CS 439 25F
Clustering: K-Means and t-SNE

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Group 24
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Project Description

- This project explores clustering patterns in New York City yellow taxi rides using K-Means and t-SNE.
- The objective is to identify natural groupings of trips based on quantitative features such as trip distance, fare amount, tip amount, pickup/drop-off locations, and time of day.
- After preprocessing and feature scaling, K-Means is applied to form clusters that may represent typical ride types (e.g., short local trips, airport runs, high-tip rides).
- t-SNE (t-Distributed Stochastic Neighbor Embedding) is used to reduce dimensionality for 2-D visualization of the cluster structure.
- The project analyzes how temporal and spatial factors affect how people use taxis and how much they spend.

What t-SNE Does and Why We Used It

What t-SNE Does

- Reduces high-dimensional data down to 2D
- Places similar points close together and separates different points
- Preserves the local structure of the data, meaning similar trips stay grouped

Why We Used It

- Our dataset has many features (distance, fare, tips, time, locations) that interact in complex ways
- Linear methods like PCA couldn't show meaningful separation (as we'll see)
- t-SNE captures non-linear patterns and reveals groups that other methods hide

How It Works (high-level)

- Finds which trips are most similar in the original dataset
- Builds a 2D layout that tries to keep those relationships intact
- Spreads out the data so clusters appear clearly on a map

What We Learned

- Airport trips, micro-trips, and high-passenger rides separate cleanly
- Everyday Manhattan rides blend into one large cluster
- t-SNE confirmed that our K-Means clusters reflect real structure in the data

Dataset Description and Sample Snapshots

Dataset Name: NYC Yellow Taxi Trip Records - January 2025

Source : NYC Taxi and Limousine Commission (TLC)

TLC Trip Record Data

Size and Format

- CSV format, ~90 MB (≈ 850K trip records)
- Average Entry Size: ~114 bytes per record
- Structure: One row per trip; 20 total columns
- Each record represents one completed yellow taxi trip

Key Columns

- Categorical identifiers - *VendorID, payment_type*
- Trip timestamps - *tpep_pickup_datetime, tpep_dropoff_datetime*
- Quantitative features - *passenger_count, trip_distance, fare_amount, tip_amount, total_amount*
- Spatial identifiers for pickup and drop-off zones - *PULocationID, DOLocationID*
- Pricing modifiers - *RatecodeID, tolls_amount, congestion_surcharge, Airport_fee*

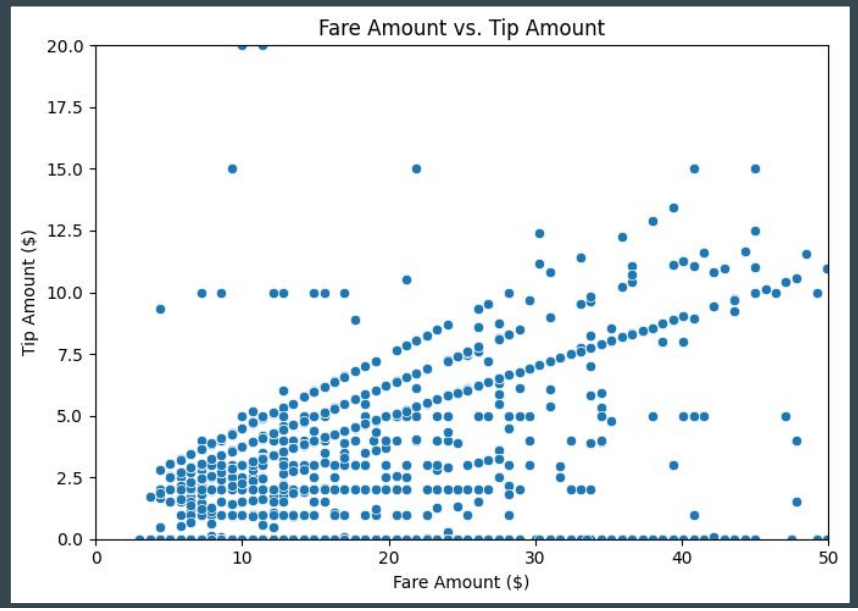
Feature Engineering for Clustering

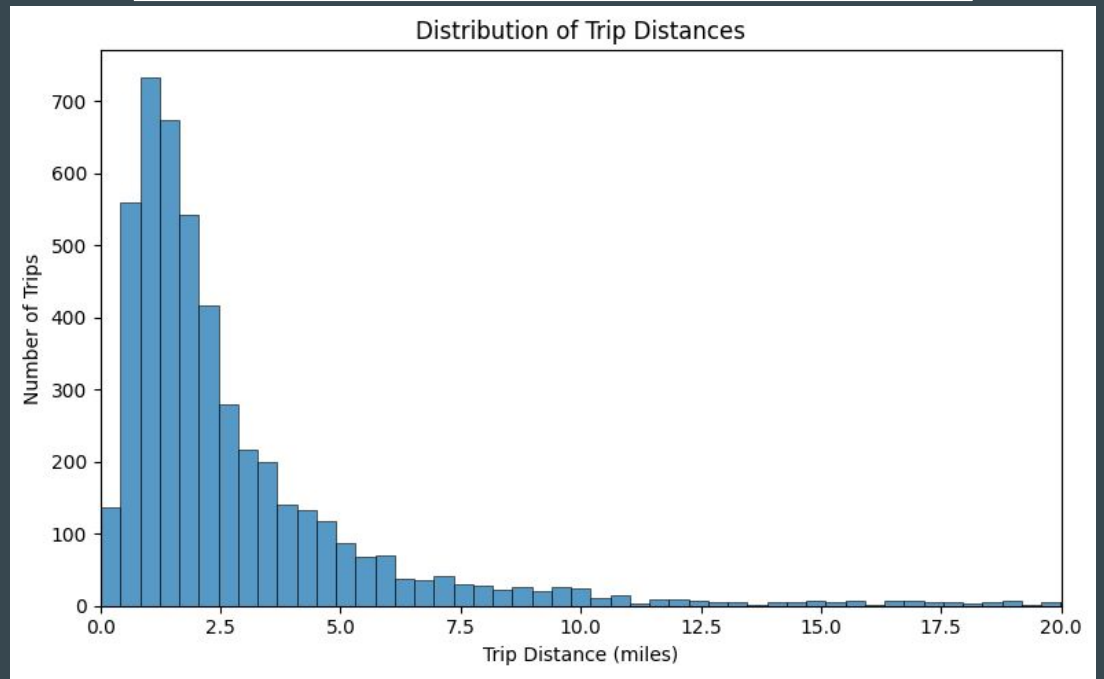
- Extracted pickup_hour and pickup_weekday from timestamps
- Filtered out trips with missing or zero distance/fare values
- Scaled numeric features with StandardScaler for uniform variance

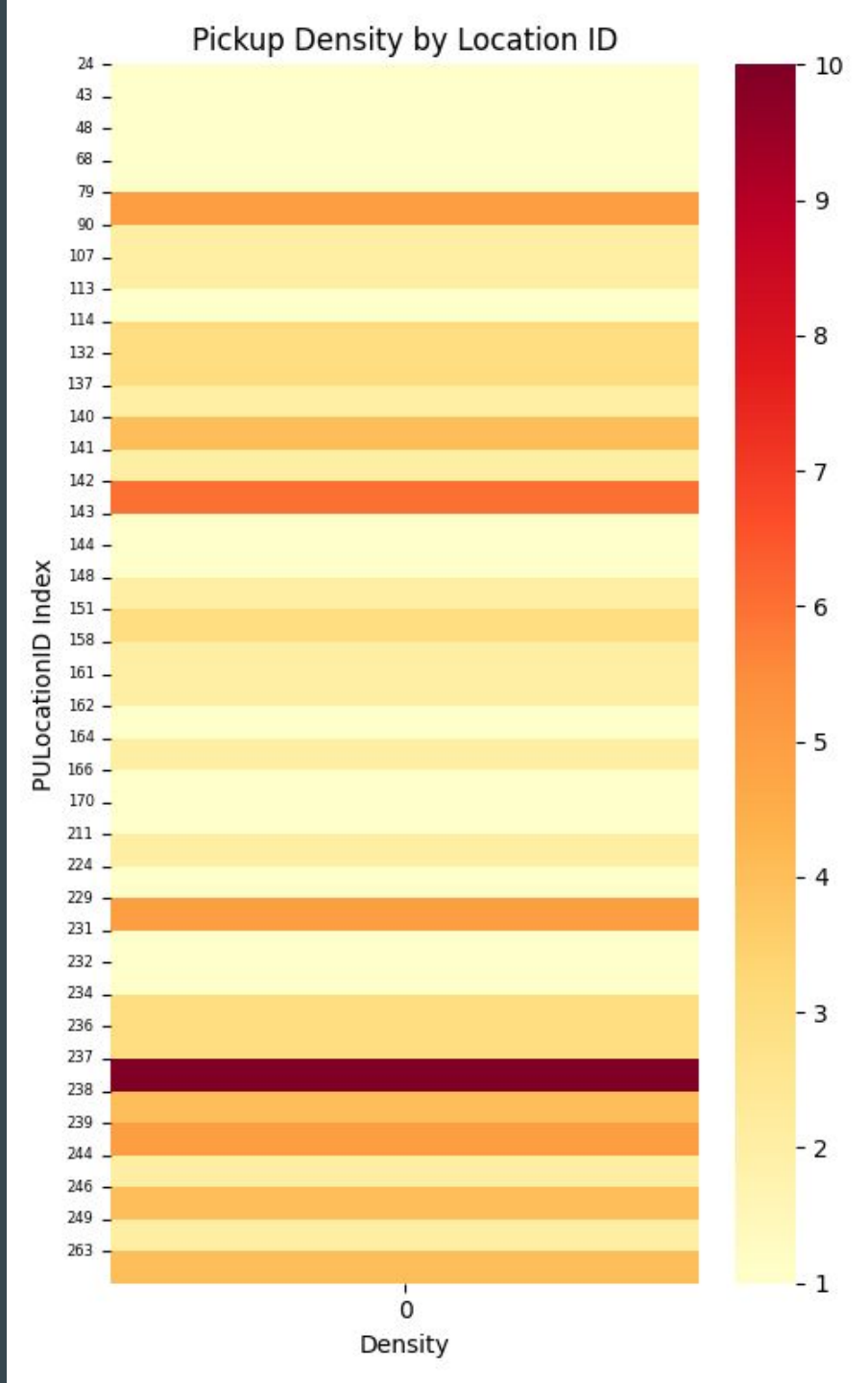
Dataset Snapshot

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	payment_type	fare_amount	extra
1	2	2025-01-01 00:14:27	2025-01-01 00:20:01	3.0	0.52	1.0	N	244	244	2	7.2	1.0
2	2	2025-01-01 00:21:34	2025-01-01 00:25:06	3.0	0.66	1.0	N	244	116	2	5.8	1.0
3	2	2025-01-01 00:48:24	2025-01-01 01:08:26	2.0	2.63	1.0	N	239	68	2	19.1	1.0
4	2	2025-01-01 00:00:02	2025-01-01 00:09:36	1.0	1.71	1.0	N	237	262	2	11.4	1.0
5	2	2025-01-01 00:20:28	2025-01-01 00:28:04	1.0	2.29	1.0	N	237	75	2	11.4	1.0
6	2	2025-01-01 00:33:58	2025-01-01 00:37:23	1.0	0.56	1.0	N	263	236	1	5.8	1.0
7	2	2025-01-01 00:42:40	2025-01-01 00:55:38	3.0	1.99	1.0	N	236	151	2	14.2	1.0
8	2	2025-01-01 00:01:41	2025-01-01 00:07:14	1.0	0.71	1.0	N	79	107	2	-7.2	-1.0
9	2	2025-01-01 00:01:41	2025-01-01 00:07:14	1.0	0.71	1.0	N	79	107	2	7.2	1.0
10	2	2025-01-01 00:05:49	2025-01-01 00:20:00	2.0	3.45	1.0	N	263	107	1	17.7	1.0
11	2	2025-01-01 00:34:40	2025-01-01 00:51:19	2.0	1.19	1.0	N	246	170	1	14.9	1.0
12	2	2025-01-01 00:55:54	2025-01-01 01:00:38	1.0	0.69	1.0	N	137	233	4	-6.5	-1.0
13	2	2025-01-01 00:55:54	2025-01-01 01:00:38	1.0	0.69	1.0	N	137	233	4	6.5	1.0
14	2	2025-01-01 00:14:14	2025-01-01 00:22:46	2.0	1.88	1.0	N	113	90	1	11.4	1.0
15	2	2025-01-01 00:32:01	2025-01-01 00:46:43	1.0	3.06	1.0	N	90	246	1	17.7	1.0
16	2	2025-01-01 00:00:37	2025-01-01 00:04:46	1.0	0.86	1.0	N	140	263	2	6.5	1.0
17	2	2025-01-01 00:11:07	2025-01-01 00:23:29	3.0	3.98	1.0	N	140	79	1	19.1	1.0
18	2	2025-01-01 00:32:47	2025-01-01 01:01:49	1.0	4.41	1.0	N	246	236	1	28.9	1.0
19	2	2025-01-01 00:32:04	2025-01-01 00:40:54	1.0	1.51	1.0	N	237	140	1	10.7	1.0
20	2	2025-01-01 00:53:47	2025-01-01 00:58:02	1.0	0.65	1.0	N	263	141	1	5.8	1.0
21	2	2025-01-01 00:16:55	2025-01-01 00:27:36	1.0	1.66	1.0	N	238	236	1	12.1	1.0
22	2	2025-01-01 00:39:33	2025-01-01 00:43:53	1.0	0.77	1.0	N	239	142	1	6.5	1.0
23	2	2025-01-01 00:59:29	2025-01-01 01:27:47	1.0	4.26	1.0	N	239	113	1	27.5	1.0
24	2	2025-01-01 00:15:41	2025-01-01 01:03:03	4.0	3.05	1.0	N	114	161	1	37.3	1.0
25	2	2025-01-01 00:39:26	2025-01-01 00:57:14	1.0	2.31	1.0	N	224	68	1	17.0	1.0
26	2	2025-01-01 00:07:07	2025-01-01 00:13:18	2.0	1.02	1.0	N	237	236	1	7.9	1.0
27	2	2025-01-01 00:22:56	2025-01-01 00:33:12	2.0	1.5	1.0	N	237	140	1	10.7	1.0
28	2	2025-01-01 00:43:44	2025-01-01 01:05:18	4.0	2.26	1.0	N	237	238	1	19.8	1.0
29	2	2025-01-01 00:52:53	2025-01-01 00:59:31	1.0	1.63	1.0	N	237	263	1	9.3	1.0
30	2	2025-01-01 00:37:14	2025-01-01 00:42:58	4.0	1.01	1.0	N	107	170	1	7.9	1.0
31	2	2025-01-01 00:46:47	2025-01-01 01:02:28	1.0	1.58	1.0	N	137	79	2	12.1	1.0
32	2	2025-01-01 00:19:52	2025-01-01 00:36:32	1.0	3.41	1.0	N	232	49	1	19.8	1.0
33	2	2025-01-01 00:25:03	2025-01-01 00:54:59	2.0	5.17	1.0	N	211	263	1	28.9	1.0
34	2	2025-01-01 00:14:46	2025-01-01 00:37:07	1.0	6.06	1.0	N	79	260	2	28.2	1.0
35	2	2025-01-01 00:11:10	2025-01-01 00:26:43	1.0	1.63	1.0	N	246	48	1	14.9	1.0
36	2	2025-01-01 00:30:40	2025-01-01 00:49:16	1.0	2.22	1.0	N	48	239	1	17.0	1.0
37	2	2025-01-01 00:52:50	2025-01-01 01:04:50	1.0	1.26	1.0	N	142	48	1	12.1	1.0
38	2	2025-01-01 00:48:18	2025-01-01 01:03:53	1.0	4.2	1.0	N	166	48	1	21.2	1.0
39	2	2025-01-01 00:36:56	2025-01-01 00:53:45	1.0	3.0	1.0	N	151	140	1	18.4	1.0
40	2	2025-01-01 00:11:13	2025-01-01 00:21:35	2.0	2.0	1.0	N	249	246	1	12.8	1.0
41	2	2025-01-01 00:19:18	2025-01-01 00:31:06	1.0	2.2	1.0	N	238	237	1	14.2	1.0
42	2	2025-01-01 00:33:54	2025-01-01 01:04:28	2.0	3.46	1.0	N	237	249	1	26.8	1.0
43	2	2025-01-01 00:09:04	2025-01-01 00:18:09	1.0	1.9	1.0	N	140	162	1	11.4	1.0

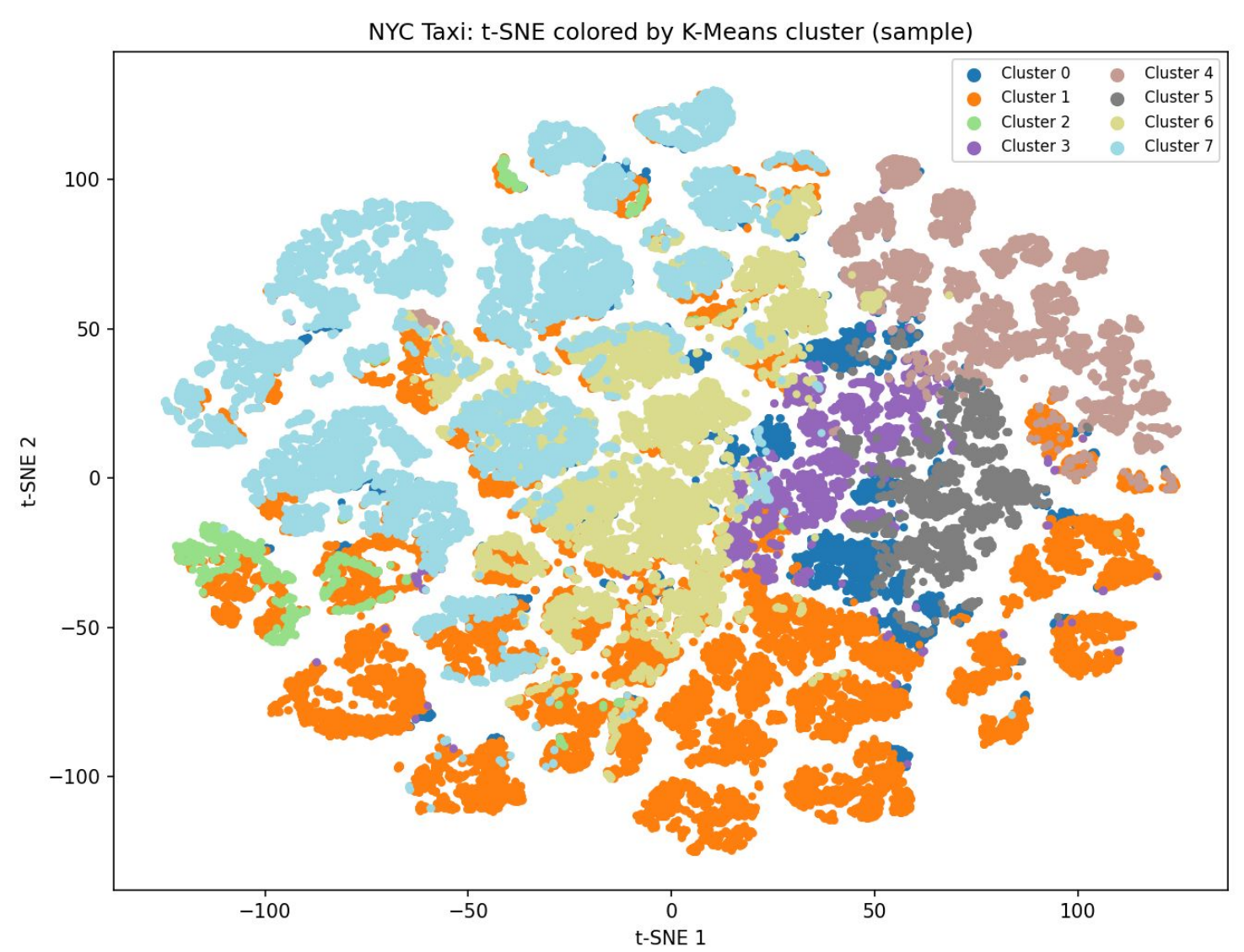
Dataset Graphs







Clusters



cluster	passenger_count	trip_distance	fare_amount	tip_amount	total_amount	PULocationID	DOLocationID	pickup_hour	pickup_weekday
0	1.25	8.47	39.04	9.89	59.53	147.54	148.38	14.66	2.99
1	1.16	2.22	12.49	2.34	19.22	158.84	149.93	5.55	2.94
2	1.17	1.75	11.70	2.45	18.71	206.50	174.05	15.38	4.54
3	1.47	14.33	63.89	1.04	74.39	140.29	140.93	13.43	2.98
4	3.78	2.29	13.55	2.52	20.79	167.73	166.20	14.95	3.36
5	1.62	17.60	75.98	16.76	104.02	141.01	150.34	14.34	3.08
6	1.16	2.07	12.56	2.42	19.81	96.80	132.82	16.40	2.99
7	1.13	1.69	11.44	2.56	19.11	200.52	200.91	15.55	1.52

Analyzing the Clusters

0: Short Midtown locals. Low distance, average tip percent ~23%.

1: Airports. 46% JFK, 22% LaGuardia. Long trips, highest fares and tips.

2: Downtown/East-side locals. Clinton East, Penn, East Village heavy. Medium distance.

3: Midtown/Chelsea/Central Park corridor. Short trips, big volume.

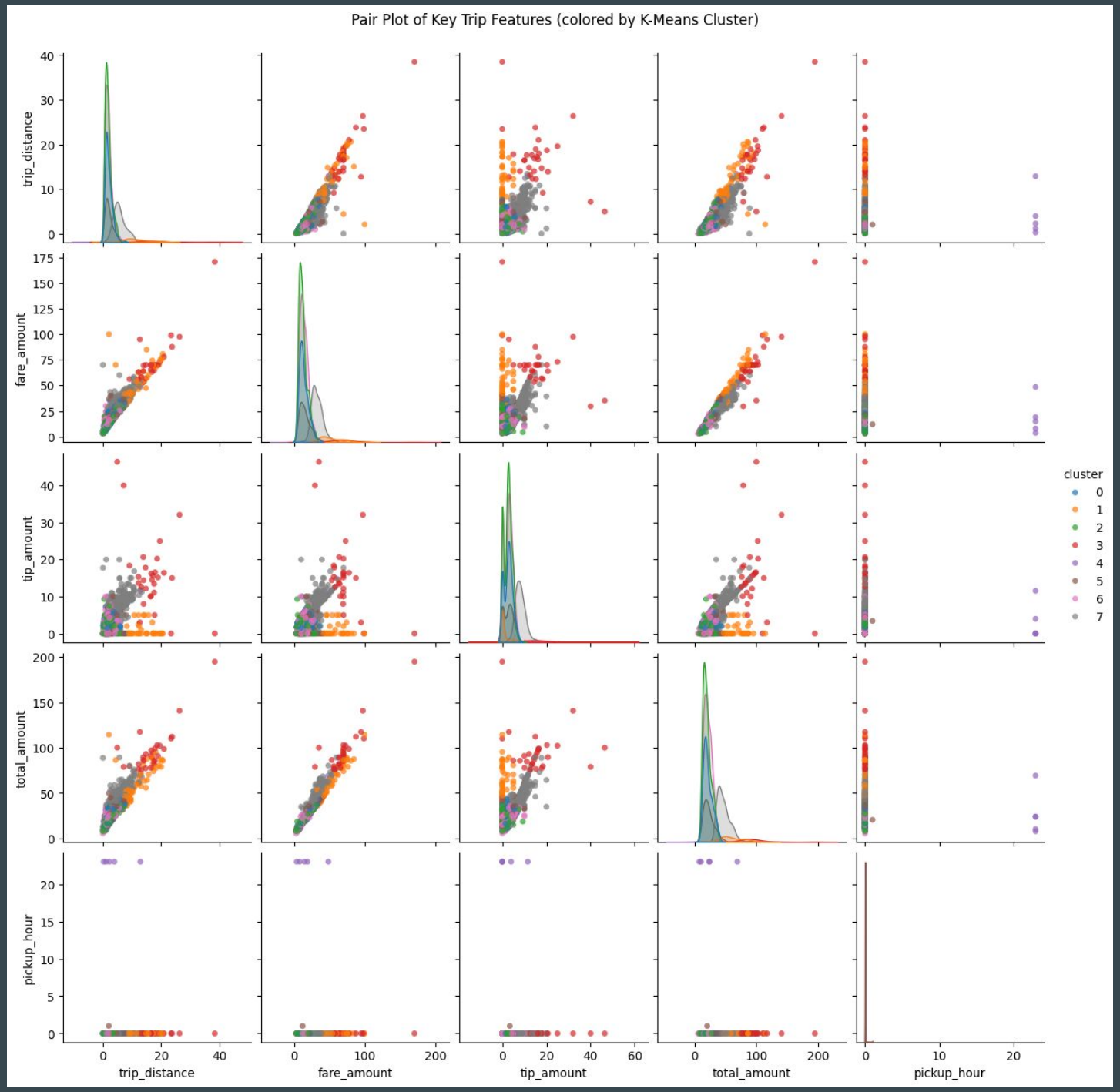
4: Upper East/West Side locals. UES/UWS dominate. Very short trips, lower fares.

5: Midtown mix including Penn, Times Sq, Murray Hill. Slightly longer than 0 & 4.

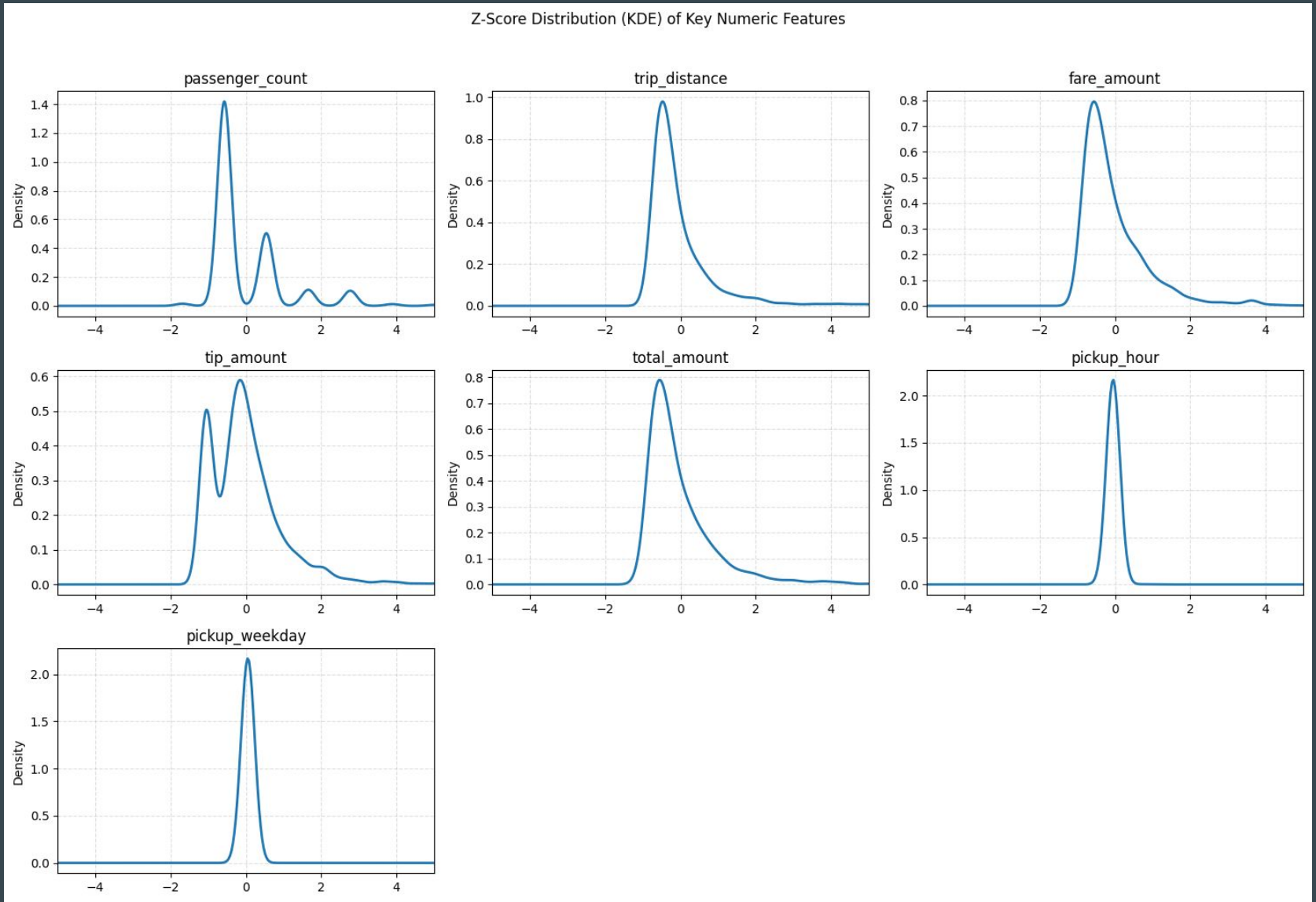
6: High passenger counts (mean ~3.8). Likely shared rides, shuttles, or data entry artifacts.

7: Outlier cluster. Size = 3.

Pair Plot


Pair Plot of Key Trip Features (colored by K-Means Cluster)
trip_distance
fare_amount
tip_amount
total_amount
pickup_hour
cluster
0
1
2
3
4
5
6
7

Z-Score Distribution



Questions to be addressed

- Can NYC taxi trips be clustered into distinct ride types?
- Which trip features most strongly define these clusters?
- What number of clusters best fits the data?
- How do ride patterns differ across times and days?
- How effectively does t-SNE visualize cluster separation?

Data Transformation Flowchart

1. **Data Import**
   - Load yellow_tripdata_2025-01.csv (≈90 MB) into a pandas DataFrame.

2. **Data Cleaning**
   - Remove rows with missing or invalid values (zero fare, zero distance).
   - Keep only numeric and relevant categorical fields (drop nonpositive distances/fares).

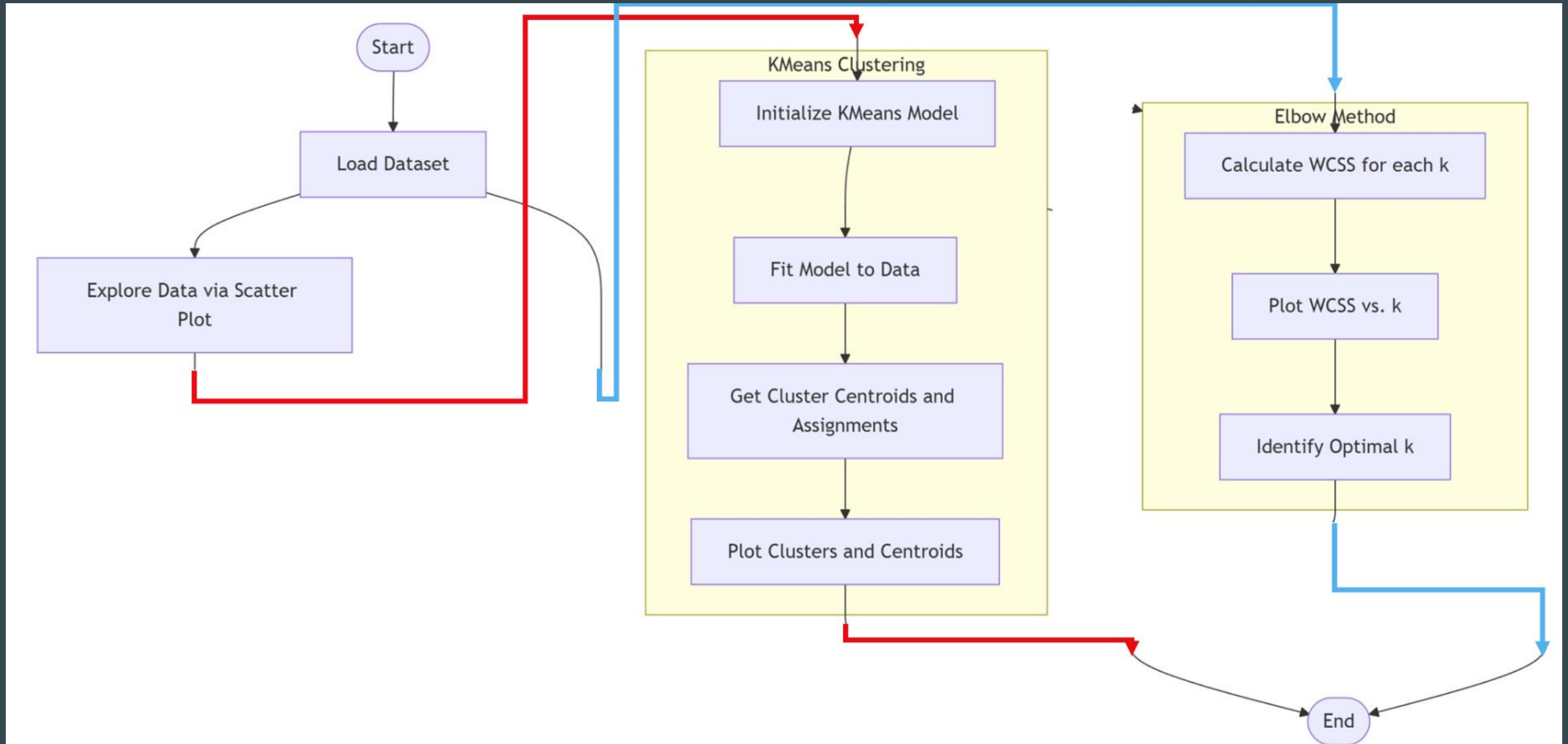
3. **Feature Engineering**
   - Extract pickup_hour and pickup_weekday from tpep_pickup_datetime.
   - Compute derived metrics such as tip_percentage = tip_amount / fare_amount.

4. **Feature Selection**
   - Choose features for clustering: ['passenger_count', 'trip_distance', 'fare_amount', 'tip_amount', 'total_amount', 'PULocationID', 'DOLocationID', 'pickup_hour', 'pickup_weekday']

5. **Scaling**
   - Standardize all numeric columns using StandardScaler.

6. **Clustering and Visualization**
   - Apply K-Means for grouping.
   - Use t-SNE for 2-D visualization of clusters.

Flowchart


Start
Load Dataset
Explore Data via Scatter Plot
KMeans Clustering
Initialize KMeans Model
Fit Model to Data
Get Cluster Centroids and Assignments
Plot Clusters and Centroids
Elbow Method
Calculate WCSS for each k
Plot WCSS vs. k
Identify Optimal k
End

Exploration Algorithms Used

Data Cleaning

- Removed invalid records (zero or negative distance/fare).
- Dropped missing values in key columns.
- Filtered out unrealistic outliers in trip distance.

Feature Engineering

- Extracted *pickup_hour* and *pickup_weekday* from timestamps.
- Created *tip_percentage = tip_amount / fare_amount* for better spending analysis.

Clustering

- K-Means Algorithm
  - Applied K-Means to group trips by numeric similarity.
  - Determined optimal *k* using the elbow method.

Dimensionality Reduction

- t-SNE (t-Distributed Stochastic Neighbor Embedding)
  - Applied t-SNE to project features into 2D.
  - Preserved local structure for visual cluster separation.

Visualization

- 2D scatter plots colored by cluster label.
- Density maps showing pickup location and time distributions.

Computational Platform and Software Libraries Used

Programming Language:
- Python 3.11

Development Environment:
- Jupyter Notebook (Anaconda distribution)

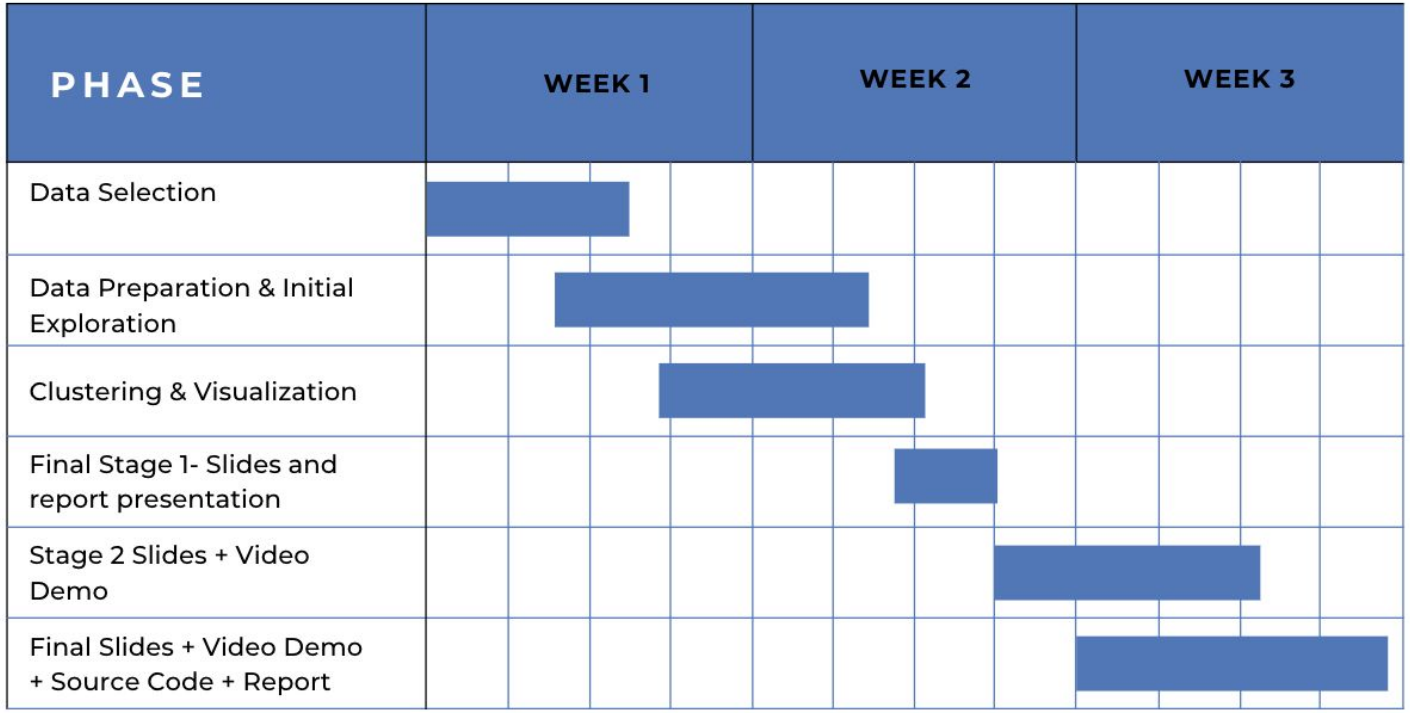
Core Libraries:
- pandas: data loading, cleaning, feature engineering
- numpy: numerical operations
- scikit-learn: clustering (K-Means), dimensionality reduction (t-SNE), scaling, PCA
- matplotlib, seaborn: visualization
- Plotly Dash, webbrowser, threading: dashboard creation

Hardware Used:
- Local machine (Windows 11, 32GB RAM)
- Dataset size ≈ 90 MB

Gantt Chart

Phase	Tasks	Deliverables / Due Date
Stage 1 - Data Preparation & Initial Exploration	Load dataset, clean data, engineer features (pickup hour, weekday), verify dataset size ≥ 8 MB	Week 10 Mon - Stage 1 Slides
Stage 2 - Clustering & Visualization	Apply K-Means and t-SNE, tune k, generate visualizations (histogram, scatter, geographic heatmap), interpret clusters	Week 14 Mon - Stage 2 Slides + Video Demo
Final Stage - Full Integration & Submission	Refine visuals and explanations, finalize code and written report (LaTeX format), record final demo	Week 15 Wed - Final Slides + Video + Source Code + Report

Clustering: K-Means and t-SNE
Project Report 1



Division of Labor

Andrew Menyhert (amm926)

- Imported and cleaned the NYC Yellow Taxi dataset
- Engineered time-based and tip-related features
- Implemented data scaling, K-Means clustering, and t-SNE visualization
- Developed and debugged the interactive Plotly Dash dashboard
- Designed final graphs and slide layouts; compiled and formatted the presentation

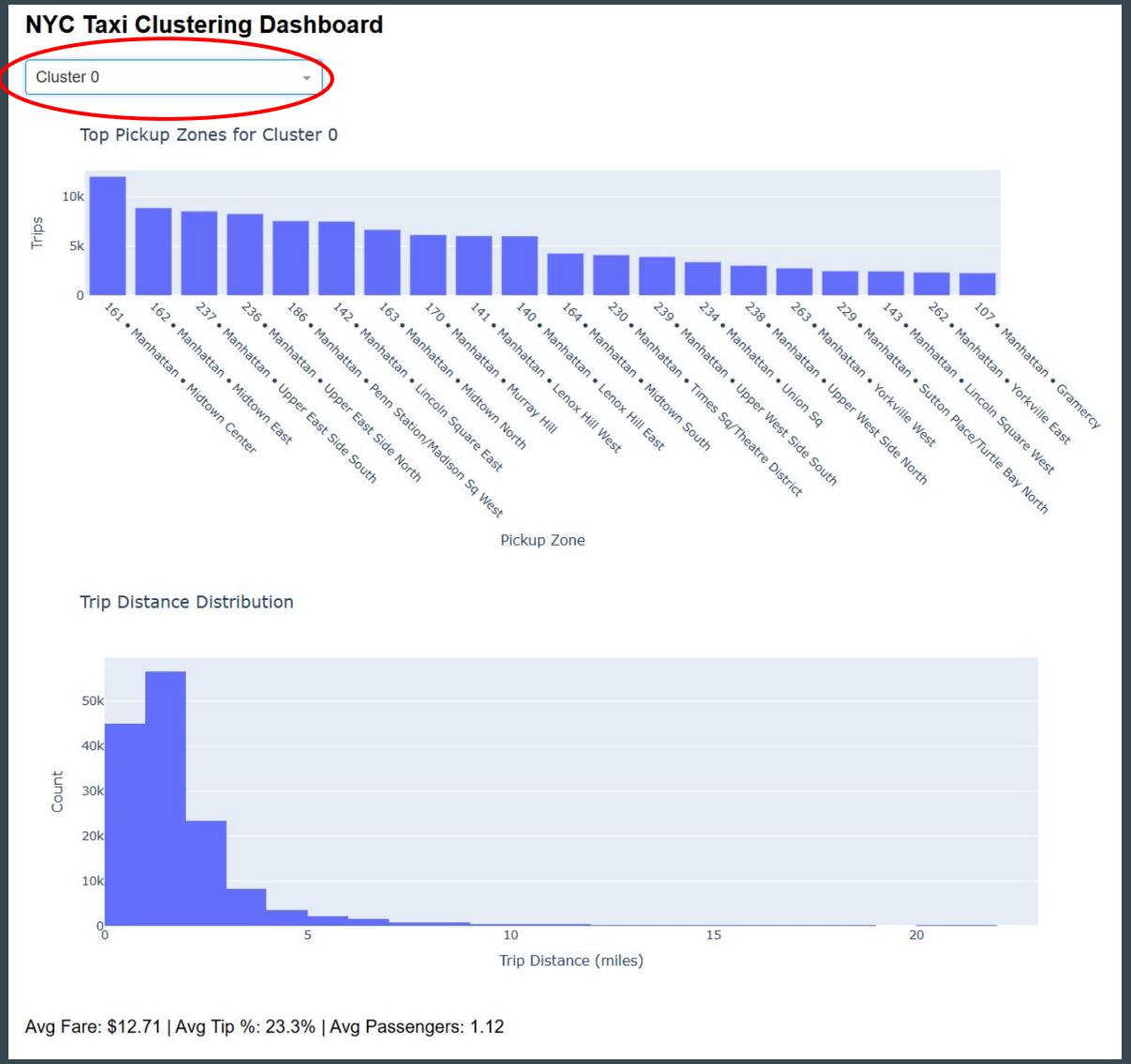
Rida Mohammad (rm1724)

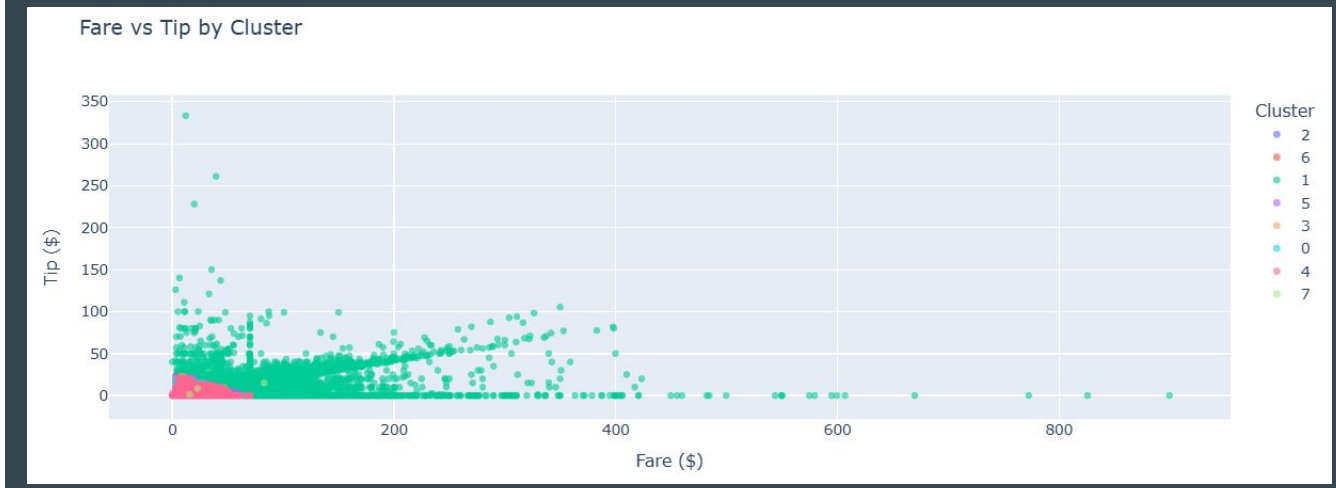
- Researched dataset details and documentation (TLC data dictionary)
- Drafted Dataset Description, Sample Snapshots, and Data Transformation Flowchart slides
- Summarized algorithm theory and Evaluation Techniques content
- Verified cluster quality metrics (Elbow method)

Kaushik Murali (km1526)

- Assisted with feature selection and outlier filtering
- Helped analyze and interpret cluster patterns (spatial and temporal)
- Prepared visualizations (Pair Plot, Z-Score Distribution)

Interactive Dashboard





Evaluation Techniques

Cluster Quality Metrics:

- Elbow Method: determines optimal number of clusters (k = 8)

Dimensionality Reduction Check:

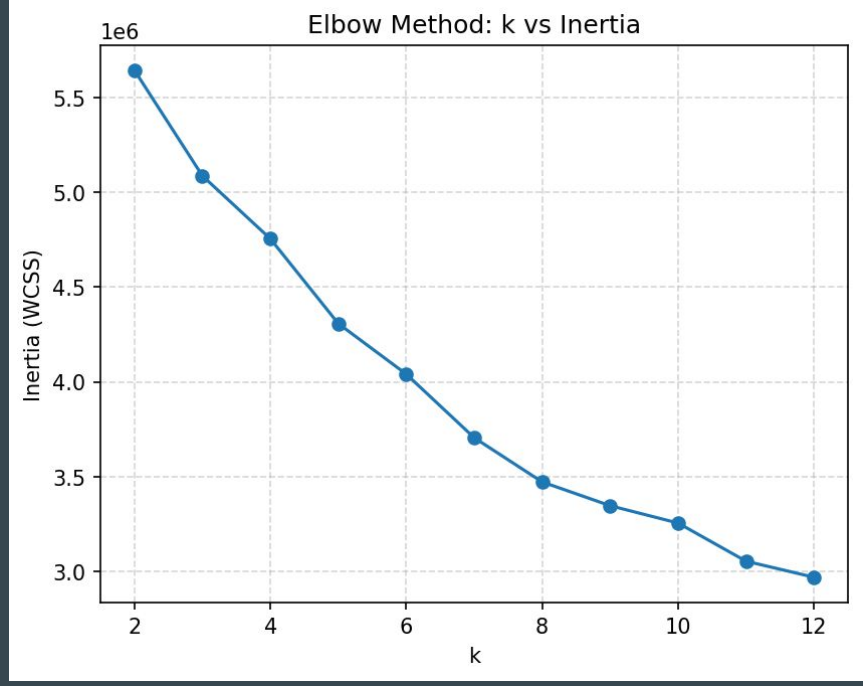
- t-SNE Visualization: validates visual separation of cluster groups

Feature Impact:

- Compared clustering results with and without spatial features (*PULocationID*, *DOLocationID*)

Validation:

- Re-clustered random subsets to test result stability
- Visually inspected cluster density patterns on NYC map



Interesting Findings - Behavioral Patterns

- Airport rides formed a distinctly isolated cluster due to extreme distance and fare values.
- Everyday Manhattan trips merged into one dominant cluster, capturing most rides in the dataset.
- Micro-trips (sub-1 mile) appeared as their own cluster, showing strong neighborhood-driven behavior.
- High-passenger trips separated clearly, indicating shared rides or data irregularities.

Interesting Findings - Technical Insights

- PCA showed little separation, meaning variance is dominated by a few continuous features.
- t-SNE revealed meaningful structure, capturing non-linear relationships between distance, fare, and location.
- Elbow method validated $k \approx 8$, with diminishing returns beyond that point.
- Location density played a large role, with a few pickup zones strongly influencing cluster shapes.

References

New York City Taxi and Limousine Commission (TLC). NYC Yellow Taxi Trip Records, January 2025.

TLC Trip Record Data

zyBooks Ch 10.2 Unsupervised Learning - K-means clustering.

zyBooks Ch. 10

Supplemental Material for Lecture 10 : Unsupervised Learning.

Supplemental Material for Lecture 10

t-SNE clearly explained. Medium - Kemal Erdem

t-SNE Clearly Explained

Link to all code/files