Knowledge Graphs for BnBs

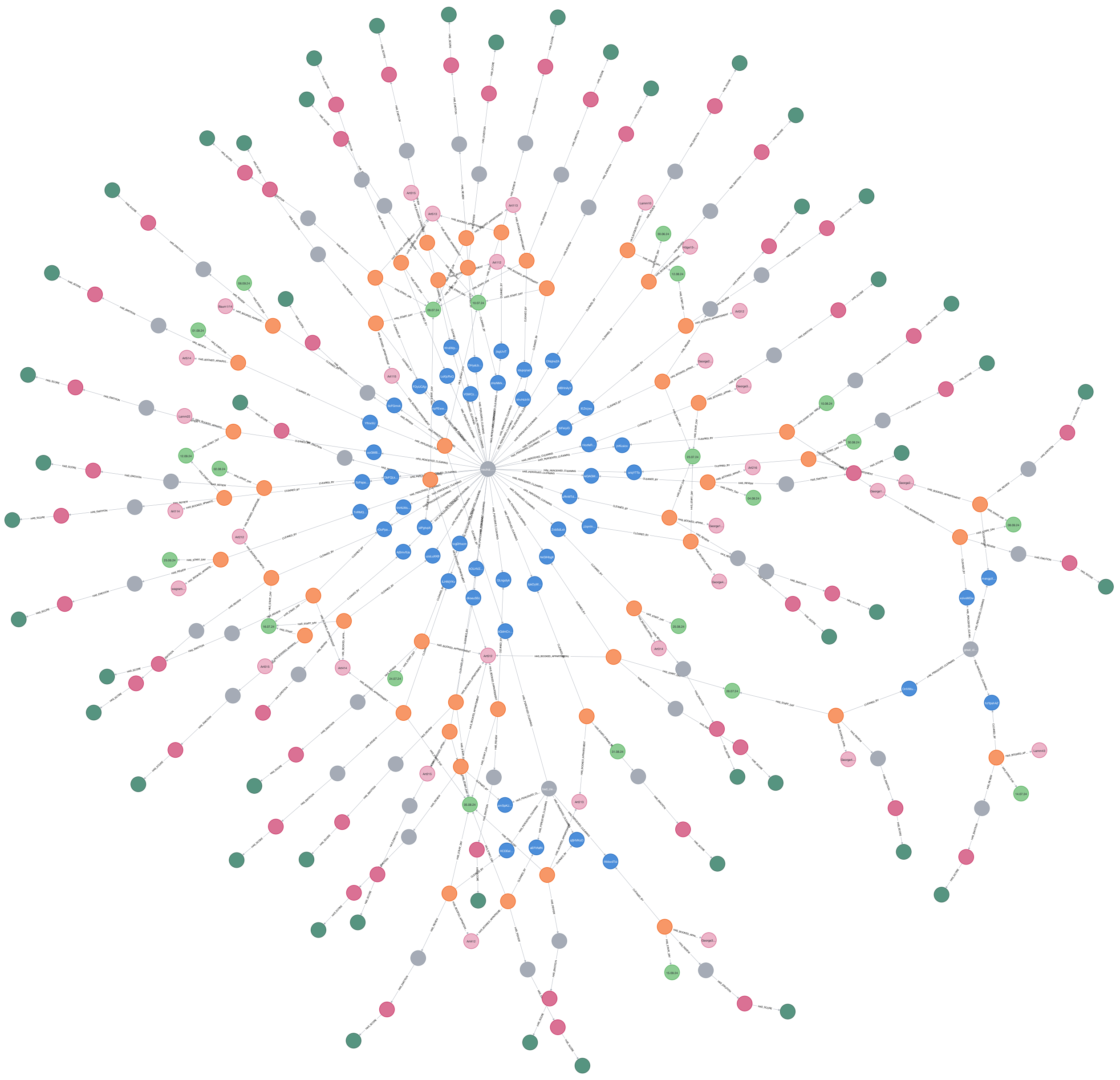


Figure 1: Cleaning_Graph

Introduction

The Scenario

Short-Term Renting business (STR) is hard, but without the right monitoring tools for customer satisfaction, it is even harder (then it has to be). This Project utilizes modern Knowledge-Graph Approaches to assist hotels and short-term rental businesses in **identifying issues** regarding their cleaning services and customer satisfactions. In particular, it is aiming at identifying if certain appartements or cleaning personals form clusters/sources of exceptionally good or bad customer experiences.

The Analytics

For this reason, this project provides a presentation layer (via a `streamlit` application) that displays the following information to the user: - A list of cleaning personal that is linked to the best/worst customer experiences. - A list of apartments that are linked to the best/worst customer experiences. - A analysis to identify if certain cleaning people or appartements became a central node in a node of dissatisfaction or form a cluster. - Advanced analytics of the customer reviews utilizing *Deep Modularity Networks* and *TransE*

Eventually, this insight could then be used to infer insights for improvements in cleaning protocols, appartements and eventually customer satisfaction.

Background

In the hotel/STR business, a common SaaS Stack is the combination of Kross Booking that provides PMS + Channel Manager + Booking Engine in one solution, in combination with TimeTac that allows for smart time tracking of all internal processes. While the above is great for managing daily operations, the amount of data insight that can be extracted out of the box is pretty limited and. Hence, business owners of certain scales that use the SaaS stack described above are left with high amounts of manual analytical effort with still limited insights
Therefore, this project tries to reduce the amount of manual effort needed, as well as to increase the quality of insight possible.

Data Source

This data that has been used to construct the KG has been derived (as depicted later on in the architecture section) from two APIs: 1. **Kross Booking**: A plattform that works as booking engine for the management of hotels/appartements. In this case, it is used to manage all bookings (and everything related) across all appartements/hotels.

2. **TimeTac**: A plattform that allows to track process times of (cleaning) people. In this case, it is used to track and access data about who has cleaned which apartment, when and for how long.

In addition (for advanced analytics), the collected reviews (via Kross Booking) are automatically translated and pre-evaluated via a sentiment analysis.
1. **Translation:** As the customers of the appartements can (and have been) writing reviews in more than 150 different languages, I had to start out by translating them. For this purpose, I used the `src/review_process_utils/review_translor.py` script that utilizes the `googleTrans` package to translate all reviews (if possible) to english.

2. **Sentiment Analysis**: In addition, for effective review filtering/pre-selection, a sentiment analysis utilizing DistilRoBERTa has been implemented to categorize the reviews along Paul Ekman's 6 basic dimensions + one neural dimension. The corresponding script can be found in `src/Review_Handler.py`

For now, this translation and sentiment analysis yielded the following additional review data for the knowledge graph:

Column Name	Data Type
Booking_ID (PK)	INT
Translated_Review_Text	TEXT
Primary_Emotion	TEXT
Cleaning_Quality	INT

For simplification purposes this table is also stored in the AWS RDS. Of course arguments for storing this data in a NoSQL Table like MongoDB or AWS Dynamo DB could be made, but due to the limited scope of this project I have decided to keep the overhead low and not setup another DB.

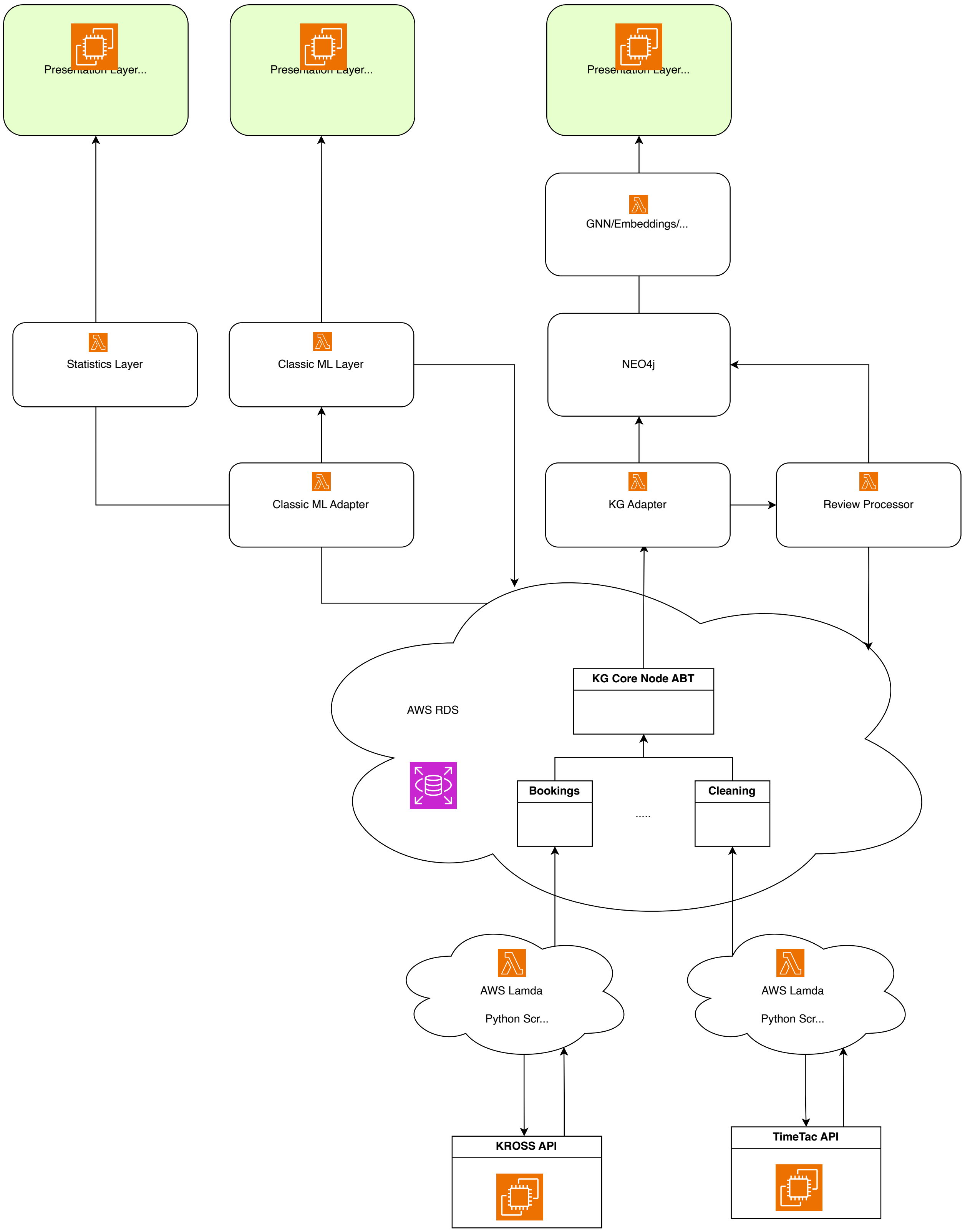
Finally, this results in the following ABT `ABT_BASE_TABLE_KG_GENERATION` that will be used for building the Knowledge Graph:

Column Name	Data Type	Source
Booking_ID (PK)	INT	KROSS
Start_date_of_stay	TIME STAMP	KROSS
Appartement	STRING	KROSS
Cleaner	STRING	TIMETAC
Translated_Review_Text	TEXT	KROSS
Primary_Emotion	TEXT	ML Model
Sentiment_Score	FLOAT	ML Model
Cleaning_Quality	INT	Manual/TransE

Side Node: For this demonstration purpose, the production data has been used and been anonymized using `src/data_anonimizer.py` and stored in `data\demo_data.csv` Due to my limited local computational resources, I have only selected a small sample from the original data. Nonetheless, this project has been designed in a scalable way and the entirety of the data could be easily processed with the help of more computational resources easily with a simple deployment to AWS.

Architecture

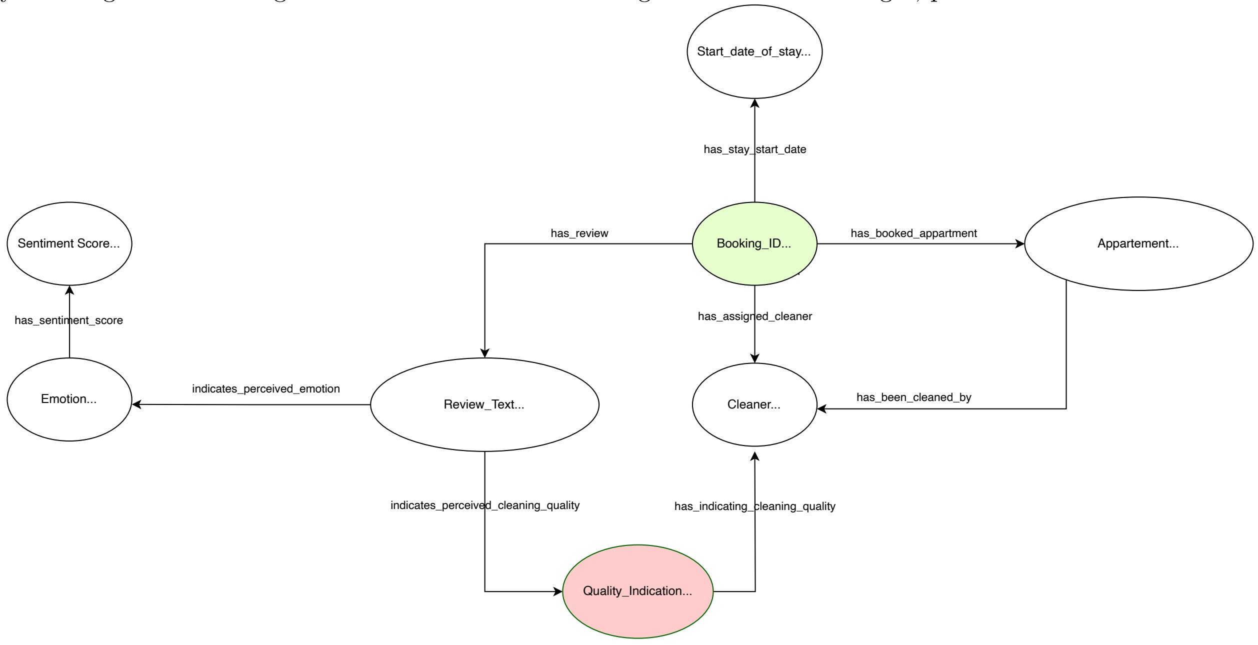
As mentioned before, the application utilizes data that has been fetched from *KROSS Booking* and *TimeTac* via their internal APIs is currently stored in a AWS RDS in multiple tables using the architecture displayed below:



In the beginning the data is being fetched from the two API's utilizing a python script that runs in a *AWS Lamda Container* that is being executed once per day (at midnight). Once the data has been fetched successfully, is then stored in extraction tables in a *PostgreSQL* DB stored in an *AWS RDS Instance* (serving as central source of truth) and then automatically (via *AWS Lamda* again) processed into the aforementioned ABT.

In the meantime, an adapter (also running in a different *AWS Lamda Container*), is daily fetching new review data from the ABT, sends the reviews to a sentiment model (`sentiment_model.py`) that returns sentiment scores for each review. After that, the data gets transformed into a graph-structure and then added to an on-premise *Neo4J* Database (dockerized) via a python script: `src/KG_Building_Handler.py`.

Through this procedure described above, the KG is continuously fed with the newest data available and therefore constantly evolving. The resulting KG then contains the following set of nodes and edges, per row in the



original ABT:
Side Node: During the initial creation, the edges to the *Qualitiy Indiction* are only available for a subgroup (The training set) , as those are edges that should be learned with the help of *TransE*.

Technologies used:

Starting out, the *AWS Suite* (running *Python* and *PostgreSQL*) was chosen for data fetching, job scheduling and classic RDBS (using PostGRES as Single Source of Truth). Part of the decision for this technology suit was it's general purpose,it's time/application proven quality, high scalability and wide array of utilities. In addition it provides a strong architectural backbone for all kind of ML-Application, being it classic, or graph based, allowing them to flourish in harmony and synergy.

Furthermore *Neo4j* was then chose as a database for storing the built Knowledge Graph(s), while other database have been investigated, some being: - Amazons's own solution - Neptune - Microsoft's Azure Cosmos DB - Dgraph - ArangoDB - OrientDB - . . . .

While each DB provided individual advantages and disadvantages, Neo4j was convincing for this project, mainly due to it's great support for graph data structure, Cypher's amazing syntax, the efficient querying and the docker support, leading to great flexibility, solid performance, and eas of use that was really appealing. The opportunity to add Neo4j in a docker container to the existing technical infrastructure in AWS (leveraging EC2) underlines the flexibility and scalability of this technology.

Methods for building the Knowledge Graph(s):

As introduced before, the `ABT_BASE_TABLE_KG_GENERATION` will be used as a starting point for the generation of a (continually updated) *Knowledge Graph* In order to do so, the data of the table above will be transformed into a Knowledge Graph based on the Ontology sketched in *Image 2*. This has been achieved with the help of `src/KG_Building_Handler.py` that sets up the KG and continuously integrates new data into it. In order to be able to potentially manage multiple KG's, each KG is built inside its own Schema. For further separation, multiple instances can easily be created due to the Docker based architecture.

Analytics / Methods

1. Knowledge Graph Embeddings

One very important factor for customer satisfaction in this industry is the quality of the appartement cleanings. With increasing numbers of properties under management, assessing this quality can become a very time-consuming and inefficient process. So the idea here is to offer the business owners a application that helps to assess the quality of the appartement cleanings. As this is a very specific use case, a general (not fine-tuned and industry specific) model like BERT is assumed to be only of limited help. Therefore, a train-dataset (50% of the entire dataset) consisting of manually labels that indicate whether a review is concerned with cleaning issues, has been created and used to learn the *cleaning_quality_was_{**Quality**}* relationship () from the original ontology with the help of TransE were the following constraint holds true:

$$Quality(x) = \begin{cases} \text{great cleaning quality,} & \text{If good cleaning explicitly mentioned} \\ \text{neutral cleaning quality,} & \text{If no problems mentioned in the review} \\ \text{bad cleaning quality,} & \text{Else} \end{cases}$$

The implementation can be found in `src/Embeddings_Handler.py`.

Embeddings Results

2. Logic Based Reasoning on the KG

- A list of cleaning personal that is linked to the best/worst customer experiences.

```
 // Match cleaning personnel and their associated reviews and emotions
 MATCH (r:Reinigungsmitarbeiter)<-[:CLEANED_BY]-(b:Booking)-[:HAS_REVIEW]->(rev:Review)-[:HAS_EMOTIO
 WHERE em.text IN ['joy', 'disgust'] // Filter for relevant emotions

 // Aggregate emotion counts and total cleanings
 WITH r, em.text AS emotion, count(em) AS emotionCount, count(DISTINCT b) AS totalCleanings
ORDER BY r.name

 // Calculate joy-to-disgust ratio
 WITH r,
      sum(CASE WHEN emotion = 'joy' THEN emotionCount ELSE 0 END) AS joyCount,
      sum(CASE WHEN emotion = 'disgust' THEN emotionCount ELSE 0 END) AS disgustCount,
      totalCleanings

 WITH r,
      joyCount,
      disgustCount,
      totalCleanings,
      CASE WHEN disgustCount = 0 THEN joyCount ELSE joyCount * 1.0 / disgustCount END AS joyDisgustRa

 // Order by joy-to-disgust ratio to rank performers
 ORDER BY joyDisgustRatio DESC

 // Return ranked list of performers with total cleanings
```

```
RETURN r.name AS cleaner,
       joyDisgustRatio AS ratio,
       totalCleanings
```

- A list of apartments that are linked to the best/worst customer experiences.

```
 // Match apartments and their associated reviews and emotions
 MATCH (a:Appartment)<-[:HAS_BOOKED_APPARTEMENT]-(b:Booking)-[:HAS_REVIEW]->(rev:Review)-[:HAS_EMOTI
 WHERE em.text IN ['joy', 'disgust'] // Filter for relevant emotions

 // Aggregate emotion counts and total bookings
 WITH a,
      em.text           AS emotion,
      count(em)         AS emotionCount,
      count(DISTINCT b) AS totalBookings
ORDER BY a.name

// Calculate joy-to-disgust ratio
WITH a,
     sum(CASE WHEN emotion = 'joy' THEN emotionCount ELSE 0 END) AS joyCount,
     sum(CASE WHEN emotion = 'disgust' THEN emotionCount ELSE 0 END) AS disgustCount,
     totalBookings

WITH a,
     joyCount,
     disgustCount,
     totalBookings,
     CASE WHEN disgustCount = 0 THEN joyCount ELSE joyCount * 1.0 / disgustCount END AS joyDisgustRa

// Order by joy-to-disgust ratio to rank apartments
 ORDER BY joyDisgustRatio DESC

// Return ranked list of apartments with total bookings
RETURN a.name          AS apartment,
       joyDisgustRatio AS ratio,
       totalBookings
```

- A analysis to identify if certain cleaning people or appartements became a central node in a node of dissatisfaction or form a cluster. I identified this via:

```
 // Find clusters of dissatisfaction based on negative emotions
 MATCH (a:Appartment)<-[:HAS_BOOKED_APPARTEMENT]-(b:Booking)-[:HAS_REVIEW]->(rev:Review)-[:HAS_EMOTI
 WHERE em.text = 'disgust'
RETURN a.name AS apartment, count(DISTINCT b) AS bookingsWithDisgust
 ORDER BY bookingsWithDisgust DESC;

  // Similarly for cleaning personnel
  MATCH (r:Reinigungsmitarbeiter)<-[:CLEANED_BY]-(b:Booking)-[:HAS_REVIEW]->(rev:Review)-[:HAS_EMOTI
  WHERE em.text = 'disgust'
 RETURN r.name AS cleaner, count(DISTINCT b) AS bookingsWithDisgust
  ORDER BY bookingsWithDisgust DESC;
```

LBR Results

3. GNNs on the KG

The first analysis concerns the high density regions, and hence grouping, meaning, I want know if the entire graph can be clustered into interesting clusters For this task I have oriented on the paper of Tsitsulin et.al. (2023) In this paper, the authors have compared the following different methods, including their basic properties and introduced their own Methode *Deep Modularity Networks* (**DMoN**).

Method	End-to-end	Unsup.	Node pooling	Sparse	Soft assign.	Stable	Complexity
Graclus	N	Y	Y	Y	N	Y	O(dn + m)
DiffPool	Y	Y	Y	N	Y	N	$O(dn^2)$
AGC	N	Y	Y	N	N	N	$O(dn^2k)$
DAEGC	N	Y	Y	Y	N	N	O(dnk)
SDCN	N	Y	Y	Y	N	N	$O(d^2n + m)$
NOCD	Y	Y	Y	Y	Y	Y	O(dn + m)
Top-k	Y	N	N	Y	N	Y	O(dn + m)
SAG	N	N	Y	N	N	N	O(dn + m)
MinCut	Y	Y	Y	Y	Y	N	$O(d^2n + m)$
DMoN	Y	Y	Y	Y	Y	Y	$O(d^2n + m)$

Intrigued by their claims, I wanted to test **DMoN** on my own knowledge graph.

Therefore, with the help of **PyTorch Geometric** I wrote a script to run this method on my onw KG. This script can be found in `src/GNN_Handler.py`. **PyTorch Geometric** was chosen over other Frameworks like DGl and Graphnets due its high compatability (seamless integration into the PyTorch ecosystem), its dedicated CUDA kernels for sparse data and mini-batch, its strong community support and its research-orientation.

GNN Results

Results:

Presentation Layer:

In order to present the determined results, I decided to use *Streamlit* to create a small dashboard, that can then be used in a real life application as **customer satisfaction and cleaning quality monitor** I chose *Streamlit* mainly due to its ease of use, its excellence when it comes to rapid prototyping that still comes with very good user experience that can be designed in a typical pythonic way. The thereby built dashboard can be found under `src/dashboards/monitoring_dashboard.py`

Conclusion:

How to use:

1. Start the Neo4j database via:

```
docker-compose up -d
```

2. Install all needed packages from the `requirements.txt`
3. Fill the Neo4j database with the (demo) data In case you want to work with the demo data, just run the `populate_KG_with_demo_data` function in `src/KG_Building_Handler.py`.

et voilà, visit http://localhost:7474/browser/ for the Neo4j Database and `TDB` for the *Streamlit Dashboard*. Enjoy the show

How to use Logic-based Reasoning:

Logic-bases reasoning as described below, can be applied to the KG by running the `run_logic_based_reasoning()` function in `src/perform_analysis.py`. The results will be presented in a dedicated streamlit dashboard that can started by running `streamlit run src/dashboards/LBR_dashboard.py`

How to use Graph Neural Networks

Deep neural network reasoning as described below, can be applied to the KG by running the `run_GNN_reasoning()` function in `src/perform_analysis.py`. The results will be presented in a dedicated streamlit dashboard that can started by running `streamlit run src/dashboards/GNN_dashboard.py`

https://distill.pub/2021/gnn-intro/