Uncertainty-Quantified Ranking of Restaurant Chains in Canada by Food Safety Compliance

Combining Data From Multiple Sources for Ranking

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Nationwide Ranking by Food Safety Compliance

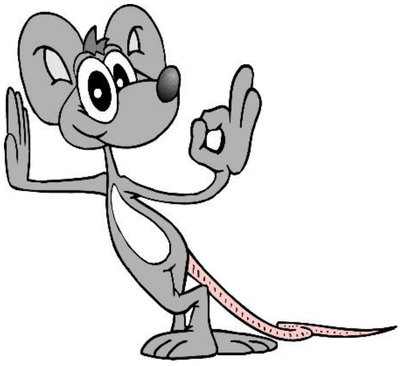
1. Starbucks
2. KFC
3. ...

UNIVERSITY OF TORONTO DCS50 CBCtelevision marketplace CANADA'S CONSUMER WATCHDOG WE'VE GOT YOUR BACK

Outline

- The problem: combining data from multiple cities to produce a nationwide ranking
- Selecting a ranking measure
- Quasi-Poisson regression for ranking
- Hierarchical Bayesian models for ranking
  - More differences between chains are identified
  - More flexible models
- Model building for exploring the dataset and producing a better ranking

The Problem



- Rank restaurant chains by food safety compliance
- Inspection reports on the number of major violations found during each inspection in 2013
  - Data from 5 Canadian cities
  - Inspectors use different standards in different cities
  - Average food safety levels may be different in different cities
- Need to quantify uncertainty

The Dataset (1)

- Data on food safety **inspections** of 100 of **stores** of 13 **chains** in 5 Canadian cities for 2013
- Approx. 3 inspections per store
- Number of major violations is recorded

1	Chain	Addr	Store	Report nc	Purpos	Date	Total Significant	TOTAL CRUCIAL	TEMPERATURE	FOOD HANDLING /HAND WASHING	KITCHEN CLEANLINESS	PEST CONTROL	CROSS-CONTAMINATION
2	Tim Hortons	2X2	T-T1	1	Routine	14-Mar-13	0						
3	Tim Hortons	2X2	T-T1	2	Routine	14-Mar-13	0						
4	Tim Hortons	2X2	T-T1	3	Routine	14-Dec-12	0						
5	Tim Hortons	6C7	T-T2	1	Routine	2-Oct-13	0						
6	Tim Hortons	6C7	T-T2	2	Routine	23-Jan-13	1				1		
7	Tim Hortons	6C7	T-T2	3	Routine	17-Sep-12	0						
8	Tim Hortons	0B6	T-T3	1	Routine	12-Jun-13	0						

The Dataset (2)

- (Very) different rates of violations in different cities
  - Rates of “major” violations differ by up to a factor of 4
  - Different standards in different cities?
- The numbers for Vancouver were assigned by an expert based on narrative inspection reports
- 2024 reports for Toronto, 1279 for Calgary, 877 for Ottawa, 472 for Vancouver, 118 for Regina

Ranking Chains in a Single City

- For each chain, compute the average/expected number of major violations found per inspection
- Standard errors are easily obtained

Halifax

Combining Data From Multiple Cities

- Data from Toronto, Vancouver, Calgary, Ottawa, and Regina
- The average number of violations per inspection differs by as much as a factor of four in different cities
  - Inspectors use different standards?
  - (Different average levels of compliance?)

Toronto *Ottawa* *Vancouver* *Calgary*

Ranking Measure

- Important to rank using a comprehensible measure!
- Rank by the *expected number of violations (using Toronto standards)* in a location of a given chain
- “If I visit a location of chain C, how many violations can I expect to encounter?”

Quasi-Poisson Regression:

$$N_{violations} \sim Poisson(\exp(c + a_{chain} + b_{city}))$$

- Unit of analysis: a single inspection visit
  - A random Canadian deciding where to go for lunch
- Model the expected number of violations as
  - $E(N_{violations}) = \exp(c + a_{chain} + b_{city})$ ⟵ log link fn
  - The larger a_{chain} , the more violations are assigned to ***chain***
  - The larger b_{city} , the more violations inspectors assign in ***city***
  - They combine multiplicatively, which makes sense

$$E(N_{violations}) = \exp(c + a_{chain} + b_{city})$$

- Rank by the number of violations that would be assigned in Toronto, based on all of the data:

  $$\exp(c + a_{chain} + b_{toronto})$$

  - The same as ranking by a_{chain}

  – "Expected number of violations using Toronto standards"

  – Standard errors for the *a* can be obtained by running quasi-Poisson regression on the data

  - Enables us to quantify uncertainty in the ranking
  - Standard errors adjusted for multiple comparisons using Tukey's Honest Significant Differences

	Major violations per inspection (adjusted to Toronto level) Non-adjusted figures given in square brackets	per 10	per 100	Worse than
Starbucks	0.11 (69.59/652) [153/652 non-adj.]	1	11	
KFC	0.13 (29.43/225) [44/225 non-adj.]	1	13	
A&W	0.17 (35.19/202) [86/202 non-adj.]	2	17	
Subway	0.18 (196.52/1087) [327/1087 non-adj.]	2	18	Starbucks
Pizza Hut	0.20 (29.20/147) [53/147 non-adj.]	2	20	
Tim Hortons	0.21 (213.06/994) [312/994 non-adj.]	2	21	Starbucks
Swiss Chalet	0.29 (66.48/229) [78/229 non-adj.]	3	29	KFC, Starbucks
Wendy's	0.30 (50.51/168) [83/168 non-adj.]	3	30	KFC, Starbucks, Subway
McDonald's	0.33 (160.46/487) [267/487 non-adj.]	3	33	A&W, KFC, Starbucks, Subway, Tim Hortons
Boston Pizza	0.36 (61.08/171) [117/171 non-adj.]	4	36	A&W, KFC, Starbucks, Subway, Tim Hortons
The Keg	0.37 (20.29/55) [32/55 non-adj.]	4		KFC, Starbucks
Second Cup	0.40 (105.70/263) [138/263 non-adj.]	4	40	A&W, KFC, Pizza Hut, Starbucks, Subway, Tim Hortons
Moxie's	0.49 (50.18/103) [104/103 non-adj.]	5	49	A&W, KFC, Pizza Hut, Starbucks, Subway, Tim Hortons

Table 4. Nationwide ranking: chains ranked by major violations per inspection, and the chains which are better than the given chain with 95% confidence. We report the estimated number of violations per inspection that would be assigned by Toronto inspectors to a location of a given chain. .

Report a set of significant differences at 95% confidence

A Bayesian Overdispersed Poisson Model

Check for overdispersion using fake-date simulation

$$city_i \sim N(0, \sigma_{city})$$

$$chain_k \sim N(0, \sigma_{chain})$$

$$\epsilon_j \sim N(0, \sigma_\epsilon)$$

overdispersion

$$\theta_j = \mu + city_{cities(j)} + chain_{chains(j)} + \epsilon_j$$

$$N\_VIOL_j \sim Poisson(exp(\theta_j))$$

(All priors are flat unless otherwise specified)

Ranking Using Samples from the Posterior Distribution

- Obtain samples from the joint posterior distribution of all the parameters using MCMC
- Rank chains by the median of the expected number of violations using Toronto standards

$$median(\sum_{c\in\{Toronto,Calgary,\ldots\}} P(c)\exp(\mu + chain_j + city_{Toronto}))$$

  - For *this* model, basically the same as ranking by the *chain* coefficients
  - P(c) is proportional to the population of city *c*

- Report differences whose joint probability is 95%

Uncertainty in the Rankings

- For a set of differences between chains, we can compute the joint probability that all the differences in the set hold
- Algorithm
  - Start with the list of all pairwise differences for (i, j) s.t. median(c_i)>median(c_j)
  - Remove differences from the list by order of significance (i.e., by P(c_i>c_j)) until the joint probability that all the differences in the list hold is >95%

	Per Inspection	Worse Than
Starbucks	0.07	
KFC	0.09	
A&W	0.11	Starbucks
Subway	0.12	Starbucks
Pizza Hut	0.13	Starbucks
Tim Hortons	0.14	KFC, Starbucks
Wendy's	0.19	A&W, Subway, KFC, Starbucks
Swiss Chalet	0.19	Tim Hortons, A&W, Subway, Starbucks, KFC
McDonald's	0.21	Pizza Hut, Starbucks, KFC, A&W, Subway, Tim Hortons
The Keg	0.22	A&W, Subway, Starbucks, KFC
Boston Pizza	0.22	Pizza Hut, Starbucks, KFC, A&W, Subway, Tim Hortons
Second Cup	0.25	Pizza Hut, Starbucks, KFC, A&W, Subway, Tim Hortons
Moxie's	0.26	Pizza Hut, Tim Hortons, Starbucks, KFC, A&W, Subway

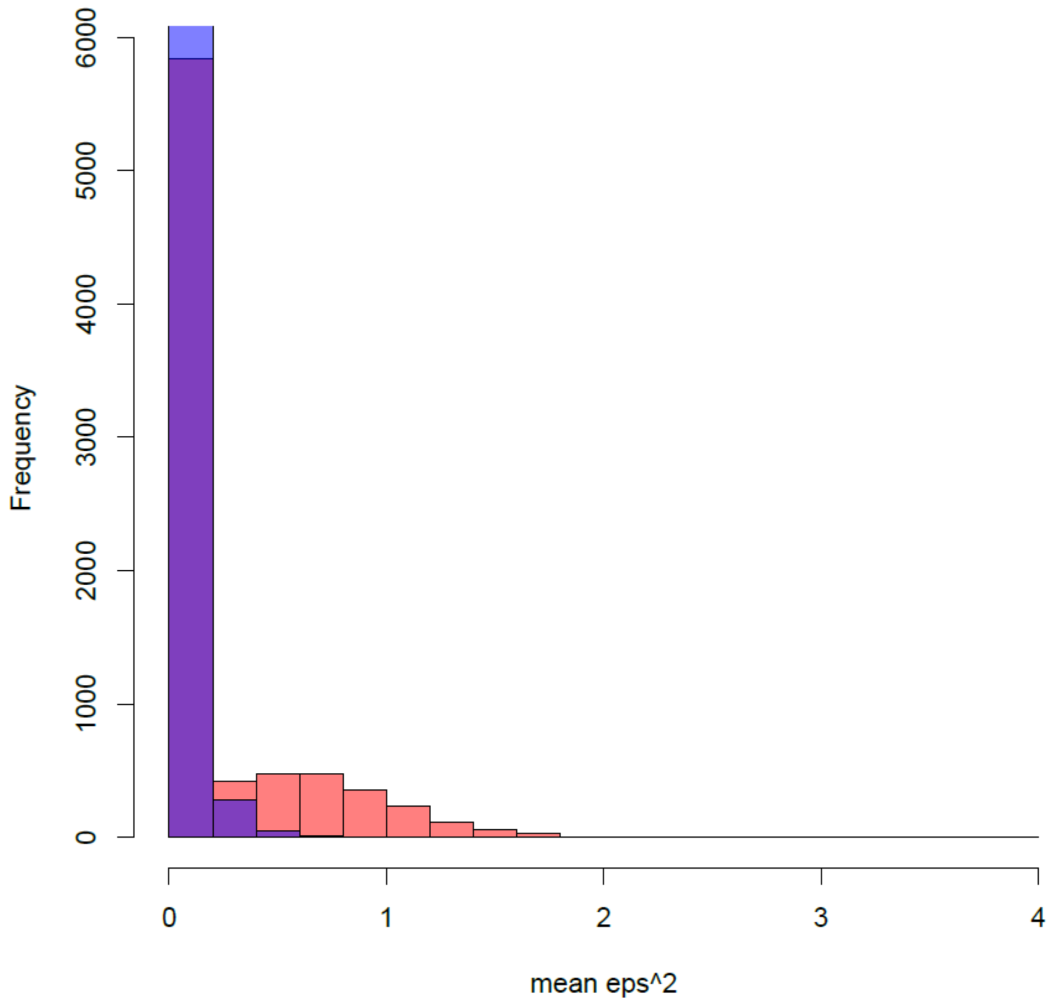
Bayesian vs. Frequentist methods

- More (41 vs. 31) differences are identified
  - The methods are not *quite* directly comparable, since the models are different
  - The rankings are almost the same

“Falsifying” the model

- Observation: data from Vancouver is substantially affecting the rank of Moxie’s
- Hypothesis: some chains are of uniform quality in all cities, and some aren’t

- Squared mean epsilon in locations belonging to the same [city, chain] pairs for actual posterior (red) and simulated (blue) parameters
- Histogram indicates systematic variation not accounted for by the city and chain parameters



$$city_i \sim N(0, \sigma_{city})$$

$$chain_k \sim N(0, \sigma_{chain})$$

$$\epsilon_j \sim N(0, \sigma_{\epsilon})$$

$$\theta_j = \mu + city_{cities(j)} + chain_{chains(j)} + \epsilon_j$$

$$N\_VIOL_j \sim Poisson(exp(\theta_j))$$

Variable Amount of Central Control

$$city_i \sim N(0, \sigma_{city})$$

$$chain_k \sim N(0, \sigma_{chain})$$

$$\epsilon_j \sim N(0, \sigma_{\epsilon})$$

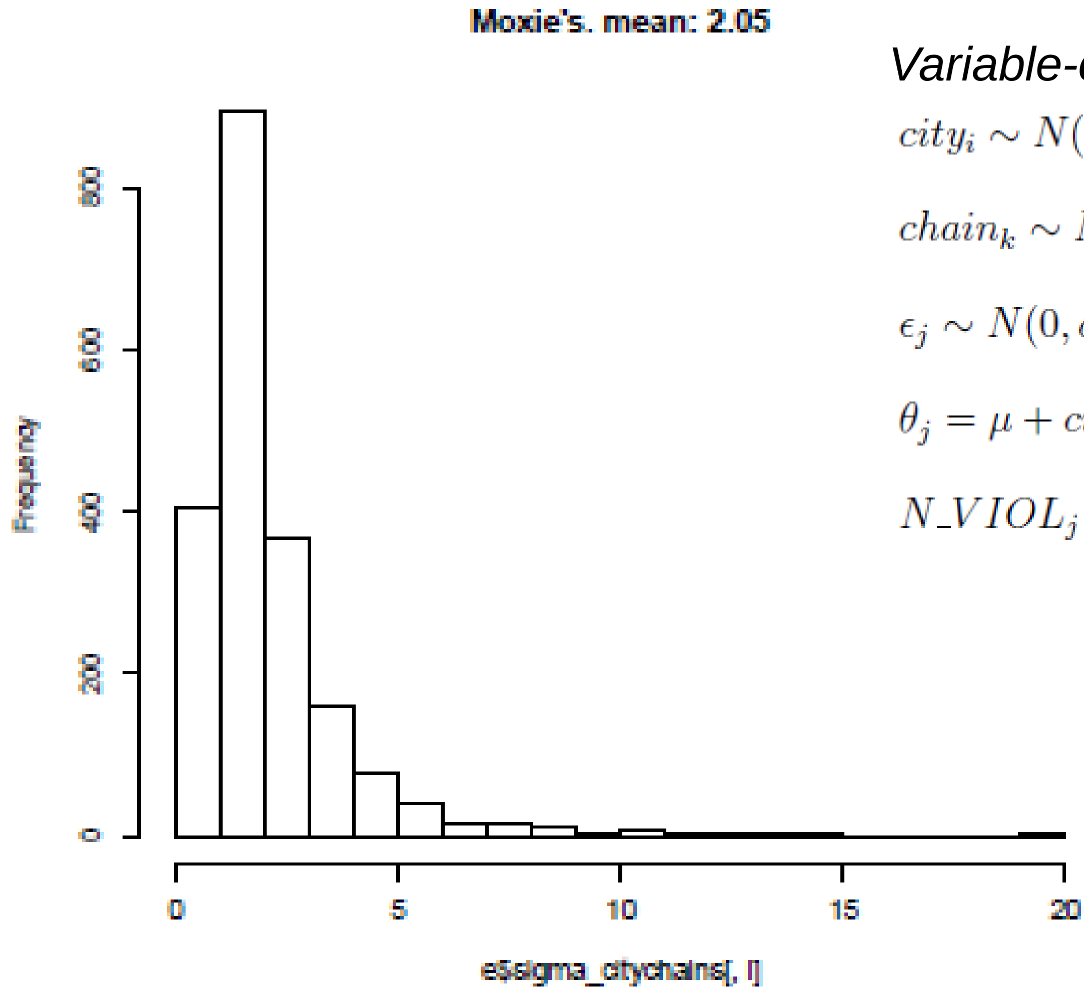
$$CITYCHAIN(i,k) \sim N(\mu + city_i + chain_k, \sigma_{citychain}(k))$$

$$\theta_j = CITYCHAIN(cities(j), chain(j)) + \epsilon_j$$

$$N\_VIOL_j \sim Poisson(exp(\theta_j))$$

If chain *k* is centrally controlled, $\sigma_{citychain}(k)$ is small

Does the Amount of Central Control Vary?



Variable-control model:

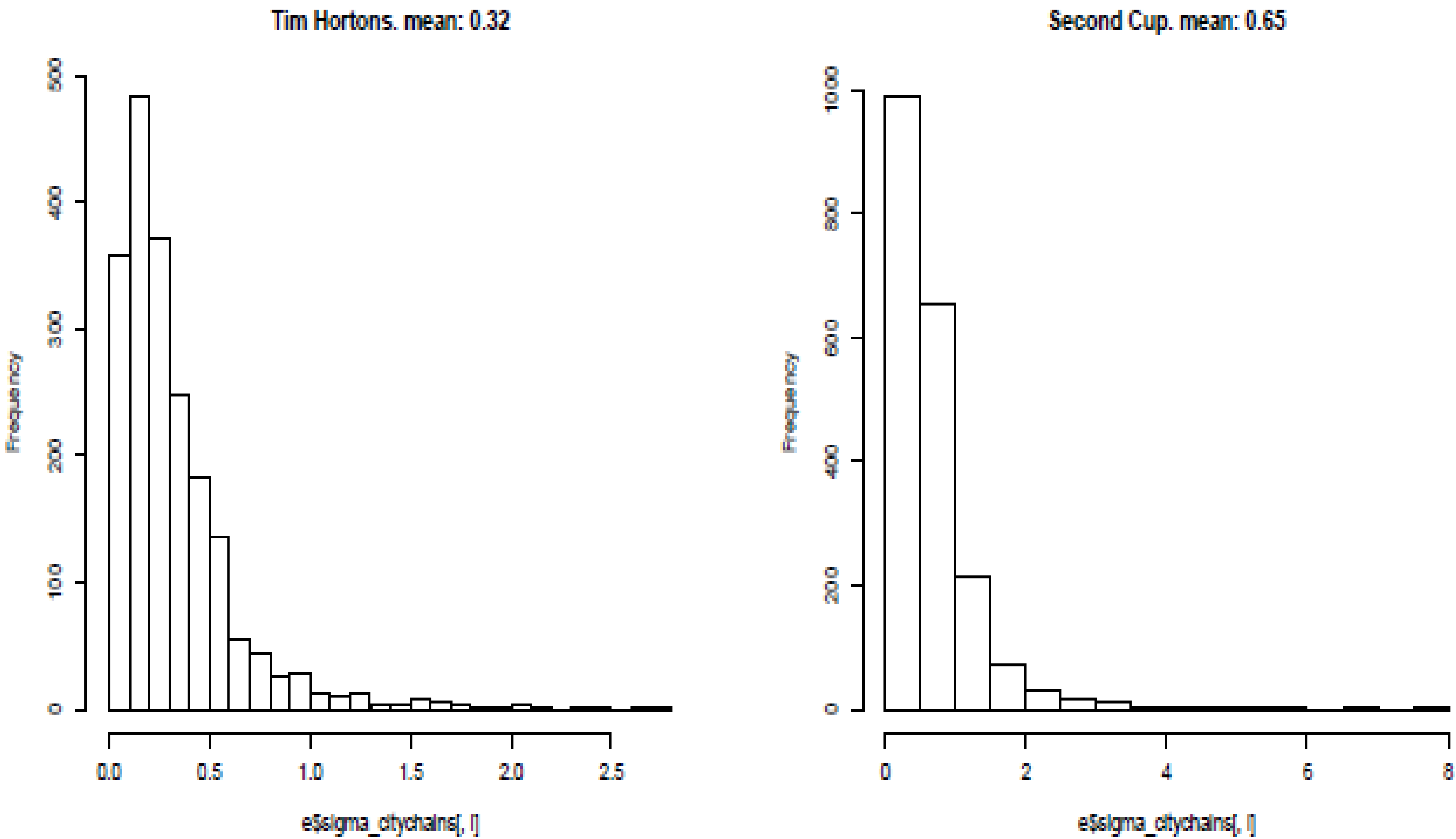
$$city_i \sim N(0, \sigma_{city})$$

$$chain_k \sim N(0, \sigma_{chain})$$

$$\epsilon_j \sim N(0, \sigma_\epsilon)$$

$$\theta_j = \mu + city_{cities(j)} + chain_{chains(j)} + \epsilon_j$$

$$N\_VIOL_j \sim Poisson(exp(\theta_j))$$



Tim Hortons. mean: 0.32
Frequency
0
100
200
300
400
500
0.0
0.5
1.0
1.5
2.0
2.5
e$sigma_citychains[, i]
Second Cup. mean: 0.65
Frequency
0
200
400
600
800
1000
0
2
4
6
8
e$sigma_citychains[, i]

Ranking using the Hierarchical Model

- Ranking using the *chain* coefficients alone would make sense if there had been a lot more major cities that weren’t sampled
  - In that case, sampling 5 cities would not be enough. Because of “explaining away” effects, there is a lot of uncertainty in the parameter estimates
- Ranking using the expected number of violations for a random diner in the 5 cities is still possible

	per Inspection	Worse than
Starbucks	0.07	
A&W	0.07	
KFC	0.10	
Subway	0.13	Starbucks
Tim Hortons	0.13	Starbucks
Pizza Hut	0.14	Starbucks
Wendy's	0.17	A&W, Starbucks
Swiss Chalet	0.20	Subway, KFC, Starbucks, A&W
McDonald's	0.22	Starbucks, A&W, KFC, Subway, Tim Hortons
Second Cup	0.23	Starbucks, A&W, KFC, Subway, Tim Hortons
The Keg	0.24	Subway, KFC, Starbucks, A&W
Moxie's	0.28	Tim Hortons, Starbucks, A&W, KFC, Subway
Boston Pizza	0.40	McDonald's, Wendy's, Starbucks, A&W, KFC, Subway, Tim Hortons, Pizza Hut

Conclusions

- The choice of ranking measure is important
- Working with the joint posterior distribution over parameters allows us to identify more differences in rank
  - To be confirmed with simulation studies
- Hierarchical model building allows us to identify interesting patterns in the data and improve the ranking