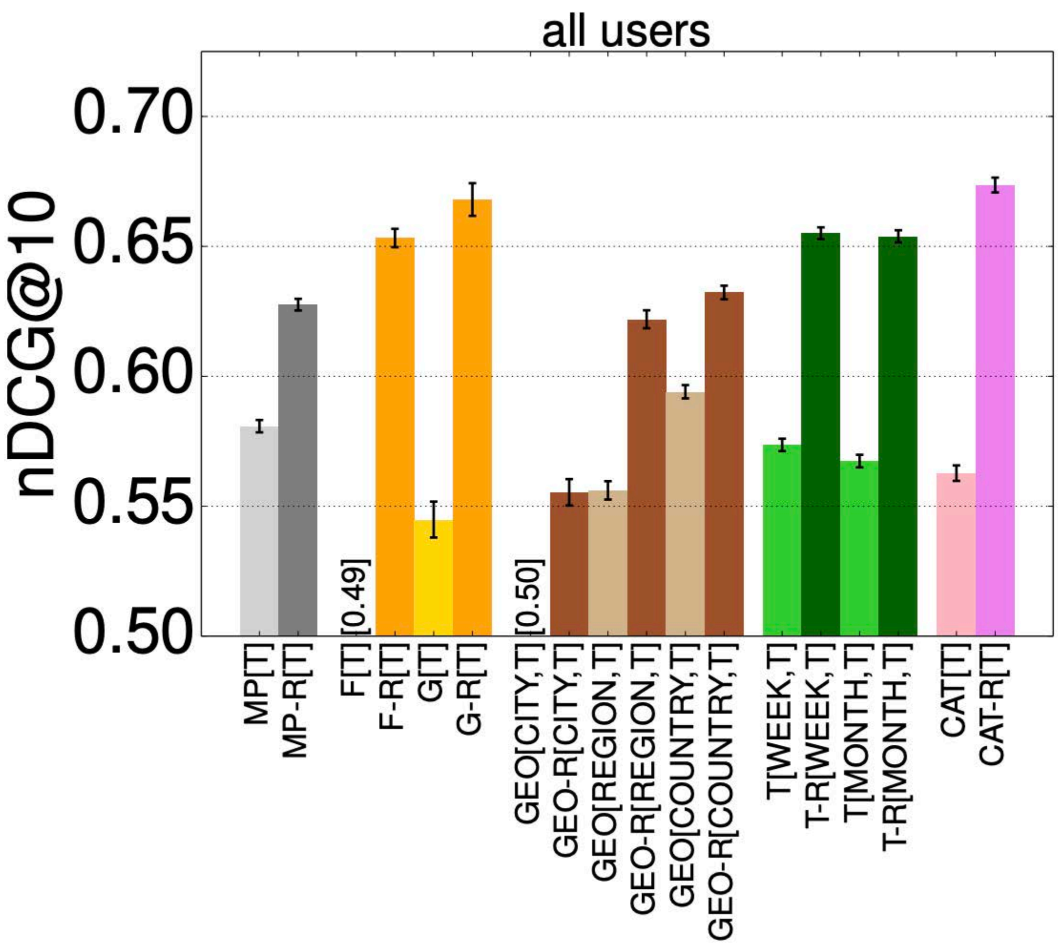
ure 16: Food types prediction quality (means and standard errors) for all users. Colors indicate different groups of hods.

Predicting Top-10 Ingredients



a) Prediction of ingredients when food type is unknown.

Predicting Top-10 Ingredients



b) Prediction of ingredients when food type is known.

Other Factors!

Gender & Food?

Impact of gender

Prof. Dr. Eva Barlösius

Head of [Leibniz Forschungszentrum Wissenschaft und Gesellschaft (LCSS)]

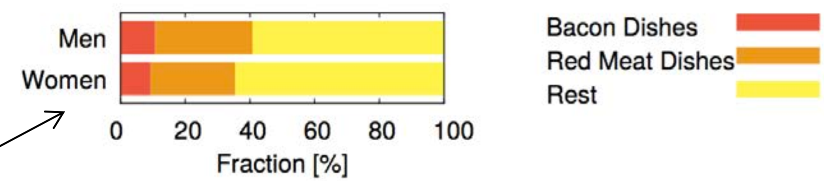
Rocicki, M., Herder, E., Kusmierczyk, T. and Trattner, C. Plate and Prejudice: Gender Differences in Online Cooking. In Proceedings of the International Conference on User Modeling and Personalisation (UMAP), 2016.

Hypotheses

H1. Men Are Better Cooks

H2. Men Cook for Impressing

H3. Women Prefer to Cook Sweet Dishes, Men Prefer to Cook Meat Dishes

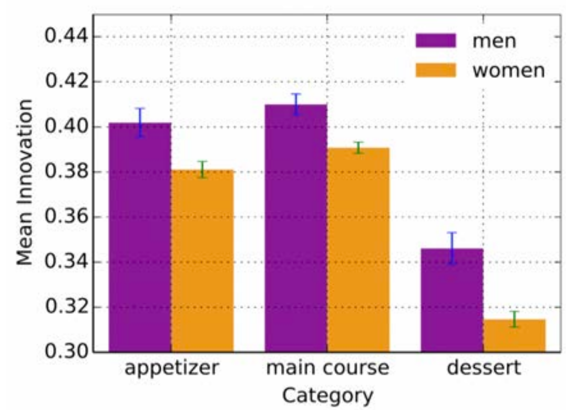


Among recipes published by female cooks, 16.5% were identified as sweet dishes, significantly more than the fraction of 7.8% for male cooks

H4. Women Use Spices More Subtly

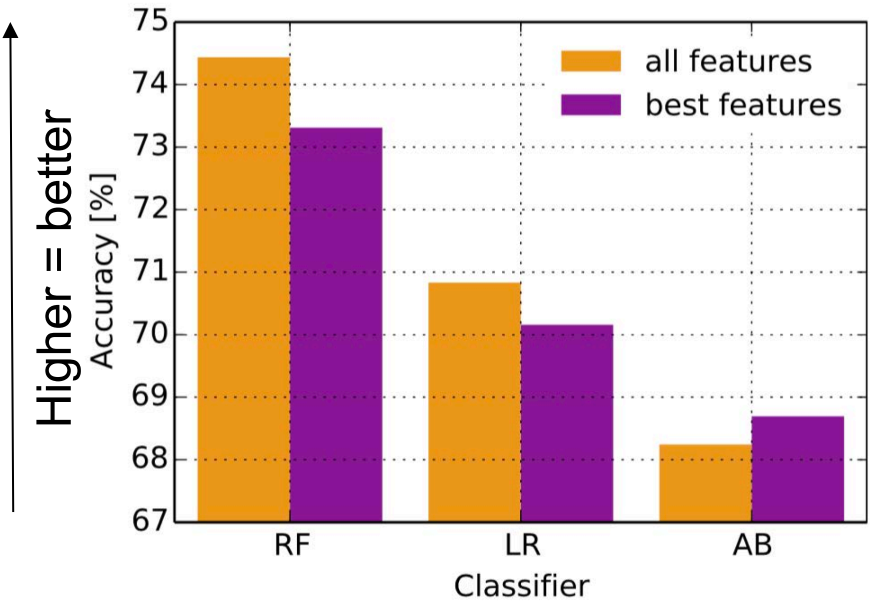
H5. Men Use More Gadgets for Cooking

H6. Men Are More Innovative

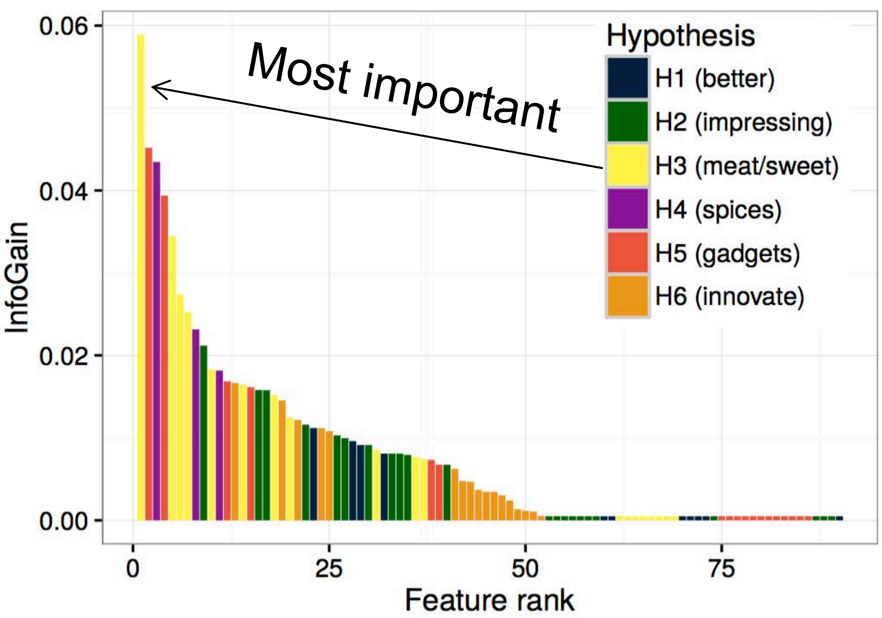


To what extent can we identify the gender of the recipe authors?

Classification Results

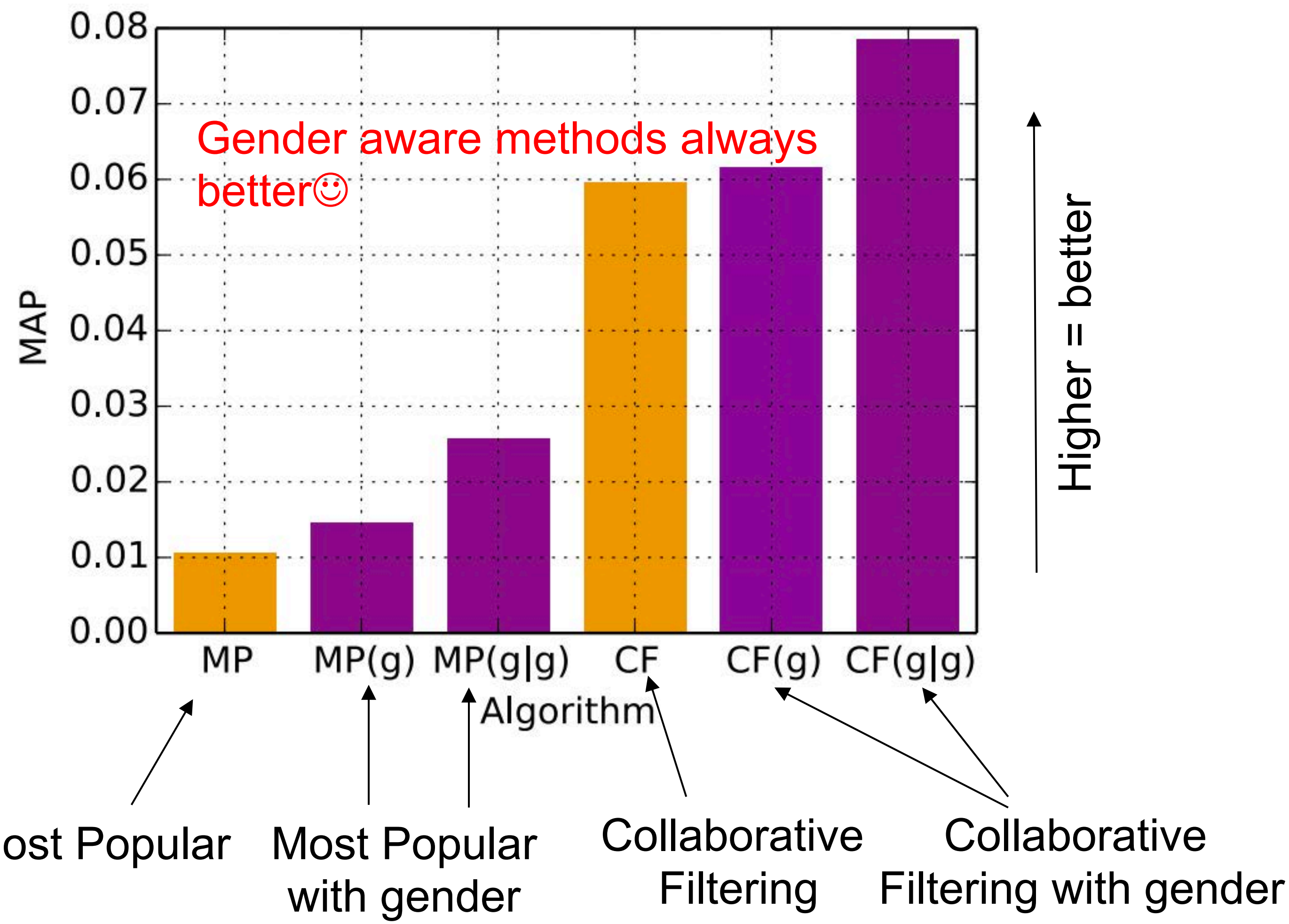


Feature Importance



RF=Random Forrest, LR=Logistic Regression, AB=Ada Boost

Gender-aware recommendations (predicting the recipes a user will like)



Part 7:
Altering Food Choice

Can we alter food choices with recommenders?

Study

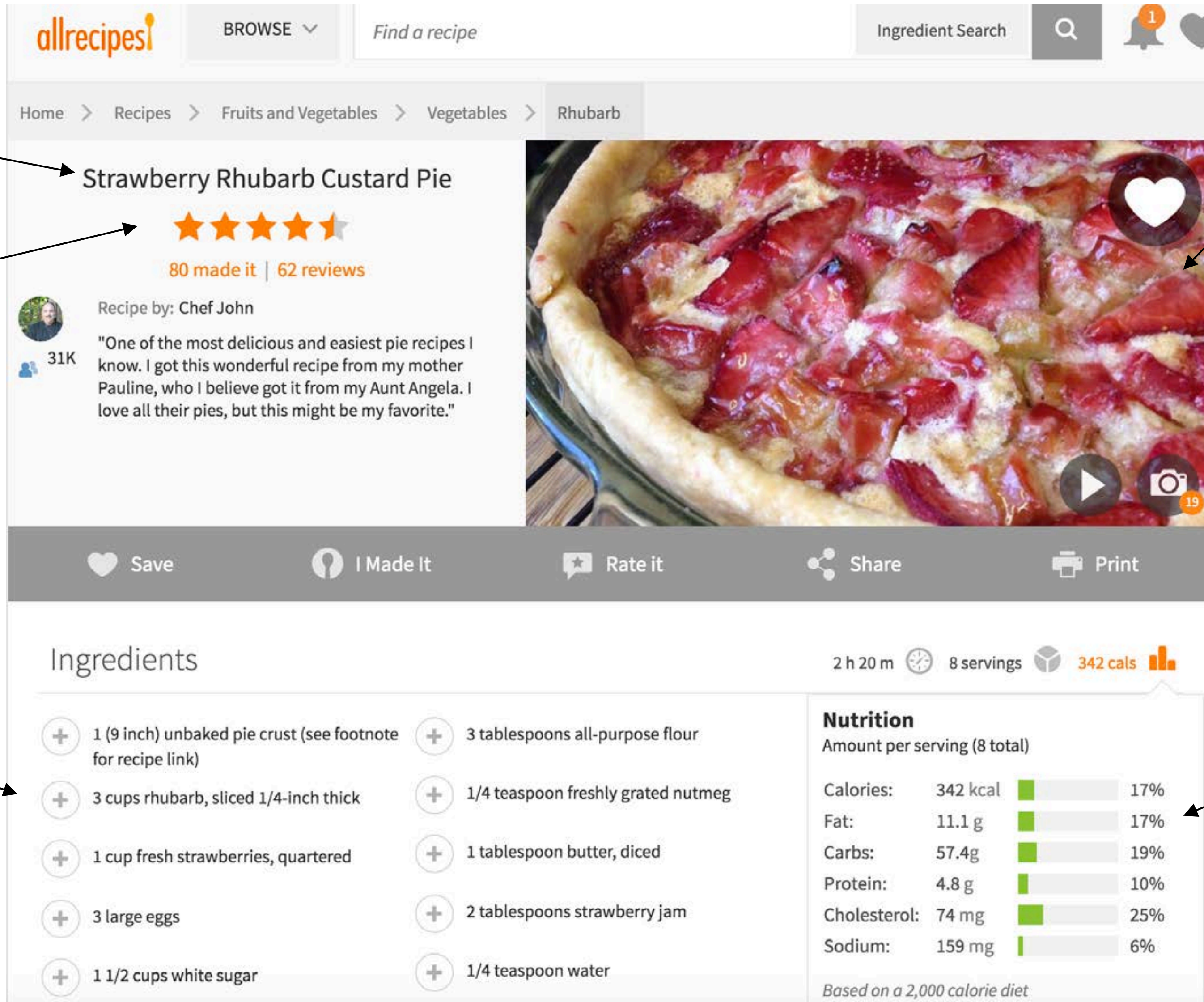
Elsweiler, D.*, Trattner, C.* and Harvey, M. (* equal contribution). **Exploiting Food Choice Biases for Healthier Recipe Recommendation**. In Proceedings of the ACM SIGIR Conference (SIGIR), 2017.

Which one of the two would you choose?

Title

User feedback

Image

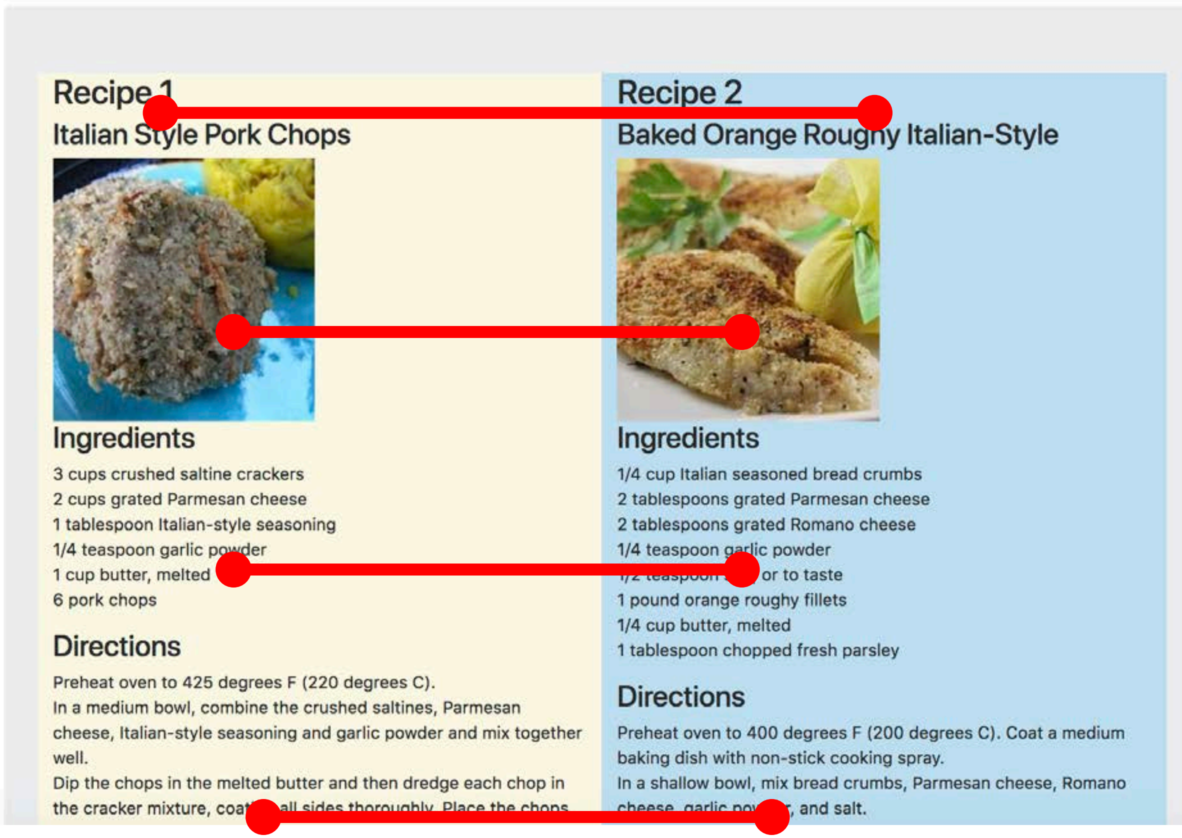


Ingredients

Nutrition

User Study

Q: Which one of the two would you choose?



User Study 1

User Study 2

Accuracy				
Feature Set	Rand.For.	Logistic	Naive Bay.	Num. Feat.
Study 1 (Instances = 1102)				
Title	49.18%	48.63%	49.36%	54
Image	**64.25%**	**58.43%**	**60.16%**	10
Ingredients	62.25%	57.89%	55.71%	12
Nutr.	**64.25%**	58.25%	54.99%	12
Pop. & Appr	64.15%	55.53%	57.89%	8
Best (Top-10)	64.24%	60.61%	60.79%	10
All	64.33%	63.06%	63.52%	96
Study 2 (Instances = 1181)				
Title	48.43%	48.09%	49.87%	54
Image	**66.21%**	**61.64%**	**59.61%**	10
Ingredients	64.35%	60.96%	53.51%	12
Nutr.	65.96%	58.59%	54.19%	12
Pop. & Appr	65.96%	59.52%	58.59%	8
Best (Top-10)	66.04%	64.86%	61.05%	10
All	66.04%	64.86%	61.05%	96

Nudging People Towards Healthy Food Choices

Developed an algorithm that can nudge people towards healthy food choices through images ☺

Less fat

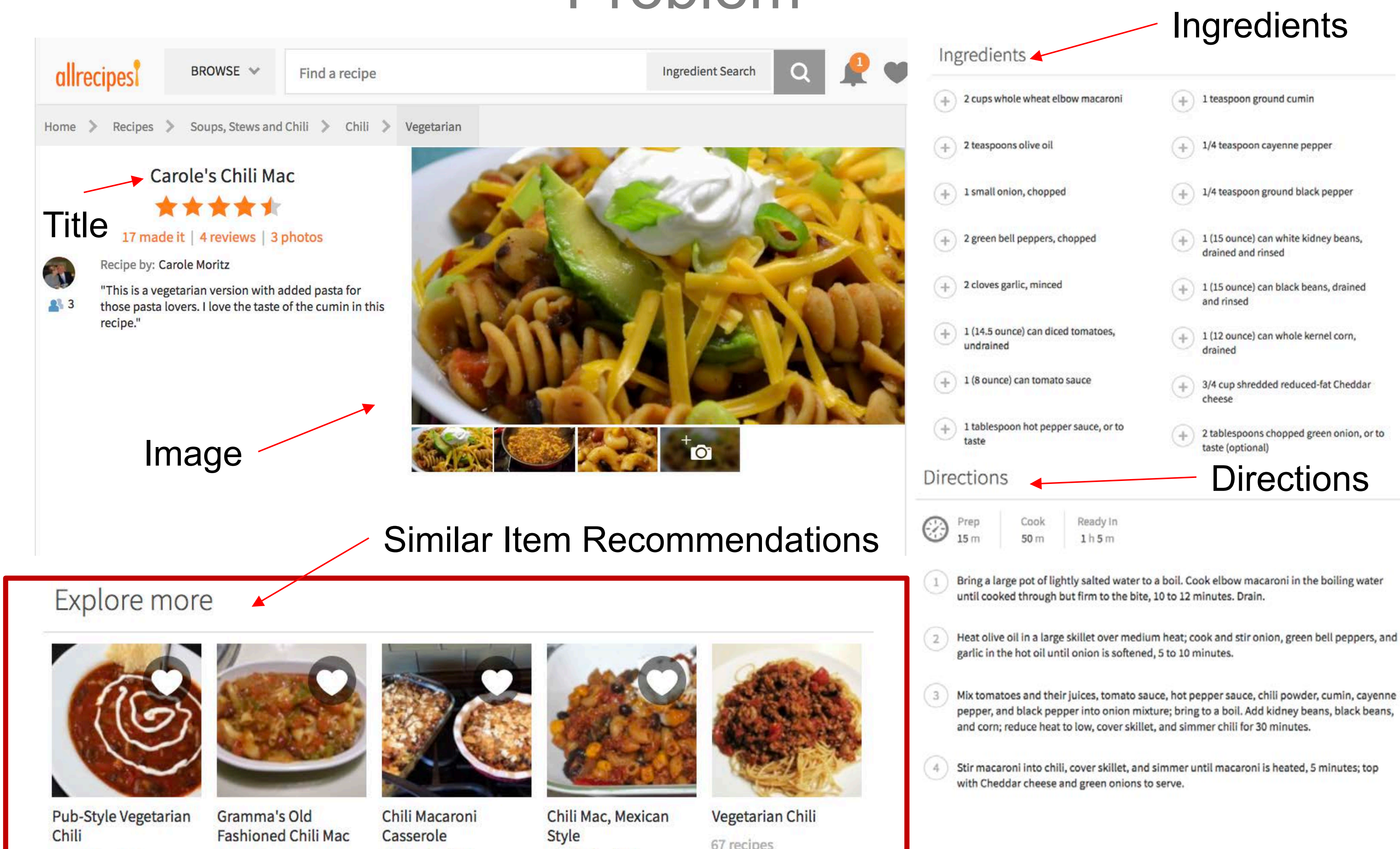
More fat

Exploiting Food Choice Biases for Healthier Recipe Recommendation. Elsweiler, D.*, Trattner, C.* and Harvey, M. (* equal contribution). In Proceedings of the ACM SIGIR Conference (SIGIR), 2017.

Part 8:
Recommending Similar Food

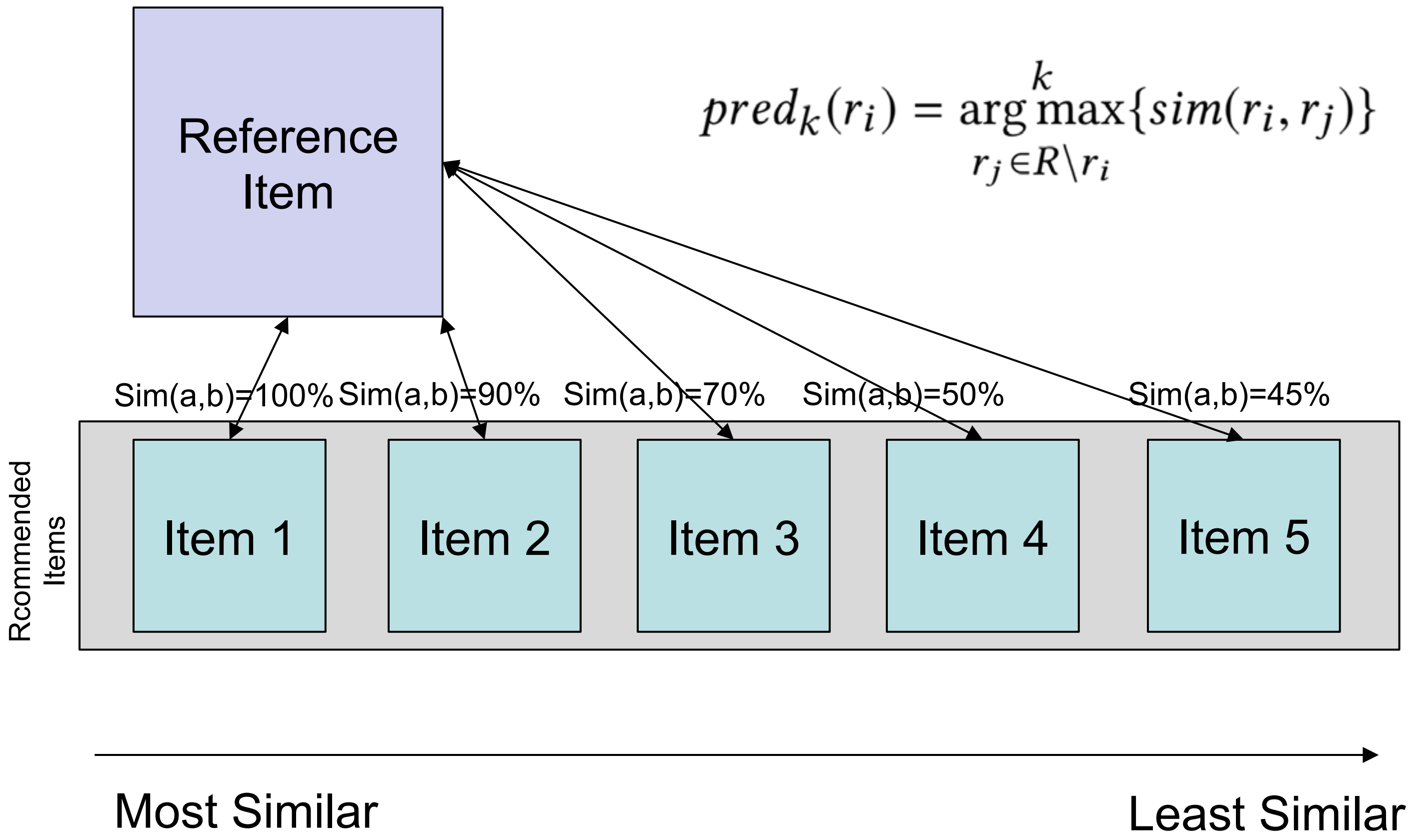
How can I build a simple similar Item recommender for food?

Problem



Ingredients
Title
Image
Directions
Similar Item Recommendations
allrecipes
BROWSE
Find a recipe
Ingredient Search
Home > Recipes > Soups, Stews and Chili > Chili > Vegetarian
Carole's Chili Mac
17 made it | 4 reviews | 3 photos
Recipe by: Carole Moritz
"This is a vegetarian version with added pasta for those pasta lovers. I love the taste of the cumin in this recipe."
Ingredients
2 cups whole wheat elbow macaroni
2 teaspoons olive oil
1 small onion, chopped
2 green bell peppers, chopped
2 cloves garlic, minced
1 (14.5 ounce) can diced tomatoes, undrained
1 (8 ounce) can tomato sauce
1 tablespoon hot pepper sauce, or to taste
1 teaspoon ground cumin
1/4 teaspoon cayenne pepper
1/4 teaspoon ground black pepper
1 (15 ounce) can white kidney beans, drained and rinsed
1 (15 ounce) can black beans, drained and rinsed
1 (12 ounce) can whole kernel corn, drained
3/4 cup shredded reduced-fat Cheddar cheese
2 tablespoons chopped green onion, or to taste (optional)
Directions
Prep 15 m
Cook 50 m
Ready In 1 h 5 m
1 Bring a large pot of lightly salted water to a boil. Cook elbow macaroni in the boiling water until cooked through but firm to the bite, 10 to 12 minutes. Drain.
2 Heat olive oil in a large skillet over medium heat; cook and stir onion, green bell peppers, and garlic in the hot oil until onion is softened, 5 to 10 minutes.
3 Mix tomatoes and their juices, tomato sauce, hot pepper sauce, chili powder, cumin, cayenne pepper, and black pepper into onion mixture; bring to a boil. Add kidney beans, black beans, and corn; reduce heat to low, cover skillet, and simmer chili for 30 minutes.
4 Stir macaroni into chili, cover skillet, and simmer until macaroni is heated, 5 minutes; top with Cheddar cheese and green onions to serve.
Explore more
Pub-Style Vegetarian Chili
Gramma's Old Fashioned Chili Mac
Chili Macaroni Casserole
Chili Mac, Mexican Style
Vegetarian Chili
67 recipes

Problem



$$pred_k(r_i) = \underset{r_j \in R \setminus r_i}{\arg\max^k} \{sim(r_i, r_j)\}$$

Paper

Trattner, C. and Jannach, D. **Learning to Recommend Similar Items from Human Judgements**. User Modeling and User-Adapted Interaction Journal. 2019.

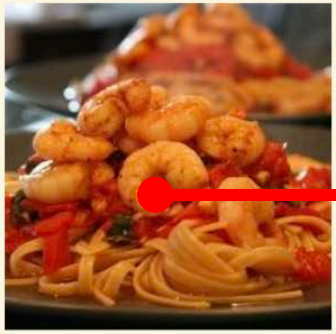
Research Questions

- ***RQ1.*** Which types of features and which specific features determine the similarity between items as perceived by users?
- ***RQ2.*** Which specific combination of features is suited to predicting user-perceived similarity levels?
- ***RQ3.*** Do models with higher prediction accuracy lead to a higher perceived item similarity?
- ***RQ4.*** How do users assess the usefulness of recommendations that are based on different similarity functions?

What makes recipes similar?

sim(a,b)

Linguine Pasta with Shrimp and Tomatoes



sim(a,b)

Ingredients

2 tablespoons olive oil
3 cloves garlic, minced
4 cups diced tomatoes
1 cup dry white wine
2 tablespoons butter
salt and black pepper to taste
1 (16 ounce) package linguine pasta
1 pound peeled and deveined medium shrimp
1 teaspoon Cajun seasoning
2 tablespoons olive oil

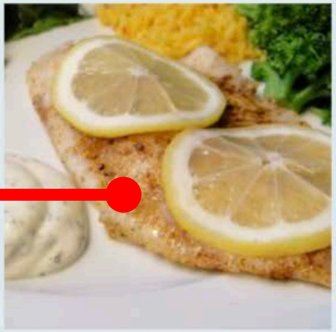
sim(a,b)

Directions

Heat 2 tablespoons of olive oil in a large saucepan over medium heat. Stir in the garlic, cook 2 minutes. Add the tomatoes, and wine. Bring to a simmer and cook 30 minutes, stirring frequently. Once the tomatoes have simmered into a sauce, stir in the butter and season with salt and pepper. Fill a large pot with lightly-salted water, bring to a rolling boil, stir in the linguine and return to a boil. Cook the pasta uncovered, stirring occasionally, until the pasta has cooked through but is still firm to the bite,

sim(a,b)

Hudson's Baked Tilapia with Dill Sauce



Ingredients

4 (4 ounce) fillets tilapia
salt and pepper to taste
1 tablespoon Cajun seasoning, or to taste
1 lemon, thinly sliced
1/4 cup mayonnaise
1/2 cup sour cream
1/8 teaspoon garlic powder
1 teaspoon fresh lemon juice
2 tablespoons chopped fresh dill

Directions

Preheat the oven to 350 degrees F (175 degrees C). Lightly grease a 9x13 inch baking dish.
Season the tilapia fillets with salt, pepper and Cajun seasoning on both sides. Arrange the seasoned fillets in a single layer in the baking dish.
Place a layer of lemon slices over the fish fillets. I usually use about 2 slices on each piece so that it covers most of the surface of the fish.
Bake uncovered for 15 to 20 minutes in the preheated oven, or until fish flakes easily with a fork.

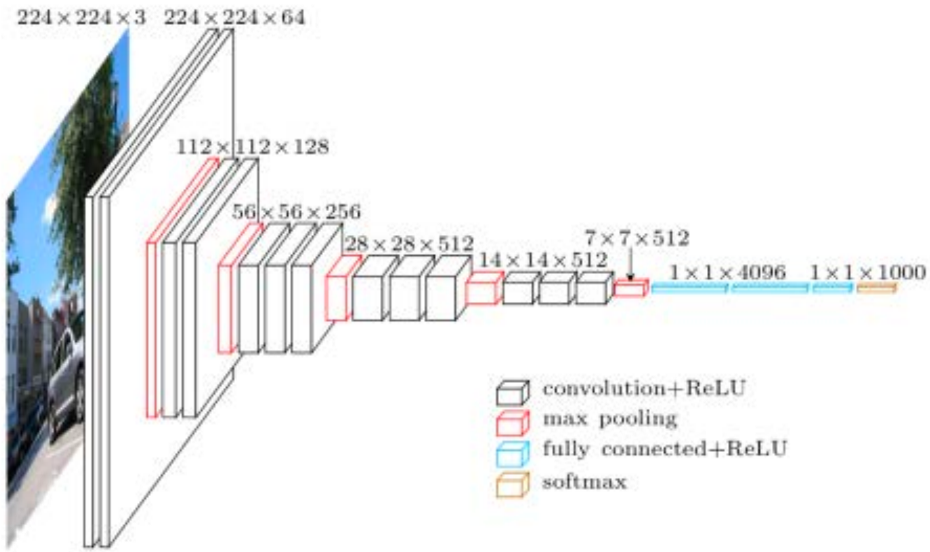
Features for Similar **Recipe** Recommendations

Table 1: Similarity metrics computed based on recipe titles, images, ingredients and cooking directions.

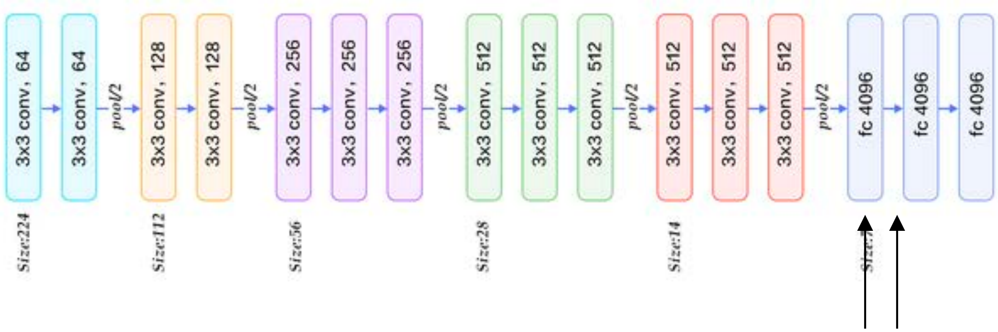
Name	Metric	Explanation
Title:LV	$sim(r_i, r_j) = 1 - \lvert dist_{LEV}(r_i, r_j)\rvert$	Title Levenshtein distance-based similarity
Title:JW	$sim(r_i, r_j) = 1 - \lvert dist_{JW}(r_i, r_j)\rvert$	Title Jaro-Winkler distance-based similarity
Title:LCS	$sim(r_i, r_j) = 1 - \lvert dist_{LCS}(r_i, r_j)\rvert$	Title Least Common Subsequence distance-based similarity
Title:BI	$sim(r_i, r_j) = 1 - \lvert dist_{BI}(r_i, r_j)\rvert$	Title Bi-gram distance-based similarity
Title:LDA	$sim(r_i, r_j) = \frac{LDA(Title(r_i))) \cdot LDA(Title(r_j))}{\lVert LDA(Title(r_i))\rVert \lVert LDA(Title(r_j))\rVert}$	Title LDA cosine-based similarity (LDA = LDA vector)
Image:BR	$sim(r_i, r_j) = 1 - \lvert BR(r_i) - BR(r_j)\rvert$	Image Brightness distance-based similarity
Image:SH	$sim(r_i, r_j) = 1 - \lvert SH(r_i) - SH(r_j)\rvert$	Image Sharpness distance-based similarity
Image:CO	$sim(r_i, r_j) = 1 - \lvert CO(r_i) - CO(r_j)\rvert$	Image Contrast distance-based similarity
Image:COL	$sim(r_i, r_j) = 1 - \lvert COL(r_i) - COL(r_j)\rvert$	Image Colorfulness distance-based similarity
Image:EN	$sim(r_i, r_j) = 1 - \lvert EN(r_i) - EN(r_j)\rvert$	Image Entropy distance-based similarity
Image:EMB	$sim(r_i, r_j) = \frac{EMB(r_i) \cdot EMB(r_j)}{\lVert EMB(r_i)\rVert \lVert EMB(r_j)\rVert}$	Image Embedding cosine-based similarity (EMB= image embedding vector)
Ing:COS	$sim(r_i, r_j) = \frac{amount(Ing(r_i)) \cdot amount(Ing(r_j))}{\lVert amount(Ing(r_i))\rVert \lVert amount(Ing(r_j))\rVert}$	Ingredients Cosine similarity (amount-based weighting in grams per 100g of a meal)
Ing:JACC	$sim(r_i, r_j) = \frac{\{Ing(r_i)\} \cap \{Ing(r_j)\}}{\{Ing(r_i)\} \cup \{Ing(r_j)\}}$	Ingredients Jaccard similarity
Ing:TFIDF	$sim(r_i, r_j) = \frac{TFIDF(Ing(r_i)) \cdot TFIDF(Ing(r_j))}{\lVert TFIDF(Ing(r_i))\rVert \lVert TFIDF(Ing(r_i))\rVert}$	Ingredients Text-based cosine similarity (TFIDF = TF-IDF weighted vector)
Ing:LDA	$sim(r_i, r_j) = \frac{LDA(Ing(r_i)) \cdot LDA(Ing(r_j))}{\lVert LDA(Ing(r_i))\rVert \lVert LDA(Ing(r_j))\rVert}$	Ingredients LDA-based cosine similarity (LDA = LDA vector)
Dir:TFIDF	$sim(r_i, r_j) = \frac{TFIDF(Dir(r_i)) \cdot TFIDF(Dir(r_j))}{\lVert TFIDF(Dir(r_i))\rVert \lVert TFIDF(Dir(r_j))\rVert}$	Cooking Directions Text-based cosine similarity (TFIDF = TF-IDF weighted vector)
Dir:LDA	$sim(r_i, r_j) = \frac{LDA(Dir(r_i)) \cdot LDA(Dir(r_j))}{\lVert LDA(Dir(r_i))\rVert \lVert LDA(Dir(r_j))\rVert}$	Cooking Directions LDA cosine-based similarity (LDA = LDA vector)

Example Image Features

DNN Images Features: VGG 16



$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}},$$



Take these layers for classification (fc1 or fc2)

VGG16 Implementation

```python
#   ctrattner Oct 16 2018
#   VGG16 feature extraction
#import matplotlib.pyplot as plt
import numpy as np
np.random.seed(2018)
from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing import image
from keras.models import Model
import glob
import os

# load pre-trained model
base_model = VGG16(weights='imagenet')
# pre-process the image
images = glob.glob("/Users/ctrattner/Desktop/Research/Movie-Data/images/*.jpg")

i = 0
for img_ in images:
    print(img_)
    i = i + 1
    head, tail = os.path.split(img_)
    print(tail)
    print(i)
    img = image.load_img(img_, target_size=(224, 224))
    img = image.img_to_array(img)
    img = np.expand_dims(img, axis=0)
    img = preprocess_input(img)
    # define model from base model for feature extraction from fc1 layer
    model = Model(input=base_model.input, output=base_model.get_layer('fc1').output)
    # obtain the output of fc1 layer
    fc1_features = model.predict(img)
    print("Feature vector dimensions: ",fc1_features)
    f = open('/Users/ctrattner/Desktop/test.out', "a")
    f.write(tail+",")
    np.savetxt(f, fc1_features, delimiter=',',fmt='%.16f')
    f.close()
```

How did we collect the ground truth?

A: Amazon’s Mechanical Turk

Amazon Mechanical Turk

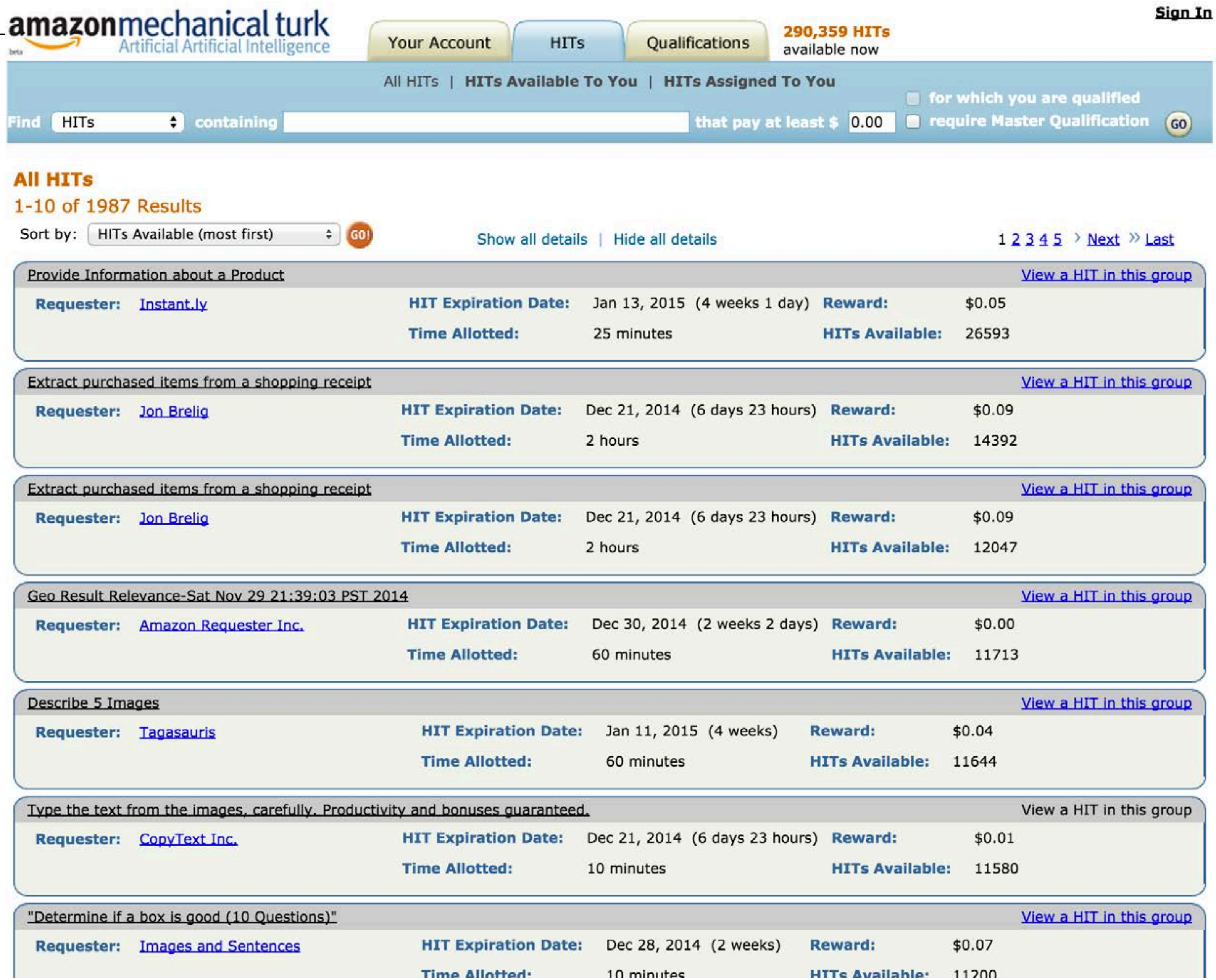
URL: https://www.mturk.com/

- Crowdsourcing platform for micro task
- Founded March 2007- 100,000 workers in over 100 countries.
- 2011 - over 500,000 workers from over 190 countries in January 2011.
- Tasks = Hits
- Workers = Turkers

What do I have to do

...as a turker?

Mtruk.com - Worker



amazonmechanical turk
Artificial Artificial Intelligence
beta
Your Account
HITs
Qualifications
290,359 HITs
available now
Sign In
All HITs | HITs Available To You | HITs Assigned To You
Find HITs containing that pay at least $ 0.00
for which you are qualified
require Master Qualification
GO
All HITs
1-10 of 1987 Results
Sort by: HITs Available (most first)
GO!
Show all details | Hide all details
1 2 3 4 5 Next Last
Provide Information about a Product
View a HIT in this group
Requester: Instant.ly
HIT Expiration Date: Jan 13, 2015 (4 weeks 1 day)
Reward: $0.05
Time Allotted: 25 minutes
HITs Available: 26593
Extract purchased items from a shopping receipt
View a HIT in this group
Requester: Jon Brelig
HIT Expiration Date: Dec 21, 2014 (6 days 23 hours)
Reward: $0.09
Time Allotted: 2 hours
HITs Available: 14392
Extract purchased items from a shopping receipt
View a HIT in this group
Requester: Jon Brelig
HIT Expiration Date: Dec 21, 2014 (6 days 23 hours)
Reward: $0.09
Time Allotted: 2 hours
HITs Available: 12047
Geo Result Relevance-Sat Nov 29 21:39:03 PST 2014
View a HIT in this group
Requester: Amazon Requester Inc.
HIT Expiration Date: Dec 30, 2014 (2 weeks 2 days)
Reward: $0.00
Time Allotted: 60 minutes
HITs Available: 11713
Describe 5 Images
View a HIT in this group
Requester: Tagasauris
HIT Expiration Date: Jan 11, 2015 (4 weeks)
Reward: $0.04
Time Allotted: 60 minutes
HITs Available: 11644
Type the text from the images, carefully. Productivity and bonuses guaranteed.
View a HIT in this group
Requester: CopyText Inc.
HIT Expiration Date: Dec 21, 2014 (6 days 23 hours)
Reward: $0.01
Time Allotted: 10 minutes
HITs Available: 11580
"Determine if a box is good (10 Questions)"
View a HIT in this group
Requester: Images and Sentences
HIT Expiration Date: Dec 28, 2014 (2 weeks)
Reward: $0.07

amazonmechanical turk Artificial Artificial Intelligence

Your Account | HITs | Qualifications

290,366 HITs available now

Sign In

All HITs | HITs Available To You | HITs Assigned To You

Find HITs containing ______ that pay at least $ 0.00 ☐ for which you are qualified ☐ require Master Qualification GO

Timer: 00:00:00 of 25 minutes

Want to work on this HIT? Accept HIT

Want to see other HITs? Skip HIT

Total Earned: Unavailable
Total HITs Submitted: 0

Provide Information about a Product

Requester: Instant.ly **Reward:** $0.05 per HIT **HITs Available:** 26592 **Duration:** 25 minutes

Qualifications Required: Total approved HITs is not less than 5000; Product Image Data Collection is not less than 90; HIT approval rate (%) is not less than 99; Location is US

FAQ new

Send Feedback

Provide Information about a Product

Click to show/hide instructions

External Link: http://s3.amazonaws.com/sb001/survey/media/images/d7a755be-7f66-4ccd-84d1-11e7c5c291ea_original.jpg

1

How is the product picture provided? (required)

- ◯ Picture is good or partially good to use (even rotated)
- ◯ Picture does not load, broken link
- ◯ Picture loads but overall resolution is too low to view (only check this IF none of the requested attribute can be identified)
- ◯ Picture is flipped or corrupted, all black, etc
- ◯ Others (if checked, pls use bottom Comment box to tell us why)

Note: If some of the attributes are clear and some aren't, please check the first choice and provide as many attributes you can identify based upon the picture given.

Brand Name (required)

______ ☐ N/A

Product Name (required)

______ ☐ N/A

Dashboard - Nicole (If you're not Nicole, click here.)

Total Earnings (What's this?)

Rewards You Have Earned	Value
Approved HITs	$15.33
Bonuses	$0.00
Total Earnings	$15.33

Your HIT Status (What's this?)

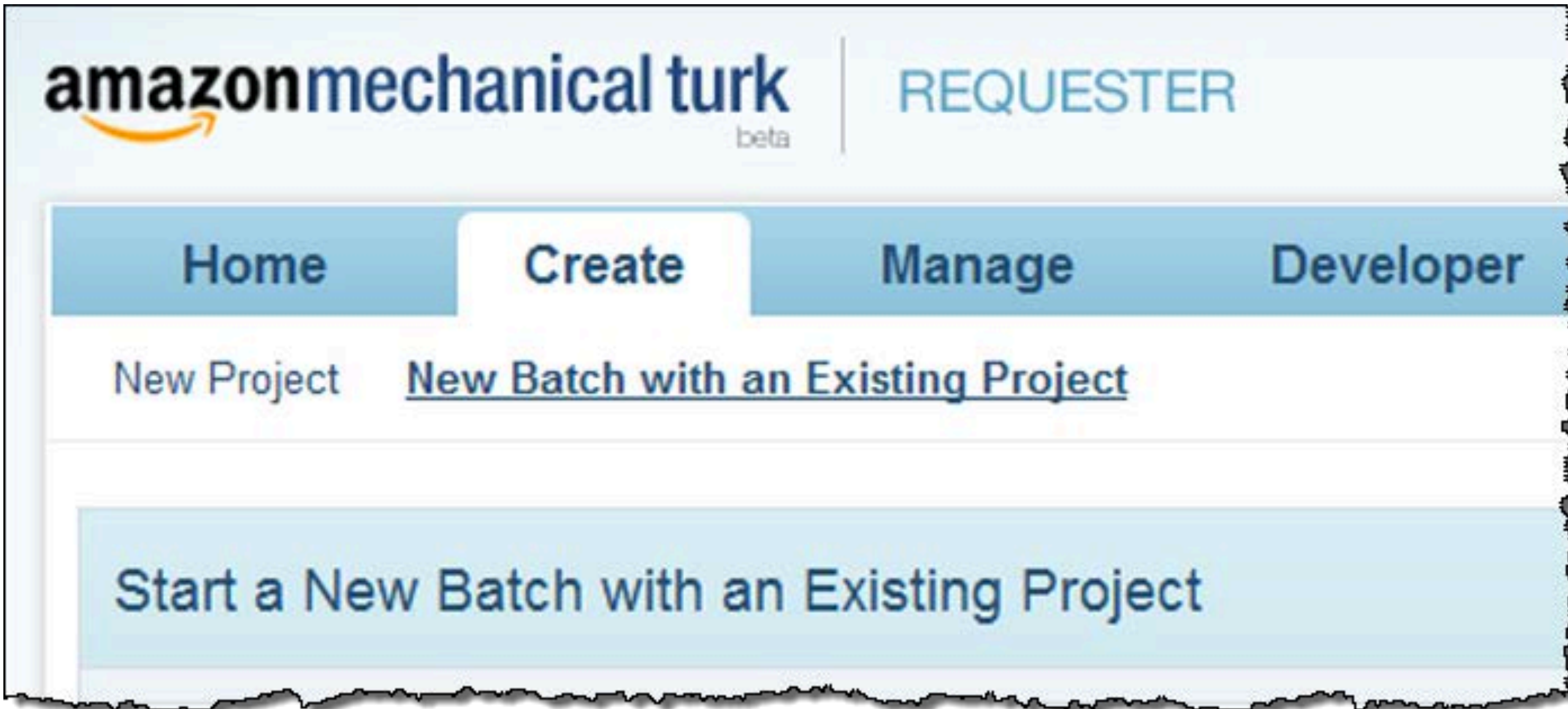
Date	Submitted	Approved	Rejected	Pending	Earnings
Today	4	0	0	4	$0.00
Mar 8, 2010	35	5	2	28	$0.27
Mar 7, 2010	79	79	0	0	$11.85
Mar 6, 2010	22	22	0	0	$3.21

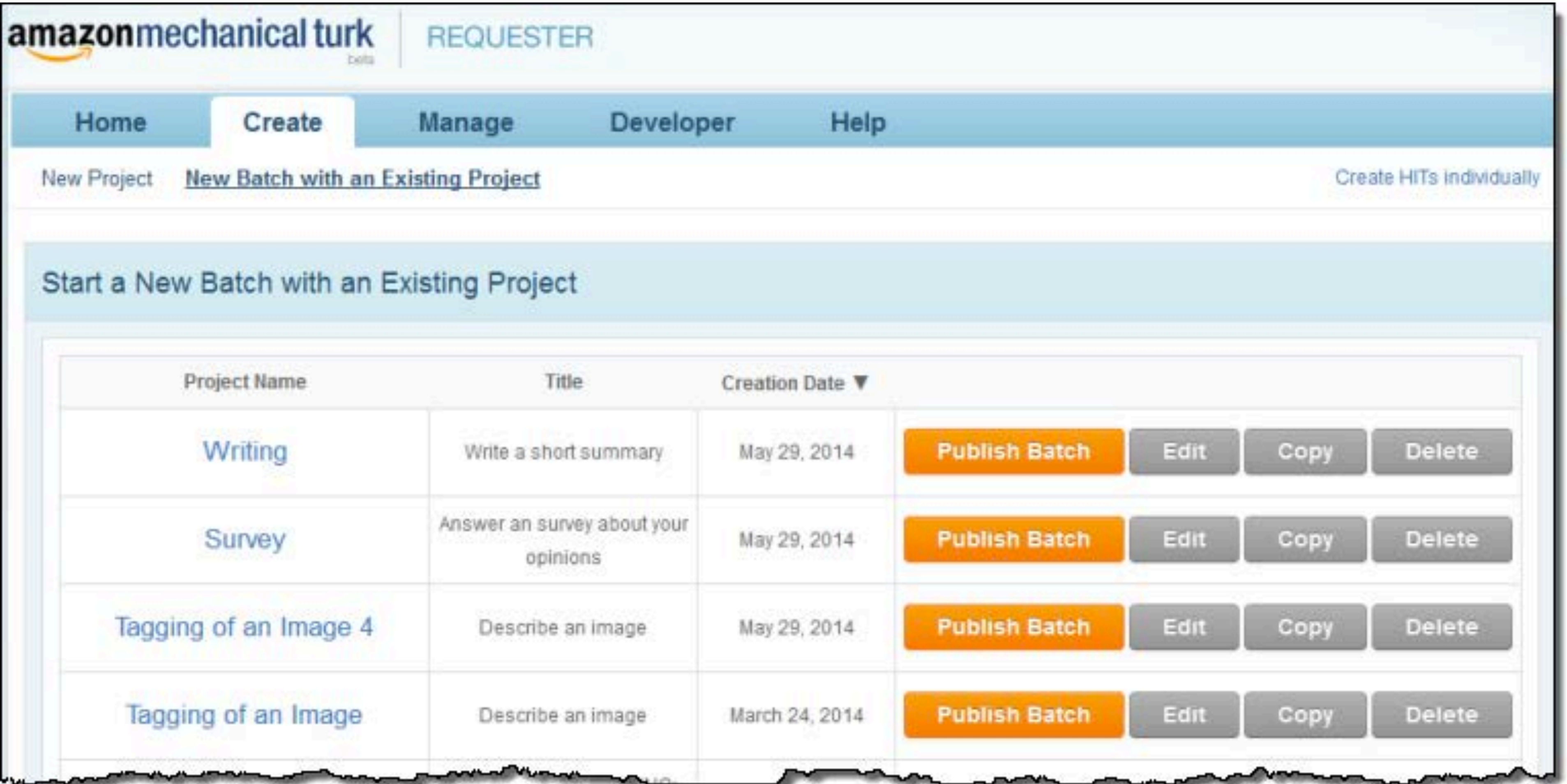
View more...

What do I have to do

...as a hit requester?

Mtruk.com - Requester


amazonmechanical turk
beta
REQUESTER
Home
Create
Manage
Developer
New Project
New Batch with an Existing Project
Start a New Batch with an Existing Project


amazonmechanical turk
beta
REQUESTER
Home
Create
Manage
Developer
Help
New Project
New Batch with an Existing Project
Create HITs individually
Start a New Batch with an Existing Project
Project Name
Title
Creation Date ▼
Writing
Write a short summary
May 29, 2014
Publish Batch
Edit
Copy
Delete
Survey
Answer an survey about your opinions
May 29, 2014
Tagging of an Image 4
Describe an image
May 29, 2014
Tagging of an Image
Describe an image
March 24, 2014

Preview HITs

1 Select HIT Template 2 Upload Input Data 3 Preview 4 Confirm and Publish

This is how your HIT will look to Workers. Make sure that any variables in the HIT are correctly replaced by your input data, then click "Next".

Tagging of an Image

Describe an image

Requester: **Reward:** $0.05 per HIT **HITs available:** 3 **Duration:** 1 Hours

Qualifications Required: Masters has been granted

HIT Preview

Instructions

You must provide 3 tags for the main subject in this image.

- Each tag must be a single word.
- No tag can be longer than 25 characters.
- The tags must describe the image, the contents of the image, or some relevant context.

Tag 1:

Tag 2:

Tag 3:

Submit

Showing HIT 1 of 3 Next HIT

Cancel Next

Confirm and Publish Batch

1 Select HIT Template 2 Upload Input Data 3 Preview 4 Confirm and Publish

Please review the information about the HIT batch, then click "Publish HITs".

Tagging of an Image

Batch Summary

Batch Name: Tagging of an Image   Description: Please view and write a tag for an image

Batch Properties

Title:	Describe an image
Description:	Please view and write a tag for an image
Batch expires in:	7 Days
Results are auto-approved and workers are paid after:	8 Hours
Master Qualification:	Masters

HITs

Number of HITs in this batch:	3
Number of assignments per HIT:	x 1
Total number of assignments in this batch:	**3**

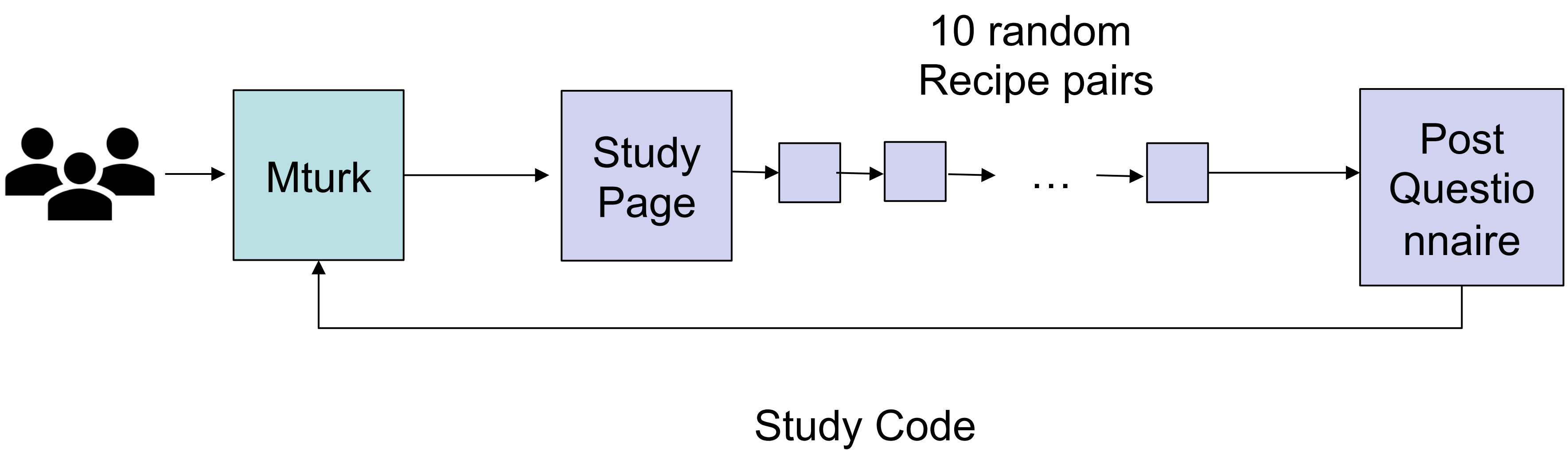
Cost

Reward per Assignment:	$0.050	
	x 3	*(total number of assignments in this batch)*
Estimated Total Reward:	$0.150	
Estimated Fees to Mechanical Turk:	+ $0.045	*(fees paid to Mechanical Turk) (fee details)*
Estimated Total Cost:	**$0.195**	*(this is the amount that will be deducted from your Available Balance when you click "Publish HITs")*
Your Available Balance:	$10,000.000	*(before clicking "Publish HITs")*
Your Projected Balance:	$9,999.805	*(after clicking "Publish HITs")*

Back   Publish HITs


Click on the name of the batch to see more details
Batches in progress (2)
'Image Tagging' @ 03 Oct 12:49
Results
Cancel this batch
Created:
October 03, 2010
Assignments Completed:
0 / 1,000
Time Elapsed:
about 5 hours
Estimated Completion Time:
Not yet available
Average Time per Assignment:
Not yet available
Effective Hourly Rate:
Not Yet Available
Batch Progress:
0% submitted
100% published
'Find a store' @ 27 Sep 07:54
Results
Cancel this batch
Created:
September 27, 2010
Assignments Completed:
2 / 7
Time Elapsed:
6 days
Estimated Completion Time:
Not yet available
Average Time per Assignment:
4 Seconds
Effective Hourly Rate:
$18.00
Batch Progress:
29% submitted
100% published

User Study Design: Ground truth study



Recipe Study

[Task 1 / 10]

To what extent are the two recipes shown below similar?

1 (Completely different) — 2 — 3 — 4 — 5 (They are more or less the same)

(Scroll to the end of page to get to the next question)

Linguine Pasta with Shrimp and Tomatoes

Ingredients

2 tablespoons olive oil
3 cloves garlic, minced
4 cups diced tomatoes
1 cup dry white wine
2 tablespoons butter
salt and black pepper to taste
1 (16 ounce) package linguine pasta
1 pound peeled and deveined medium shrimp
1 teaspoon Cajun seasoning
2 tablespoons olive oil

Directions

Heat 2 tablespoons of olive oil in a large saucepan over medium heat. Stir in the garlic, cook 2 minutes. Add the tomatoes, and wine. Bring to a simmer and cook 30 minutes, stirring frequently. Once the tomatoes have simmered into a sauce, stir in the butter and season with salt and pepper. Fill a large pot with lightly-salted water, bring to a rolling boil, stir in the linguine and return to a boil. Cook the pasta uncovered, stirring occasionally, until the pasta has cooked through but is still firm to the bite,

Hudson's Baked Tilapia with Dill Sauce

Ingredients

4 (4 ounce) fillets tilapia
salt and pepper to taste
1 tablespoon Cajun seasoning, or to taste
1 lemon, thinly sliced
1/4 cup mayonnaise
1/2 cup sour cream
1/8 teaspoon garlic powder
1 teaspoon fresh lemon juice
2 tablespoons chopped fresh dill

Directions

Preheat the oven to 350 degrees F (175 degrees C). Lightly grease a 9x13 inch baking dish.
Season the tilapia fillets with salt, pepper and Cajun seasoning on both sides. Arrange the seasoned fillets in a single layer in the baking dish.
Place a layer of lemon slices over the fish fillets. I usually use about 2 slices on each piece so that it covers most of the surface of the fish.
Bake uncovered for 15 to 20 minutes in the preheated oven, or until fish flakes easily with a fork.

Results

Recipe Study: 400 turker

with 98% hit accept rate and min. 500 hits in the past

In total: 4,000 user estimates

Recipe Results: User Characteristics

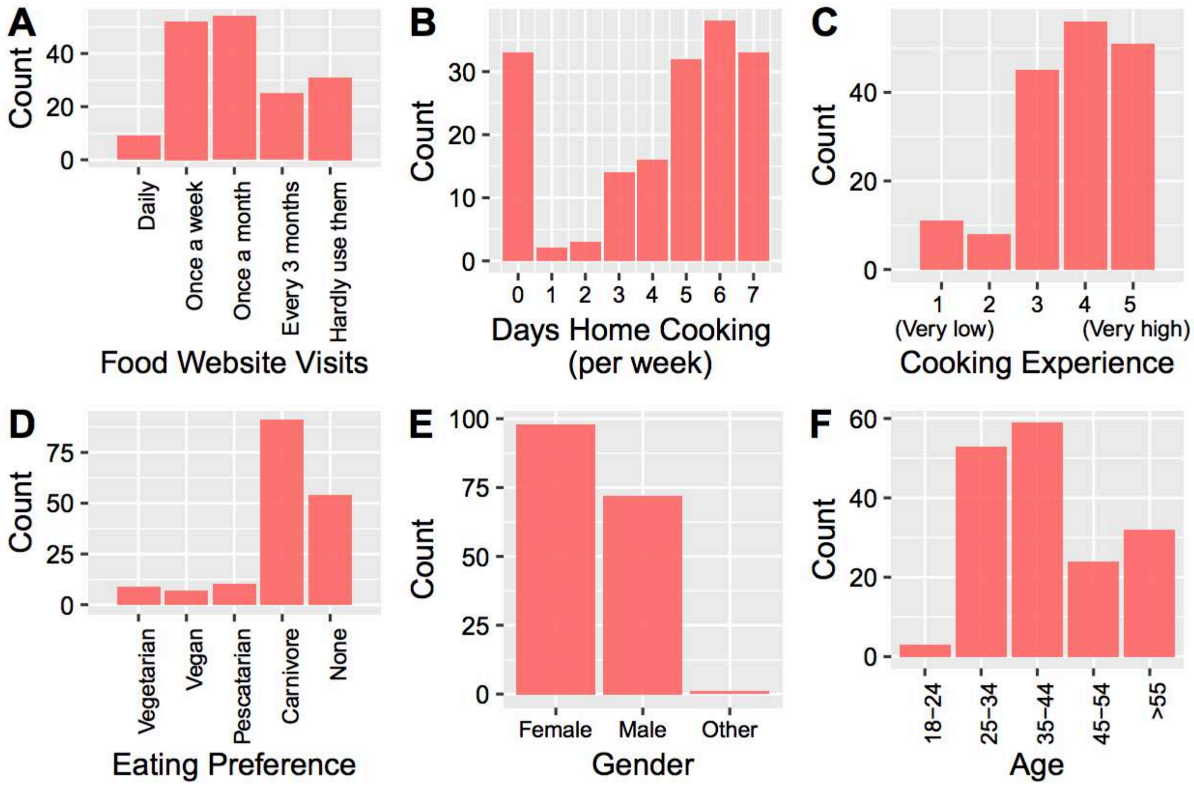


Figure 2: Crowdworker characteristics of the similarity assessment study.

~45% of all users passed the attention check

RQ1. Which types of features and which specific features determine the similarity between items as perceived by users?

Recipe Results: Feature Correlations

Table 2: Similarity metric correlation (Spearman) with user similarity estimates. ρ_{pass} indicate correlations with users who passed the attention check, while ρ_{all} denotes all users. Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Metric	ρ_{pass}	ρ_{all}
Title:LV	0.48^{***}	0.38^{***}
Title:JW	0.46^{***}	0.35^{***}
Title:LCS	0.50^{***}	0.40^{***}
Title:BI	0.48^{***}	0.38^{***}
Title:LDA	0.22^{***}	0.19^{***}
Image:BR	0.18^{**}	0.14^{*}
Image:SH	0.16^{*}	0.11^{*}
Image:CO	0.29^{***}	0.20^{***}
Image:COL	0.09^{*}	0.07^{*}
Image:EN	0.34^{***}	0.28^{***}
Image:EMB	0.44^{***}	0.34^{***}
Ing:COS	0.54^{***}	0.44^{***}
Ing:JACC	0.51^{***}	0.41^{***}
Ing:TFIDF	$\mathbf{0.56}^{***}$	$\mathbf{0.44}^{***}$
Ing:LDA	0.45^{***}	0.36^{***}
Dir:TFIDF	0.50^{***}	0.40^{***}
Dir:LDA	0.54^{***}	0.43^{***}

Higher is better
1 = 100%

Recipe Results: Cue Usage

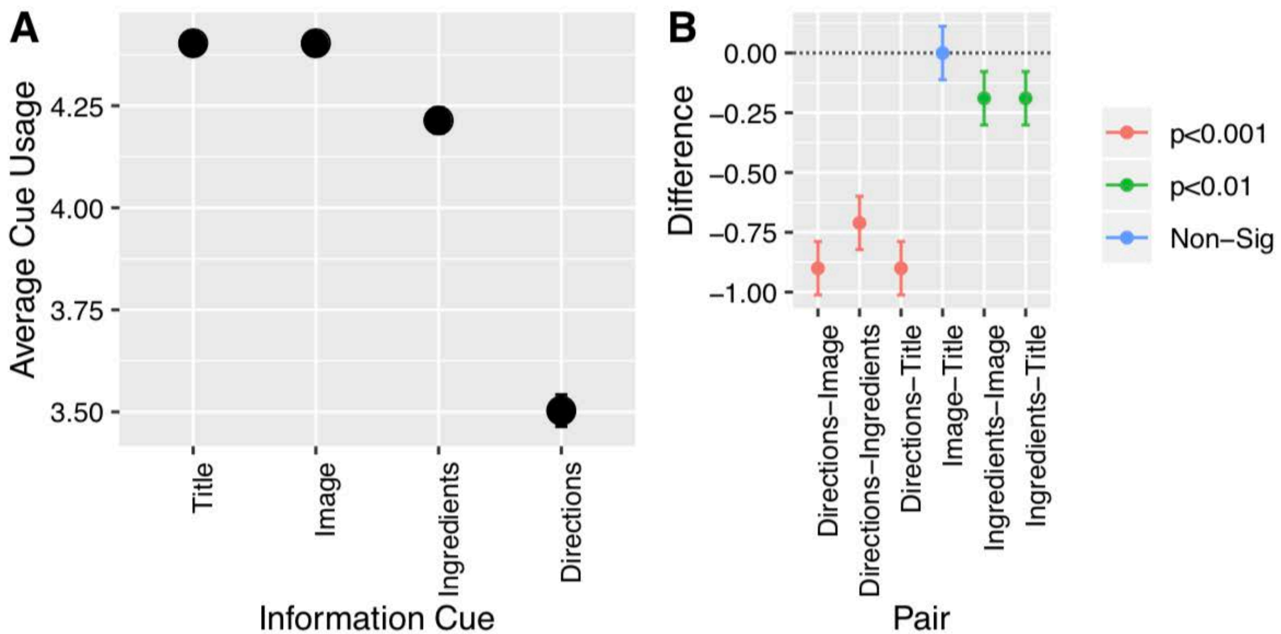


Figure 3: (A) Information cue usage (means and std. errors) and (B) Pairwise comparison. Scale: 1 (not at all) — 5 (totally agree).

RQ2. Which specific combination of features is suited to predicting user-perceived similarity levels?

Recipe Results: Machine Learning performance when features are combined

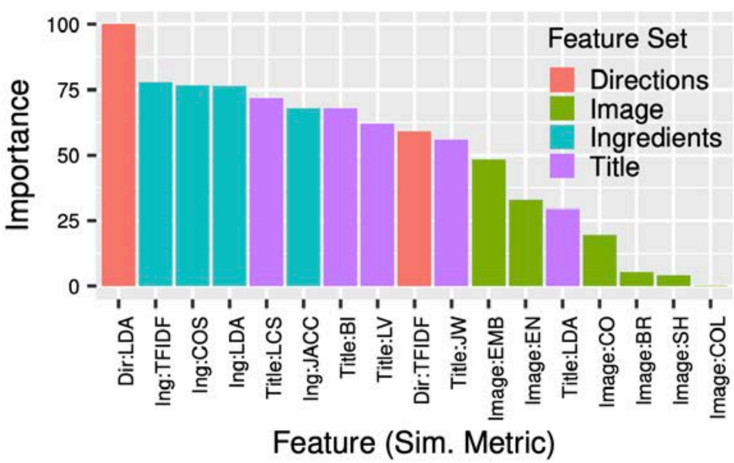
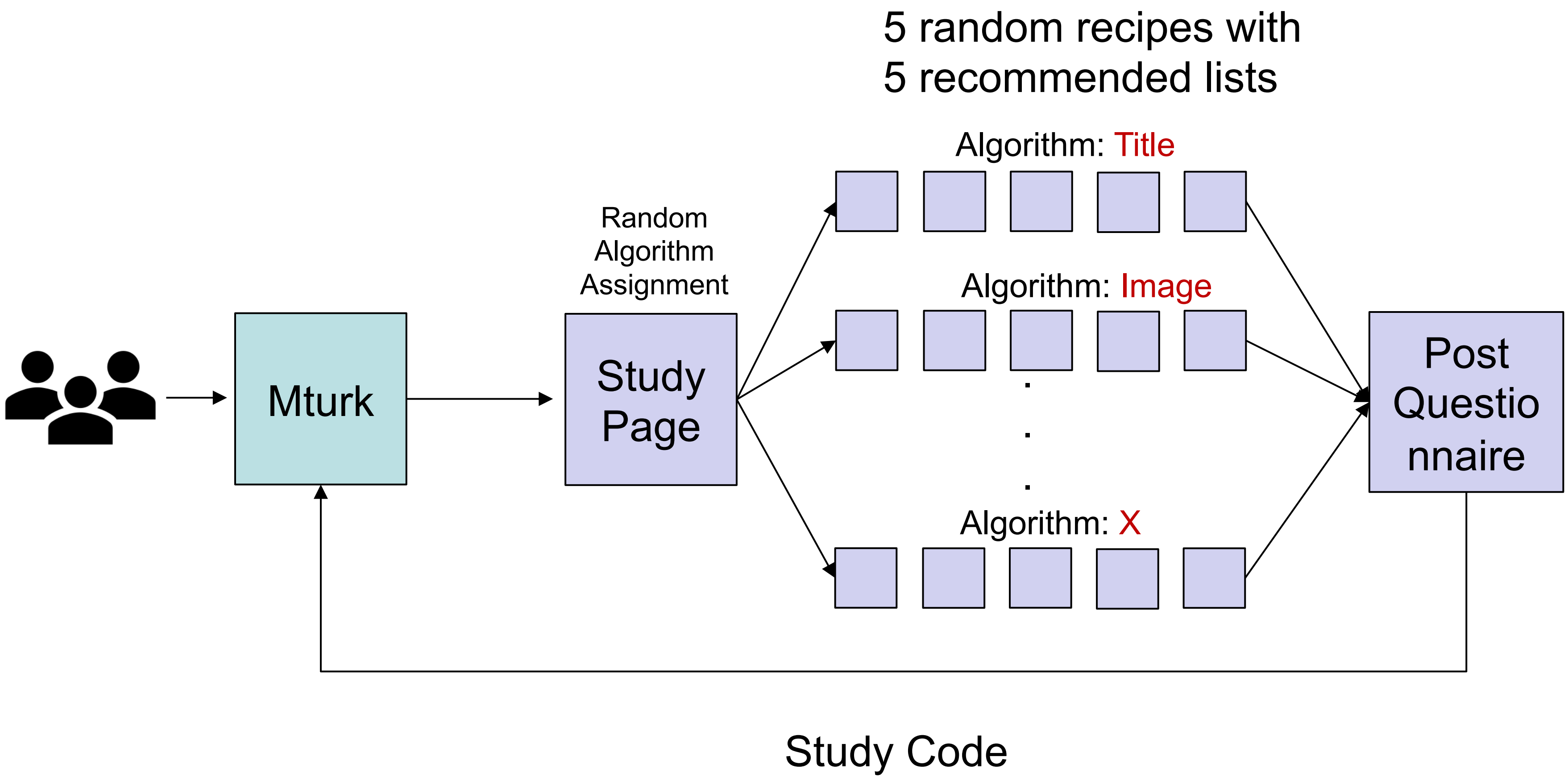


Figure 4: Feature importance for the best performing ridge regression model.

Table 6: Results when considering only one information cue at the time.

Method	RMSE	R^2	MAE	ρ
(Instances = 1,539)				
Ridge Regression per Information Cue				
Title	1.0245	0.3079	0.8348	0.5278
Image	1.0680	0.2478	0.8706	0.4969
Ingredients	0.9449	0.4096	0.7493	0.6080
Directions	**0.9390**	**0.4190**	**0.7480**	**0.5998**
All (Ridge)	**0.8654**	**0.5063**	**0.6651**	**0.6625**

User Study Design: Validation Study



Recipe Study

[Task 1 / 5]

Have a look at the reference recipe and the recommended similar recipe list!

(Scroll down to answer the survey questions)

Reference Recipe

Juiciest Hamburgers Ever

Ingredients

2 pounds ground beef
1 egg, beaten
3/4 cup dry bread crumbs
3 tablespoons evaporated milk
2 tablespoons Worcestershire sauce
1/8 teaspoon cayenne pepper
2 cloves garlic, minced

Directions

Preheat grill for high heat.
In a large bowl, mix the ground beef, egg, bread crumbs, evaporated milk, Worcestershire sauce, cayenne pepper, and garlic using your hands. Form the mixture into 8 hamburger patties.
Lightly oil the grill grate. Grill patties 5 minutes per side, or until well done.

Recommended Similar Recipes

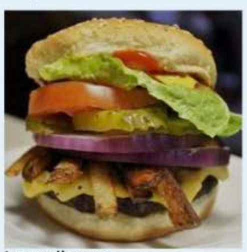
Hamburgers by Eddie

To what extent is this recipe similar to the reference recipe?

1 (Completely different) 2 3 4 5 (Very Similar)

How likely is it that you will try this recipe?

1 (Not at all) 2 3 4 5 (Will try)



Ingredients

1 pound ground beef
1 egg
2 teaspoons minced garlic
1 tablespoon steak sauce (e.g. A-1), or to taste

Directions

Preheat an outdoor grill for high heat.
In a medium bowl, mix together the ground beef, egg, and garlic. Mix in steak sauce until mixture is sticky

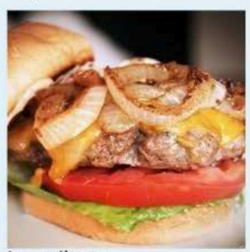
Best Hamburger Ever

To what extent is this recipe similar to the reference recipe?

1 (Completely different) 2 3 4 5 (Very Similar)

How likely is it that you will try this recipe?

1 (Not at all) 2 3 4 5 (Will try)



Ingredients

1 1/2 pounds lean ground beef
1/2 onion, finely chopped
1/2 cup shredded Colby Jack or Cheddar cheese
1 teaspoon soy sauce
1 teaspoon Worcestershire sauce
1 egg
1 (1 ounce) envelope dry onion soup mix
1 clove garlic, minced
1 tablespoon garlic powder
1 teaspoon dried parsley

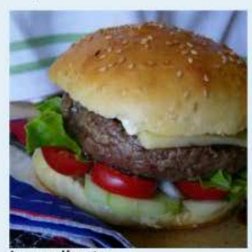
Garlic and Onion Burgers

To what extent is this recipe similar to the reference recipe?

1 (Completely different) 2 3 4 5 (Very Similar)

How likely is it that you will try this recipe?

1 (Not at all) 2 3 4 5 (Will try)



Ingredients

2 pounds ground beef
1 tablespoon Worcestershire sauce
3 cloves garlic, minced
1/2 cup minced onion
1 teaspoon salt
1/2 teaspoon ground black pepper
1 teaspoon Italian-style seasoning

Directions

In a large bowl, mix together the beef, Worcestershire sauce, garlic, onion, salt, pepper and Italian

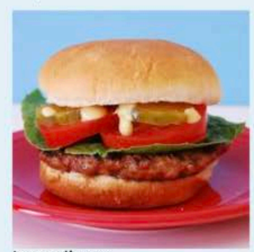
Juicy Lucy Burgers

To what extent is this recipe similar to the reference recipe?

1 (Completely different) 2 3 4 5 (Very Similar)

How likely is it that you will try this recipe?

1 (Not at all) 2 3 4 5 (Will try)



Ingredients

1 1/2 pounds ground beef
1 tablespoon Worcestershire sauce
3/4 teaspoon garlic salt
1 teaspoon black pepper
4 slices American cheese (such as Kraft®)
4 hamburger buns, split

Directions

Combine ground beef, Worcestershire sauce, garlic salt, and pepper in a large bowl, mix well.

Biggest Bestest Burger

To what extent is this recipe similar to the reference recipe?

1 (Completely different) 2 3 4 5 (Very Similar)

How likely is it that you will try this recipe?

1 (Not at all) 2 3 4 5 (Will try)

Ingredients

2 pounds ground beef
1 onion, chopped
1 teaspoon salt
1 teaspoon ground black pepper
1 teaspoon dried basil
1/4 cup Italian seasoned bread crumbs
1 tablespoon grated Parmesan cheese
1/3 cup teriyaki sauce
6 slices American cheese
6 onion rolls

Results

Recipe Study: 800 users

with 98% hit accept rate and min. 500 hits in the past

In total: 24,000 user estimates

RQ3. Do models with higher prediction accuracy lead to a higher perceived item similarity?

Recipe Results: Perceived Sim & Interest in Trying Recommendations

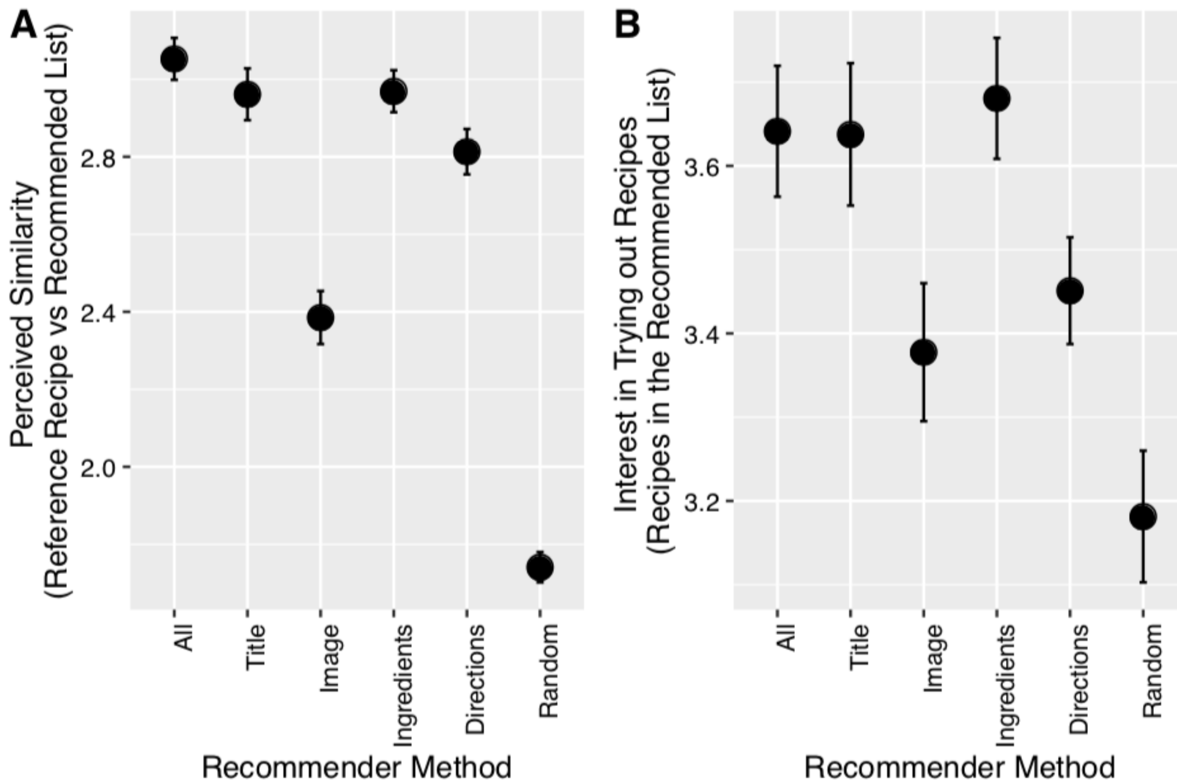


Figure 7: (A) Perceived similarity (reference recipe vs recommended list) and (B) Interest in trying out a recommendation (means and std. errors). Scale: 1 (not at all) — 5 (very similar/will try).

RQ4. How do users assess the usefulness of recommendations that are based on different similarity functions?

Recipe Results: Helpfulness, Diversity, Surprise, Excitingness

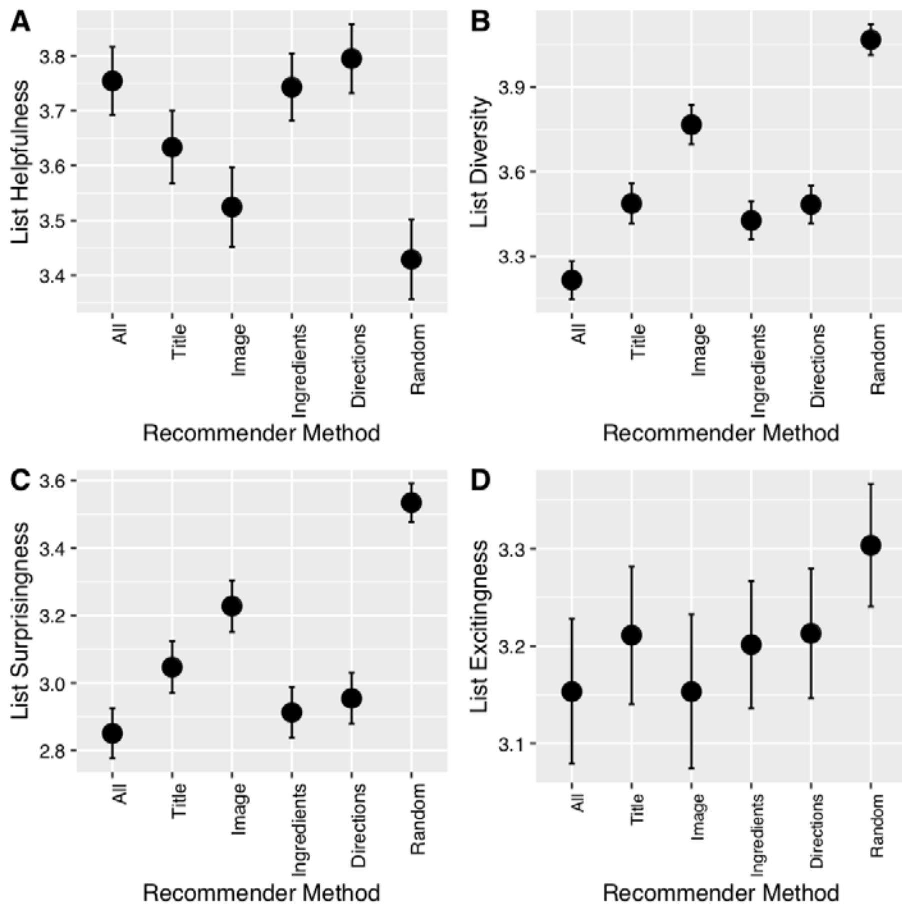


Figure 8: (A) Helpfulnes, (B) Diversity, (C) Surprisingness and (D) Excitingnesss of the recommended lists (means and std. errors). Scale: 1 (not at all) — 5 (totally agree).

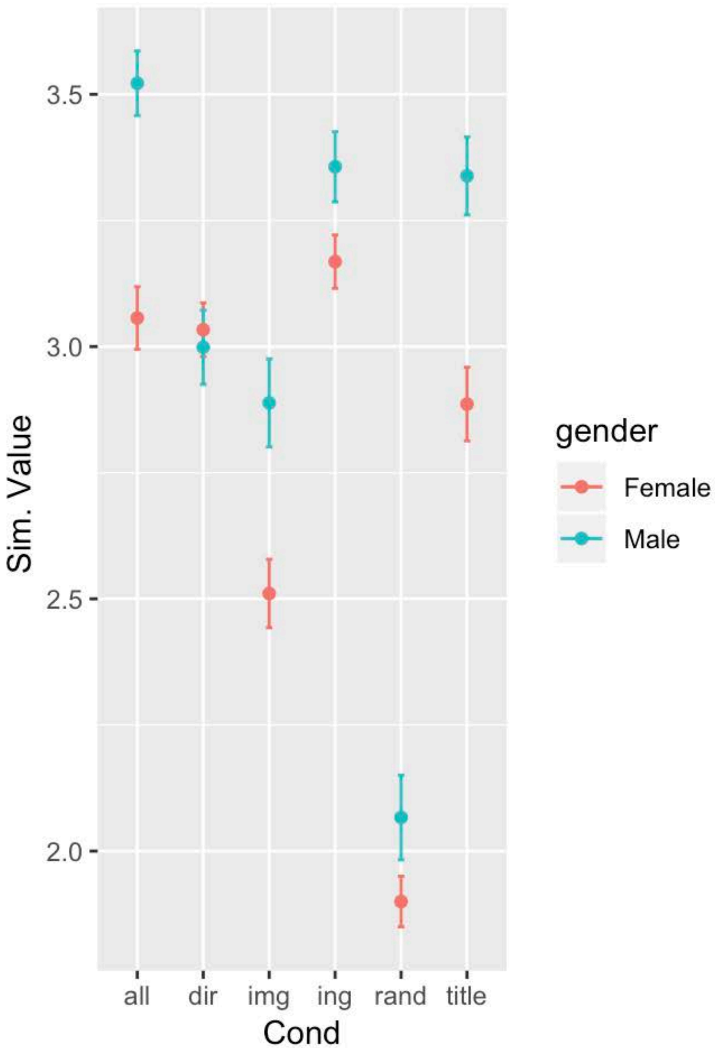
Conclusions

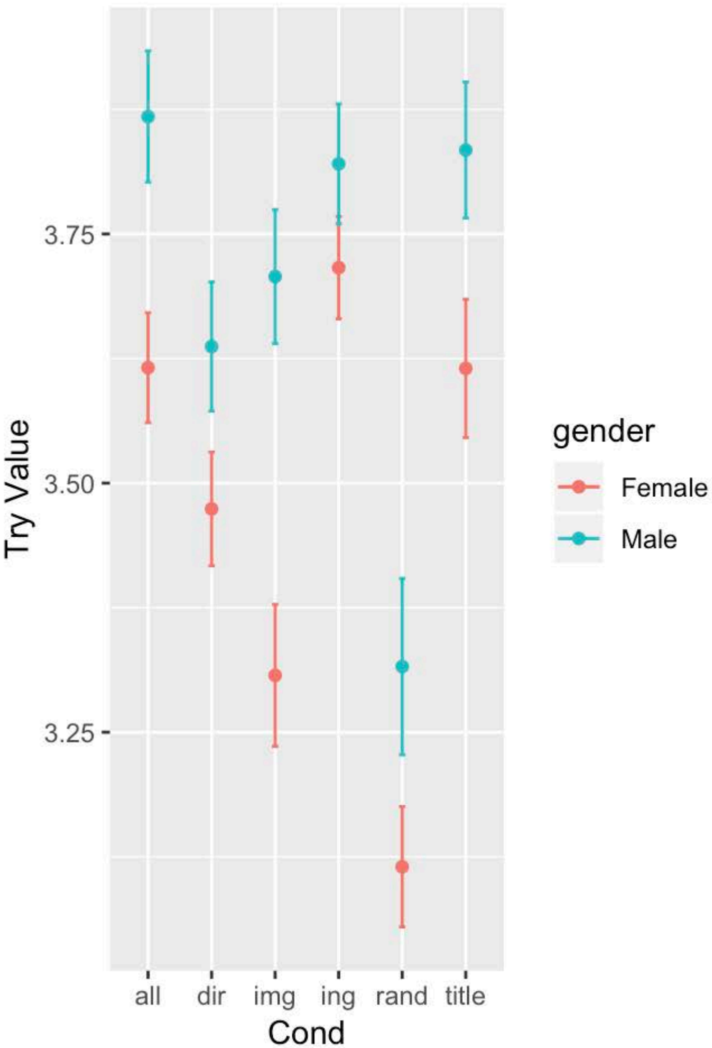
- Our work demonstrates the *feasibility of learning similarity functions from human judgements*.
- It also turned out that *considering these human judgements is a necessity*, because *experts can err* and because self assessments by users regarding the relative importance of certain factors might be misleading.
- Our experiments and studies also showed that it is important to consider several aspects in parallel.

What are we currently working on?

(User Characteristics)

User Characteristics





Part 9:
Collaborative Filtering vs Content-based

And what about CB vs CF in the Food Domain?

Trattner, C. and Elsweiler, D. **An Evaluation of Recommendation Algorithms for Online Recipe Portals**. In Proceedings of the HealthRecSys workshop co-located with ACM RecSys, 2019.

CF vs CB in Recipe RecSys

Table 2: Results of the recommender experiment – collaborative (CF) vs content-based (CB) – in the dense data sample with all users. Best features in each set (CF and CB) are bolded. Top-5 (↑) and Bottom-5 (↓) single content features are also marked.

Method	Algorithm	AUC
CF	BPR	**.7094**
	WRMF	.6881
	UserKNN	.6962
	ItemKNN	.6909
	MostPopular	.6864
	LDA	.6863
CB	Title:Levenstein-Distance	.5468 (↑)
	Title:Bigram-Distance	.5500 (↑)
	Title:LCS-Distance	.5424
	Title:LDA-Text-Cosine	.5353
	Title:Jaro-Winkler-Distance	.5324
	Title:All	.5523
	Image:Cosine-Embeddings	.5322
	Image:Colorfulness-Distance	.5072 (↓)
	Image:Contrast-Distance	.5175
	Image:Sharpness-Distance	.5109
	Image:Entropy-Distance	.5080 (↓)
	Image:Brightness-Distance	.4991 (↓)
	Image:All	.5425
	Ingredients:Cosine-Text	.5547
	Ingredients:Cosine-LDA-Text	.5653 (↑)
	Ingredients:Jaccard	.5502
	Ingredients:Cosine	.5575
	Ingredients:All	.5718
	Directions:Cosine-LDA-Text	.5606 (↑)
	Directions:Cosine-Text	.5210
	Directions:All	.5731
	Ratings:Number-Distance	.4789 (↓)
	Ratings:Average-Distance	.4832 (↓)
	Ratings:All	.5249
	Health:FSA	.5775 (↑)
	CB:All	**.5883**
	Random	.4989

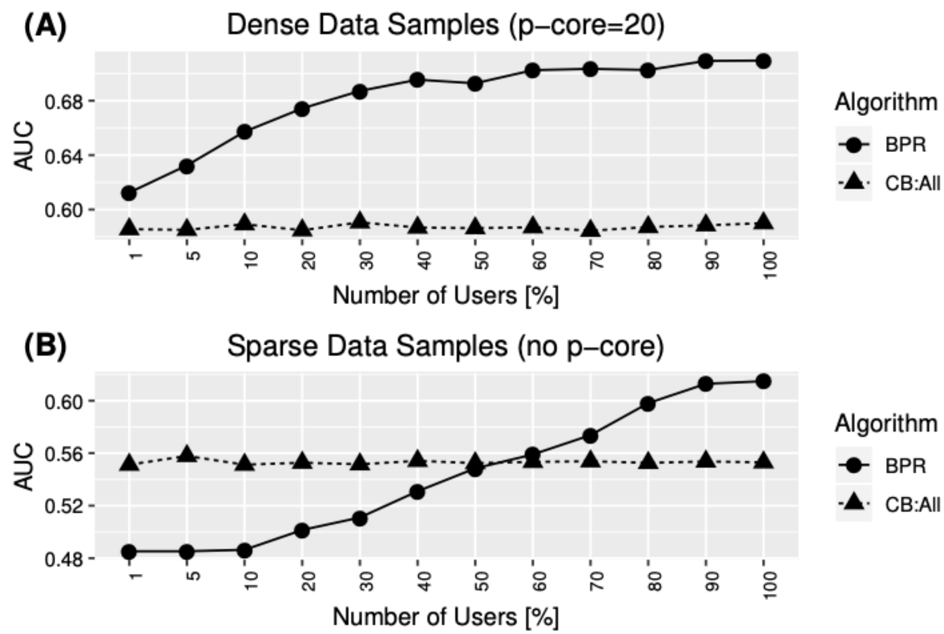


Figure 1: (A) shows the results in the dense data samples (= p-core filtered) where each user has at least 20 item interactions and each item is at least 20-times interacted with, (B) shows the results in the sparse data samples (=no p-core).

Part 10:
The Future & Conclusions

What is the Future?

Sustainable Food Recommender Systems

What online data say about eating habits. Trattner, C. and Elsweiler, D. NATURE Sustainability, 2019

Conclusions

- In order to get started with Food RecSys:

  Food Recommender Systems: Important Contributions, Challenges and Future Research Directions. Trattner, C. and Elsweiler, D. Collaborative Recommendations: Algorithms, Practical Challenges and Applications, World Scientific Publishing Co. Pte. Ltd., 2018.

- If you need data or code - email me ☺
- Rest can be found on my website: http://christophtrattner.com

Thank you!

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THANK
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TINGKI
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CHALTU
NUHUN
SNACHALHUYA
SPASSIBO
YUSPAGARÀTAM
WABEEJA
MAITEKA
HUI
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EKHMET
GUI
HATUR
UNALCHÉESH
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