Topic Modeling Yelp Reviews By Sentiment

Capstone Project 2 • Miguel Montano

Problem Statement

The Problem

Thanks to resources like Yelp, consumer perspectives of individual businesses are currently plentiful, but finding actionable insight remains the proverbial needle in the haystack

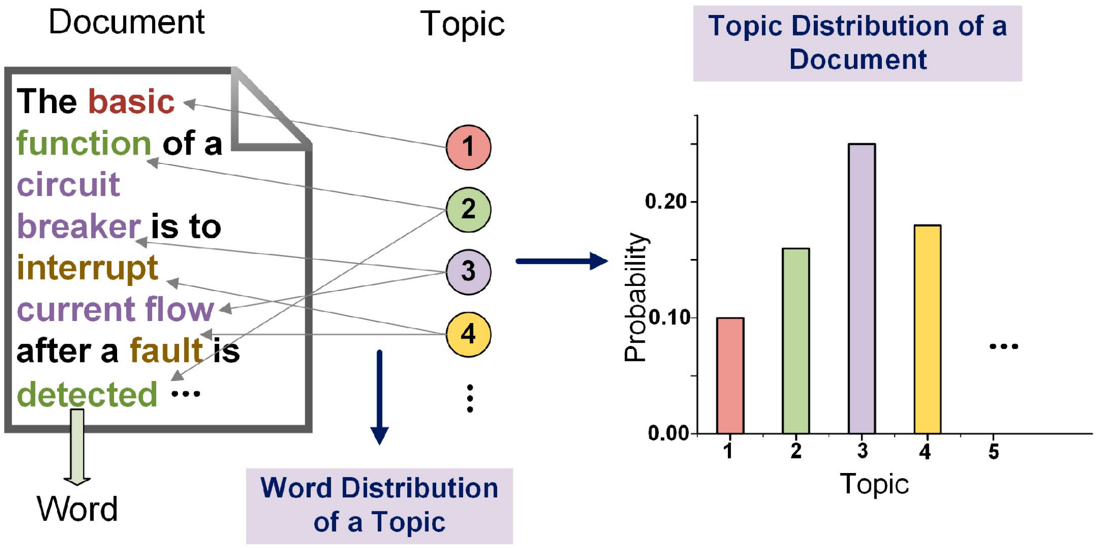
Potential Clients

- Individual Businesses being reviewed on Yelp
- Analysts seeking sentiment specific topics in a sector
- Special interest groups dedicated to local industries

A Solution

I propose an approach that utilizes the existing rating system in Yelp reviews to infer sentiment, attributing low and high ratings to negative and positive sentiment respectively, and creating a Scikit-Learn pipeline that trains a Latent Dirichlet Allocation Topic Model for each set, extracting topics that are being discussed when users write reviews with strong opinions

Background - Latent Dirichlet Allocation (LDA)



- 'generative probabilistic model'
- Sets of observations can be described by unobserved groups, 'Topics', that explain similarities between parts of the data
- If observations are words collected into documents, each document is a mix of some topics and each word's presence is attributable to a topic
- Works as a way of 'soft clustering' the documents, as each can belong to a combination of topics, which is key in this case as reviewers may write about more than one subject

Methodology

Exploratory Data Analysis → **Data Wrangling** → **Baseline Model** → **LDA Pipeline**

Exploratory Data Analysis

Visually & Statistically Summarize Main Characteristics

- Business profiles
- Star ratings
- Reviews

Data Wrangling

Delineate Procedure To Prepare for Modeling

- Text preprocessing
- Sentiment partitioning
- Feature extraction

Baseline Model

Test LDA Model

- Prepare data succinctly
- Train on subset
  (Food Industry Reviews)
- Visualize using pyLDAvis

LDA Pipeline

Create Scikit-Learn Pipeline to Streamline Process

- Construct custom objects
- Provide usage examples:
  - Individual Business
  - Food Industry

Exploratory Data Analysis

Datasets were originally in a JSON format, and each was imported into Pandas DataFrames

Links to Data:

- Yelp Academic Dataset
- Taxonomy Of Yelp Categories
- U.S. & Canada State/Province Codes

- **Business Profiles**
  - **Overview**
  - **Deep Dive into Top States**
    - Location of Businesses
    - Business Count
    - Average Star Rating
    - Distribution of Ratings
    - Average Number of Reviews Per Star Rating
- **Categories**
- **Food Industry Subset**
  - **Business Profiles**
    - Average Star Rating Per Year
  - **Reviews**
    - Average Length of Reviews Per Star Rating
    - Distribution of Review Lengths By Year

Business Profiles Overview

```
BUSINESSES OVERVIEW

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 188593 entries, 0 to 188592
Data columns (total 16 columns):
address         188593 non-null object
attributes      162807 non-null object
business_id     188593 non-null object
categories      188052 non-null object
city            188593 non-null object
hours           143791 non-null object
is_open         188593 non-null int64
latitude        188587 non-null float64
longitude       188587 non-null float64
name            188593 non-null object
neighborhood    188593 non-null object
postal_code     188593 non-null object
review_count    188593 non-null int64
stars           188593 non-null float64
state           188593 non-null object
state_name      188003 non-null object
dtypes: float64(3), int64(2), object(11)
memory usage: 23.0+ MB
```

Descriptive Statistics:

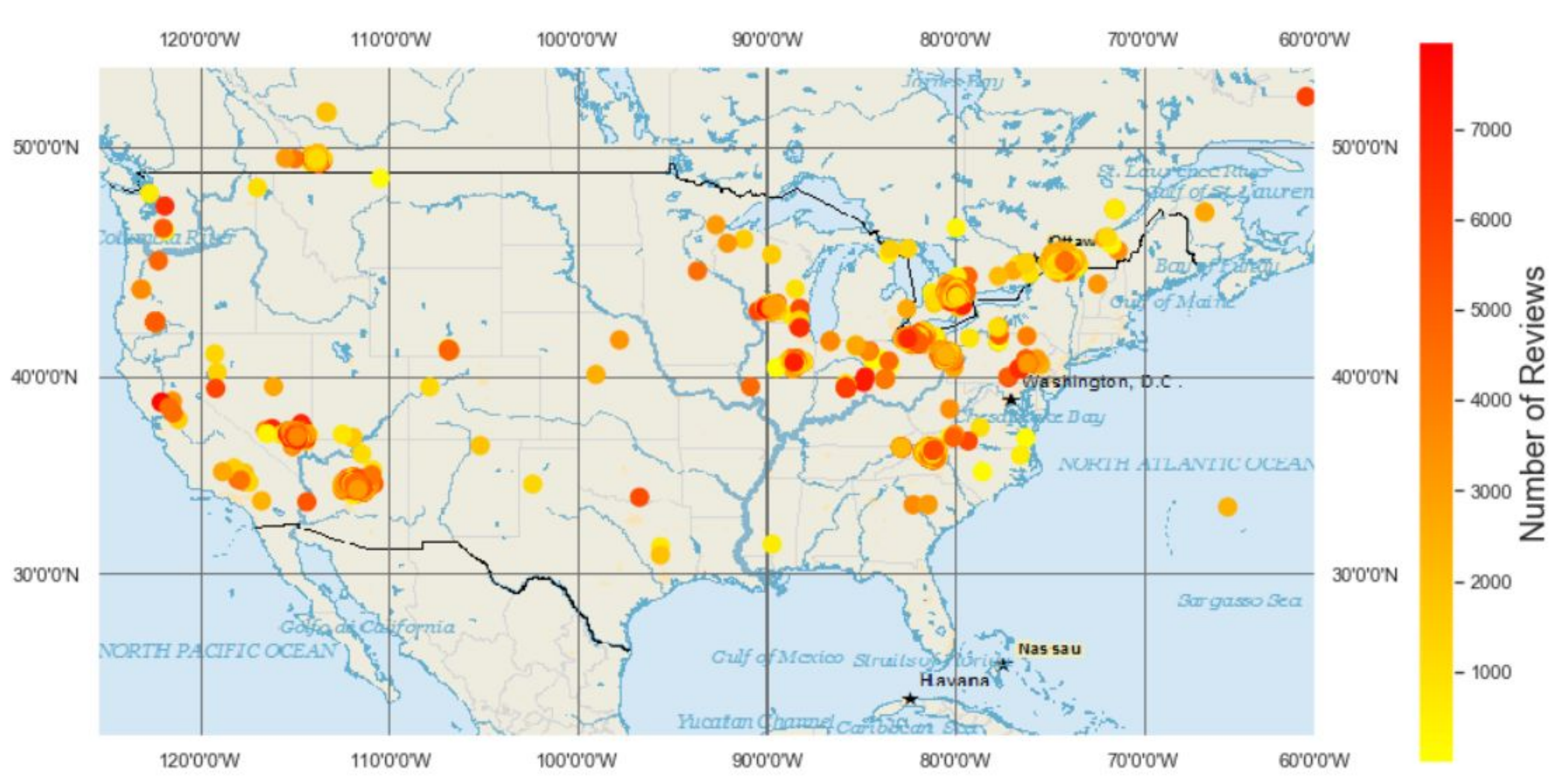
	is_open	latitude	longitude
count	188593.000000	188587.000000	188587.000000
mean	0.830391	38.506793	-97.490873
std	0.375290	5.122684	17.693360
min	0.000000	-71.753941	-180.000000
25%	1.000000	33.630878	-112.279276
50%	1.000000	36.143595	-111.777460
75%	1.000000	43.593106	-79.982958
max	1.000000	85.051129	115.086769

	stars	review_count
count	188593.000000	188593.000000
mean	3.631550	31.797310
std	1.016783	104.124212
min	1.000000	3.000000
25%	3.000000	4.000000
50%	3.500000	9.000000
75%	4.500000	24.000000
max	5.000000	7968.000000

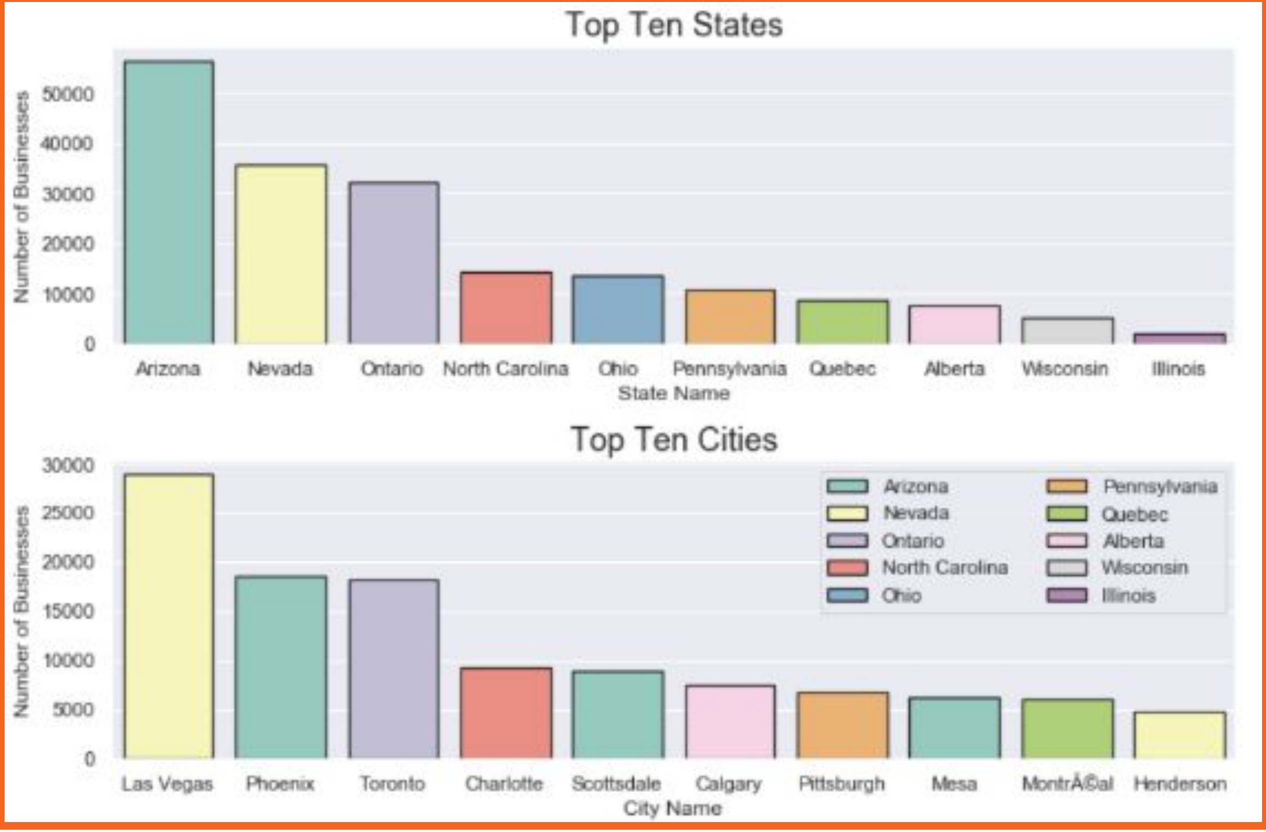
Highlights:

- 5,996,750 reviews are accounted for in Business DataFrame (99.996% of All Reviews)
- 99.14% of All Businesses are in the Top 10 States

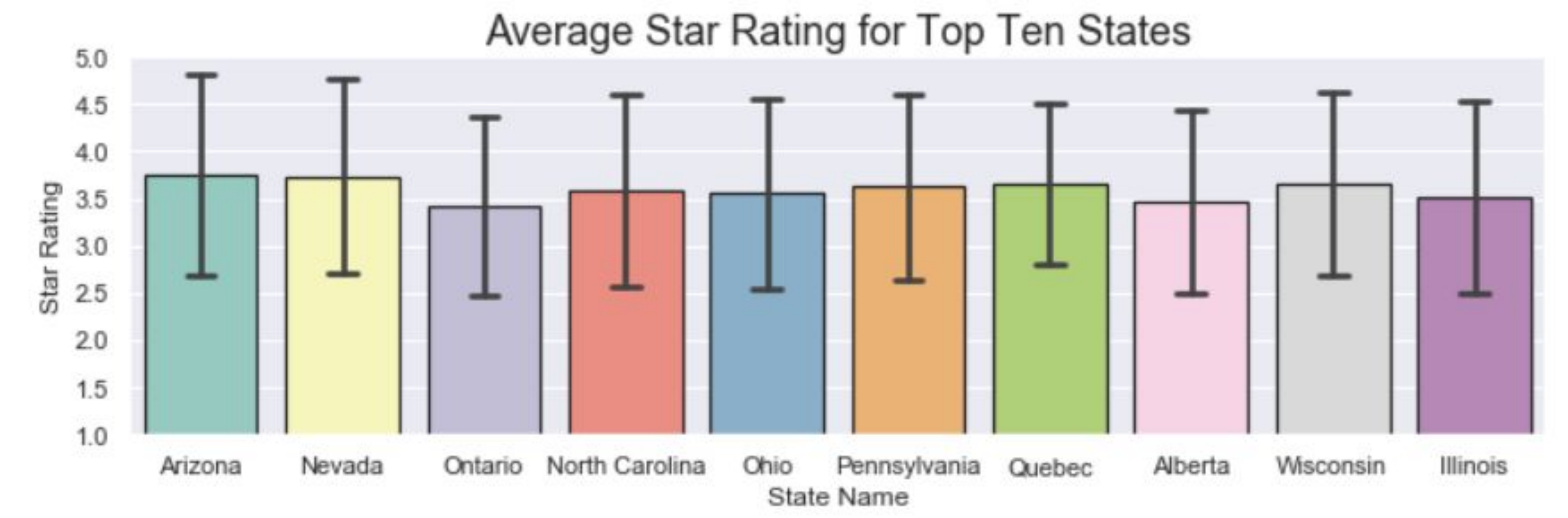
Location of Businesses in the Top States



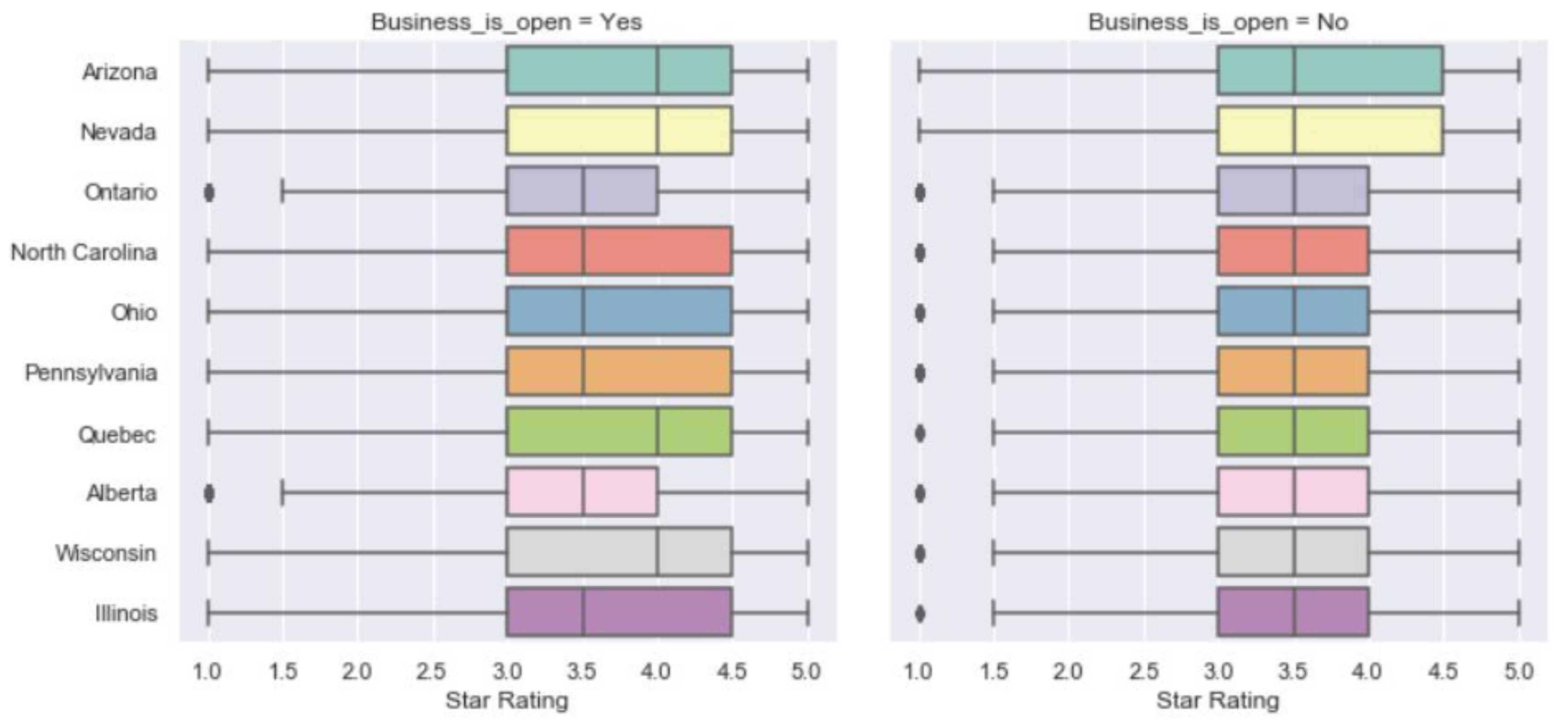
Top Locations by Business Count



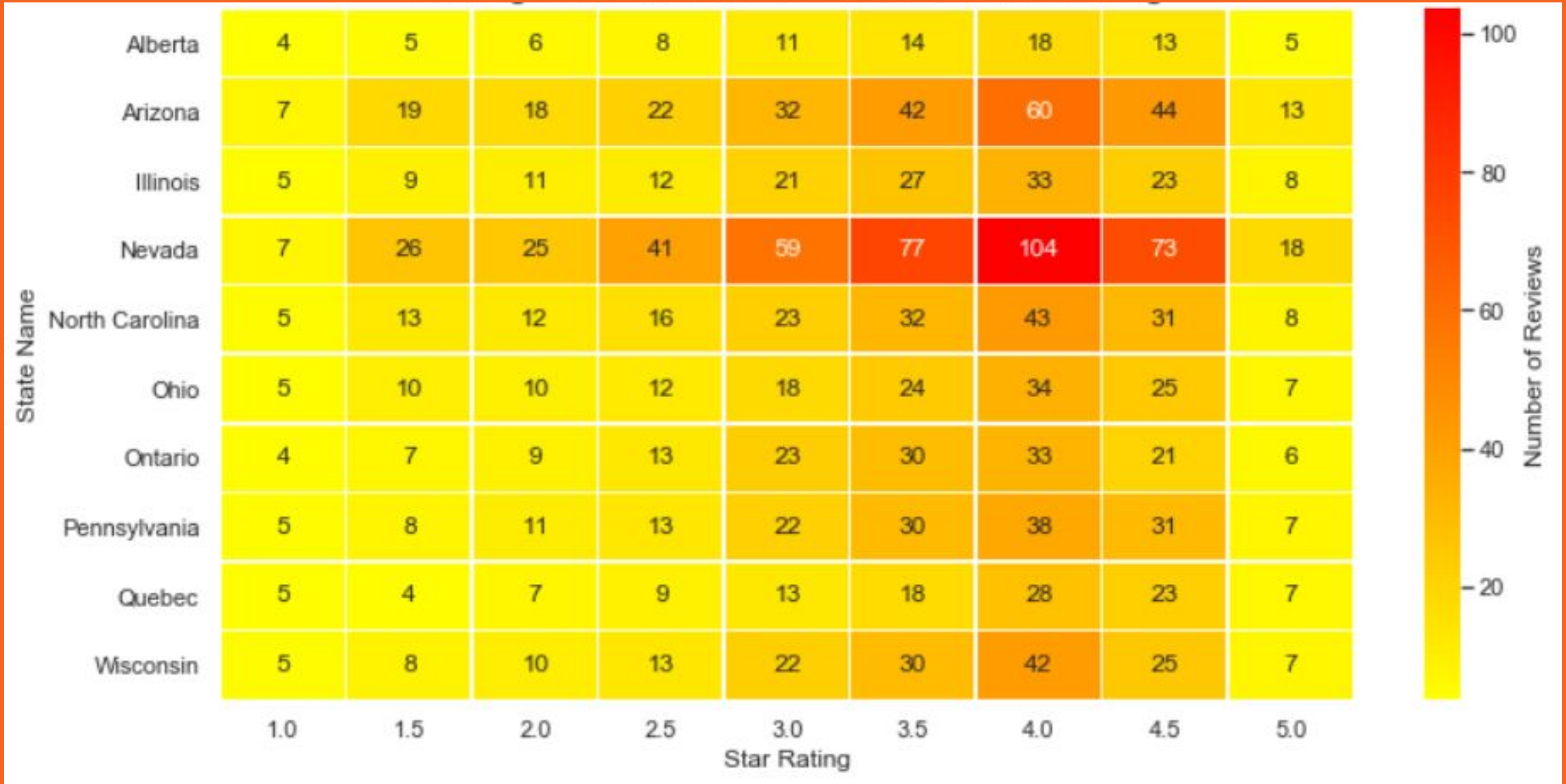
Average Star Rating By State



Distribution of Star Ratings for Top Ten States



Average Number of Reviews Per Star Rating For Top States



Categories Overview & Top Ten Food Tags

```
CATEGORIES OVERVIEW

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1539 entries, 0 to 1538
Data columns (total 5 columns):
alias                1539 non-null object
country_blacklist    349 non-null object
country_whitelist    518 non-null object
parents              1539 non-null object
title                1539 non-null object
dtypes: object(5)
memory usage: 60.2+ KB
```

```
Top 10 Food Tags:
1. Restaurants
2. Food
3. Nightlife
4. Bars
5. Coffee & Tea
6. Sandwiches
7. Fast Food
8. American (Traditional)
9. Pizza
10. Burgers
```

Highlights:

- There are 118 unique parent tags, and categories can possess multiple parents
- Of the Top 10 Food tags, numbers one and two have a higher frequency in the overall Yelp dataset than the next eight combined, which might be because they are typically used in combination with other more specific tags

Food Industry Business Profiles Overview

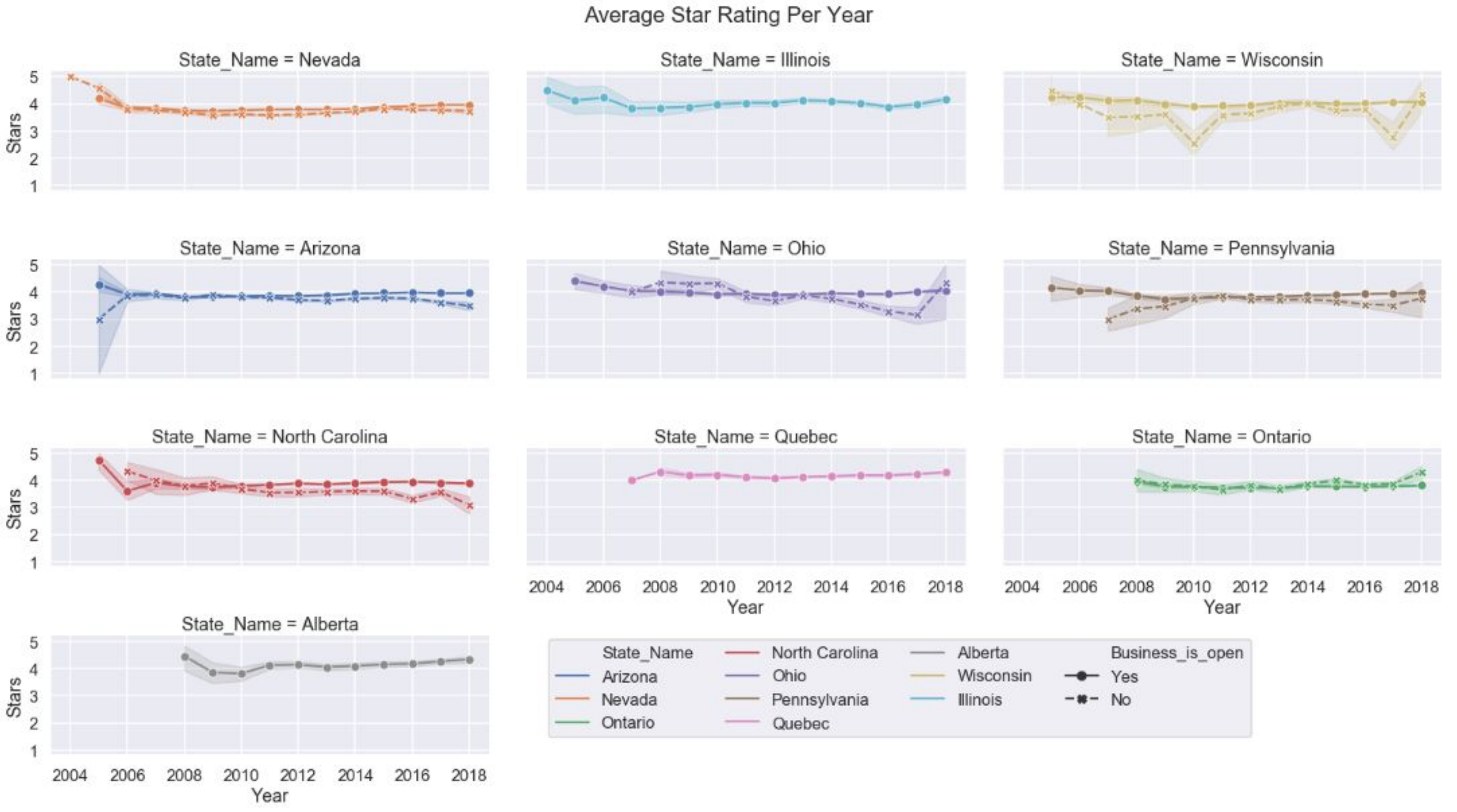
```
FOOD INDUSTRY OVERVIEW

<class 'pandas.core.frame.DataFrame'>
Int64Index: 73536 entries, 0 to 188590
Data columns (total 17 columns):
address          73536 non-null object
attributes       71567 non-null object
business_id      73536 non-null object
categories       73536 non-null object
city             73536 non-null object
hours            55299 non-null object
is_open          73536 non-null int64
name             73536 non-null object
neighborhood     73536 non-null object
postal_code      73536 non-null object
review_count     73536 non-null int64
stars            73536 non-null float64
state            73536 non-null object
state_name       73144 non-null object
latitude         73535 non-null float64
longitude        73536 non-null float64
color            73536 non-null object
dtypes: float64(3), int64(2), object(12)
memory usage: 10.1+ MB
```

```
Descriptive Statistics:
            is_open  review_count         stars
count  73536.000000  73536.000000  73536.000000
mean       0.738047     55.236796      3.494764
std        0.439700    145.715852      0.823946
min        0.000000      3.000000      1.000000
25%        0.000000      6.000000      3.000000
50%        1.000000     16.000000      3.500000
75%        1.000000     49.000000      4.000000
max        1.000000   7968.000000      5.000000
            latitude     longitude
count   73535.000000  73536.000000
mean       40.020325    -92.323266
std         5.360234     18.120518
min       -71.753941   -123.587426
25%        35.233611   -112.073403
50%        41.152726    -81.439480
75%        43.695149    -79.431609
max        59.438181    115.086769
```

Highlights:

- 38.9% of all businesses profiles belong to the Food industry
- Food establishments have 20 more reviews per business than the population average (55.2 vs. 31.8)
- Closing rate is 9.2% higher for food businesses

Average Food Industry Star Rating Per Year for Top States



Food Industry Reviews

```
FOOD REVIEWS OVERVIEW

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1905325 entries, 0 to 1905324
Data columns (total 9 columns):
business_id    object
cool           int64
date           datetime64[ns]
funny          int64
review_id      object
stars          int64
text           object
useful         int64
user_id        object
dtypes: datetime64[ns](1), int64(4), object(4)
memory usage: 130.8+ MB
```

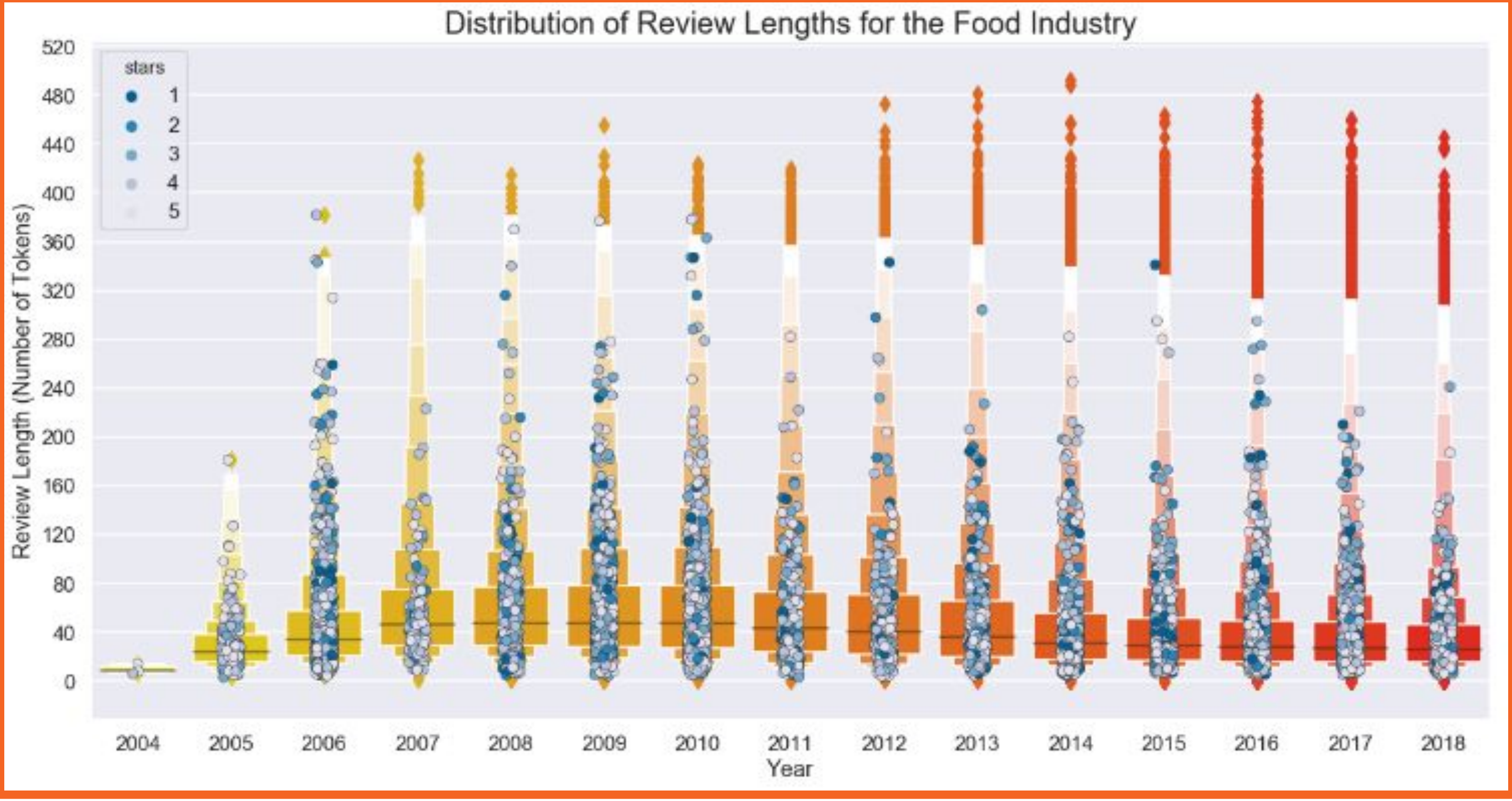
	cool					funny					useful				
	mean	std	min	max	count	mean	std	min	max	count	mean	std	min	max	count
stars															
1	0.307	2.144	0	505	162220	0.727	3.710	0	637	162220	1.610	8.598	0	1118	162220
2	0.428	1.872	0	172	157849	0.636	2.178	0	274	157849	1.398	5.250	0	1234	157849
3	0.634	2.603	0	245	241866	0.579	2.849	0	435	241866	1.201	3.741	0	805	241866
4	0.838	3.130	0	229	512665	0.556	3.094	0	566	512665	1.202	3.509	0	245	512665
5	0.608	2.322	-1	208	830725	0.371	3.240	0	991	830725	0.910	2.707	-1	215	830725

Highlights:

- 31.7% of all reviews in Yelp academic dataset are for businesses in the food industry
- A majority of reviews do not garner any additional ‘cool’, ‘funny’, or ‘useful’ tags
- If they do have such a tag, it is likely that they are reviews giving favorable ratings of 4-5 stars (70% of all reviews and 68% of reviews with additional tags)

Average Length of Food Industry Reviews Per Star Rating

Distribution of Review Lengths By Year for the Food Industry



Data Wrangling

- With Gensim, NLTK, and Pandas libraries
- Using Food Industry reviews subset
- Define steps to be implemented in future pipeline

- Text Preprocessing
  - Tokenization
  - Normalization
  - Stopword Removal
  - Lemmatization
- Sentiment Partitioning
  - ‘negative’ or ‘positive’
  - Based on star rating
- Feature Extraction
  - Map words to unique integer ids
    - Collect word frequency
  - Create vectors from documents
    - Bag-of-Words approach
    - Two final corpora, one for ‘negative’, and one for ‘positive’ reviews

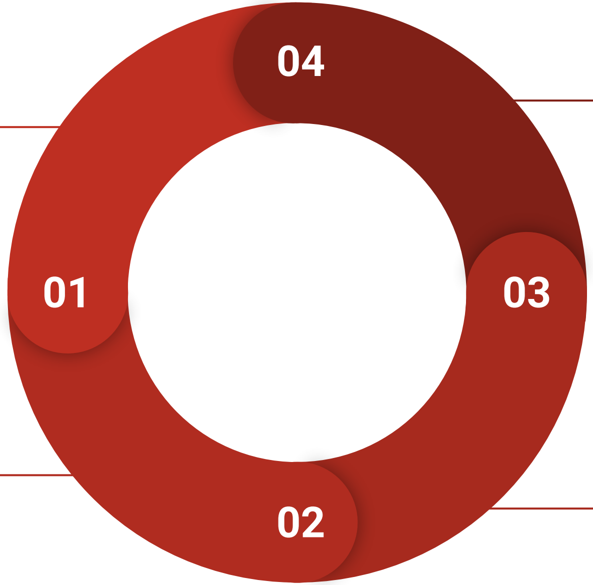
Text Preprocessing

Tokenization

Remove punctuation/special characters and transform passages from one long string into lists of word strings

Normalization

Convert all text to lower-case, expand contractions, remove numerals and accent marks



Lemmatization

Eliminate affixes from a word by capturing the canonical forms based on a word's lemma, or chosen representative, in this case assigning a Verb category tag to the tokenized parts of a sentence

Stopwords Removal

Remove words below three characters, and those which contribute little to overall meaning

Sentiment Partitioning

Negative Reviews

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 319968 entries, 13 to 1904179
Data columns (total 14 columns):
business_id         319968 non-null object
cool                319968 non-null int64
date                319968 non-null datetime64[ns]
funny               319968 non-null int64
review_id           319968 non-null object
stars               319968 non-null int64
text                319968 non-null object
useful              319968 non-null int64
user_id             319968 non-null object
year                319968 non-null int64
State_Name          319968 non-null object
Business_is_open    319968 non-null object
tokens              319968 non-null object
review_length       319968 non-null int64
dtypes: datetime64[ns](1), int64(6), object(7)
memory usage: 36.6+ MB
```

Positive Reviews

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1342441 entries, 0 to 1904177
Data columns (total 14 columns):
business_id         1342441 non-null object
cool                1342441 non-null int64
date                1342441 non-null datetime64[ns]
funny               1342441 non-null int64
review_id           1342441 non-null object
stars               1342441 non-null int64
text                1342441 non-null object
useful              1342441 non-null int64
user_id             1342441 non-null object
year                1342441 non-null int64
State_Name          1342441 non-null object
Business_is_open    1342441 non-null object
tokens              1342441 non-null object
review_length       1342441 non-null int64
dtypes: datetime64[ns](1), int64(6), object(7)
memory usage: 153.6+ MB
```

Post Text Processing

Negative Food Industry Reviews

```
1904080    Decor is nice but slow service, pastries were not good at all, tiramisu just ok but too thick. C...
1904091    Came in and order at 3.16 pm waited for 30 mins. Still haven't gotten our order. Hopefully next ...
1904147               Good atmosphere and location, but the taste of the coffee and deserts are horrendous.
1904178    We traveled 30 minutes to this spot since we been here once before and wanted to come back to tr...
1904179    OVERHYPED and OVERRATED.\n\nYes it's aesthetically pleasing to the eyes. Nice greenhouse in the ...
Name: text, dtype: object

1904080    [decor, nice, slow, service, pastries, good, tiramisu, litchi, rise, pastrie, flavor, come, choo...
1904091          [come, order, wait, mins, haven, get, order, hopefully, time, come, bavk, better, service]
1904147                            [good, atmosphere, location, taste, coffee, desert, horrendous]
1904178    [travel, minutes, spot, want, come, different, things, yelp, google, show, close, arrive, exactl...
1904179    [overhyped, overrate, aesthetically, please, eye, nice, greenhouse, middle, beautiful, victorian...
Name: tokens, dtype: object
```

Positive Food Industry Reviews

```
1904173    Friends night out and I chose Gabi Coffee and Bakery and everyone loved this place.  5 stars for...
1904174    This is a hidden gem in Las Vegas! The aesthetic and history surely creates an experience to the...
1904175    This is my favorite hang in Las Vegas!!! Because of the indoor atrium and korean decor it's like...
1904176    Little confusing to find cause of just having a big brown door and no sign. But when you walk in...
1904177    Their desserts are super cute and you can tell that the staff puts hard work into them, consider...
Name: text, dtype: object

1904173    [friends, night, choose, gabi, coffee, bakery, love, place, star, vibe, decor, ambiance, wish, h...
1904174    [hide, vegas, aesthetic, history, surely, create, experience, personal, favorite, latte, perfect...
1904175                        [favorite, hang, vegas, indoor, atrium, korean, decor, like, vegas, love]
1904176    [little, confuse, cause, have, brown, door, sign, walk, inside, like, different, little, world, ...
1904177    [desserts, super, cute, tell, staff, put, hard, work, consider, small, detail, cake, enjoy, expe...
Name: tokens, dtype: object
```

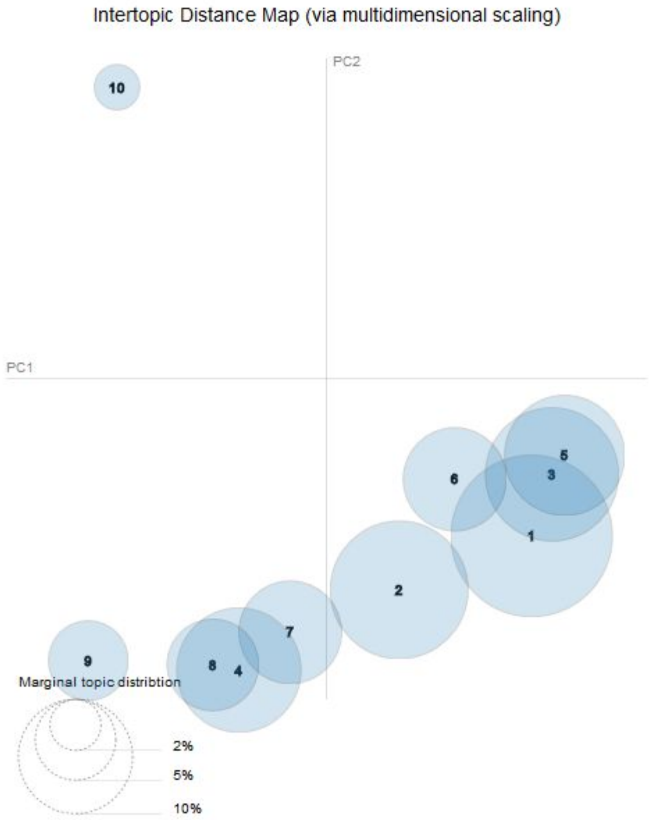
Baseline Model

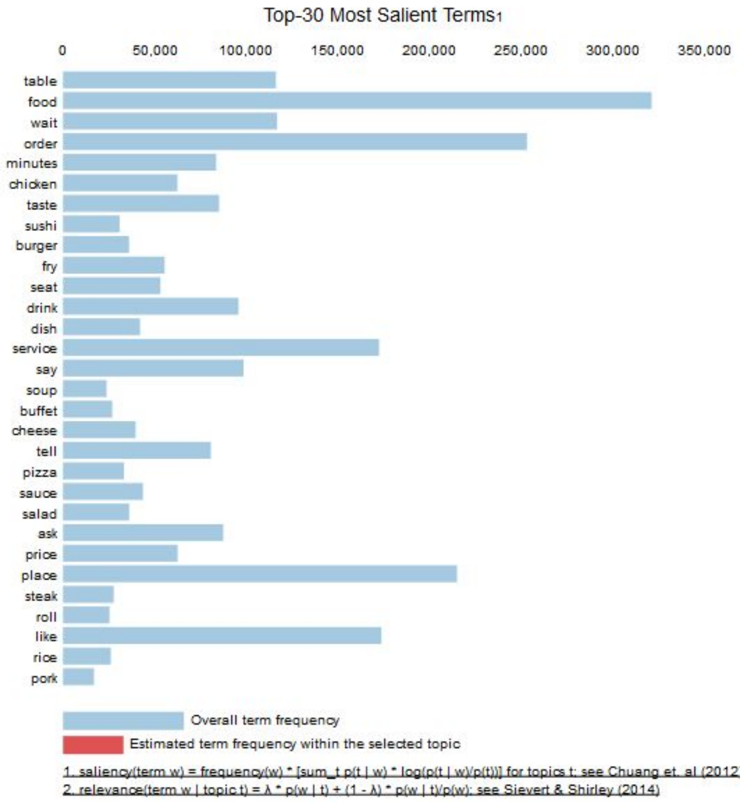
- Using Gensim LDA model
  - Trained on Food Industry reviews
- One instance for each sentiment
  - Ten topics per model
- Unigrams or (bag-of-words) vectors
  - Ignores context or phrasing

Baseline - Negative Review Topics

```
Topic: 0
Words: 0.045*"food" + 0.033*"place" + 0.024*"good" + 0.023*"service" + 0.018*"price"
Topic: 1
Words: 0.040*"order" + 0.039*"food" + 0.036*"come" + 0.031*"wait" + 0.024*"service"
Topic: 2
Words: 0.024*"order" + 0.021*"fry" + 0.018*"burger" + 0.017*"pizza" + 0.016*"salad"
Topic: 3
Words: 0.019*"hair" + 0.012*"movie" + 0.010*"italian" + 0.010*"asada" + 0.010*"indian"
Topic: 4
Words: 0.028*"soup" + 0.025*"dish" + 0.022*"chicken" + 0.021*"pork" + 0.018*"order"
Topic: 5
Words: 0.031*"table" + 0.017*"restaurant" + 0.016*"seat" + 0.012*"host" + 0.011*"party"
Topic: 6
Words: 0.020*"like" + 0.018*"food" + 0.016*"chip" + 0.016*"order" + 0.016*"tacos"
Topic: 7
Words: 0.024*"place" + 0.020*"like" + 0.014*"drink" + 0.011*"people" + 0.010*"look"
Topic: 8
Words: 0.026*"food" + 0.023*"sushi" + 0.020*"buffet" + 0.017*"roll" + 0.016*"like"
Topic: 9
Words: 0.024*"say" + 0.018*"tell" + 0.016*"order" + 0.014*"time" + 0.013*"ask"
```

Baseline - Negative Review Topics

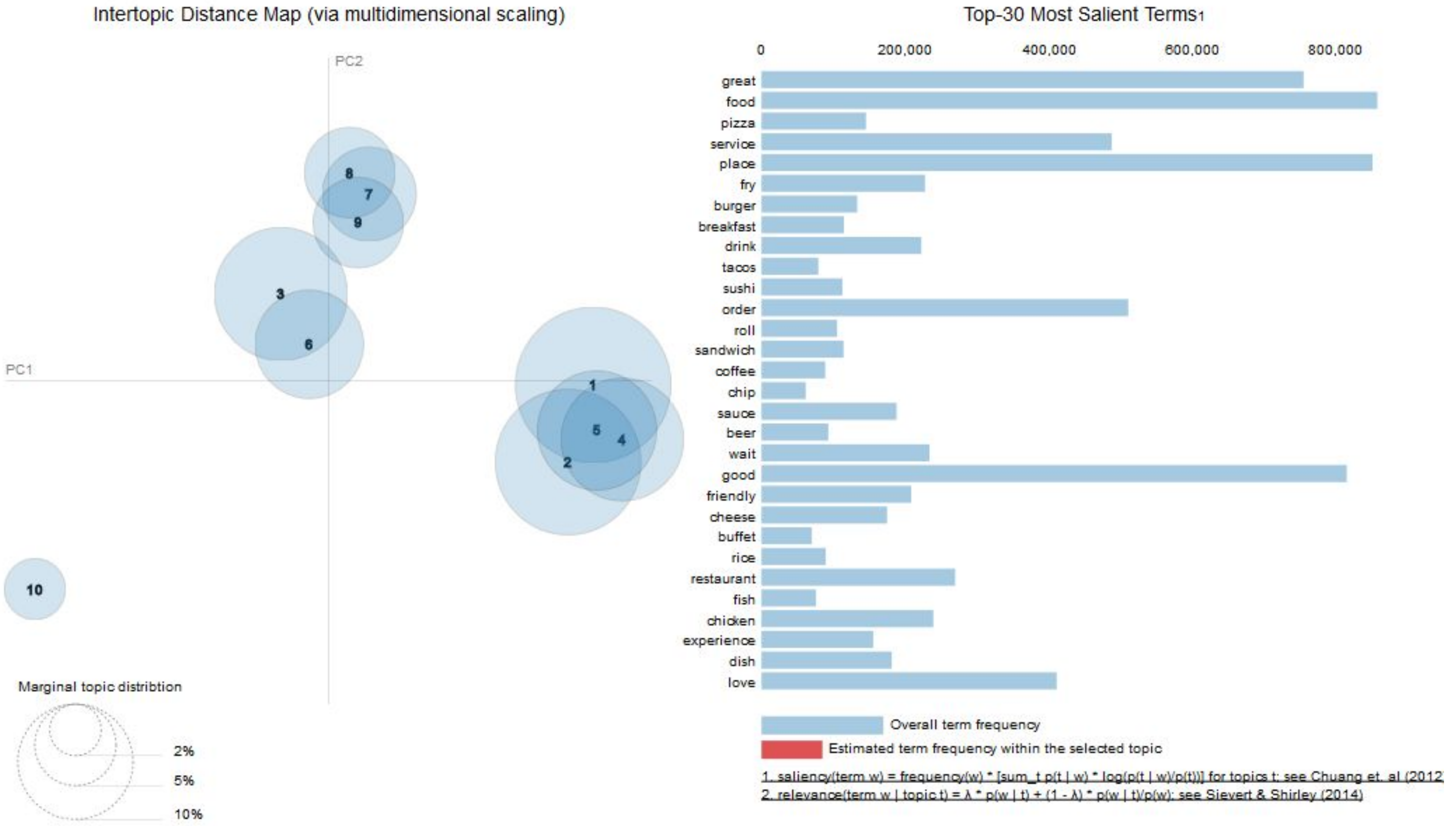




Baseline - Positive Review Topics

```
Topic: 0
Words: 0.025*"breakfast" + 0.019*"coffee" + 0.016*"cream" + 0.015*"buffet" + 0.013*"brunch"
Topic: 1
Words: 0.020*"place" + 0.016*"like" + 0.014*"drink" + 0.012*"good" + 0.008*"pretty"
Topic: 2
Words: 0.032*"fry" + 0.027*"good" + 0.025*"chicken" + 0.022*"burger" + 0.019*"order"
Topic: 3
Words: 0.026*"order" + 0.020*"food" + 0.020*"time" + 0.020*"come" + 0.015*"wait"
Topic: 4
Words: 0.045*"place" + 0.029*"food" + 0.028*"love" + 0.027*"best" + 0.020*"time"
Topic: 5
Words: 0.046*"tacos" + 0.027*"chip" + 0.027*"mexican" + 0.021*"salsa" + 0.020*"taco"
Topic: 6
Words: 0.070*"great" + 0.061*"food" + 0.042*"place" + 0.042*"service" + 0.040*"good"
Topic: 7
Words: 0.092*"pizza" + 0.024*"italian" + 0.021*"pasta" + 0.019*"crust" + 0.018*"sauce"
Topic: 8
Words: 0.018*"order" + 0.018*"good" + 0.018*"roll" + 0.016*"rice" + 0.016*"dish"
Topic: 9
Words: 0.013*"steak" + 0.012*"dish" + 0.011*"dinner" + 0.011*"dessert" + 0.009*"restaurant"
```

Baseline - Positive Review Topics

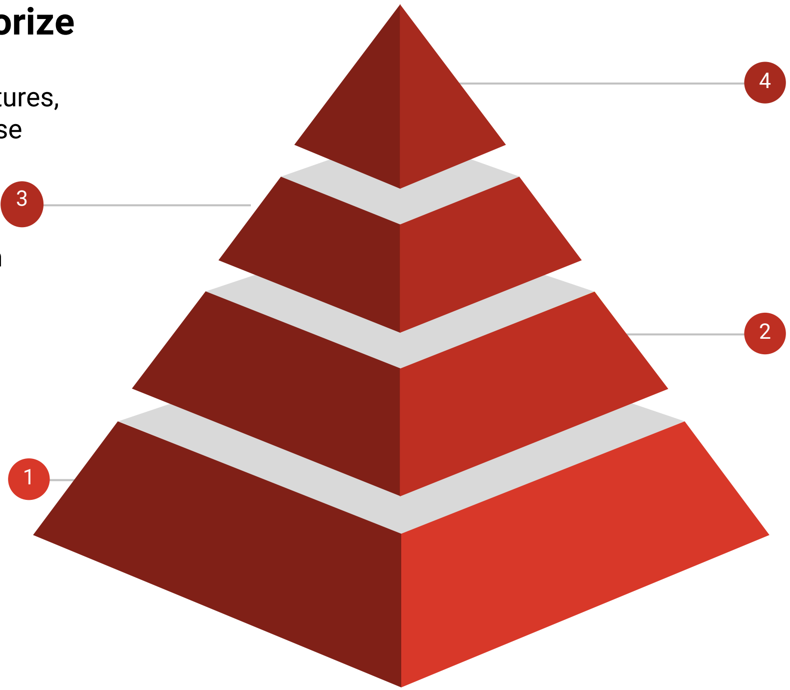


LDA Pipeline

- Sequentially applies the transformations necessary for generating a topic model
- Custom objects were built by wrapping Gensim modules and Pandas functions, while inheriting Scikit-Learn BaseEstimator and TransformerMixin classes

- **Components**
  - **Transformers**
    - Yelp Review Selector
    - Preprocess
    - Vectorize
  - **Estimator**
    - LDA Estimator
- **Implementation**
  - **LDA Metrics**
    - Combination of graphical and statistical evaluations
  - **Individual Business Example**
  - **Food Industry Example**

Pipeline Components



Yelp Review Selector

Selects Yelp reviews based on specified criteria, with the option of returning all review data in a pandas DataFrame, or simply the review text filtered by sentiment as a pandas Series.

Preprocess

Preprocess text data, in this case the Yelp reviews themselves, per specifications; with the option to expand final vector space with n-grams..

Vectorize

Create a vector space of features, where each feature is a sparse vector extracted from each document, in this case preprocessed Yelp reviews, consisting of terms and term weights.

LDA Estimator

Trains an instance of Gensim's Latent Dirichlet Allocation Model, with the option to create a pyLDAvis figure from the result

LDA Metrics

Statistical Measures

- Approximate how well the probability model predicts topic based on given samples:
  - Variational Bound
  - Log Perplexity

- Attempts to represent numerically how interpretable topics are to humans:
  - Coherence Model

Graphical Representations

- Topic Terms and Weights
- Most Representative Review Per Dominant Topic
- Distribution of Topic Contributions
- Dominant Topic Frequency
- Dominant Topic Distribution Among Documents
- pyLDAvis Visualization

LDA Pipeline - Individual Business Example

Construction

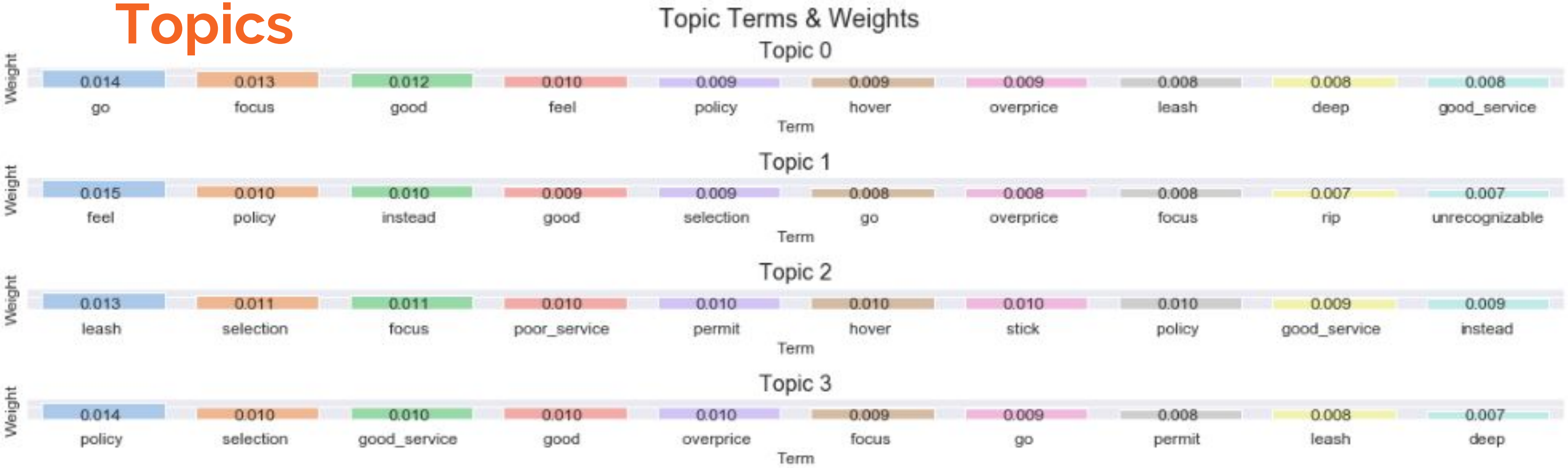
- A random business with at least 500 reviews was selected, 'Postino Arcadia' from Phoenix, Arizona
- Two separate pipelines were constructed, one for negative (3 or less star) reviews, and one for positive (4-5 star) reviews
- Using term frequency weighting, possessing trigrams, and removing the two most frequent tokens, as well as any tokens occurring in less than two reviews
- Ten passes were run over the training corpora, and four topics were drawn

Scores

```
Individual Business - Negative Reviews (Trigrams)

Variational Bound: -29457
Log Perplexity: -6.383
Coherence Score: 0.544
Coherence Per Topic
Topic 3: 0.587
Topic 2: 0.562
Topic 0: 0.536
Topic 1: 0.492
```

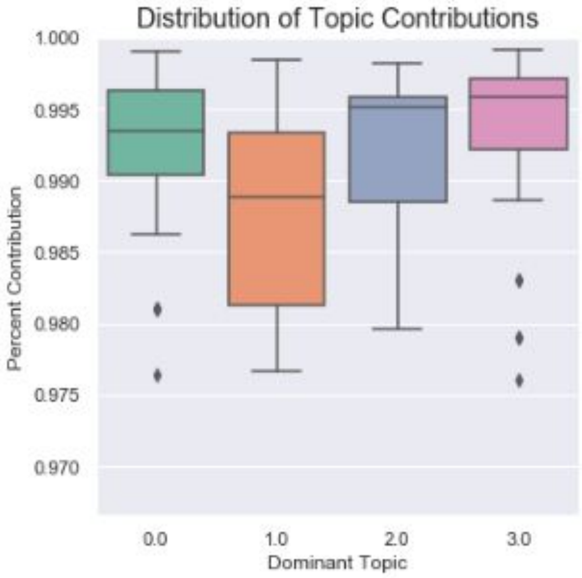
```
Individual Business - Positive Reviews (Trigrams)

Variational Bound: -41914
Log Perplexity: -9.082
Coherence Score: 0.536
Coherence Per Topic
Topic 2: 0.594
Topic 0: 0.543
Topic 1: 0.540
Topic 3: 0.466
```

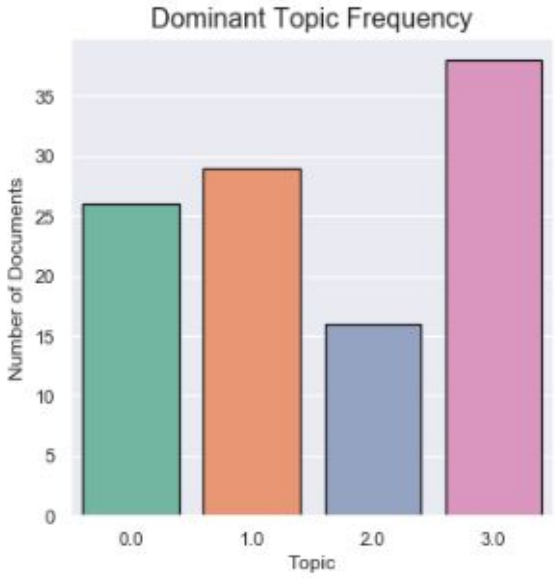
Individual Business Example - Negative Review Topics

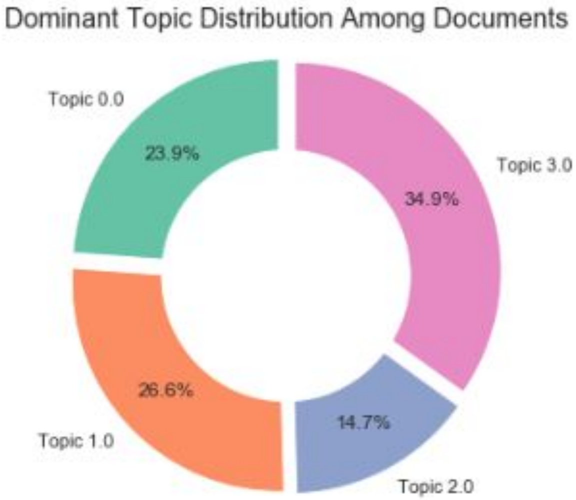


Topic	Topic_%_Contribution	Topic_Keywords	Most_Representative_Text
0.0	0.9990	go, focus, good, feel, policy, hover, overprice, leash, deep, good_service	This was my favorite restaurant. But not anymore. Today is my Birthday & thanks to them my day i...
1.0	0.9984	feel, policy, instead, good, selection, go, overprice, focus, rip, unrecognizable	We decided to visit this place while in the area based on all of the strong reviews from our fel...
2.0	0.9982	leash, selection, focus, poor_service, permit, hover, stick, policy, good_service, instead	Postino is normally one of our favorite local spots to grab a drink and some dinner. Last night ...
3.0	0.9991	policy, selection, good_service, good, overprice, focus, go, permit, leash, deep	I won't even venture to guess why so many people like this place. But a few notes: no, it is not...

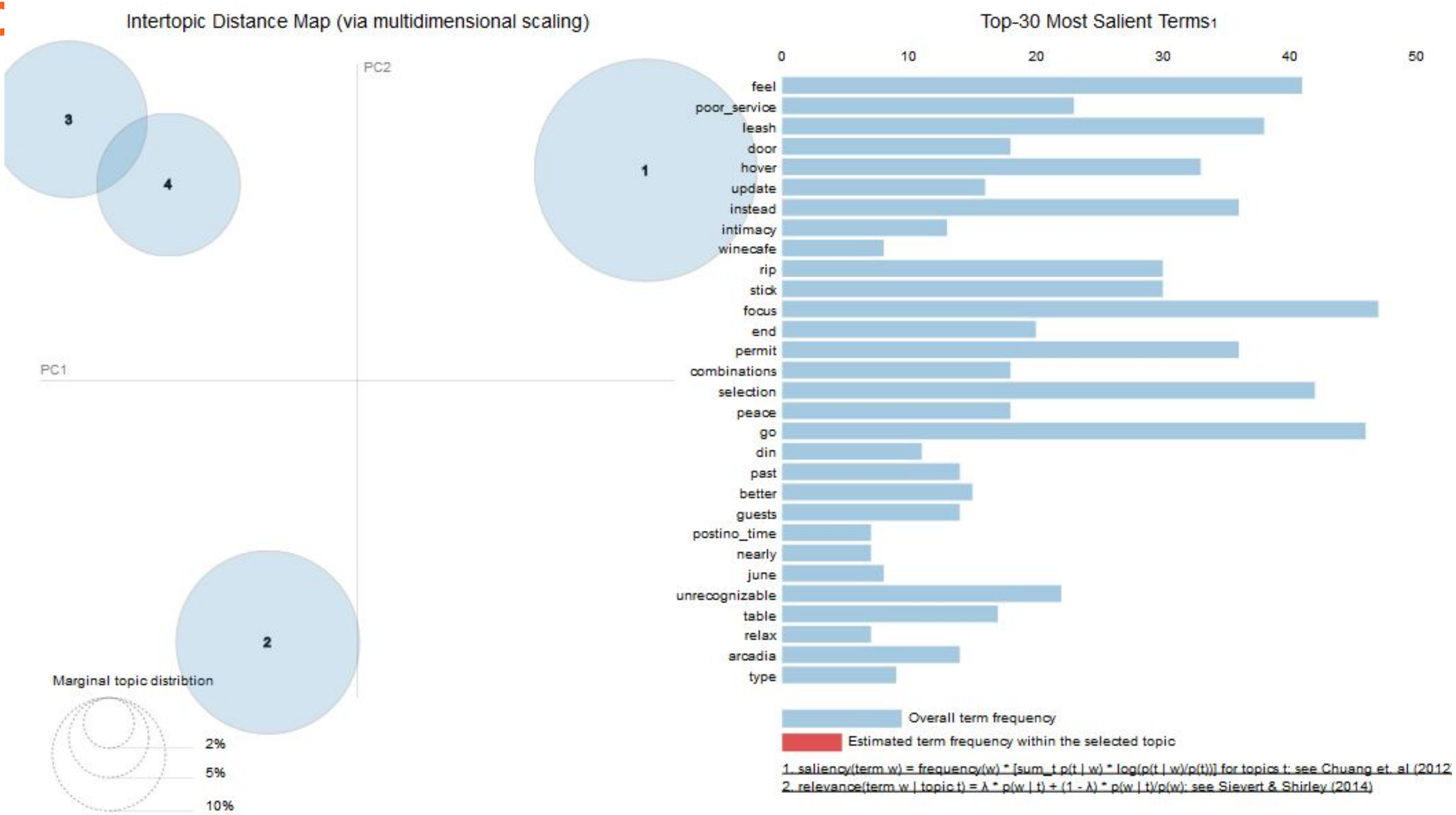
Individual Business Example - Negative Review Topics



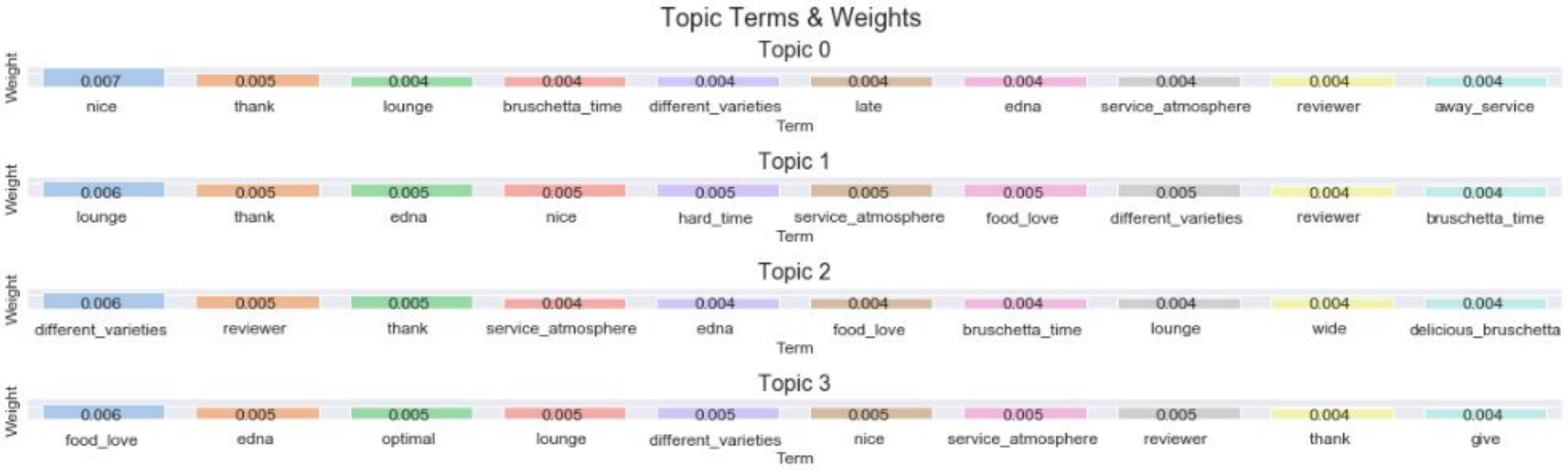




Individual Business Example - Negative Review Topic

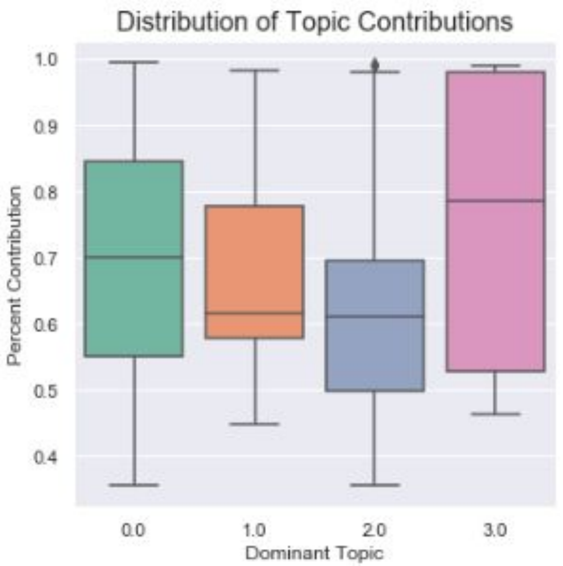


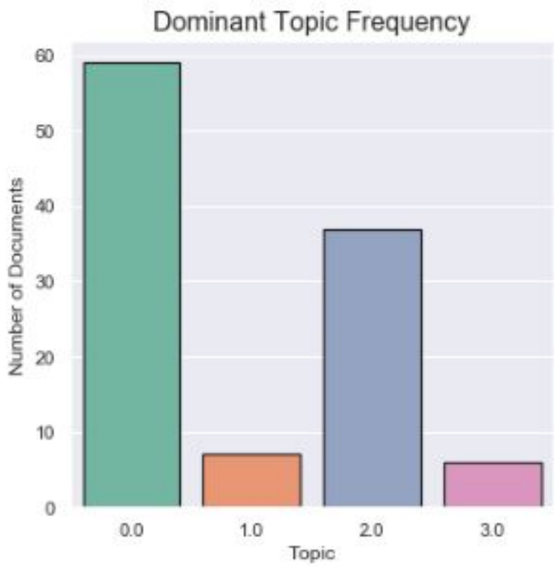
Individual Business Example - Positive Review Topics

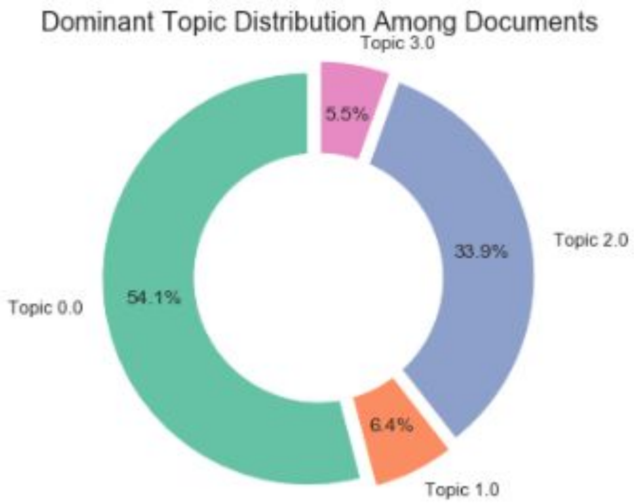


Topic	Topic_%_Contribution	Topic_Keywords	Most_Representative_Text
0.0	0.9959	nice, thank, lounge, bruschetta_time, different_varieties, late, edna, service_atmosphere, revie...	Visiting Postino Wine Cafe makes me feel like I am in another city... an urban, metro, pedestria...
1.0	0.9831	lounge, thank, edna, nice, hard_time, service_atmosphere, food_love, different_varieties, review...	Nothing worth writing about except the bruschetta. Most of the wine tastes like cheap box wine a...
2.0	0.9924	different_varieties, reviewer, thank, service_atmosphere, edna, food_love, bruschetta_time, loun...	I came here to meet a friend who I hadn't seen in ages. Some how the waitress assumed we just ne...
3.0	0.9911	food_love, edna, optimal, lounge, different_varieties, nice, service_atmosphere, reviewer, thank...	Food was ok bread was stale on my sandwich. But service was not good at all! God for bid you ask...

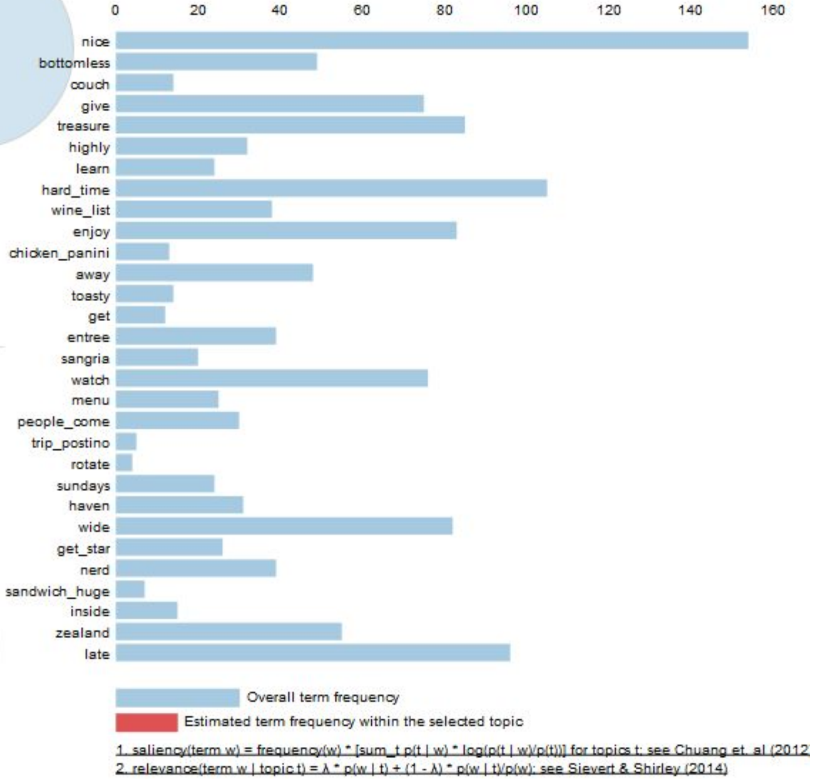
Individual Business Example - Positive Review Topics







Individual Business Example - Positive Review Topics



LDA Pipeline - Food Industry Example

Construction

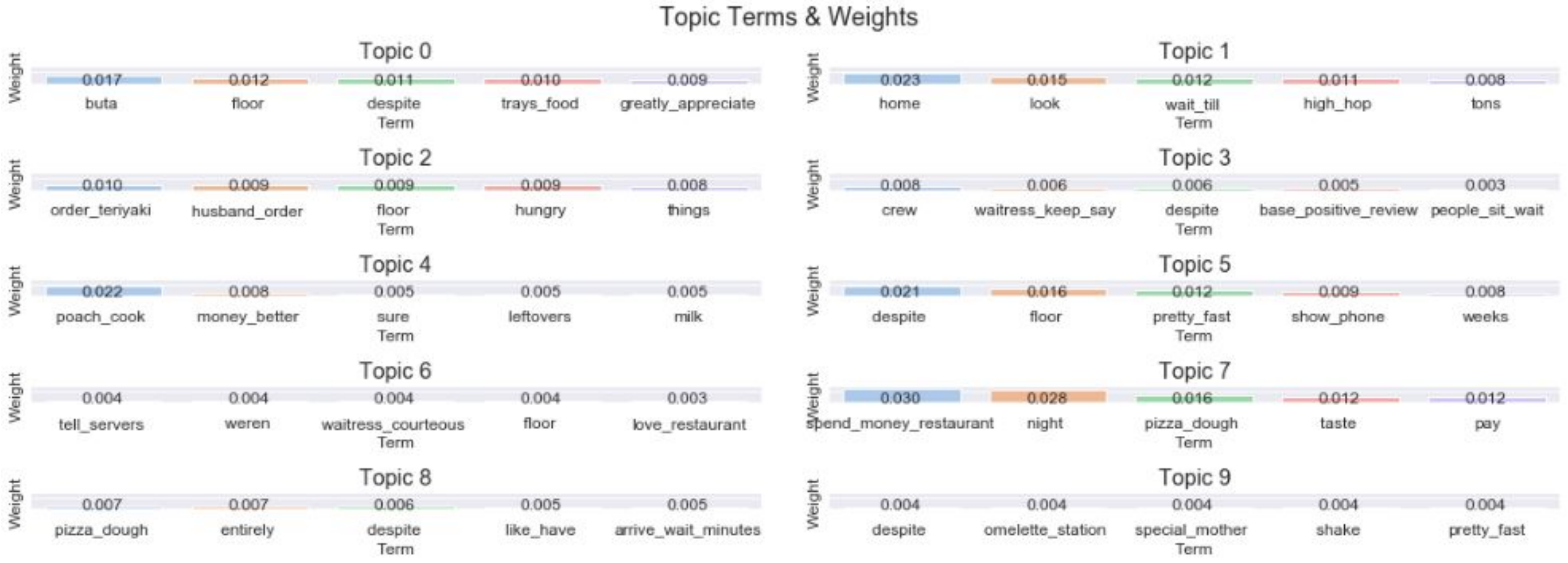
- For a more global analysis using dataset with a wide variety of constituents, we will be taking another look at the Food Industry reviews used in baseline model
- Two separate pipelines were constructed, one for negative (1-2 star) reviews, and one for positive (4-5 star) reviews
- Using term frequency weighting, possessing trigrams, and removing the three most frequent tokens, as well as any tokens occurring in less than ten reviews
- Larger sample size allows for splitting into train/test sets, as may be necessary in real-world scenarios, where train model may need to be tested against new emerging data

Scores

```
Food Industry - Negative Reviews (Trigrams)

Variational Bound: -5452816
Log Perplexity: -11.207
Coherence Score: 0.542
Coherence Per Topic
Topic 6: 0.668 Topic 0: 0.544
Topic 3: 0.645 Topic 7: 0.474
Topic 9: 0.578 Topic 1: 0.471
Topic 2: 0.563 Topic 8: 0.470
Topic 4: 0.553 Topic 5: 0.454
```

```
Food Industry - Positive Reviews (Trigrams)

Variational Bound: -16619774
Log Perplexity: -11.544
Coherence Score: 0.525
Coherence Per Topic
Topic 5: 0.598 Topic 7: 0.521
Topic 4: 0.582 Topic 9: 0.503
Topic 0: 0.550 Topic 3: 0.476
Topic 1: 0.549 Topic 6: 0.476
Topic 2: 0.544 Topic 8: 0.456
```

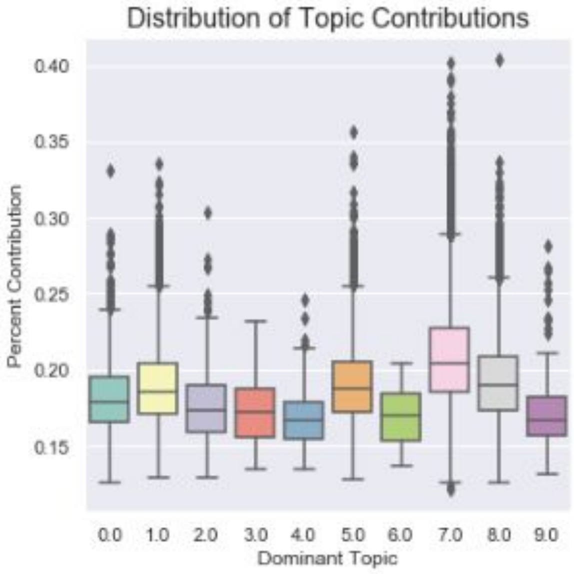
Food Industry Example - Negative Review Topics

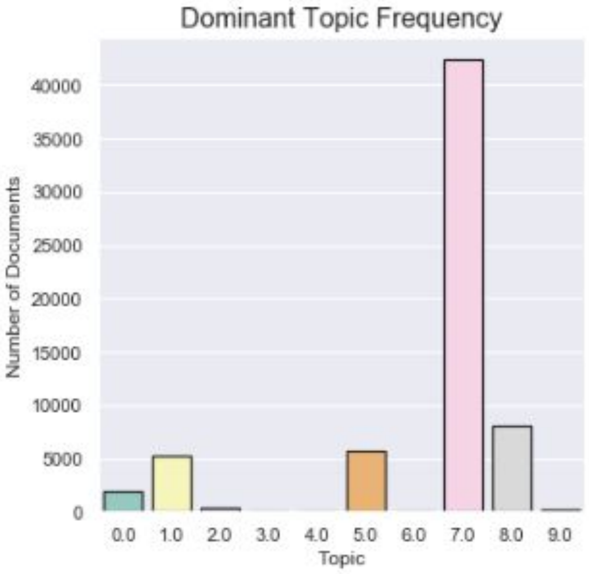


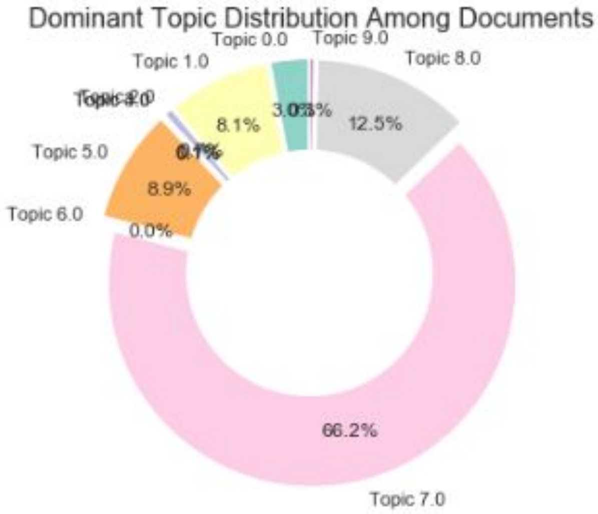
Food Industry Example - Negative Review Topics

Topic	Topic_%_Contribution	Topic_Keywords	Most_Representative_Text
0.0	0.3308	buta, floor, despite, trays_food, greatly_appreciate, selections, manager_run, greet, decently_f...	Always on the top of the Brunch list, I had to try it, to my dismay, it did not live up to it's ...
1.0	0.3360	home, look, wait_till, high_hop, tons, slam_check, place_try_hard, despite, waitress_come_table,...	Server was a straight bitch , didn't add my blazin rewards after I personally gave her my number...
2.0	0.3039	order_teriyaki, husband_order, floor, hungry, things, night, shift, service_food_good, despite, ...	Originally, I would have rated them five stars because I thought their food was awesome. At the...
3.0	0.2315	crew, waitress_keep_say, despite, base_positive_review, people_sit_wait, potato, price_match, pr...	Ahhh, Grimaldis, I love you so...BUT you really disappointed me today. We were at the mall with...
4.0	0.2456	poach_cook, money_better, sure, leftovers, milk, home, chinese_mexican_food, waitress_come_table...	So this Italian Restaurant was on my to do wish list so I finally gave it a try and I was dissap...
5.0	0.3568	despite, floor, pretty_fast, show_phone, weeks, poorly, specifically_state, couple_time, case, t...	I used to love coming here, the smell of someone else's Gandhi would trigger my own urge to get ...
6.0	0.2046	tell_servers, weren, waitress_courteous, floor, love_restaurant, lack_authenticity, especially, ...	Oyster specials were good and meaty for $2.50 each.\n\nI came here to try the Live Lobster pho t...
7.0	0.4020	spend_money_restaurant, night, pizza_dough, taste, pay, hop, horrible, food_inconsistent, high_h...	There are a lot of high reviews and 5 stars for this place and I am confused as to why. I in no ...
8.0	0.4044	pizza_dough, entirely, despite, like_have, arrive_wait_minutes, serve, stone_cold, pay, waitress...	Avant de commencer, je dois dire que je ne connais rien Ã la cuisine polonaise et que ce restau...
9.0	0.2819	despite, omelette_station, special_mother, shake, pretty_fast, taste, binge, close_kitchen, yest...	After hearing so many people talk about shake shack we all had to go check it out... After waiti...

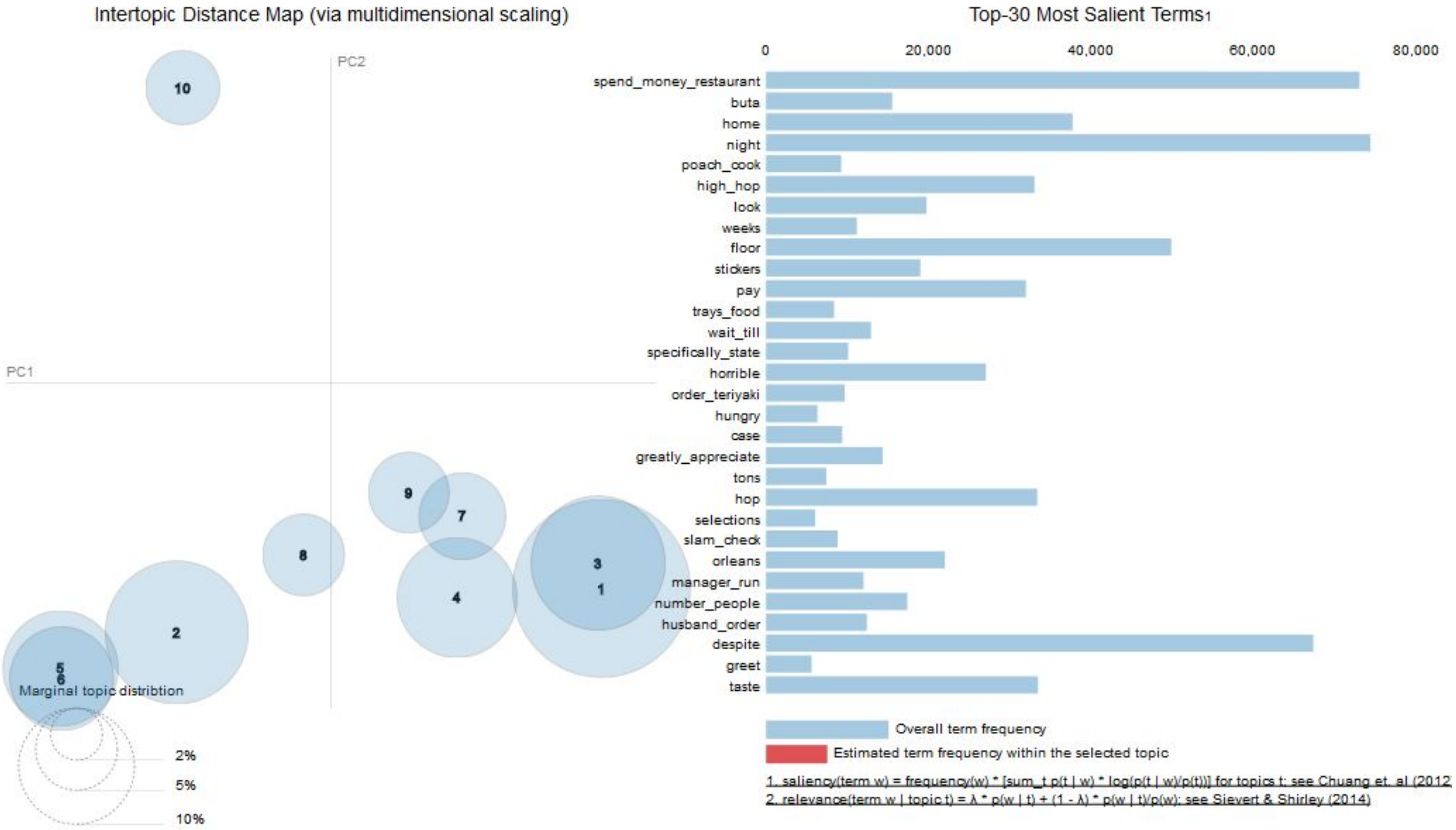
Food Industry Example - Negative Review Topics



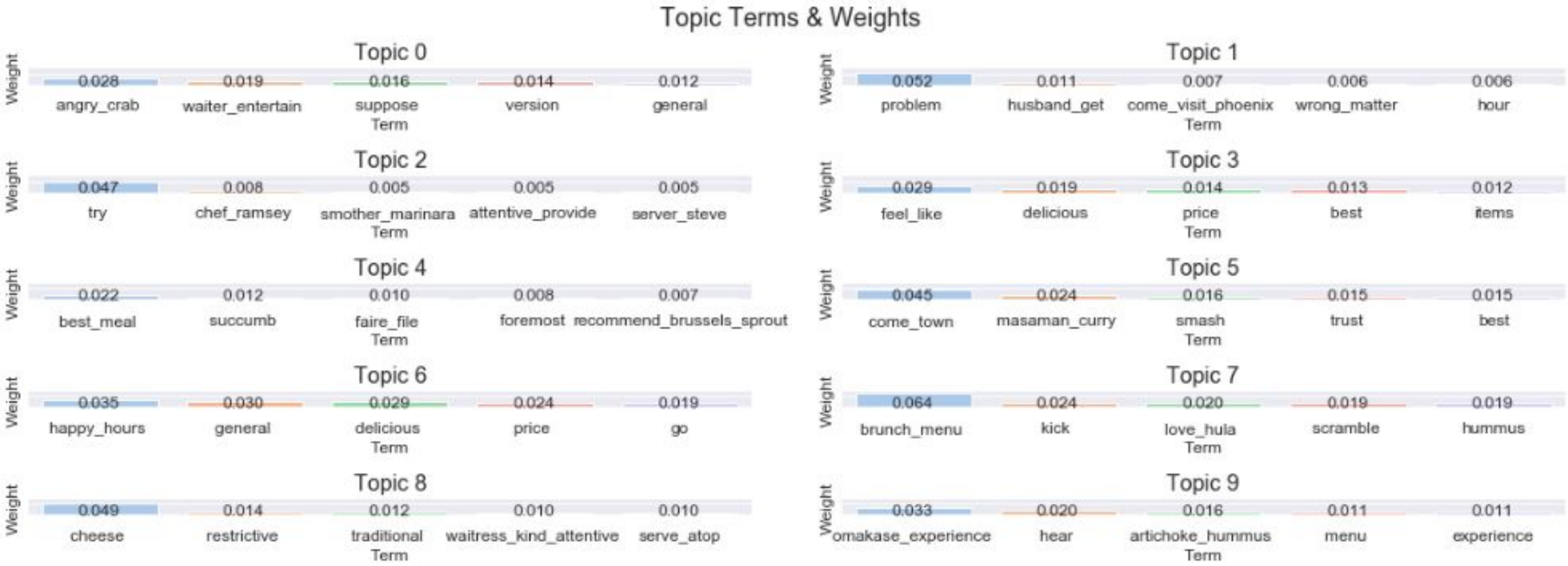




Food Industry Example - Negative Review Topics



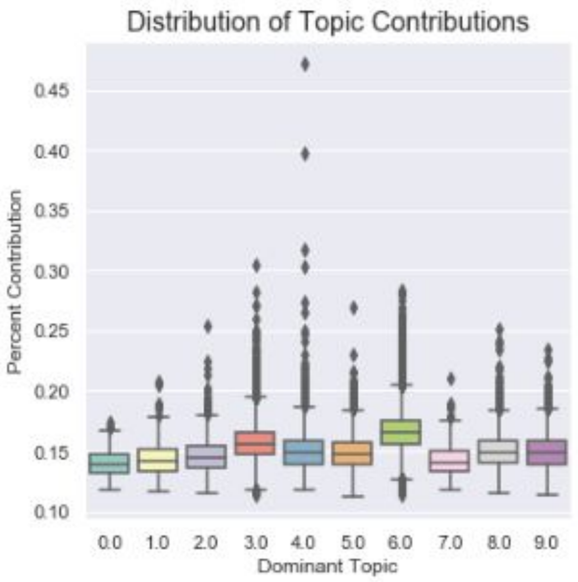
Food Industry Example - Positive Review Topics

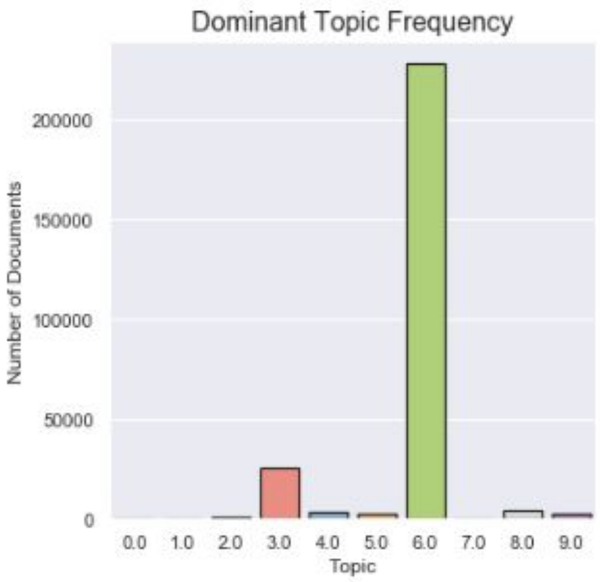


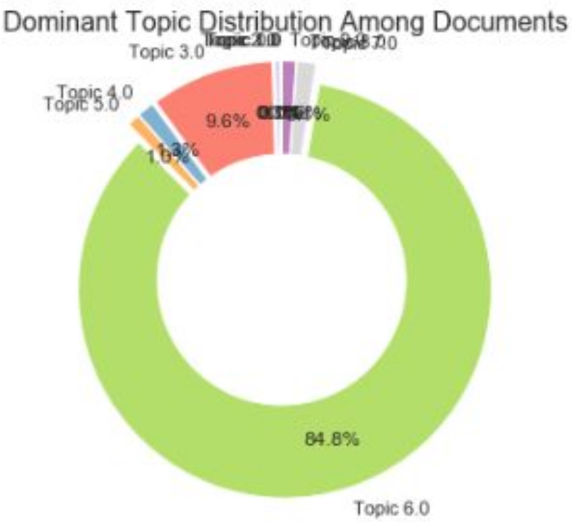
Food Industry Example - Positive Review Topics

Topic	Topic_%_Contribution	Topic_Keywords	Most_Representative_Text
0.0	0.1744	angry_crab, waiter_entertain, suppose, version, general, chef_ramsey, surely, original, price, c...	Its a bit difficult to say if the food here is any good or not. I'm writing this review while go...
1.0	0.2078	problem, husband_get, come_visit_phoenix, wrong_matter, hour, menu, quality_quantity, nutella_ba...	I came in on thursday to order a 50th anniversary cake. The lady helping me was friendly and he...
2.0	0.2538	try, chef_ramsey, smother_marinara, attentive_provide, server_steve, north_phoenix, boyfriend_ta...	The atmosphere is really elegant at this place especially at the top floor. Our server did a rea...
3.0	0.3052	feel_like, delicious, price, best, items, run, meat_combo_platter, cheese, second_night, toast	Famous Daves... Famous Daves....\nYes, I know a few.\n\nDavid Lynch \nDavid Cassidy \nDavid Bore...
4.0	0.4726	best_meal, succumb, faire_file, foremost, recommend_brussels_sprout, dress, artichoke_hummus, fe...	Buffet-Restaurants haben fast alle Hotels in Las Vegas. Im teuren Vegas eine MÃ¶glichkeit, gut u...
5.0	0.2690	come_town, masaman_curry, smash, trust, best, rito, flavorful, ahead_time, delicious, hand	I am no expert on soul food, but the fried chicken is finger lickin' good. Please don't sue me, ...
6.0	0.2841	happy_hours, general, delicious, price, go, plastic_bag, say_hour_wait, food_general, feel_like,...	This is definitely the best bar in the area. It has a ton of British charm, European and domesti...
7.0	0.2109	brunch_menu, kick, love_hula, scramble, hummus, kinda_slow, remind_mexican, potato_casserole, fe...	I totally agree with the other Yelpers! It is the best authentic Chinese food in Vegas. Prices...
8.0	0.2511	cheese, restrictive, traditional, waitress_kind_attentive, serve_atop, taste, crisp_fresh, best,...	Sunday at Noon and we were able to get a table immediately even though it was a packed house. F...
9.0	0.2350	omakase_experience, hear, artichoke_hummus, menu, experience, terrace_cafe, pineapple_fry, mexic...	Hints: Bone-In Rib Steaks\nBone-In Rib Steaks\nBone-In Rib Steaks\nBone-In Rib Steaks\nBone-In R...

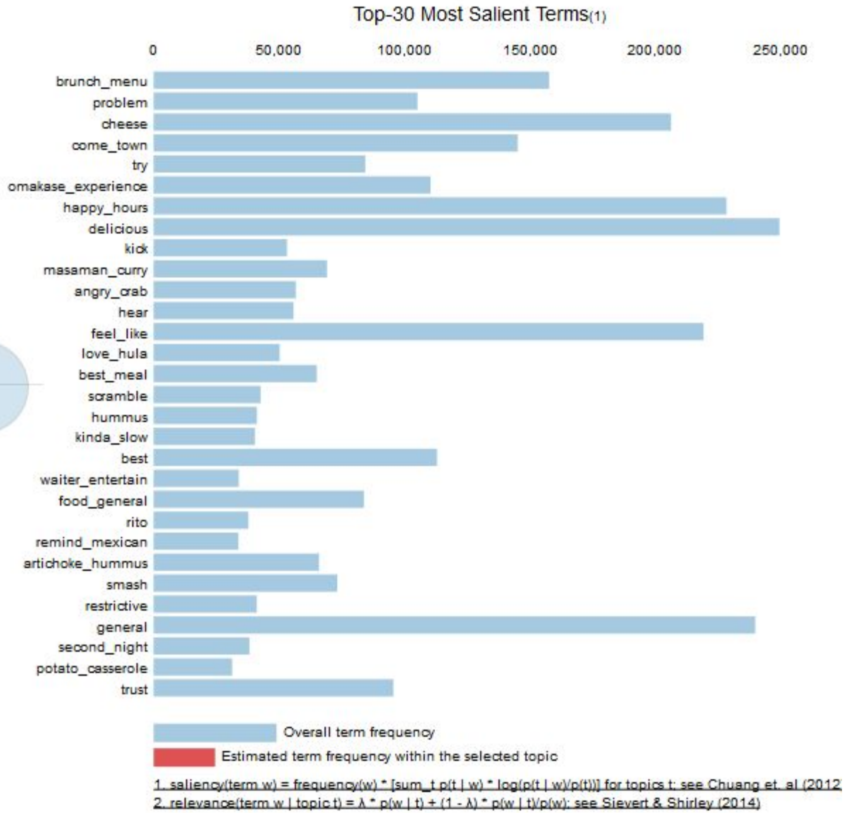
Food Industry Example - Positive Review Topics







Food Industry Example - Positive Review Topics



Client Recommendations

Based on the possible implementations of the product constructed and the results that may obtained from it, the following are some insightful uses that I would promote to any future clients:

- **To determine the direction of favorability for a particular product or initiative**
  - Success of a loss-leader in creating profitable upsell scenarios
  - Response to rebranding or new marketing strategy
  - Reception of an aesthetic change such as a remodel or relocation

- **To assess global versus local analysis**
  - Alongside a market penetration analysis to boost insight
  - Verifying Consistency in customer service across localities for a chain of businesses
  - Distinguishing between circumstantial and pervasive issues for a particular industry

Conclusion

In constructing this text analysis pipeline I encountered several problems consistent with common parables in reference materials, a notable one being that the quality of the topic model output rests tremendously on the quality of the preprocessing steps taken prior to training. The initial extraction of the text data from the overall Yelp academic dataset, and the subsequent transformation into a serviceable vector that can be used to train an LDA model, were both some of the most computationally expensive and consequential aspects of the overall procedure. Minor changes in these steps, such as filtering the vocabulary or adding n-grams to the corpus, often led to drastically differing results, which themselves proved uniquely challenging to interpret. Moving forward I would add more visualizations such as word clouds to assist in readability, as the success of each topic model created hinges on a combination of the user's domain knowledge and the ease in which it can be interpreted