APAN 5310 Project Report

Team Members: Yuxuan Chen, Yishan Liu, Xianghui Meng, Haoxiang (Steven) Huo

Overview

Dream Homes NYC is a real estate company that assists people in buying and selling luxury homes in New York City. Our team of database specialists has been invited to address two primary challenges. First, we will transform years of archived, unstructured data—ranging from legacy spreadsheets to scanned documents—into a clean, well-organized repository that supports efficient search and analysis. Second, we will implement an automated pipeline to combine and merge multiple real-time data sources into this unified system, eliminating the need for any manual data transfers. As all of our group members are international students who have experienced the challenges of finding and renting housing in New York City, we're excited to explore and find a solution to handle the large volume of data across properties, clients, and agents.

We chose to work on Dream Homes NYC because its centralized database is complex, and we're passionate about using technology to simplify real-world challenges. We're motivated by the opportunity to apply our database expertise to turn chaotic information into clear, actionable insights, helping organizations make faster, smarter decisions and reduce the workload of data tasks for employees. To ensure we deliver the best solution to the goal, we began by sharing a small, cleaned sample of our combined property, client, and transaction data with a link to the full dataset on GitHub, and explaining why it reflects Dream Homes NYC's real-world needs. Then we'll explain step by step through our database design, complete with a PDF ER diagram that includes all of the relationships and cardinality between tables, which were created through SQL code. Next, we'll detail our automated ETL process in Python that imports data from old records and current data sources, explains every transformation choice, and loads everything into our new schema. Once the data is in place, we'll show advanced analyses with the exact SQL or Python code and the resulting insights to answer those key business questions. We'll also explain how analysts can query the database directly (or via Python/R) while managers and executives can view clear, automatically refreshed dashboards in Metabase. Finally, we'll cover our plans for database performance, redundancy, and a cloud-based deployment, then wrap up with a concise conclusion that highlights how our relational database, ETL pipeline, and analytics work together to give Dream Homes NYC faster, smarter decision-making and a single source of truth.

This unified database will reduce manual errors, eliminate duplicate records, and save time spent on data cleanup. Brokers will be able to price listings based on the latest comparable sales in minutes, rather than days, and marketing teams can see in real-time which channels are driving inquiries, allowing them to reallocate budgets on the fly. Managers and executives will have clear, automatically updated dashboards that show revenue trends, agent performance, and neighborhood activity in a short time, letting them spot problems or opportunities as they emerge. Analysts will spend less time wrangling files and more time uncovering insights, like which client segments are most likely to convert or which amenities boost sale prices, while non-technical staff can rely on intuitive dashboards.

Task Division

Category	Task	Assigned Member(s)	Planned DDL
Business Understanding	Define detailed business requirements and client goals	Yuxuan Chen	Week 8
Database Schema	Design a normalized ERD (20+ tables in 3NF), including entities and relationships	Yishan Liu	Week 8
Data Simulation	Generate and clean sample data simulate messy or semi-structured input	Steven Huo	Week 8
Table Creation	Write SQL DDL scripts to define all tables and constraints in PostgreSQL	Xianghui Meng	Week 8
Data Loading	Create Python/SQL scripts to load data into the database and write code for analytical procedure	Xianghui Meng	Week 9
Complex Queries	Write 8 complex SQL queries to support business decisions	Yuxuan Chen	Week 10
Dashboards	Design and build interactive dashboards using Metabase or Power BI	Steven Huo	Week 11
Customer Interaction Plan	Write Customer Interaction Plan	Yishan Liu	Weak 11

Final Report	Co-author project report, including intro, schema design, queries, and business insights	All Members	Week 12
Final Presentation	Prepare slides and live demo walkthrough; each member presents part of the work	All Members	Week 12

Business Insights

Dream Homes NYC has asked us to build a system that makes their operations faster, keeps every record accurate, and delivers the best experience for both agents and clients. At its core, the database will track each office's profile—including its name, location, contact information, operating hours, and current manager—while maintaining a comprehensive employee directory that records employment status, departmental assignment, device allocation, and reporting relationships. It will also support detailed client records by capturing personal and contact data, recording individual budget ranges, structuring property preferences in a dedicated table, and preserving client feedback entries in a separate log. Every property listing will be modeled in full, with address details, listing characteristics, standardized amenities, current status, listing date, and all related media assets such as photographs and floor plans.

Beyond basic record-keeping, the system will document every scheduled appointment—identifying the agent, client, property, date, time, and outcome—and will record all transactions through distinct tables for sales, rentals, payments, and leases. Commissions will be computed and stored automatically, ensuring transparent earnings tracking for agents. Normalization of data into interrelated tables gives Dream Homes NYC real-time insight into office performance, agent productivity, transaction progress, and client objectives—empowering data-driven decisions and finely tuned, personalized property suggestions. Clients in turn enjoy a more responsive experience, receiving proactive, goal-aligned recommendations and timely updates that keep them informed and confident throughout their real estate journey.

Database Design (with ER-Diagram)

This schema follows a strict Third Normal Form design to eliminate redundancy and ensure integrity. Office and Employee tables capturing where the work happens and who's doing it, Client and ClientRole tracking every home-seeker and whether they're buyers, sellers, renters or landlords, and PropertyType alongside Property defining each listing's category and its full address, price, and status. Detailed attributes live in dedicated tables: PropertyFeature for amenities, PropertyMedia for photos and floor plans; while Appointment logs every showing, tying together agents, clients, and properties with timestamps. Transactional workflows then span Transaction and Commission for sales and fee splits, Lease and PaymentRecord for rentals and payments, and MarketingCampaign with ClientLead to manage outreach and new inquiries. Finally, the Document table ensures every contract, inspection report, or appraisal is linked back to its property or deal, so no file ever slips through the cracks .

This structure not only prevents data duplication and update anomalies, but it also makes relationships clear: foreign keys enforce, for example, that every client's assigned_agent_id matches an existing employee, that each property belongs to a valid office and listing agent, and that every lease or payment ties back to real clients and staff. By giving each table a single responsibility and stitching them together with well-defined keys and constraints, Dream Homes NYC gains a flexible, scalable backbone for richer customer interactions—whether generating personalized follow-up reminders, aggregating a client's viewing history, or rolling out new features like maintenance requests without ever rewriting existing tables ans_psql.

Example Tables:

CLIENTS TABLE:

1. **client_id: INT** Numeric IDs fit in a 32-bit range. Declared **PRIMARY KEY** and **NOT NULL** to uniquely identify each client.

2. **full_name: VARCHAR(200) NOT NULL** 200 characters accommodate long personal or company‑contact names. **NOT NULL** because every client record needs a name.

3. **client_type: VARCHAR(20) NOT NULL** Values like "individual" or "company." 20 chars cover common labels. **NOT NULL** to enforce knowing who/what the client is.

4. **email: VARCHAR(100) NOT NULL UNIQUE** Email addresses seldom exceed 100 chars. **NOT NULL** because we require contact info, **UNIQUE** to prevent duplicates.

5. **phone: VARCHAR(20) NULL** Allows formatting characters, country codes, extensions. **NULL** because not every client may provide a phone number.

6. **assigned_employee_id: INT NOT NULL FOREIGN KEY → employees.employee_id**. Enforces that each client is managed by a valid employee.**NOT**

NULL because every client must have an assigned agent.

7. **created_at: TIMESTAMP NOT NULL DEFAULT CURRENT_TIMESTAMP** Records when the client was added. **NOT NULL** so there's always a creation timestamp.

Relationship: Many **clients** → one **employee** (each client is handled by exactly one employee; an employee may serve many clients).

EMPLOYEES TABLE:

1. **employee_id: INT** Fits in a 32-bit integer. **PRIMARY KEY** and **NOT NULL** to uniquely reference each staff member.

2. **first_name: VARCHAR(50) NOT NULL**, **last_name: VARCHAR(50) NOT NULL** 50 chars handle most personal names. **NOT NULL** because both parts of the name are required.

3. **email: VARCHAR(100) NOT NULL UNIQUE** Company emails rarely exceed 100 chars. **UNIQUE** to avoid duplicate accounts, **NOT NULL** for contact.

4. **phone: VARCHAR(20) NULL** Same reasoning as clients—optional contact.

5. **hire_date: DATE NOT NULL** Stores the date they joined; **NOT NULL** to track tenure.

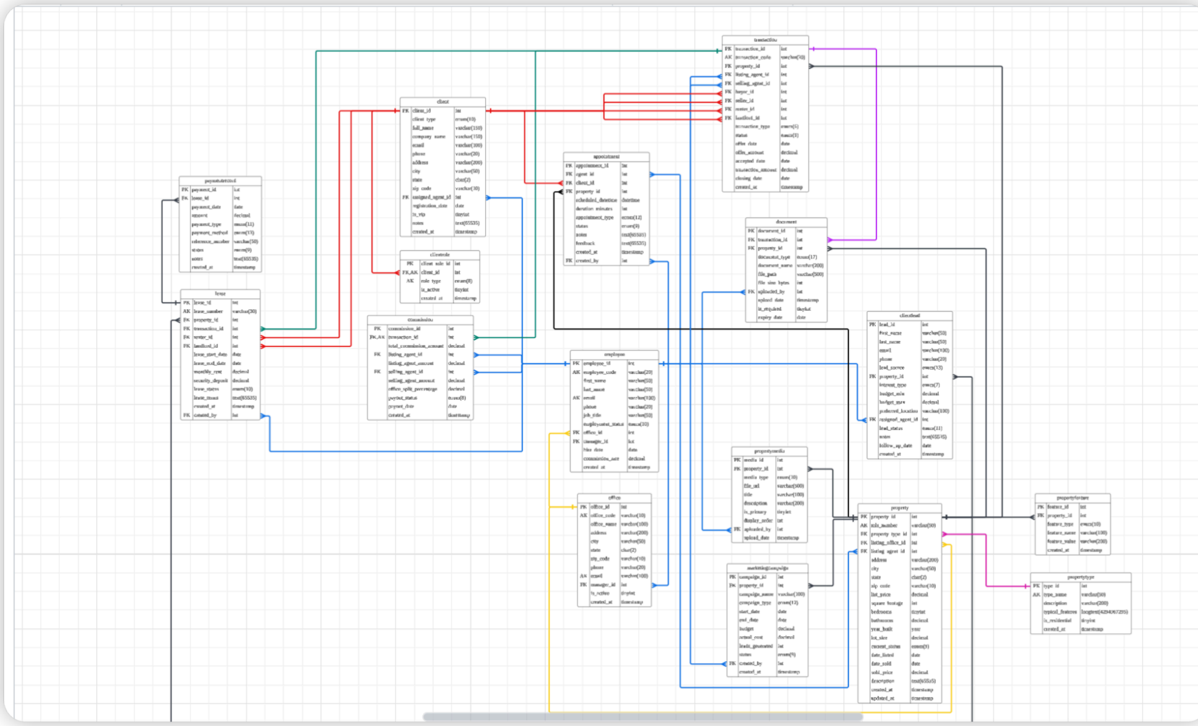
6. **office_id: INT NOT NULL FOREIGN KEY → offices.office_id**. Ensures every employee belongs to an existing office. **NOT NULL** because every employee must be assigned to an office.

7. **manager_id: INT NULL FOREIGN KEY → employees.employee_id** (self-reference). **NULL** for top-level managers who report to no one.

8. **created_at: TIMESTAMP NOT NULL DEFAULT CURRENT_TIMESTAMP** Timestamp of when the employee record was created; always present.

Relationship: One **employee** → many **clients** (via assigned_employee_id), and hierarchical reporting within **employees** (via manager_id).

ER Diagram:



https://lucid.app/lucidchart/7503e903-67a6-4ec5-a783-1eb32a0a3aed/edit?viewport_loc=-431%2C-247%2C9488%2C4103%2C0_0&invitationId=inv_cdf8abc9-9e77-4379-b06e-7f32298eb5fa

Data Simulation:

Creating realistic sample data for our Dream Homes NYC database turned out to be more challenging than we initially expected. We quickly realized that manually creating sample data would give us overly clean, perfect records that don't reflect the messy reality of real business data. Instead, we decided to use AI Agent tool to generate sample datasets that actually mirror the chaos and inconsistencies we'd encounter when working with years of accumulated real estate records from spreadsheets, emails, and various systems.

The key insight was that real-world data is never perfect. Date formats vary wildly—some records might show "2025/1/26" while others use "Jan 18 2025." Commission information might be split as "Listing 50% Selling 50%" in one record and "Office split pending" in another. Even worse, information sometimes ends up in the wrong fields entirely, like seller details accidentally appearing in buyer information fields or appointment notes mixed in with contact details. These aren't just theoretical problems—they're exactly the kind of issues our ETL pipeline needs to handle gracefully.

To tackle this, we developed a comprehensive data generation approach (prompt engineering) that intentionally introduces realistic messiness when we work with LLM Agents. We created detailed rules for all 49 data fields, explicitly defining what belongs where and what common mistakes to avoid. For example, we made sure buyer information stays in buyer fields, seller information stays in seller fields, and contact details don't get contaminated with viewing schedules or background descriptions. We also built in business logic consistency—Manhattan properties cost more than Brooklyn ones, dates follow logical sequences, and commission calculations actually add up correctly.

Our AI fine-tuned Agent (used Claude Opus 4 model) generates 60+ realistic transaction records covering properties across Manhattan, Brooklyn, New Jersey, and Connecticut, with appropriate pricing that reflects actual market conditions. Each transaction includes complex, interconnected information like detailed appointment histories, commission splits between multiple agents, and comprehensive client profiles with realistic budgets and preferences. This gives our ETL pipeline a proper workout, testing how well it can parse, clean, and organize complex nested data.

transaction_id	mls_listing_number	property_address_full	listing_office_name	listing_office_address	listing_office_phon	property_type	status_current	transaction_type
TXN-2025-001	MLS8202793	536 Atlantic Ave Brooklyn NY 11211	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	Co-op	SOLD	sale
TXN-2025-002	MLS8408828	746 Washington St Jersey City NJ 07204	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	TH	SOLD	sale
TXN-2025-003	MLS8569213	512 Washington St Jersey City NJ 07200	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	TH	RENTED	rental
TXN-2025-004	MLS8102422	285 Smith St Brooklyn NY 11213	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	Condo	SOLD	sale
TXN-2025-005	MLS8561588	914 Court St Brooklyn NY 11230	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	TH	RENTED	rental
TXN-2025-006	MLS8532881	320 Greenwich Ave Fairfield CT 06902	Dream Homes CT	1200 Post Rd Fairfield CT 06824	(203) 555-0500	SFH	ACTIVE	sale
TXN-2025-007	MLS8946341	700 River Rd Jersey City NJ 07034	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	TH	ACTIVE	sale
TXN-2025-008	MLS8457049	951 Washington St Newark NJ 07257	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	Condo	ACTIVE	sale
TXN-2025-009	MLS8915729	162 East 86th St Unit 7B New York NY 10032	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	TH	RENTED	rental
TXN-2025-010	MLS8447640	773 Monroe St Newark NJ 07220	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	Condo	RENTED	rental
TXN-2025-011	MLS8208952	687 River Rd Jersey City NJ 07276	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	TH	RENTED	rental
TXN-2025-012	MLS8908181	301 Greenwich Ave Fairfield CT 06822	Dream Homes CT	1200 Post Rd Fairfield CT 06824	(203) 555-0500	TH	PENDING	sale
TXN-2025-013	MLS8750840	416 West End Ave Unit 27B New York NY 10001	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	Co-op	PENDING	sale
TXN-2025-014	MLS8399416	288 Atlantic Ave Brooklyn NY 11201	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	TH	PENDING	sale
TXN-2025-015	MLS8587052	520 Monroe St Edgewater NJ 07282	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	SFH	PENDING	sale
TXN-2025-016	MLS8553789	446 Park Ave Unit 16A New York NY 10070	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	TH	PENDING	sale
TXN-2025-017	MLS8297489	949 West End Ave Unit 10D New York NY 10110	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	Condo	ACTIVE	sale
TXN-2025-018	MLS8483697	999 Post Rd Stamford CT 06864	Dream Homes CT	1200 Post Rd Fairfield CT 06824	(203) 555-0500	TH	ACTIVE	sale
TXN-2025-019	MLS8025874	241 Fifth Ave Unit 10A New York NY 10027	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	Co-op	PENDING	sale
TXN-2025-020	MLS8316323	835 Park Ave Unit 26B New York NY 10118	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	TH	SOLD	sale
TXN-2025-021	MLS8058697	841 East 86th St Unit 28D New York NY 10097	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	SFH	ACTIVE	sale
TXN-2025-022	MLS8353052	256 Post Rd Stamford CT 06902	Dream Homes CT	1200 Post Rd Fairfield CT 06824	(203) 555-0500	TH	SOLD	sale
TXN-2025-023	MLS8379831	67 Broadway Unit 14C New York NY 10030	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	Co-op	ACTIVE	sale
TXN-2025-024	MLS8239314	914 East 86th St Unit 20D New York NY 10032	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	Condo	SOLD	sale
TXN-2025-025	MLS8320229	803 Bedford Ave Brooklyn NY 11205	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	Co-op	ACTIVE	sale
TXN-2025-026	MLS8847954	813 Monroe St Newark NJ 07192	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	Co-op	ACTIVE	sale
TXN-2025-027	MLS8657500	571 Washington St Edgewater NJ 07254	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	Co-op	SOLD	sale
TXN-2025-028	MLS8099770	912 Bergen Ave Jersey City NJ 07177	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	TH	PENDING	sale
TXN-2025-029	MLS8383277	255 Newark Ave Edgewater NJ 07089	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	Co-op	RENTED	rental
TXN-2025-030	MLS8684078	166 Bergen Ave Edgewater NJ 07271	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	Co-op	SOLD	sale
TXN-2025-031	MLS8449539	642 Madison Ave Unit 2A New York NY 10004	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	Condo	RENTED	rental
TXN-2025-032	MLS8505510	478 Bedford Ave Brooklyn NY 11201	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	SFH	RENTED	rental
TXN-2025-033	MLS8513172	311 Grand St Brooklyn NY 11217	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	TH	SOLD	sale
TXN-2025-034	MLS8878140	210 Park Ave Unit 12D New York NY 10118	Dream Homes Manhattan	120 Broadway Suite 2701 New York NY 10271	(212) 555-0100	Co-op	RENTED	rental
TXN-2025-035	MLS8481295	250 Washington St Newark NJ 07144	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	TH	SOLD	sale
TXN-2025-036	MLS8591990	838 Newark Ave Jersey City NJ 07105	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	Co-op	SOLD	sale
TXN-2025-037	MLS8033667	138 Main St Greenwich CT 06870	Dream Homes CT	1200 Post Rd Fairfield CT 06824	(203) 555-0500	Co-op	SOLD	sale
TXN-2025-038	MLS8079874	817 Smith St Brooklyn NY 11212	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	TH	PENDING	sale
TXN-2025-039	MLS8767776	755 Smith St Brooklyn NY 11211	Dream Homes Brooklyn	345 Court St Brooklyn NY 11231	(718) 555-0400	TH	SOLD	sale
TXN-2025-040	MLS8650041	284 Washington St Edgewater NJ 07122	Dream Homes NJ	890 Bergen Ave Jersey City NJ 07306	(201) 555-0300	TH	SOLD	sale

Dream Homes NYC Data

Example Data

This approach has several practical advantages over traditional sample data creation. We can quickly generate large datasets that include the kinds of edge cases and variations we might miss when creating data manually. The AI-generated records help us discover potential issues before we encounter real data, and we can easily refine our generation rules as we learn more about common data quality problems. Most importantly, it gives us confidence that when we process Dream Homes NYC's actual historical data and ongoing feeds, our system will handle the inevitable inconsistencies without losing important business information.

ETL Process

Our ETL is a single Python module, EnhancedDreamHomesETL, that reads the master CSV (dream_homes_nyc_dataset_v8.csv) and loads it into dream_homes_db on PostgreSQL. The module converts semi-structured records into typed rows that fit our schema and keeps natural keys stable so the job is safe to re-run. This section documents the schema context we load into, the cleaning done during extraction, the normalization decisions in the Transform stage, and the exact loading logic for each table group.

0) Schema context for loading

The schema is in third normal form and the ETL respects its boundaries. Offices manage employees (Office→Employee, 1:M). A client's master profile is stored once and roles are attached separately (Client→ClientRole, 1:M), because the same person can be a buyer in one deal and a landlord in another. Property categories are standardized in PropertyType; each Property is keyed by MLS number and owns many features and media items (Property→PropertyFeature/PropertyMedia, 1:M). Appointment records are time-stamped facts that connect an agent, a client, and a property. Commercial activity is unified in Transaction, with Commission as a 1:1 extension. Rentals add Lease (1:1 from Transaction) and many PaymentRecord rows (Lease→PaymentRecord, 1:M). Document and MarketingCampaign attach to properties or deals. These cardinalities determine our insert order and the natural keys we use for deduplication.

1) Data source and extract

We read the CSV into a pandas DataFrame with UTF-8 decoding; empty cells become NaN. Extraction is non-destructive: we keep the original tokens and rely on typed converters and mappers in Transform/Load to handle irregular text. We do not pre-drop duplicate lines; idempotent inserts on natural keys prevent duplication of base entities.

2) Cleaning rules (and how we treat unusual values)

Type coercion happens first and never crashes the batch. The helpers safe_decimal, safe_int, and safe_date convert values and return NULL on failure; each failure is logged as a WARNING. We rely on database constraints for sanity (for example, non-negative monetary amounts where enforced by DDL). When essential monetary fields for a deal are missing, the

Transaction insert for that row is skipped, while the related Property still loads if its required fields parse.

3) Transform: normalization decisions and functions

The archived files contain composite strings and free-text categories. The Transform stage breaks them into atomic columns, maps labels to enums, and expands lists into child rows, so the database can enforce constraints and analytics do not rely on ad-hoc regex filters.

- Address parsing. parse_address splits a full address into address, city, state, zip_code using a right-to-left rule to fix state/ZIP and capitalization cues for city vs street. For Office inserts, missing parts default to NYC placeholders (city New York, state NY, ZIP 10001); for Property we insert the parsed parts as they are (the dataset supplies complete addresses).
- Beds/Baths. parse_bed_bath_info interprets strings such as "3BR/2.5BA" and "Studio/1BA" and returns numeric counts (bedrooms:int, bathrooms:float).
- Client blurb. parse_client_info separates name | profession | Budget … | notes and standardizes K/M suffixes into numeric ranges; it returns name, profession, min/max budget, and notes.
- Appointments. parse_appointment_history expands a bar-separated history into one record per event, mapping phrases like "Final walkthrough" to the inspection enum. The raw sentence is kept in notes.
- Features and documents. Comma lists are split into one row per amenity in PropertyFeature; parse_documents_required maps document names to our enum (e.g., *Title Report* → title_report).
- Category mapping. map_property_type, map_transaction_status (property status), map_transaction_status_enum (transaction status), map_campaign_type, map_lead_source, and map_payout_status align upstream spellings with our enums (for example, "Direct Mail/Direct Marketing" → advertisement, "PAID" → paid).
- Fallbacks. If offer_date is missing we use listing_date or today's date; if offer_amount is missing we fall back to final_price or list_price. All fallbacks are explicit in the log.

4) Load: table-by-table logic and keys

The loader proceeds in dependency order. Each insert checks for an existing row using an indexed business key and then performs an upsert where supported.

- Office. Look up by office_name. If absent, insert_or_get_office creates a deterministic office_code, parses the address, applies NYC defaults when needed, and inserts one row.

- Employee. Deduplicate by email. insert_or_get_employee parses the full name, sets job_title='Agent', and lets the database trigger generate employee_code. An office must exist first (Office→Employee is 1:M).
- Client and ClientRole. insert_or_get_client creates one master row per email (or a stable synthetic email if missing) and immediately adds a role in ClientRole that matches the deal type: buyer/seller for sales; renter/landlord for rentals (Client→ClientRole is 1:M). ON CONFLICT (client_id, role_type) DO NOTHING prevents duplicate role assignments.
- PropertyType. insert_or_get_property_type maps abbreviations (e.g., TH → Townhouse) and ensures a single row per type.
- Property. The loader uses the CSV mls_listing_number as the natural key for Property.mls_number. It then issues an INSERT into PostgreSQL with typed address fields, list price, square footage, bedrooms, bathrooms, and the mapped status; ON CONFLICT (mls_number) updates current_status and list_price to make re-runs idempotent.
- PropertyFeature. After the property exists, the amenity list is split and written one per row (feature_type='amenity'), using ON CONFLICT DO NOTHING where a uniqueness rule is defined.
- Transaction. Keyed by transaction_code (from the CSV column transaction_id). The insert links the property, listing and selling agents, and the parties (buyer/seller or renter/landlord) according to the deal type; status is mapped to our enum. Required dates and amounts use the fallbacks above. A database check enforces that sales cannot carry renter/landlord and rentals cannot carry buyer/seller. ON CONFLICT (transaction_code) updates status and transaction_amount.

Secondary facts (post-commit). After the core commit, child facts are attached in separate transactions—each wrapped in its own try/except with an independent commit/rollback, so a non-critical failure cannot erase the core insert:

- insert_appointments writes event rows for showings and inspections (status='completed', scheduled_datetime at midnight of the event date, created_by = listing agent).
- insert_commission_record records total commission and agent splits. If explicit split amounts are parsed from text, we use them; otherwise, and in the absence of a parsed selling split, the listing agent receives the full amount. ON CONFLICT (transaction_id) DO NOTHING protects the 1:1 relation.
- insert_documents creates required document rows and, when an appraisal amount is present together with an inspection date, also creates an appraisal report entry.

- insert_client_leads converts a buyer blurb and lead source into a structured lead; by rule, interest_type='renting' when budget_max < 50,000, otherwise buying. Leads are inserted with status converted.
- insert_property_media seeds a primary photo and a floor plan for each property.
- For rentals, a Lease is created with derived start/end dates (from lease_start_end or defaulting to closing_date + 365 days) and a lease_number derived from the transaction code, followed by PaymentRecord rows for the security deposit (if present) and the first month's rent.
- MarketingCampaign is inserted when campaign type and spend are present (status completed), using the mapped campaign enum.

5) Validation, deduplication, and idempotency

Lookups hit indexed columns where relevant: office name, employee email, client email, MLS number, and transaction code. Base entities use ON CONFLICT to convert duplicates into updates where business rules allow (for example, Property, Transaction, Commission, ClientRole). Secondary entities that are additive by nature (features, media, documents, appointments, leads, payments, campaigns) are attached after the core commit; repeated loads of the same CSV will append additional rows in those child tables.

6) Transaction boundaries and logging

The base chain (Office → Employee → Client/ClientRole → PropertyType → Property → Transaction) runs inside a single database transaction and commits or rolls back as a unit. Each secondary group (appointments, commissions, documents, leads, media, lease, payments, campaigns) is wrapped in its own transaction with an immediate commit on success and a localized rollback on failure. Logging is at three levels: INFO for progress, WARNING for recoverable data issues and fallbacks, and ERROR for row-level rollbacks with the relevant keys.

7) Runtime notes

The loader performs row-by-row inserts via psycopg2 with explicit commits at safe points. With our current dataset (≈50 rows), a full run completes well under a minute, including normalization and secondary inserts. The job can be re-run safely for base entities because keys, enum mappings, and upserts are consistent across entities.

Analytics Applications

To enable Dream Homes NYC to truly turn data into productivity, during the code implementation process, we translated all queries into scenario-based decision-making actions.

Firstly, the analysis of "what functions can be purchased in different price ranges" was made into an interactive heat map: The agent only needs to drag the slider on the iPad, and the client can see in real time the three most frequently seen supporting facilities at 500,000, 750,000 and 1,000,000. On the spot, the viewing list can be reduced to the five units that best fit the budget, saving the time of back-and-forth communication.

What the marketing team cares about most is whether the money is well spent. With this in mind, we have solidified the lead cost, conversion rate and ROI of each channel in the "Marketing cockpit" of Metabase. At 8 a.m. every day, the dashboard automatically pushes a wech-style summary: Last night, the Instagram AD brought 23 leads, expected to convert 3 orders, with an ROI of 5.4 times. Google keywords only brought in 7 leads, and the ROI dropped to 1.2 times. Based on this, the marketing manager can complete the budget reallocation for the week before 10 a.m., instead of waiting until the end of the month as in the past to find that half of the advertising expenses have been wasted.

For landlords, the most concerning issue is undoubtedly "How much more rent can I earn by installing this set of facilities?" Therefore, we have encapsulated the rental premium calculation into a one-click report: select "gym", "doorman", and "rooftop garden", and the system immediately provides an average premium of 320 US dollars, 280 US dollars for doormen, and 150 US dollars for the gym, and displays the area with the highest premium according to the district heat map. Based on this, the landlord decided to prioritize upgrading the security guard system, expecting to recoup the investment in 14 months, rather than blindly spending money on decoration.

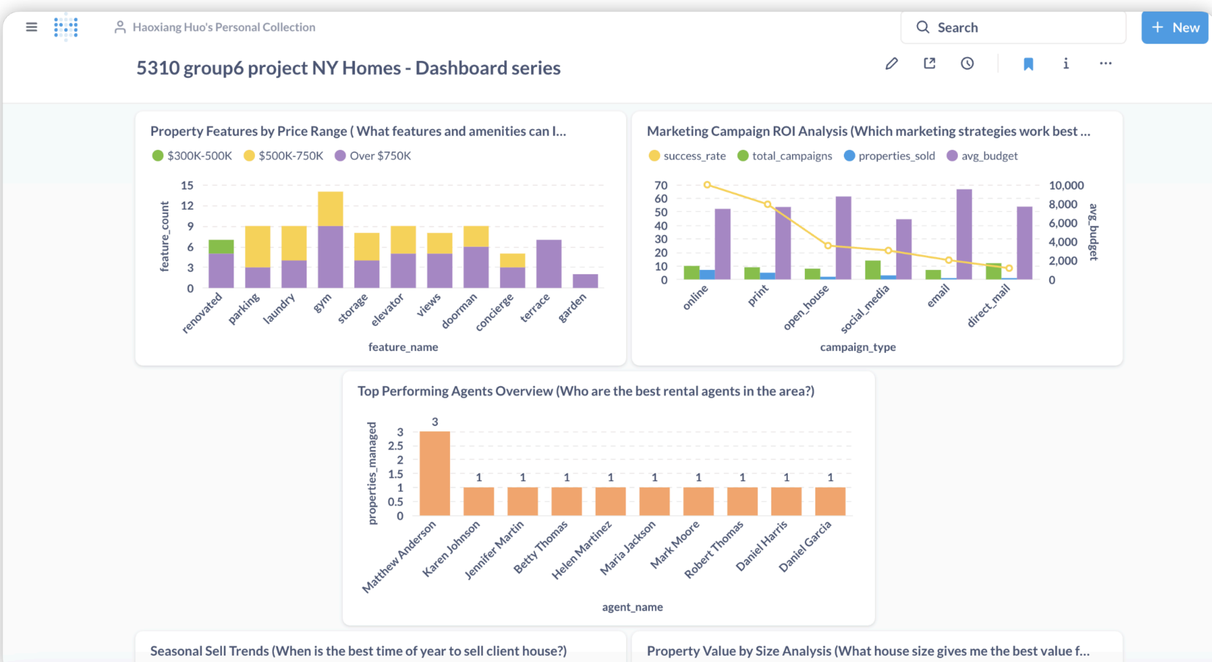
In the past, the timing of selling a house was entirely based on experience. Now, we use the quarterly transaction speed to inform customers of the most favorable time to list. The system will automatically send emails to all potential sellers every March. According to the data of the past two years, houses listed from April to June can be sold on average within 32 days, which is 20 days faster than at the end of the year, and the premium is 3% higher. After receiving the email, the customer only needs to click "Book Valuation", and the schedule will be automatically arranged to the first week of April. The transaction rhythm is completely driven by data.

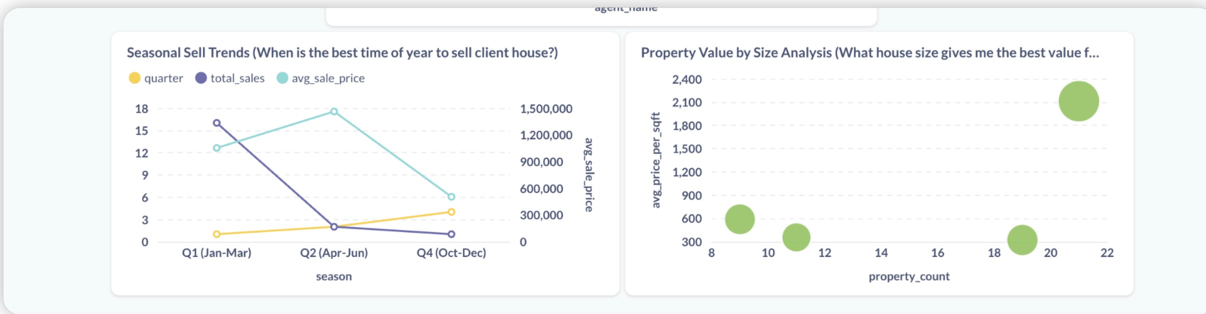
For the lease structure, we calculated the vacancy rate, rent and deposit for the three models of short-term rental, public rental and long-term rental all at once. The operation team found that although the unit price of short-term rental is 15% higher, the vacancy period is extended by 8%, and the overall income is actually lower. So the background system changed the default recommended contract from 6 months to 12 months. The system automatically highlighted "Annual rent is more cost-effective" on the tenant signing interface, which not only stabilized the cash flow but also saved the labor of repeated renting.

The security premium of the area that investors care about most has been made into an enlarged map: the darker the color, the higher the proportion of security facilities and the more expensive the housing price. When investors click on any postal code, the average housing price, security coverage rate and the predicted increase in the next 12 months of the area will immediately pop up. With just a few mouse movements, one can identify the value trough of "few security facilities, low housing prices, but a subway under construction", and complete the acquisition before the price increase.

Finally, the lead conversion funnel and the ROI of marketing activities were merged into one "Today's Battle Map". The sales morning meeting turns on the large screen, allowing you to immediately see which channel failed yesterday and which broker had the highest conversion rate. The system automatically redistributes 20% of the fallen leads to the top three brokers of the week, ensuring that every potential customer can be followed up within 24 hours. Data is no longer a monthly report but a metronome that directs business in real time.

Metabase Dashboard:





Conclusion

In this task, we helped Dream Homes NYC transform the initially scattered old forms and scanned copies into an online data warehouse that can be accessed at any time. The database itself follows the three normal forms, eliminating redundancy. Foreign keys and constraints ensure that every record is trustworthy. The Python-automated ETL operates silently every night, flowing new properties, customers, transactions, and payments into the corresponding tables. If an error occurs, it rolls back, ensuring that the report appears on time the next day even when unattended. Twelve business-level queries cover the most frequently asked questions by brokers, marketers, renters, and investors. Metabase hides these technical details behind the scenes, allowing any role to use clicks instead of code.

Finally, we have enabled brokers to take out their mobile phones at the viewing site and check the average transaction price of the same community last month within two seconds. The marketing manager can directly pull out the ROI of each lead in the budget meeting and immediately cut off inefficient channels. Executives can open the dashboard to see the total revenue for the quarter, occupancy rate, and which office has the fastest transaction rate. Decision-making has been shortened from weeks to hours. More importantly, this architecture is horizontally scalable on the cloud: doubling the number of listings and tenfold the concurrent queries, all that is needed is to add nodes, without touching a single line of business code. Dream Homes NYC now has a truly "data heart" that grows along with the business. In the future, whether it is to integrate smart home IoT data, conduct machine learning valuation, or launch a customer self-service house-finding mini-program, it can smoothly grow on the existing schema without having to start from scratch.

Github Link:
https://github.com/StevenHuo-CU/APAN5310-Group6-Project-DreamHome-NYC