



DATABASE-DRIVEN SENTIMENT ANALYSIS

A MACHINE LEARNING APPROACH TO IDENTIFYING MALICIOUS YELP REVIEWS

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INTRODUCTION

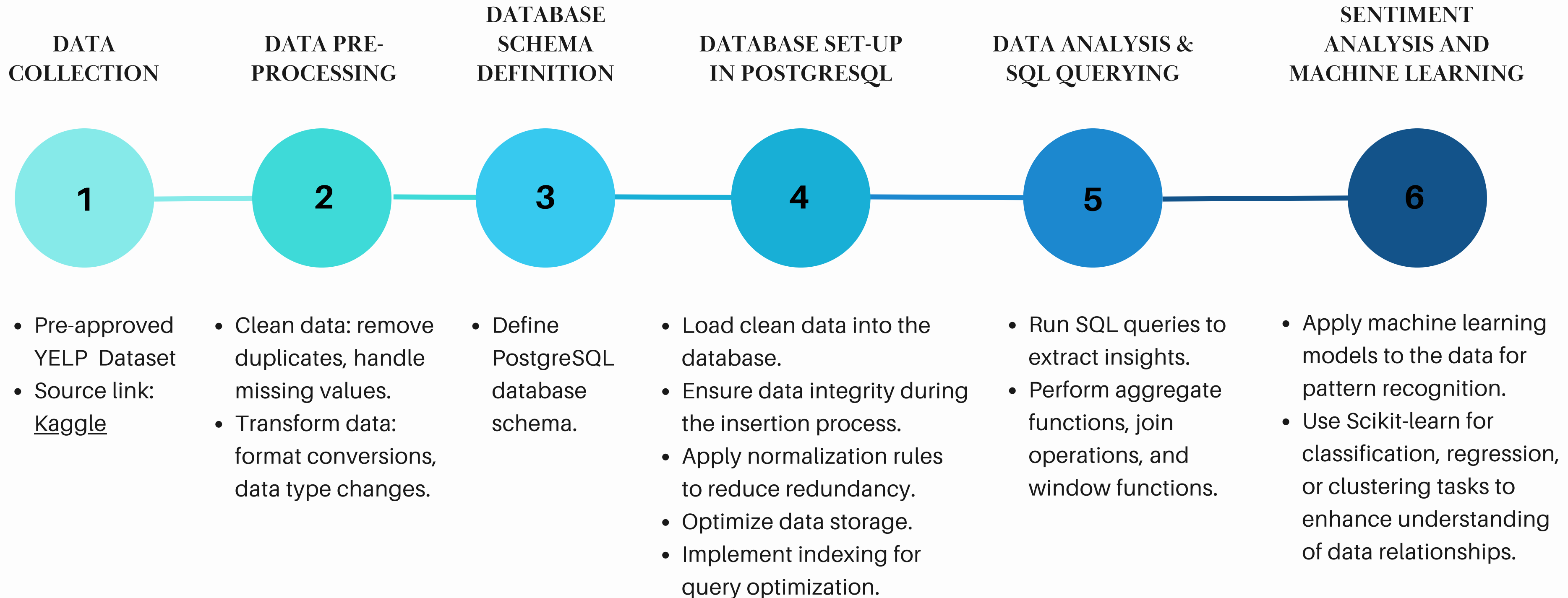
Context: In today's digital age, online reviews significantly impact consumer behavior and business reputation. However, the prevalence of fake or malicious reviews can undermine trust in these digital platforms.

Challenge: Differentiating between genuine and malicious reviews remains a complex issue due to the subtle nuances in language and the vast volume of data.

Project Objective: A Database Management and Machine Learning Approach to Identifying Authentic Yelp Reviews to develop a robust system that uses advanced database management techniques to accurately identify authentic reviews on Yelp. The use of machine learning is illustrative, supporting the primary focus on database management for this class.

Importance: By improving the accuracy of review authenticity, we aim to enhance user trust in Yelp's review system, thereby supporting better decision-making for consumers and fairer conditions for businesses.

APPROACH



WHY POSTGRES QL?



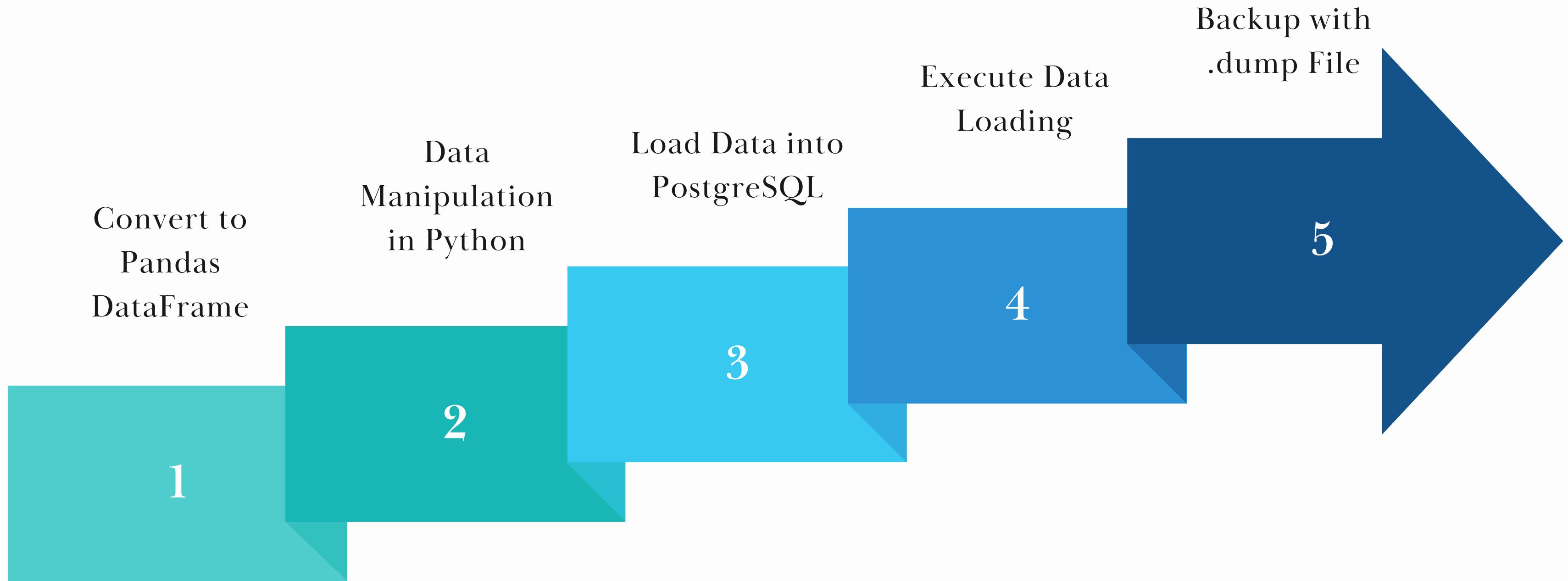
Relational database management is done in SQL.

Its strong syntax, which accurately defines and manipulates data, helps it effectively handle structured data. SQL lets users get data, update records, and manage database structures using simple instructions.

- **Full-Text Search:** PostgreSQL has full-text search capabilities, which are essential for analyzing and searching through large volumes of text-based reviews.
- **Procedural Languages:** Supports various procedural languages like PL/pgSQL, which allows for writing complex stored procedures and functions for data analysis.
- **Extensibility:** It can be extended with custom functions developed in different programming languages such as C, Perl and Python (in our case) allowing for custom analytics.
- **Robust Security:** It offers strong security features to protect sensitive data.
- **Machine Learning Integration:** It can be integrated with machine learning tools, enabling the application of algorithms directly within the database for identifying patterns indicative of malicious content.
- **Open Source:** Being open-source, it has a wealth of plugins and tools, which is useful for our sentiment analysis on the Yelp Data.

UPLOADING DATA INTO POSTGRESQL

> FOR DATA STORAGE AND MANAGEMENT



UPLOADING DATA INTO POSTGRESQL

> CODE SNIPPETS

```
# Function to load df to PostgreSQL
def load_dataframe_to_postgresql(df, engine, table_name, chunksize=5000):
    """
    Load a pandas DataFrame into a PostgreSQL table.
    """
    df.to_sql(table_name, engine, if_exists='append', index=False, chunksize=chunksize)

# Database credentials and connection
username = 'team1'
password = 'yelpdata'
host = 'localhost'
port = '5434'
database = 'yelpdb'
engine = create_engine(f'postgresql://{username}:{password}@{host}:{port}/{database}')
```

```
# Data manipulation: Remove "date" columns and duplicate rows
if 'date' in df_review.columns:
    df_review.drop(columns=['date'], inplace=True)
df_review.drop_duplicates(inplace=True)

if 'yelping_since' in df_user.columns:
    df_user.drop(columns=['yelping_since'], inplace=True)
df_user.drop_duplicates(inplace=True)

if 'date' in df_tip.columns:
    df_tip.drop(columns=['date'], inplace=True)
df_tip.drop_duplicates(inplace=True)

df_business.drop_duplicates(inplace=True)
df_checkin.drop_duplicates(inplace=True)
```

```
# Load the DataFrame into PostgreSQL
load_dataframe_to_postgresql(df_business, engine, 'business')
load_dataframe_to_postgresql(df_review, engine, 'review')
load_dataframe_to_postgresql(df_user, engine, 'user')
load_dataframe_to_postgresql(df_tip, engine, 'tip')
load_dataframe_to_postgresql(df_checkin, engine, 'checkin')

# Backup the database
subprocess.run([
    'pg_dump',
    '-U', username,
    '-W',
    '-F', 'c',
    '-d', database,
    '-f', 'yelpdb.dump'
], check=True)

print("Export and Backup completed")
```



Export and Backup completed

UPLOADING DATA INTO POSTGRESQL

> ON POSTGRESQL

The screenshot displays the pgAdmin interface with the following components:

- Object Explorer:** Shows the hierarchy of the database. The 'Schemas (1)' folder is selected, showing the 'public' schema.
- Schemas (1):** A list of database objects under the 'public' schema, including Aggregates, Collations, Domains, FTS Configurations, FTS Dictionaries, FTS Parsers, FTS Templates, Foreign Tables, Functions, Materialized Views, Operators, Procedures, Sequences, Tables (7), and Trigger Functions. The 'Tables (7)' folder is highlighted.
- Tables (7):** A list of tables: businesses, ca_reviews, checkins, and il_data. The 'il_data' table is selected, showing its columns: review_id, user_id, business_id, stars, text, business_name, business_address, business_city, business_state, business_categories, and user_name.
- Database activity:** A section on the right showing database activity. It includes a 'Sessions' tab, a search bar, and a table with columns for PID and User.

Tuples in	Tuples out	Block I/O
100	1,000	80
75	750	60
50	500	40
25	250	20
0	0	0

Database activity

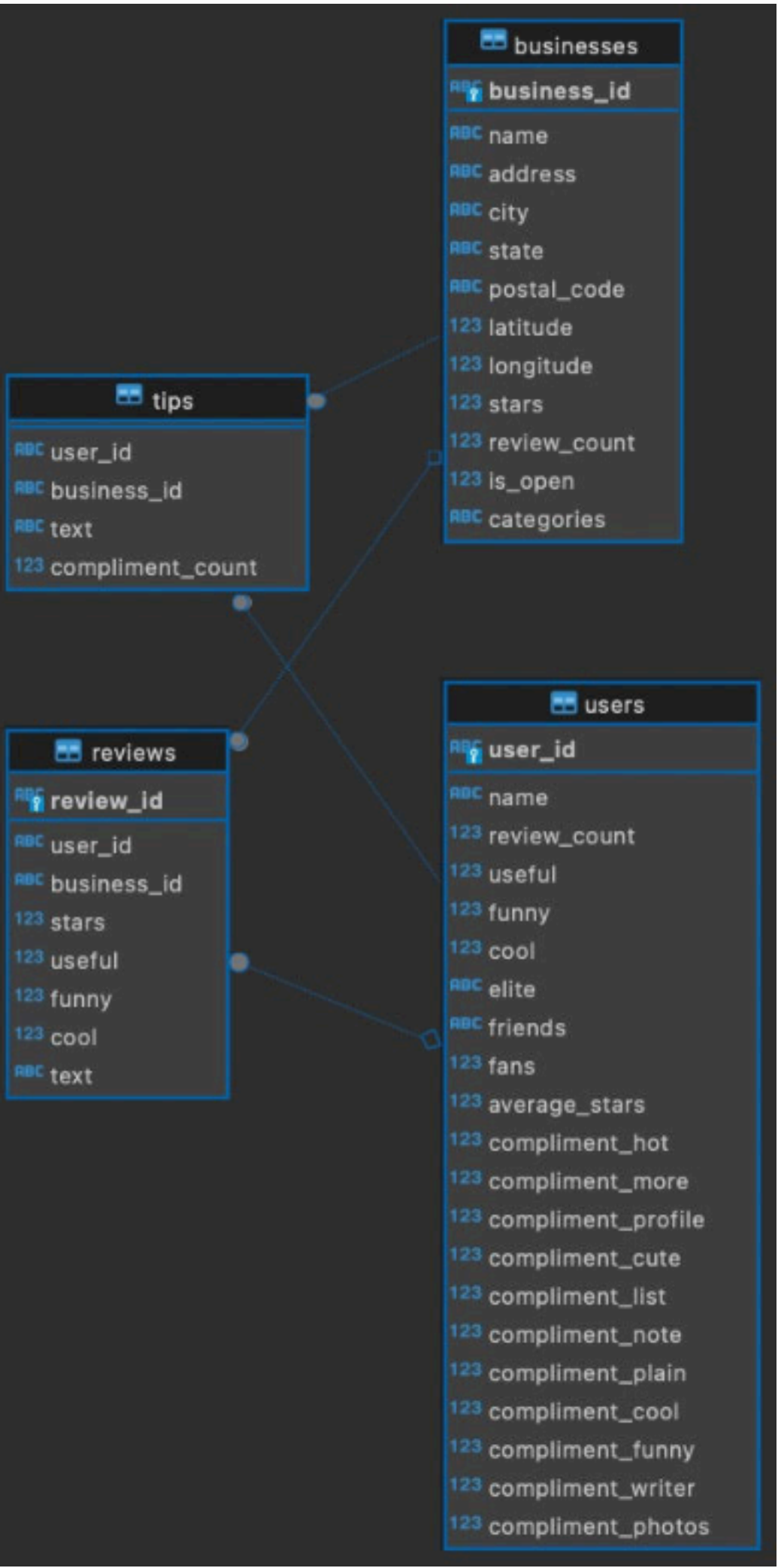
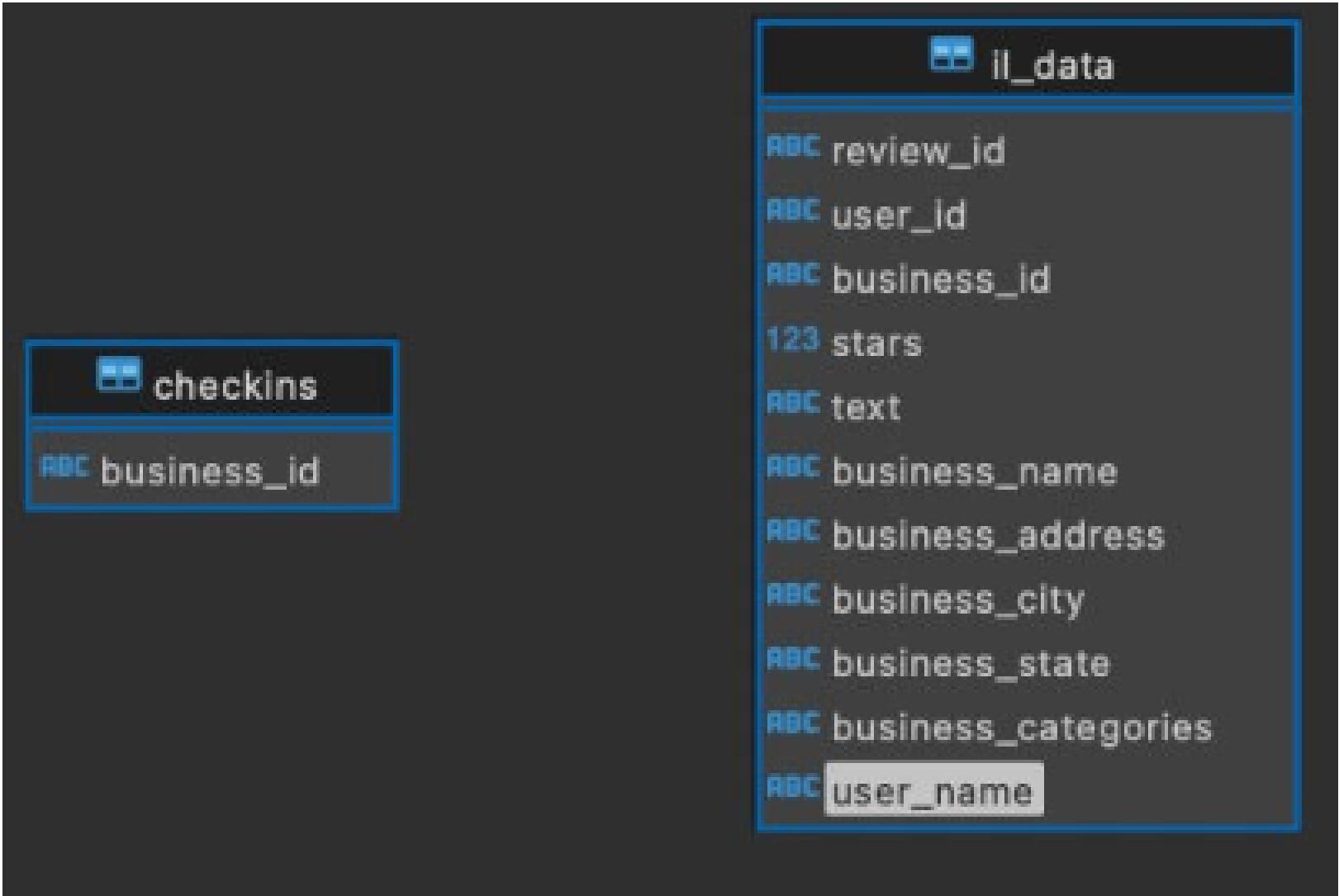
Sessions Locks Prepared Transactions

Active sessions only

Search

PID	User
-----	------

ENTITY RELATIONAL(ER) DIAGRAM FROM DBEAVER



CREATING A TABLE FOR ILLINOIS DATA IN SQL

```
# Define the SQL query
create_table_query = text("""
CREATE TABLE IF NOT EXISTS IL_data AS
SELECT r.review_id, r.user_id, r.business_id, r.stars, r.text,
       b.name AS business_name, b.address AS business_address, b.city AS business_city,
       b.state AS business_state, b.categories AS business_categories,
       u.name AS user_name
FROM reviews r
JOIN businesses b ON r.business_id = b.business_id
JOIN users u ON r.user_id = u.user_id
WHERE b.state = 'IL';
""")

# Execute the query to create a new table
with engine.begin() as conn: # auto-commit at the end of the block
    conn.execute(create_table_query)

print("Table IL_data created successfully.")
```



Table IL_data created successfully.

LIMITATIONS AND PROBLEMS FACED

1. Data Scope and Size Limitations

- Computational Limits: Full dataset processing is resource-intensive, limiting real-time analysis.
- Geographic Focus: Limited to Illinois due to dataset size (*total 8GB of data*).

2. Machine Learning Model Constraints

- Model Simplicity: Models were basic, focusing on educational and demonstrative purposes.
- Feature Limitation: Use of advanced features and techniques was restricted by the project's educational scope.

3. Technical Challenges

- Tool Integration: Initially faced difficulties integrating SQL database operations with Python-based machine learning.
- Performance Optimization: Challenges in balancing model accuracy with computational efficiency.

REVIEW ANALYSIS WITH SENTIMENT AND QUALITY METRICS

1. Sentiment Extremity Calculation:

- Uses TextBlob to assess sentiment polarity and subjectivity.
- Assumptions: Flags reviews as extreme if polarity is greater than 0.8 or less than -0.8 combined with subjectivity over 0.5, or if a 5-star review has fewer than 5 words.

2. Review Quality Assessment:

- Assumptions: Identifies poor quality based on text length under 50 characters, word diversity less than 70% of total words, subjectivity over 0.8, or excessive punctuation.

3. Calculation of likely_fake:

- Combines flags from sentiment extremity and quality assessments.
- Assumptions: Reviews are marked as likely_fake if they score 2 or more based on these criteria, suggesting multiple signs of being fake or of low quality.

	extreme_sentiment	poor_quality	likely_fake
0	0	0	0
1	0	1	0
2	0	1	0
3	0	1	0
4	0	0	0
likely_fake			
0	154347		
1	1146		
Name: count, dtype: int64			

DEVELOPMENT OF RANDOM FOREST CLASSIFIER

Model Overview

- Utilizes a Random Forest Classifier within a machine learning pipeline to identify reviews likely to be fake.

Model Pipeline Components

- Text Processing: Uses TfidfVectorizer with a maximum of 1000 features.
- Numerical Data Scaling: Applies StandardScaler to features like stars, extreme sentiment, and poor quality.
- Class Imbalance Handling: Integrates SMOTE for balancing the classes in training data.

Random Forest Configuration

- Class Weight: Balanced
- Max Depth: 10
- Min Samples Split: 10
- Min Samples Leaf: 4
- Max Features: Square root of the number of features

Key Takeaway

- The developed Random Forest Classifier effectively identifies potentially fake reviews by leveraging both textual and numerical data, offering a robust tool for enhancing review authenticity analysis.

RANDOM FOREST CLASSIFIER FINDINGS



Classification Report:

	precision	recall	f1-score	support
0	0.99	0.96	0.98	2629
1	0.96	0.99	0.98	2575
accuracy			0.98	5204
macro avg	0.98	0.98	0.98	5204
weighted avg	0.98	0.98	0.98	5204

	text
5687	Food always excellent and wait staff is awesome. Really great service by Kelly today.
16726	Had an awesome breakfast, burrito was incredible.Jack is the best server I've had ever! Great service!
5749	Best Vietnamese food in the area. Great service and delicious food. Five stars well deserved, thank you VPho
14835	Great food and awesome Marquita a. The tuna tostadas and fish tacos are the best . Everything is really good!
18442	Awesome food! Papa a la huancaína was incredible. Cute atmosphere and great self serve service!
401	Awesome brunch. The food was great! Service also great. Seiw was our server, very nice lady. Loved the crab legs.
12412	One of the best restaurants in Carmel! Great food, great service, great atmosphere. We are here now enjoying a delicious meal.
8922	Always great!!! The service is good. Fingersteaks are the best ever!! Steaks, shrimp etc are excellent.
9251	Best Mac and cheese I ever had, so good and flavorful, everything was delicious and great service..
9621	Best bar/food in town!?\nFood is amazing , great staff and environment awesome vibes. A MUST try!!\n-Ace The Barber
	fake_probability
5687	0.905975
16726	0.904668
5749	0.902897
14835	0.902549
18442	0.901813
401	0.901101
12412	0.901034
8922	0.900246
9251	0.899928
9621	0.899831

DEVELOPMENT OF LSTM MODEL

Model Overview

- Develops a Long Short-Term Memory (LSTM) classifier to identify fake reviews by analyzing both textual and numerical features.

Model Components

- Text Processing: Utilizes a Tokenizer to convert text to sequences and pads them to a uniform length for LSTM processing.
- Numerical Data Processing: Standardizes features such as star ratings and sentiment indicators using StandardScaler.

LSTM Configuration

- Architecture: Consists of an Embedding layer, a Spatial Dropout layer, an LSTM layer, and a Dense output layer.
- Parameters: Embedding dimension of 128, LSTM units of 100, and dropout rates of 0.2 for both LSTM and recurrent units.
- Optimization: Uses Adam optimizer and binary cross-entropy loss function, tracking accuracy, precision, and recall.

Key Takeaway

- The LSTM classifier robustly handles sequential text data and additional features to effectively pinpoint likely fake reviews, proving crucial for maintaining integrity in review platforms.

LSTM MODEL FINDINGS



163/163 3s 16ms/step

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	2629
1	1.00	1.00	1.00	2575
accuracy			1.00	5204
macro avg	1.00	1.00	1.00	5204
weighted avg	1.00	1.00	1.00	5204

text

58Had a wonderful experience with JT and Ashley Furniture store!! He was helpful even when I had to change my order.

101We had my friends bridal shower here and it was so beautiful! The staff was so friendly and helpful! Everyone at the Wine Tap was AMAZING!! Of course, food was delicious too!

217Great pizza! Great staff! Just be sure that you are patient if you show up at dinner time, this place is always hopping!

422Awesome products..awesome salon and awesome people. Love it here at ulta in fairview!

499Excellent service, excellent food, wonderful view. The filet mignon is unmatched anywhere in this area. Great date night.

...

51550They have the best burgers, and the fry sauce is amazing!! I would recommend trying them kinda like Steak n shake but 30 times better.

51551Brooke was our waitress tonight. She is awesome. We loved her friendliness and her go with the flow personality!

51621What a wonderful, beautiful, meditative space. Like a Six Flags of spirituality.

51716Food was good! I had a tomato soup bread bowl with a grilled cheese! Will eat here again.

51816Helped me with my car purchase, reliable, and the car was well taken care of! Daryl is awesome!!

[587 rows x 2 columns]

INTERACTIVE DEMONSTRATION OF LSTM FAKE REVIEW DETECTION

Demo Components

- User Interaction: Allows users to enter their own review text.
- Sentiment and Quality Analysis: Automatically calculates sentiment extremity and review quality.
- Data Preprocessing: Applies tokenization, padding, and scaling to prepare user input for prediction.
- Prediction Execution: Uses the trained LSTM model to determine if the review is likely fake.
- Result Display: Outputs whether the entered review is classified as 'Fake' or 'Not Fake'.

Sample Interaction

1. User is prompted to input a review.
2. System processes the review through the LSTM model.
3. The system displays the prediction outcome.

Extended Functionality

- Review Retrieval: Fetches reviews from the database for specified states to analyze and predict.
- Fake Review Analysis: Identifies and displays reviews predicted as fake.
- Word Cloud Generation: Visualizes common words from fake reviews to highlight prevalent themes or expressions.

```
# Predict the authenticity of the entered review and display the result
result = predict_review(user_input, stars=5)
print("The review is predicted as:", result)
```

```
The review is predicted as: Not Fake
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-packages/sklearn/ba
warnings.warn(
```

```
user_input = input("Enter a review text: ")  
print(user_input)
```

```
# Predict the authenticity of the entered review and display the result
result = predict_review(user_input, stars=5)
print("The review is predicted as:", result)
```

The review is predicted as: Fake



CONCLUSION AND FUTURE DIRECTIONS

Database Management Integration

- PostgreSQL Utilization: Managed large datasets with PostgreSQL, employing a specialized schema for Yelp data to support complex SQL queries.
- Localized Data Analysis: Developed a PostgreSQL table for Illinois data to enhance geographical analysis and database efficiency.
- Database Operations: Executed essential operations such as data insertion, updates, and backups using pg_dump for data integrity.

Machine Learning Integration

- Model Development: Created models to analyze textual and numerical data from the database, effectively predicting fake reviews.
- Real-Time Analysis: Integrated models within the database framework to dynamically classify reviews from PostgreSQL, showcasing real-world machine learning applications in database management.

Enhancing Project Capabilities

Advanced Model Development:

- Upgrade to more sophisticated machine learning algorithms to handle larger datasets and enhance insight extraction.
- Introduce an authentic fake review dataset for accurate model training and validation.

THANK YOU

ANY QUESTIONS?