Improving businesses with topic modeling

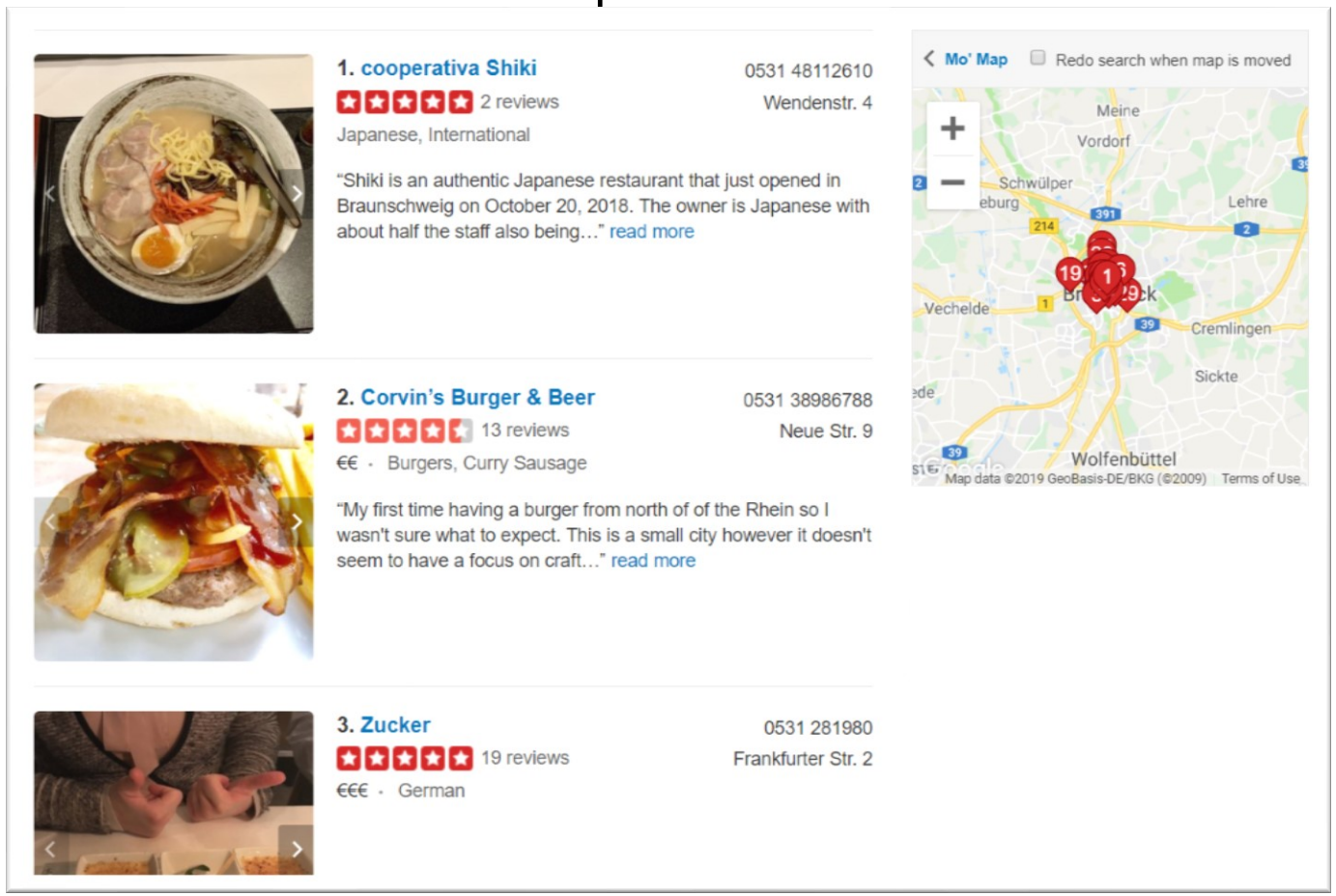
on the Yelp dataset

Elvira Pupka-Lipinski

Content

1. Yelp

- Crowd-sourced review forum
- Offers a recommendation portal for restaurants and shops
- Short form of **Yel**low **P**ages



https://www.yelp.com/search?find_desc=Restaurants&find_loc=Braunschweig%2C+Niedersachsen%2C+Deutschland&ns=1

1. Yelp

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Corvin‘s Burger & Beer in Braunschweig

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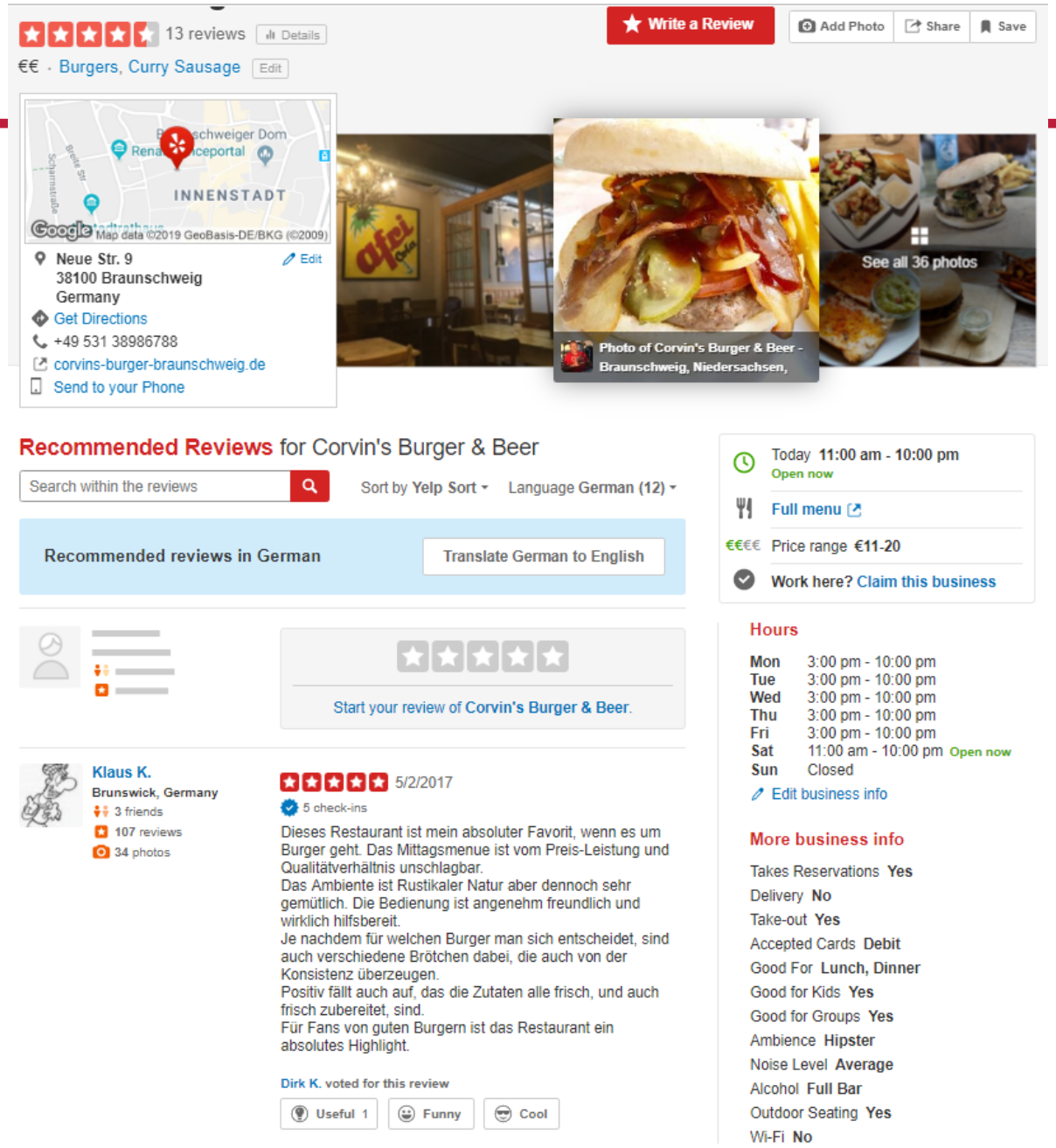

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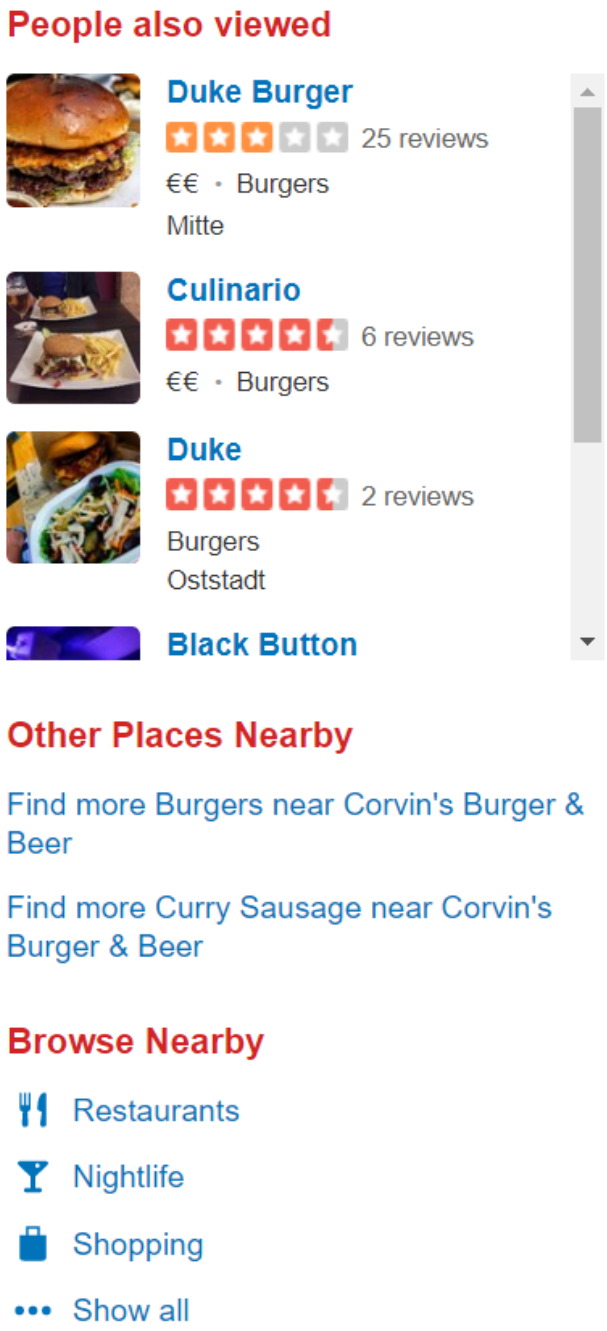

1. Yelp

- Yelp: crowd-sourced review forum
- Offers a recommendation portal for restaurants and shops
- Short form of **Yel**low **P**ages
- Yelp offers their dataset for analyzing the data and sharing the discoveries (https://www.yelp.com/dataset/challenge)

2. Possible tasks

- Decision guidance for Users
  - Determination of the 3 best dishes in a Restaurant (already exists)
  - Suggestions for businesses due to users‘ previous patterns
    - Beneficial while traveling
  - Suggestions for business due to similar users (clustering)

- Determination of the probability of closure of a business
  - Not possible due to the lack of needed data

- Improvements for business
  - Opening new business? What do the citizen in Pittsburgh want? What is important to consider?
  - What can I as a business owner improve?

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- Improvements for business
  - Opening new business? What do the citizen in Pittsburgh want? What is important to consider?
  - **What can I as a business owner improve?**

3. Approach: What can I as a business owner improve?

1. Building a pipeline allowing business owners to answer this question
2. Suggesting improvements for business ID: 'c0yPNU-BqS65u0vIKP7P0w‘ as an example

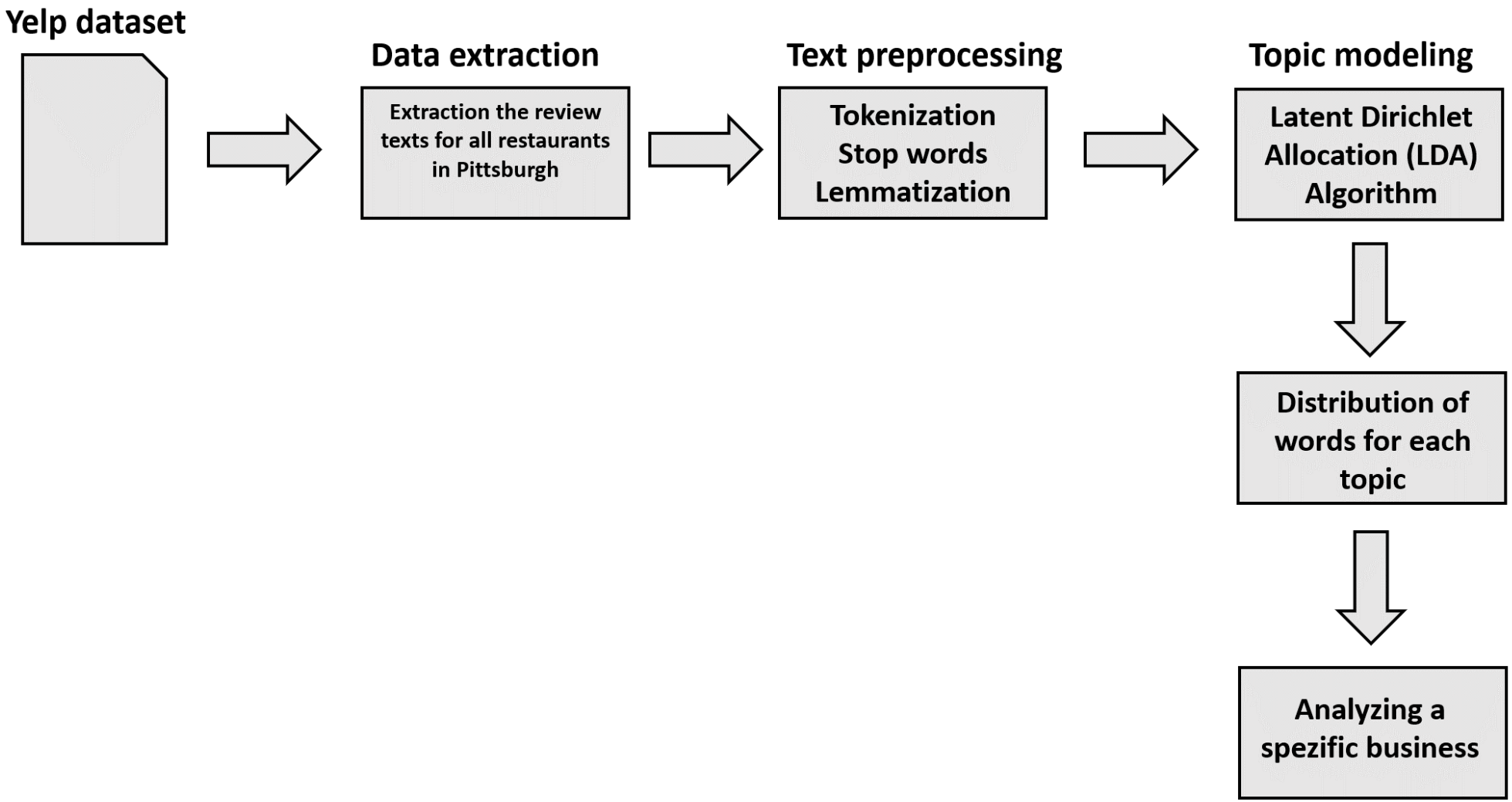
3. Business improvements

- Improvements for business
  - What can I as a business owner improve?
    - Idea: Extracting the topics the owner needs to improve
    - Approach: Topic modeling

Topic	Avg Stars
Food	4.0
Service	2.0
Location	4.0

→ **Improvement in service is needed**

3. Workflow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Tokenization
Stop words
Lemmatization
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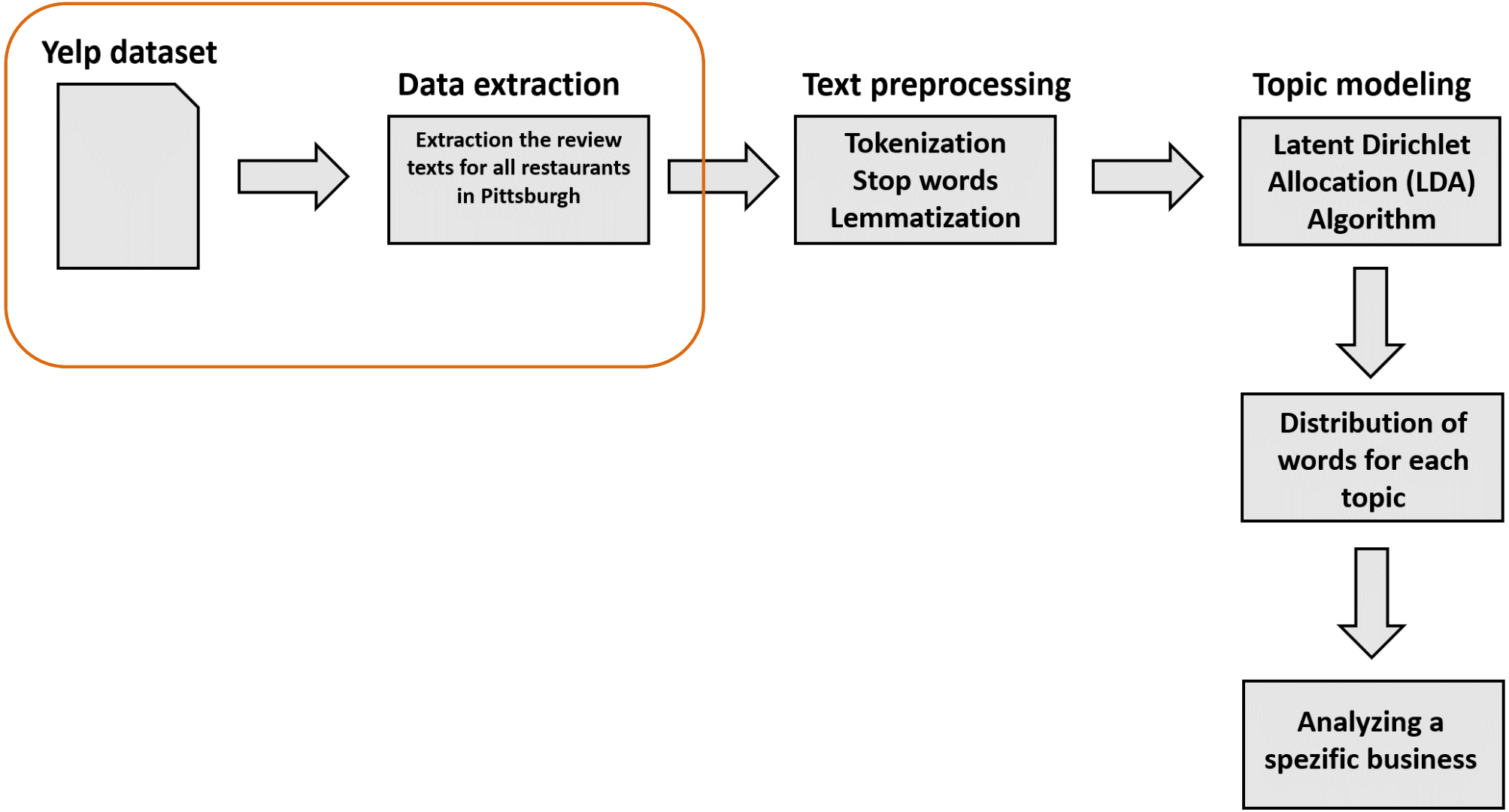
Latent Dirichlet Allocation (LDA) Algorithm
Distribution of words for each topic
Analyzing a spezific business

3. Workflow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3. Yelp dataset – Data Extraction

- Datasets
  - **business.json:** business data, location, attributes and categories (business_id)
  - **review.json:** full review data such as text, date and stars (review_id, user_id, business_id)
  - **user.json**: user information such as the average star rating and the users' friends (user_id)
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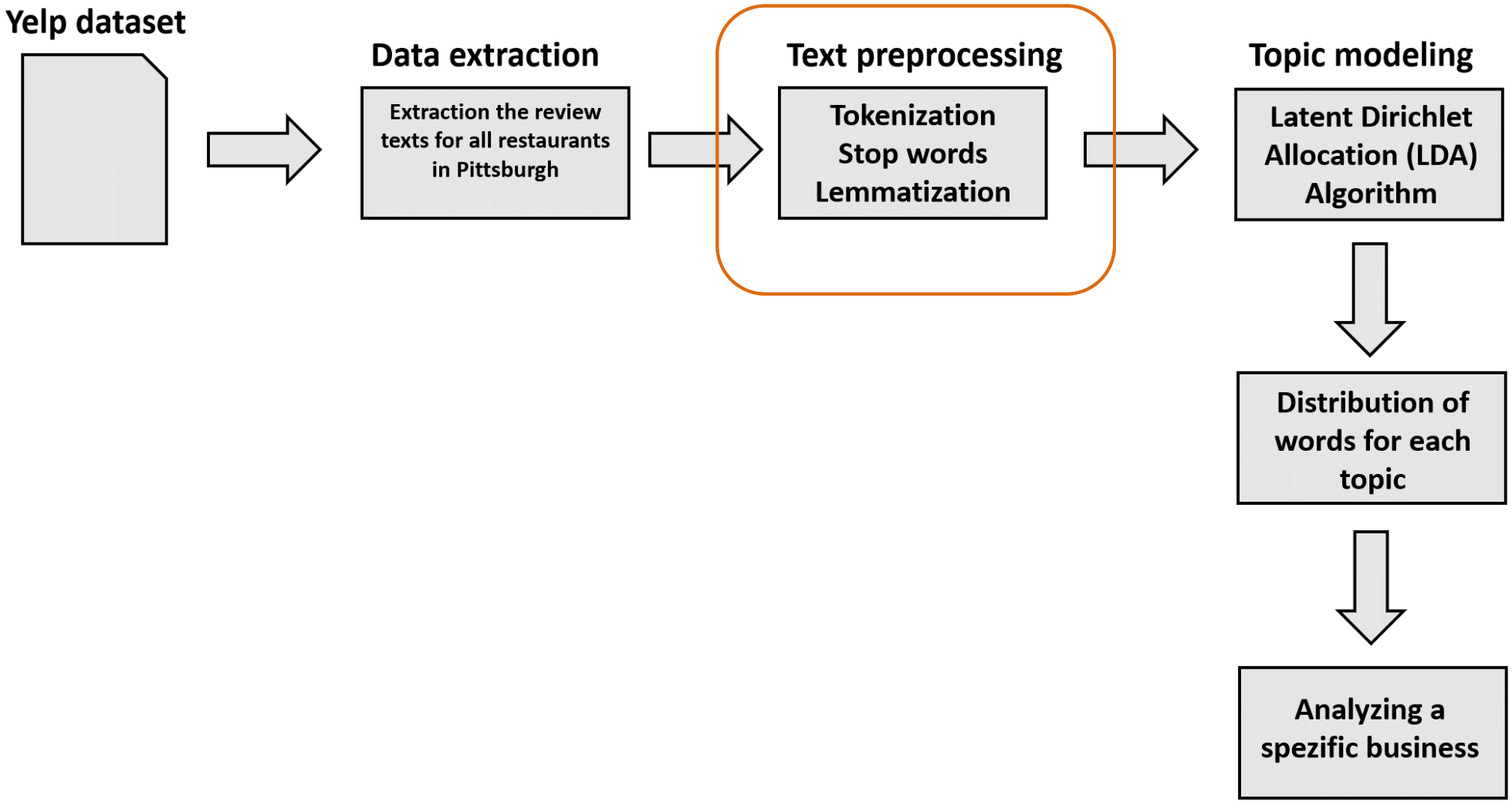
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3. Text preprocessing

“I definitely enjoyed my meal at avenue b, but with a meal that comes at a hefty price, I don't know if it's worth another trip. If I'm paying that much, the food BETTER be mind blowing.”

- **Lowering all characters:**

→ “i definitely enjoyed my meal at avenue b, but with a meal that comes at a hefty price, i don’t know if it's worth another trip. if i'm paying that much, the food better be mind blowing.”

- **Removing all punctuation:**

→ “i definitely enjoyed my meal at avenue b but with a meal that comes at a hefty price i don't know if it worth another trip if i paying that much the food better be mind blowing”

- **Tokenization:** Tokenization is the process of splitting the given text into smaller pieces called tokens.

→ ['i', 'definitely', 'enjoyed', 'my', 'meal', 'at', 'avenue', 'b', 'but', 'with', 'a', 'meal', 'that', 'comes', 'at', 'a', 'hefty', 'price', 'i', 'do', "n't", 'know', 'if', 'it', 'worth', 'another', 'trip', 'if', 'i', 'paying', 'that', 'much', 'the', 'food', 'better', 'be', 'mind', 'blowing’]

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→['i', 'definitely', 'enjoyed', 'my', 'meal', 'at', 'avenue', 'b', 'but', 'with', 'a', 'meal', 'that', 'comes', 'at', 'a', 'hefty', 'price', 'i', 'do', "n't", 'know', 'if', 'it', 'worth', 'another', 'trip', 'if', 'i', 'paying', 'that', 'much', 'the', 'food', 'better', 'be', 'mind', 'blowing‘]

- **Removing stop words:**

→['definitely’, 'enjoyed’, 'meal’, 'avenue’, 'b’, 'meal’, 'comes’, 'hefty’, 'price’, 'n't’, 'know’, 'worth’, 'trip’, 'paying’, 'food’, 'mind’, 'blowing']

3. Text preprocessing

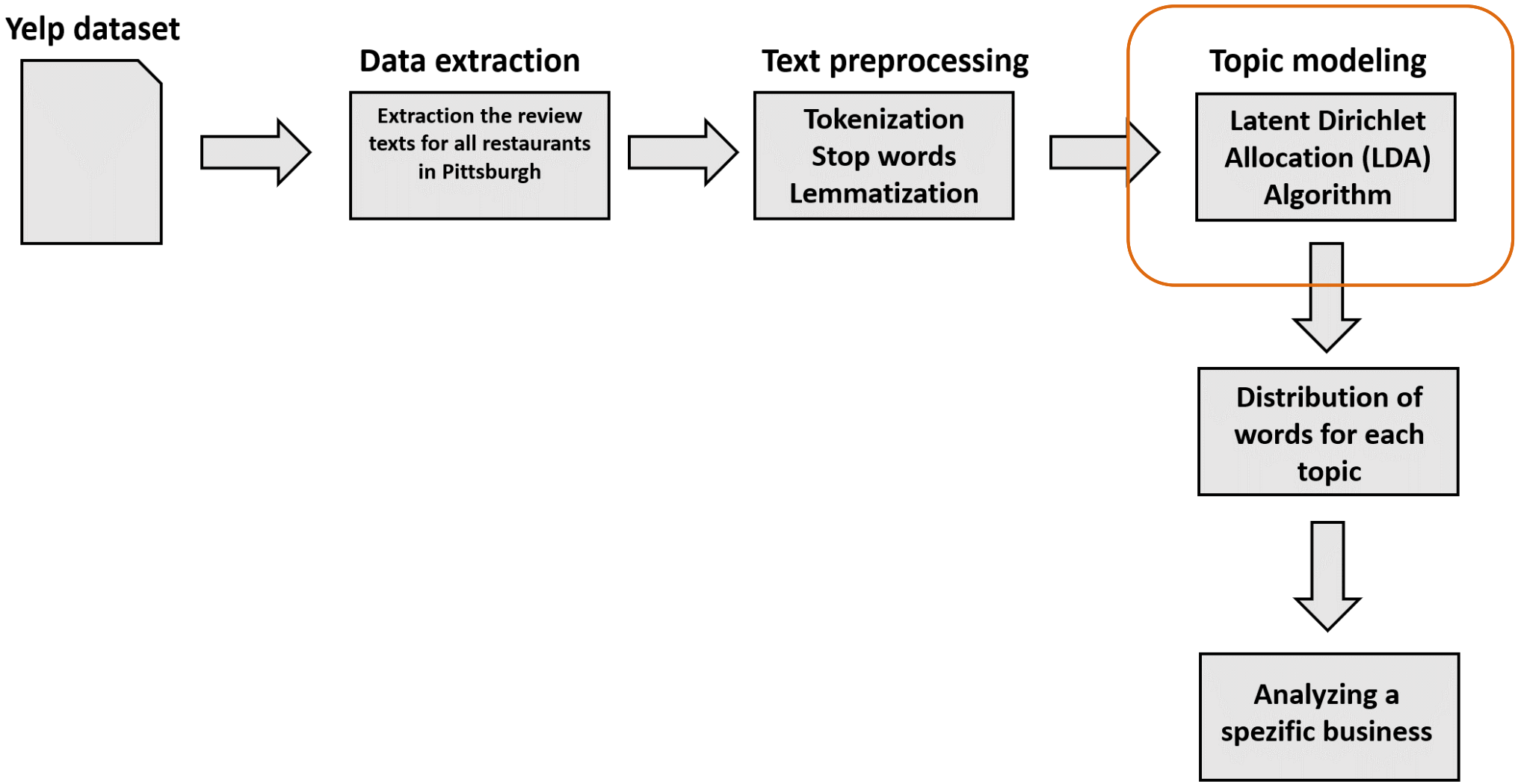
- **Stop words:**

→['definitely', 'enjoyed', 'meal', 'avenue', 'b', 'meal', 'comes', 'hefty', 'price', 'n't', 'know', 'worth', 'trip', 'paying', 'food', 'mind', 'blowing']

- **Lemmatization**: reduce inflectional forms to a common base form

→['definitely', 'enjoy', 'meal', 'avenue', 'b', 'meal', 'come', 'hefty', 'price', 'n't', 'know', 'worth', 'trip' 'pay', 'food', 'mind', 'blow']

3. Workflow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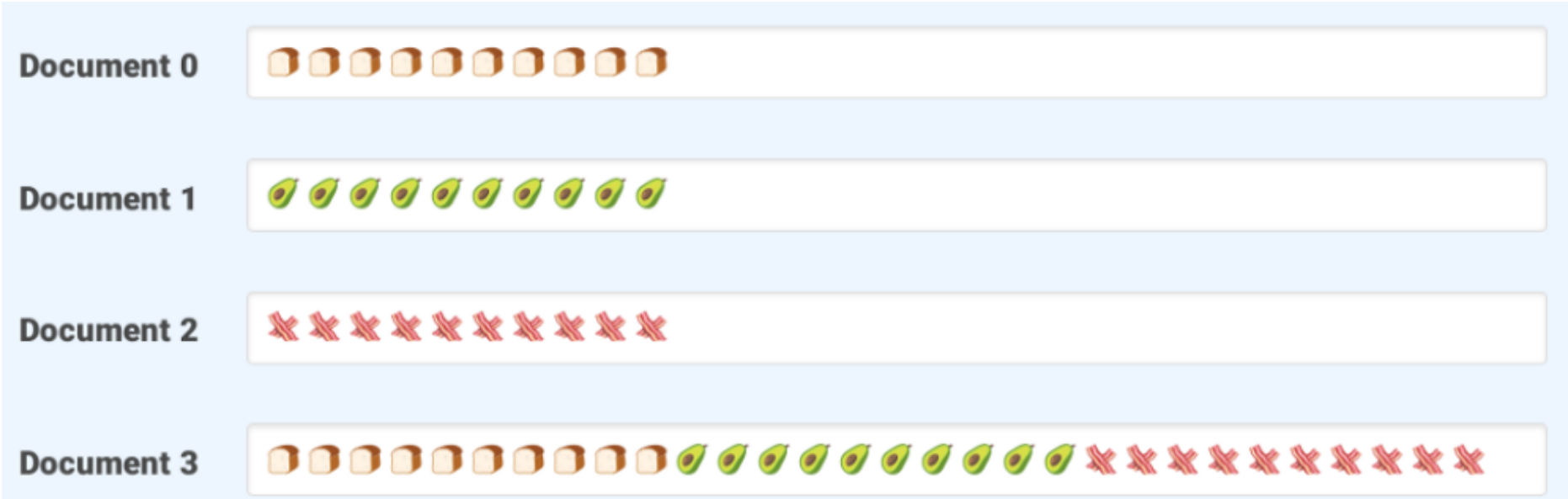
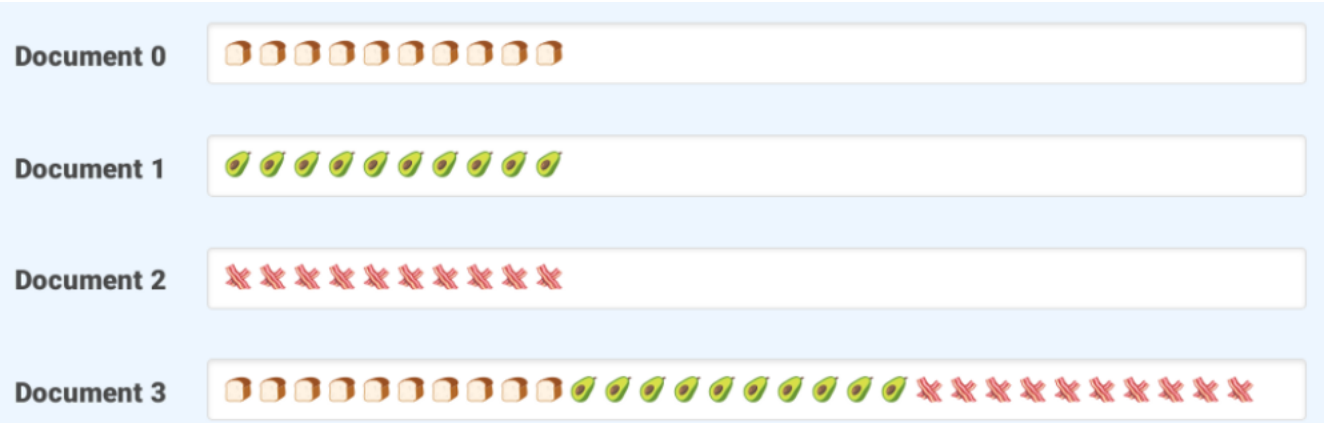
3. Approach: Latent Dirichlet Allocation

- Generative statistical model for topic discovery
- Unsupervised learning



https://medium.com/@lettier/how-does-lda-work-ill-explain-using-emoji-108abf40fa7d

3. Approach: Latent Dirichlet Allocation



Word vs.Topic Matrix (θ)

	Topic 0	Topic 1	Topic 2
	0.000	0.000	0.999
	0.999	0.000	0.000
	0.000	0.999	0.000
	Topic 0	Topic 1	Topic 2

Document vs.Topic Matrix (ϕ)

	Topic 0	Topic 1	Topic 2
Document 0	0.030	0.030	0.939
Document 1	0.939	0.030	0.030
Document 2	0.030	0.939	0.030
Document 3	0.333	0.333	0.333
	Topic 0	Topic 1	Topic 2

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3. Approach: Latent Dirichlet Allocation

- LDA's assumption on how documents are generated:

1. Determine a unique set of words, determine amount of documents and the amount of words per document, determine amount of topics, determine α & β
2. Calculation the probability of each word per topic (Word vs.Topic Matrix (θ))
   - drawing a Dirichlet distribution for each topic
   - hyperparameter β: controls the distribution of words in topics

Word vs.Topic Matrix (θ)

	Topic 0	Topic 1	Topic 2
🍞	0.000	0.000	0.999
🥑	0.999	0.000	0.000
🌶	0.000	0.999	0.000
	Topic 0	Topic 1	Topic 2

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3. Approach: Latent Dirichlet Allocation

- LDA's Assumtion on how documents are generated:

3. Calculation the probability of each Topic per Document (Document vs.Topic Matrix (ϕ))
   - drawing a Dirichlet distribution for each document
   - hyperparameter α: controls the mixture of topics for any given document

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3. Approach: Latent Dirichlet Allocation

- LDA's Assumtion on how documents are generated:

4. Building the actual document

	Topic 0	Topic 1	Topic 2
🍞	0.000	0.000	0.999
🥑	0.999	0.000	0.000
🥓	0.000	0.999	0.000
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	Topic 0	Topic 1	Topic 2

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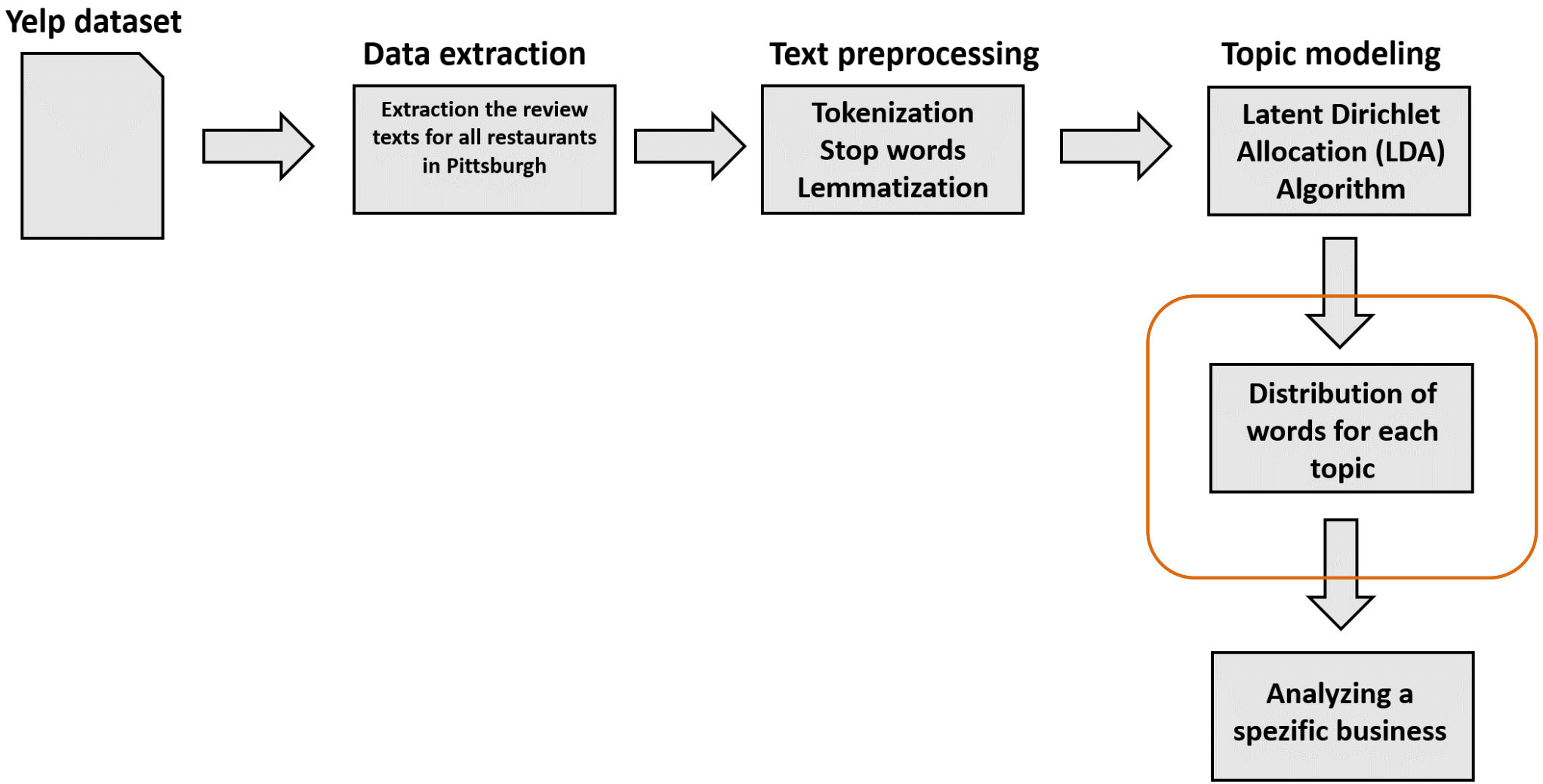
3. How does LDA works for topic modeling?

- $p(Topics, \theta, \phi \mid Documents)$
  - variables depend on each other
  - NP-hard problem
  - → approximation of p using variance inference
    - distribution $q(Topics, \theta, \phi \mid Documents)$
    - minimizing Kullback-Leibler divergence

3. Workflow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4. Results

- Top 10 words in topics for Pittsburgh and Restaurants:

  - Topic 0: ['food', 'place', 'service', 'try', 'restaurant', 'price', 'chicken', 'time', 'come', 'like']
  - Topic 1: ['pizza', 'burger', 'order', 'fry', 'cheese', 'like', 'sauce', 'wing', 'eat', 'place']
  - Topic 2: ['taco', 'dish', 'delicious', 'order', 'flavor', 'sauce', 'thai', 'restaurant', 'meal', 'dessert‘]
  - Topic 3: ['food', 'time', 'order', 'place', 'come', 'service', 'table', 'wait', 'drink', 'bar']
  - Topic 4: ['place', 'sandwich', 'beer', 'pittsburgh', 'coffee', 'love', 'like', 'breakfast', 'brunch', 'selection‘]

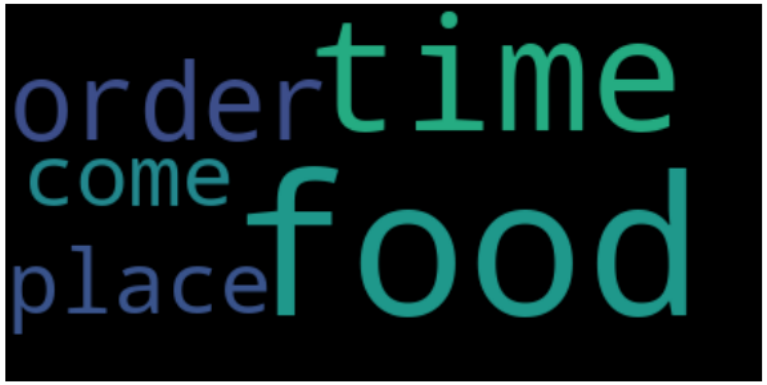
4. Results

Top words of Topic 0

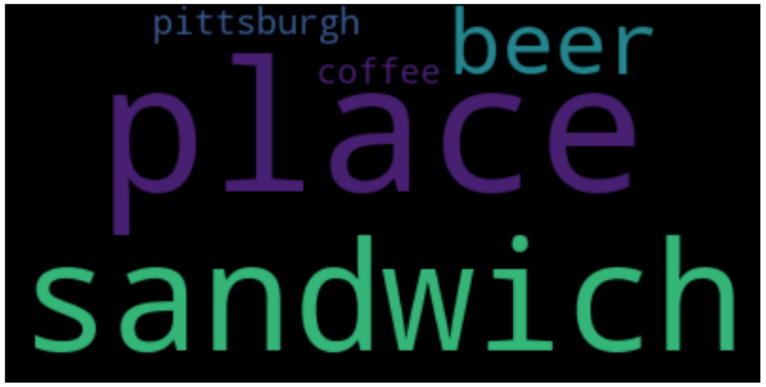
Top words of Topic 1

Top words of Topic 2

Top words of Topic 3



Top words of Topic 4



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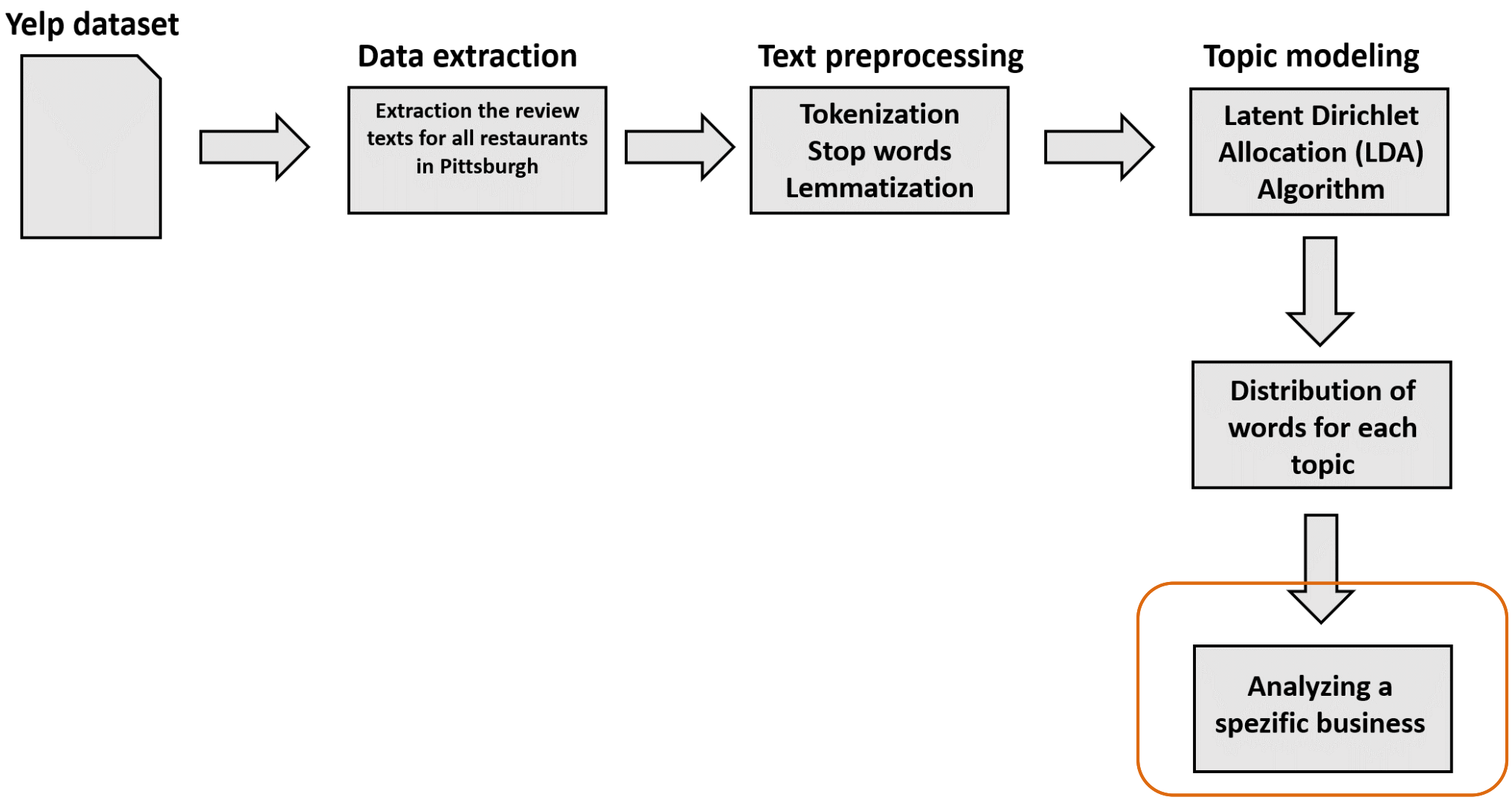
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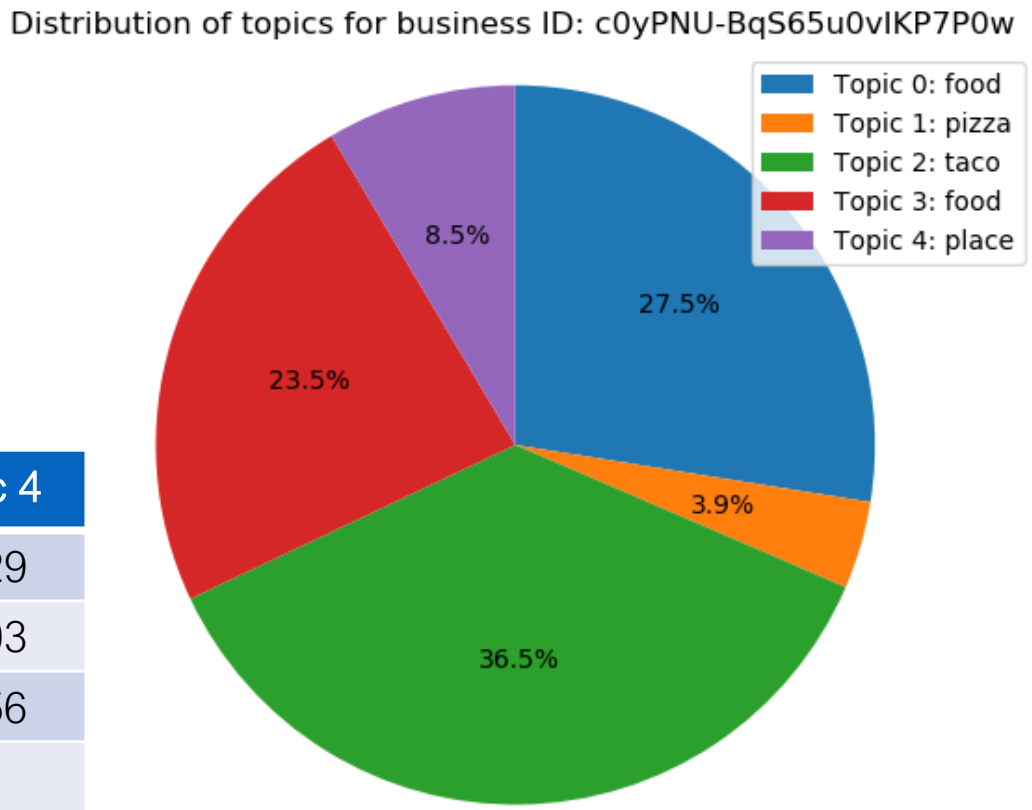
4. Results

- Business ID: 'c0yPNU-BqS65u0vIKP7P0w‘
  - name: Avenue B
  - city: Pittsburgh
  - stars: 4.0
  - review_count: 228
  - categories: American (New), Restaurants

- Prediction:

	Topic 0	Topic 1	Topic 2	Topic 3	Topic 4
Review 1	0.884	0.029	0.029	0.029	0.029
Review 2	0.216	0.121	0.658	0.003	0.003
Review 3	0.0029	0.299	0.317	0.325	0.056
…	…	…	…	…	…



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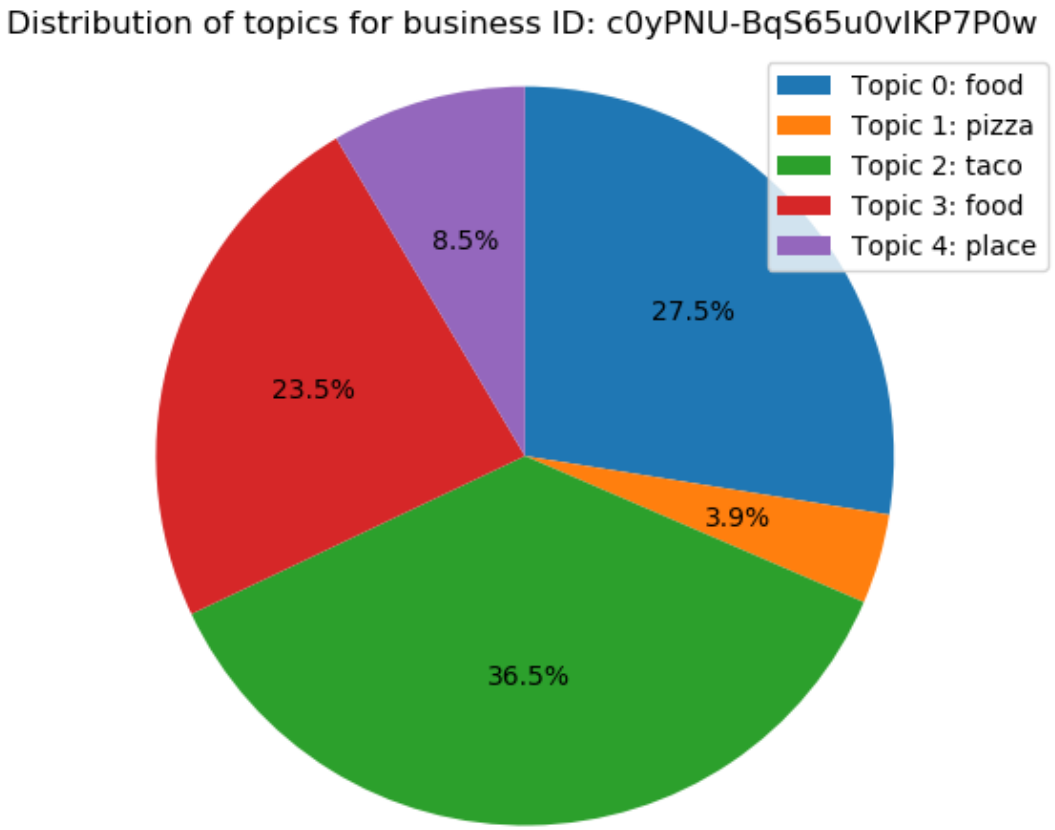


Topic 0: ['food', 'place', 'service', 'try', 'restaurant', 'price', 'chicken', 'time', 'come', 'like']

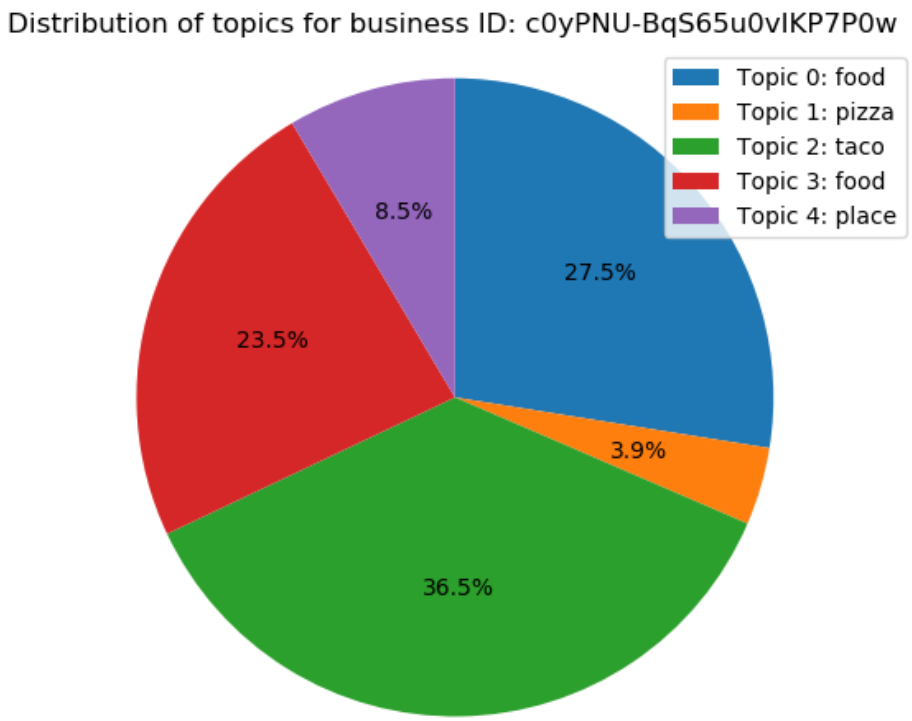
Topic 1: ['pizza', 'burger', 'order', 'fry', 'cheese', 'like', 'sauce', 'wing', 'eat', 'place']

Topic 2: ['taco', 'dish', 'delicious', 'order', 'flavor', 'sauce', 'thai', 'restaurant', 'meal', 'dessert']

Topic 3: ['food', 'time', 'order', 'place', 'come', 'service', 'table', 'wait', 'drink', 'bar']

Topic 4: ['place', 'sandwich', 'beer', 'pittsburgh', 'coffee', 'love', 'like', 'breakfast', 'brunch', 'selection']

4. Results



Topic 0: ['food', 'place', 'service', 'try', 'restaurant', 'price', 'chicken', 'time', 'come', 'like']

- **Menu?**

Topic 1: ['pizza', 'burger', 'order', 'fry', 'cheese', 'like', 'sauce', 'wing', 'eat', 'place']

- **Fast food**

Topic 2: ['taco', 'dish', 'delicious', 'order', 'flavor', 'sauce', ‘’thai', 'restaurant', 'meal', 'dessert‘]

- **Mexican and Thai food**

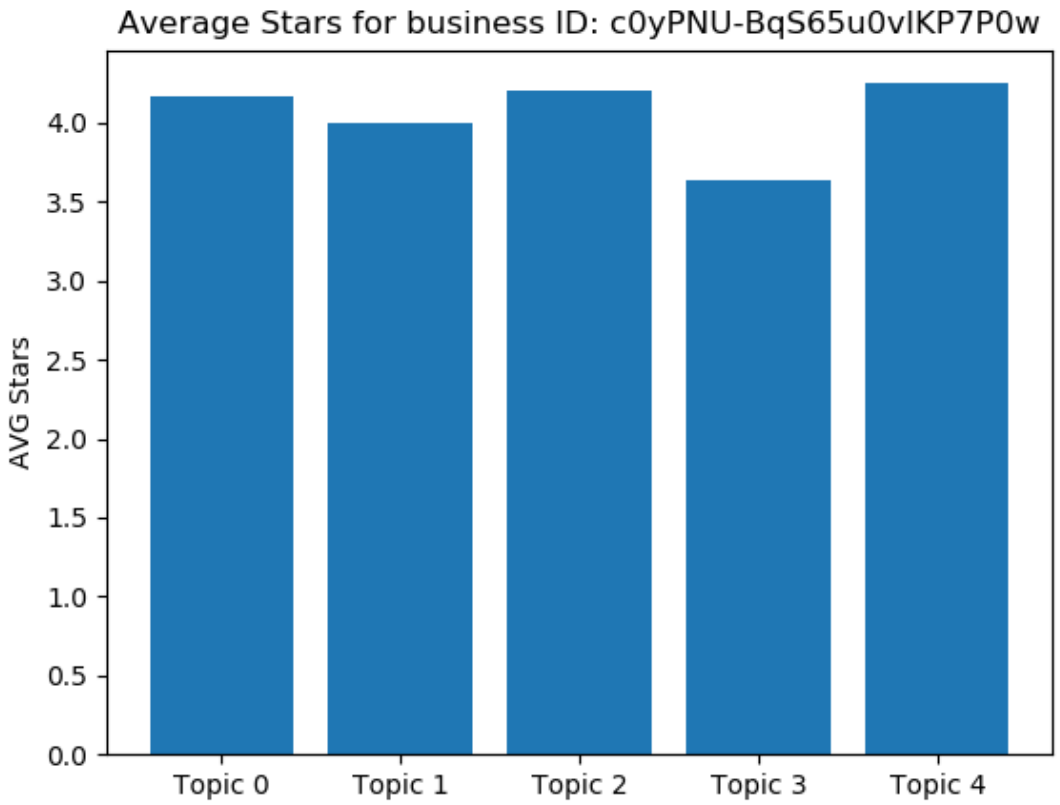
Topic 3: ['food', 'time', 'order', 'place', 'come', 'service', 'table', 'wait', 'drink', 'bar']

- **Restaurant / Diner?**

Topic 4: ['place', 'sandwich', 'beer', 'pittsburgh', 'coffee', 'love', 'like', 'breakfast', 'brunch', 'selection‘]

- **Café**

4. Results

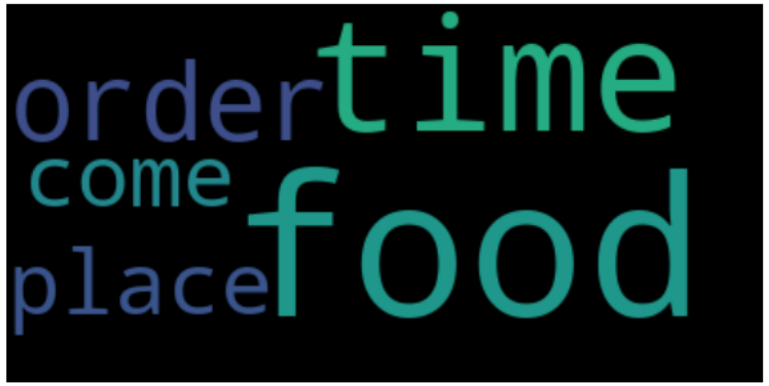


→Less average stars for Topic 3 ('food', 'time', 'order', 'place', 'come', 'service', 'table', 'wait', 'drink', 'bar') Restaurant / Diner

5. Discussion

Top words of Topic 0

Top words of Topic 3



- Working pipeline implemented
- Topic 0 and 3 are pretty similar
  - 5 topics for LDA are not optimal
  - Default values for α and β
  - Only used 1-grams

6. Prospects

- Determine α and β
  - Grid search

- Determine the number of topics (k)
  - Grid search
  - HDP-LDA

- Expanding code to answer the question: What do the citizen in Pittsburgh want? What is important to consider when opening a new business?
  - Analysis of all businesses in the area

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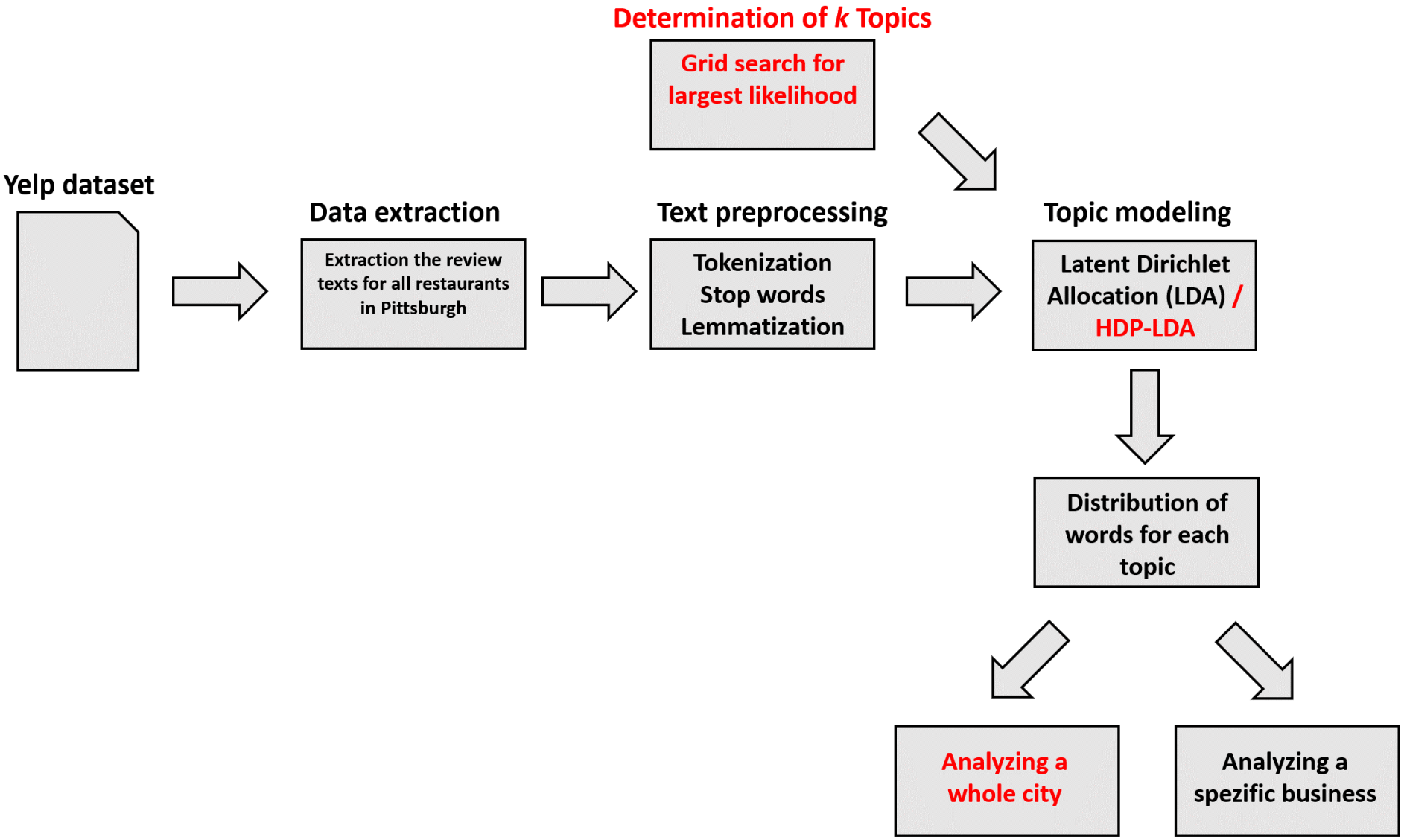
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6. Prospects

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  - Grid search
- Determine the number of topics (k)
  - Grid search
  - HDP-LDA
- Expanding code to answer the question: What do the citizen in Pittsburgh want? What is important to consider when opening a new business?
  - Analysis of all businesses in the area
- Evaluation of the results
  - Score: approximate log-likelihood
- Using a database for storage

Thank you for your attention