

# CS 520 - Data Integration, Warehousing and Provenance

Data Curation Project - Yelp Dataset

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# Topics to be Covered

Overview and Data Intro Data Curation and Analysis

Conclusion

# **Understanding the Dataset**

#### Domain

The dataset represents user-generated reviews and business details from the Yelp platform, providing a comprehensive insight into local businesses, primarily in the North American region.

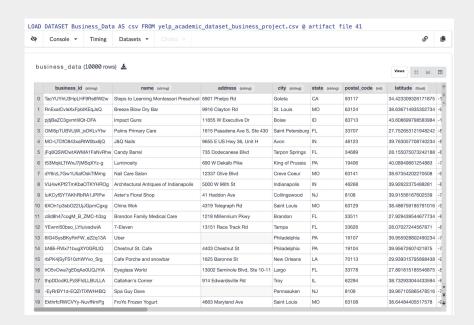
#### Resources

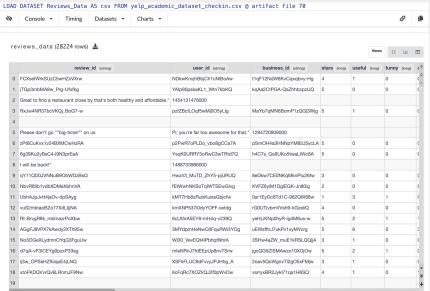
The dataset was available on the Kaggle's platform via the following link: [Kaggle Yelp Dataset](https://www.kaggle.com/datasets/yelp-dataset/yelp-dataset/data).

#### **Dataset Characteristics**

- Dataset Size: 10,000 Records
- Attributes: Diverse attributes such as `address`, `categories`, `city`, `latitude`, `longitude`, `name`, `postal\_code`, `review\_count`, `stars`, among others.
- Data Format: Data was in JSON format

# **Understanding the Dataset**





# **Understanding the Dataset**

#### Attributes - Business Dataset

#### Reviews Dataset

Attribute	Description	
business_id	Unique identifier for each business	
name	Name of the business	
address Street address of the business		
city	City where the business is located	
state	State where the business is located	
postal_code	Postal or ZIP code of the business location	
latitude	Geographic latitude of the business	
longitude	Geographic longitude of the business	
stars	Average star rating of the business (e.g., 1 to 5 scale)	
review_count	Number of reviews received by the business	
is_open Indicator if the business is currently open or closed		
attributes	Various attributes of the business (e.g., WiFi, parking)	
categories	Types or categories the business falls into	
hours	Operating hours of the business	

Attribute	Description	
review_id	Unique identifier for each review	
user_id	Identifier for the user who posted the review	
business_id	Unique identifier for each business reviewed	
stars	Star rating given by the user (e.g., 1 to 5 scale)	
date	Date when the review was posted	
text	Text content of the review	
useful	Number of users who found the review useful	
unny Number of users who found the review funn		
cool	Number of users who found the review cool	

# **Preliminary Observations - Business Dataset**

#### Attributes Data Types

```
The total number of rows are - 10000
The total number of features are - 14
The datatype of various features is -
business_id
                object
                object
name
address
                object
                object
city
                object
state
postal code
               float64
latitude
               float32
longitude
               float32
stars
               float32
review_count
                 int16
is_open
                  bool
attributes
                object
                object
categories
```

#### Null Values

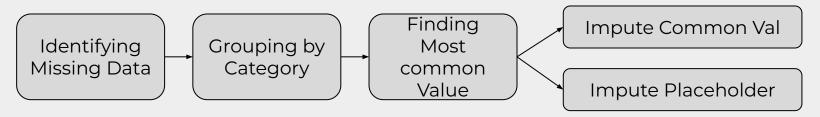
```
Checking the Null/Missing values Feature-
business_id
name
address
                349
city
state
postal code
                372
latitude
longitude
stars
review_count
is_open
attributes
                964
categories
                649
hours
dtype: int64
```

# Data Cleaning Strategies - Business Data

Handling the Missing Values for Column 'Attribute and Hours'

For each category c in our DataFrame, we found the most common value v in attributes and hours.

For all rows r where r.categories = c and r.attribute (or r.hours) is null, we assigned v to r.attribute (or r.hours). If no common value is found, assign 'Not specified'.

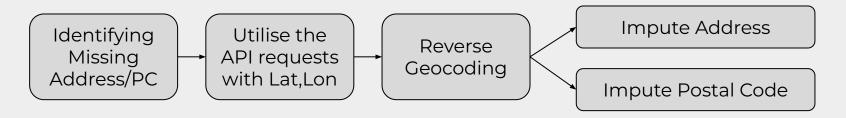


Different business categories might have distinct common attributes and operating hours. Grouping by category allows for a more accurate and contextually relevant imputation.

# Data Cleaning Strategies - Business Data

Handling the Missing Values for Column 'Address and Postal Code'

For each row r in our DataFrame, if r.address or r.postal\_code is null, use the OpenStreetMap Nominatim API to perform reverse geocoding based on r.latitude and r.longitude. Assign the obtained address to r.address and the postal code to r.postal\_code.



For each identified row with missing data, send a request to the Nominatim API using the row's latitude and longitude to obtain the corresponding address and postal code.

# Data Cleaning Strategies - Business Data

Ensuring Consistency and Dropping Missing 'Categories'

Given the low number of missing values (only 4) for the 'categories' column in the dataset, it is decided to drop these rows to maintain data integrity.

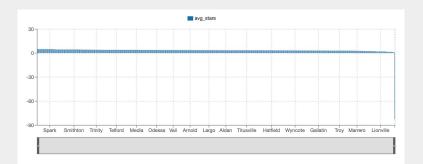
For all rows in our DataFrame that have a postal\_code, ensure that the data type of postal\_code is a string.

Saving as New Dataset

```
Remaining null values in each column:
business_id
address
city
state
postal code
latitude
longitude
stars
review count
is_open
attributes
categories
dtype: int64
Number of rows assigned with new address: 348
Number of rows assigned with new postal code: 371
```

# **Analysis on Business Data**

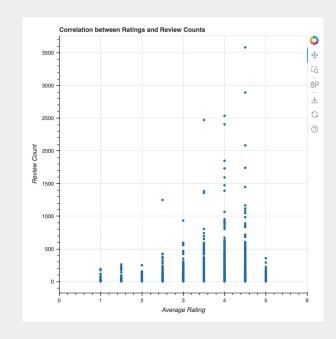
#### Average Star Ratings



#### Category Based Businesses

	categories (string)	city (string)	business_count
0	'BusinessAcceptsCreditCards': 'True'	Philadelphia	69
1	"'BusinessParking': """"""{'garage': False"""	Philadelphia	65
2	'BusinessAcceptsCreditCards': 'True'	Tampa	61
3	'street': True	Philadelphia	59
4	'BusinessAcceptsCreditCards': 'True'	Indianapolis	53
5	'street': False	Philadelphia	49
6	'RestaurantsPriceRange2': '2'	Philadelphia	45
7	'street': False	Tucson	42
8	"'BusinessParking': """""""{'garage': False"""	Tucson	41

# Correlation Between Ratings and Review Counts



# **Preliminary Observations - Reviews Dataset**

#### Attributes Data Types

```
The total number of rows are - 28224
The total number of features are - 9
The datatype of various features is -
review_id
               object
user id
               object
business id
               object
              float64
stars
useful
             float64
              float64
funny
cool
              float64
               object
text
date
              float64
dtype: object
Computing the duplicate rows
```

8266

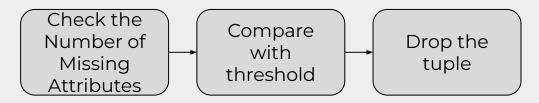
#### Null Values

```
Computing the Null/Missing values
review id
               7773
              10459
user_id
business_id
              13670
              17787
stars
               18019
useful
              18103
funny
              18172
cool
              17808
text
date
               21962
dtype: int64
```

# Data Cleaning Strategies - Reviews Data

Handling the Duplicate and Incomplete Data

Records without IDs in reviews dataset may exist due to data entry errors or extraction issues. A filtering method was used to remove these records, ensuring data quality for analysis.



Initial number of rows: 28224

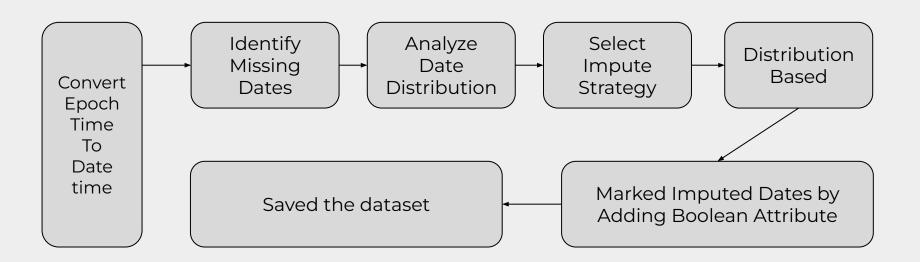
Number of rows after dropping missing IDs: 14553

Number of rows after filtering based on null count: 10000

Total number of rows removed: 18224

# Data Cleaning Strategies - Reviews Data

Handling the Missing Values of Column 'Date'



# Data Cleaning Strategies - Reviews Data

Why Use Distribution

**Maintains Data Integrity**: Imputing dates based on existing distributions maintains the integrity of the dataset, ensuring that the imputed dates are representative of the actual data patterns.

**Avoiding Misleading Analysis:** Placeholders can skew results and give a false impression of data trends. Time-based analysis preserves the natural variance and distribution of the data.

# Integrating the Datasets

#### Combining the Datasets

#### Integration Process:

Step 1: Identify the common key ('business\_id') between datasets.

Step 2: Merge datasets on 'business\_id' using an inner join.

Step 3: Retain relevant columns from both datasets for comprehensive analysis.

Step 4: Review the integrated dataset to ensure accuracy and completeness.

#### **Key Features for Analysis:**

Business Dataset: Contains details about businesses (e.g., name, location, attributes).

Reviews Dataset: Contains customer reviews and ratings for businesses.

# Integrating the Datasets

