# Yelp final report

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#### **Data set**

- Yelp released a sample of its data set as part of the Yelp Dataset Challenge
- 1.6M reviews by 366K users for 61K businesses in ten cities

#### Questions

- If you've gone to business A, what is the increased chance you've gone to business
  B?
- Which businesses are the most connected?
- Can we predict whether a business will have high connectivity from other features?

## **Algorithms**

- Association rules
- Network analysis
- Boosted random forest

#### **Association rules**

- Used to understand the relationship within data
- People who go to A also go to B
- Key statistics: support, confidence, and lift

Support (A) = 
$$Pr(A) = \frac{\# users \ who \ have \ reviewed \ A}{\# users}$$

Support 
$$(A \& B) = Pr(A \& B) = \frac{\# users \ who \ have \ reviewed \ A \ and \ B}{\# users}$$

Confidence 
$$(A \& B) = \frac{Support (A \& B)}{Support (A)}$$

$$Lift(A \& B) = \frac{Confidence(A \& B)}{Support(B)}$$

### Calculation of a-rules / big data

- AWS EMR
- MapReduce to calculate support of every business. Yielded 60,785 pairs.
- Much more complicated MapReduce to calculate confidence and lift of every business pair. Yielded ~48M pairs.

## Findings: Top lift business-pairs

#### - All in Scotland

biz_a	biz_b	state	lift
Forbidden Planet	Southside Books	EDH, Scotland	464903.2
Princes Mall	Jack Wills	EDH, Scotland	474816.9
House of Fraser	Princes Mall	EDH, Scotland	474816.9

## Findings: Top lift by state

#### - Seem to make sense

biz_a	biz_b	state	lift
Vino Lounge	Lyte Lounge & Bistro	AZ	331618.2
Harris Teeter	Target Stores	NC	339154.9
Garcia's Pizza In a Pan	CUMTD	IL	268610.7
Grill Burger Kitchen	Pita Factory	ON, Canada	186535.2
Cielo	Basislager	BW, Germany	248713.6

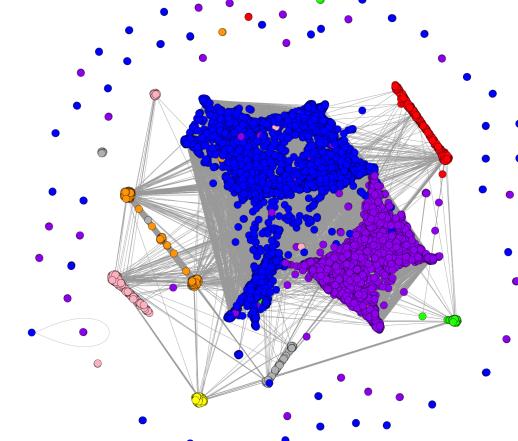
### Findings: Top lift across state lines

- A lot (but not all) are travel related

biz_a	biz_b	state	lift
Carolina Family Restaurant	Maple Leaf Air Canada Lounge	NC-QC	82904.5
Walmart	Museum of Edinburgh	SC-EDH	74614.1
Chicks w Spiritual Gifts	Spiritual Connections	AZ-CA	74614.1
BodyN'Sole	Rockstar Snowcones	IL-NV	82904.5

## **Network analysis**

 Network is too big to evaluate in its entirety, but we can use businesses with high lift to approximate the network



#### **Calculation of connectivity**

- RiGraph
- Key statistics are degrees and betweenness.
- Degrees: Biz A shares its customers with many other businesses.
- Betweenness is a measure of crossover appeal. People with different tastes all go to Biz A.

# **Findings**

Biz	State	Degrees
Multrees Walk	EDH, Scotland	982
Bruntsfield	EDH, Scotland	962
Bedlam Theatre	EDH, Scotland	940

Biz	State	Betweenness
Cold Stone Creamery	NC	3878903
Le Mondial De La Biere	QC, Canada	2851884
Rascals	EDH, Scotland	2533497

## **Machine learning**

- Can we predict whether a business will have high crossover appeal based on its other attributes?
- Census data was included as well so analysis limited to US
- Attempting to parallelize manually

### **Findings**

- PIZZA
- Best model had .36 precision and .46 recall
- 10% of all business defined as between
- Certain census tracts are influential, more so than attributes of those tracts
- Opening and closing times matter

## Interesting things we learned

- AWS EMR configuration options
- MRJob steps
- Parallelization in Python

### Challenges

#### mrjob v0.4.4 documentation

Home » Guides » Elastic MapReduce

← EMR Bootstrapping Cookbook | Advanced EMR usage →

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#### Troubleshooting

- Using persistent job flows
- Finding failures after the fact
- Determining cause of failure when mrjob can't

#### **Troubleshooting**

Many things can go wrong in an EMR job, and the system's distributed nature can make it difficult to find the source of a problem. mrjob attempts to simplify the debugging process by automatically scanning logs for probable causes of failure. Specifically, it looks at logs relevant to your job for these errors:

#### Stuff to come

- Parallelize network analysis and machine learning components
- Winning \$5000—Prof. Wach's share will depend on our grade

# **Appendix**

Stuff only Prof. Wachs cares about

#### MapReduce: Support

- mapper yields business id, 1
- combiner yields business id, sum(counts)
- reducer yields business id, sum(counts)

### MapReduce: Confidence and lift

- First mapper yields user, biz
- First combiner yields user, biz list
- First reducer yields biz pair, 1
- Second mapper yields biz pair, count
- Second combiner yields biz pair, count sum
- Second reducer yields biz pair, count sum
- Final mapper init loads MR Support results
- Final mapper yields biz pair, list with support, confidence, and list stats