

# Customer Data Managment

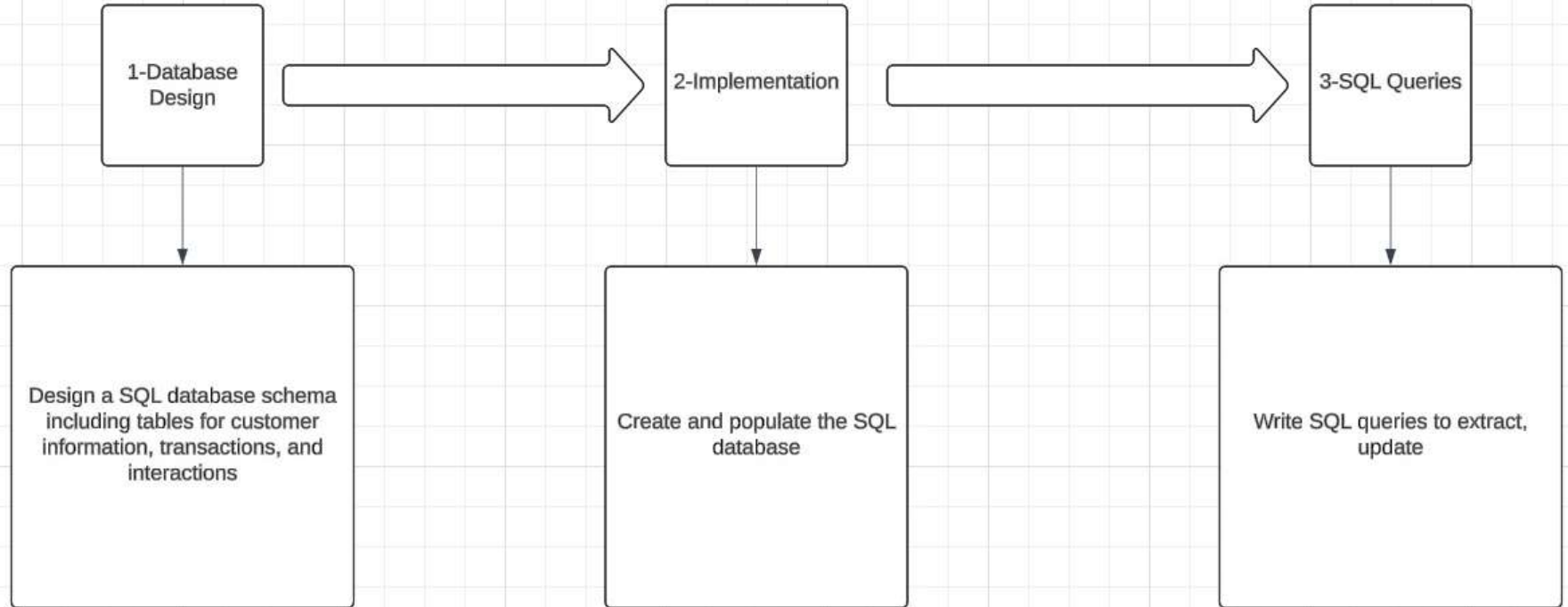
Team:

1. Mohamed Sameh (leader)
2. Rawan Amr
3. Esraa Osama
4. Mohamed Ibrahim
5. Shahd Waleed
6. Ali Sherif

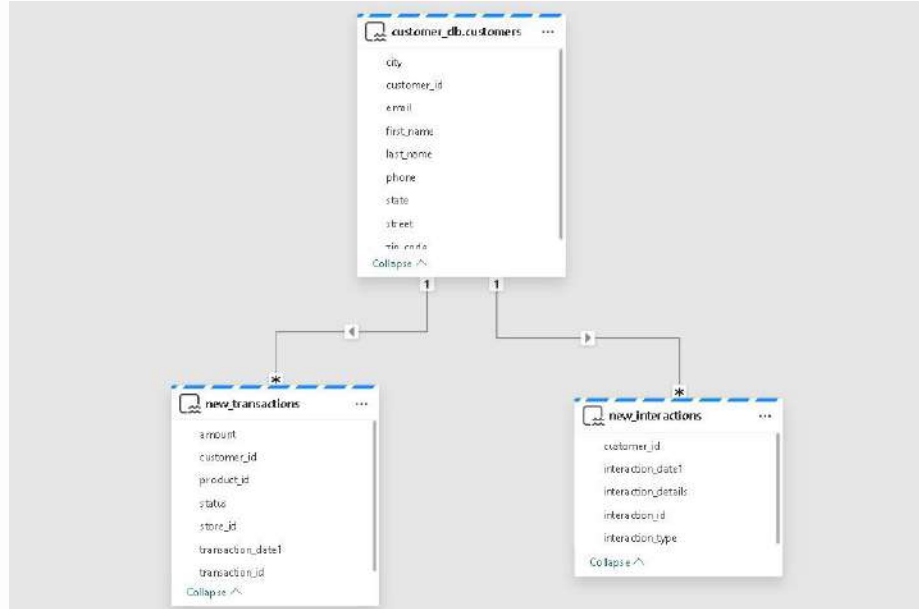
# Contents of this template

<b><u>Week 1</u></b>	Data Managment & SQL Database Setup
<b><u>Week 2</u></b>	Data Warehousing & Python Programming
<b><u>Week 3</u></b>	Data Science & Model Building
<b><u>Week 4</u></b>	Using Predictive Model & Final presentation

## Week 1: Data Management and SQL Database Setup

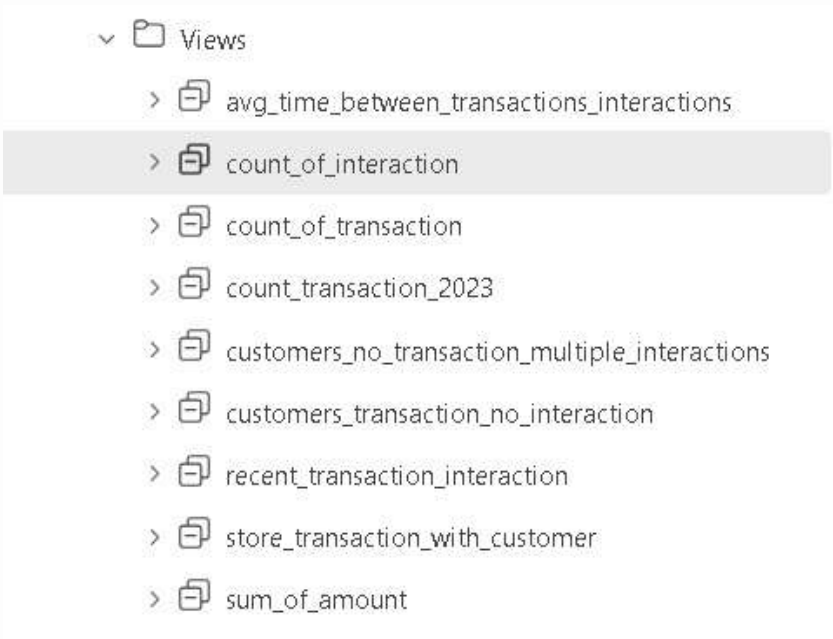


# Here is the schemas of week 1



Contains the tables of the customers info like shown

# Views for week 1

- 
- A screenshot of a database interface showing a list of views under a 'Views' folder. The 'count\_of\_interaction' view is highlighted with a grey background. Each view is preceded by a right-pointing arrow and a document icon.
- Views
    - > avg\_time\_between\_transactions\_interactions
    - > count\_of\_interaction
    - > count\_of\_transaction
    - > count\_transaction\_2023
    - > customers\_no\_transaction\_multiple\_interactions
    - > customers\_transaction\_no\_interaction
    - > recent\_transaction\_interaction
    - > store\_transaction\_with\_customer
    - > sum\_of\_amount

Views to extract the data of the customers

# Views data preview

Data preview - count\_of\_interaction

Showing 1000 rows

	ABC first_name	123 count_of_interaction
1	Marylyn	2
2	Ciera	1
3	Ling	1
4	Divina	2
5	Pinkie	2
6	Shirely	1
7	Jerome	3
8	Lissa	3
9	Klara	8
10	Vernetta	3
11	Takako	1
12	Antony	1
13	Joaquin	3
14	Adam	4
15	Ami	1
16	Domingo	3
17	Rosa	2
18	Syreeta	1
19	Melani	1
20	Kimberli	2
21	Zelma	2
22	Addie	1
23	Sheba	1
24	Mariette	1
25	Williamae	1

✓ Succeeded (0 sec 938 ms)

Columns: 2 Rows: 1000

# Views data preview

Data preview - count\_transaction\_2023

Showing 1000 rows

Search

	abc_full_name	count_transaction_2023
1	Michel Blankenship	1
2	Bernetta Summers	1
3	Ann Heath	1
4	Genny Hensley	2
5	Lean Stark	1
6	Ara Vazquez	1
7	Houston Vasquez	1
8	Jina Cooper	1
9	Theo Reese	1
10	Damian Mills	1
11	Rodolfo Buck	2
12	Ayanna Rhodes	1
13	Susann Bass	2
14	Rolanda Larsen	1
15	Aleta Stone	1
16	Julius Holt	1
17	Burma Summers	1
18	Rosa Kinney	1
19	Sarah Kirkland	1
20	Jenna Saunders	1
21	Jovita Bishop	2
22	Kristofer Craig	2
23	Tomika Wilder	2
24	Arlena Buckner	3
25	Delfina Gilliam	1

Succeeded (1 sec 92 ms)


Columns: 2 Rows: 515

# Views data preview

Data preview - sum\_of\_amount

Showing 1000 rows

	ABC full_name	12F sum_of_amount
1	Michel Blankenship	4672.46
2	Bernetta Summers	5967.2
3	Ara Vazquez	1983.56
4	Houston Vasquez	3156.59
5	Jina Cooper	1694.73
6	Theo Reese	6341.89
7	Renay Atkins	1026.25
8	Ouyen Houston	1079.26
9	Miquel Neal	1112.99
10	Burma Summers	4048.74
11	Jovita Bishop	9961.95
12	Kristofer Craig	5843.12
13	Tornika Wilder	3266.74
14	Martha Burgess	1603.66
15	Carson Macias	10584.03
16	Evelina Manning	2463.45
17	Shawnda Glover	9369.6
18	Lynn McMahon	6390.22
19	Hope Cotton	1968.94
20	Basil Ballard	2362.79
21	Ann Heath	4154.78
22	Genny Hensley	3854.02
23	Rodolfo Buck	3403.58
24	Aleta Stone	4072.68
25	Julius Holt	454.15

 Succeeded (9 sec 755 ms)

Columns: 2 Rows: 1000



# Stored procedures

- ✓  Stored Procedures
  -  UpdateTransactionByCustomerName
  -  UPDATE\_transaction\_status
  -  UPDATE\_interactio\_type
  -  UpdateCustomerInfo

Procedures to update customer data

# Example of using stored procedures

```
4  
5 SELECT * FROM [customer_data_management_1].[customer_db].[customers] WHERE customer_id = 22;
```

Messages Results Save as table Open in Excel Explore this data (preview) Copy Search

	123	customer_id	ABC	first_name	ABC	last_name	ABC	phone	ABC	email	ABC	street	ABC	city	ABC	state	123	zip_code
1		22		Adelle		Larsen		NULL		adelle.larsen@gm...		663 West Kirgand...		East Northport		NY		11731

Before updating

# Example of using stored procedures

```
EXEC [customer data management_1].[customer_db].[UpdateCustomerInfo] @CustomerID = 22, @Email = 'john.new@example.com'
```

After applying the stored procedure

```
5 SELECT * FROM [customer data management_1].[customer_db].[customers] WHERE customer_id = 22;
```

Messages

**Results**

Save as table

Open in Excel

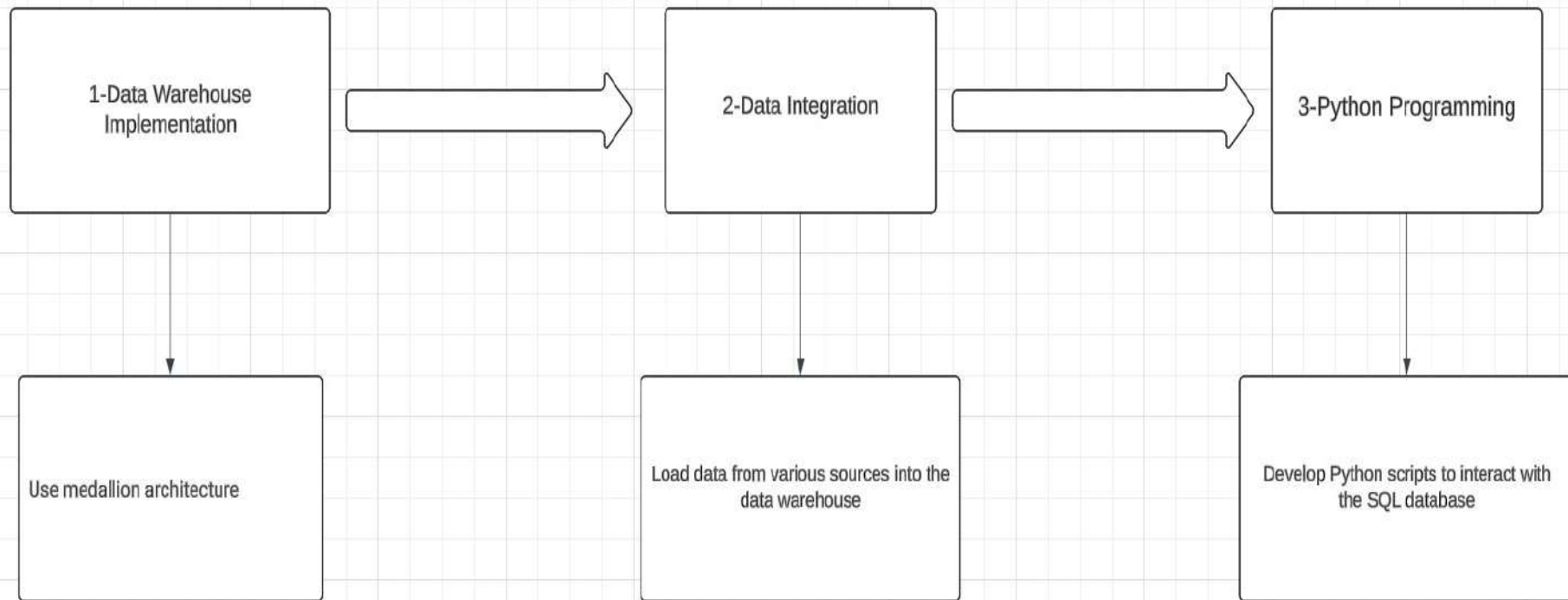
Explore this data (preview)

Copy

Search

	customer_id	first_name	last_name	phone	email	street	city	state	zip_code
1	22	Adelle	Larsen	NULL	john.new@exampl..	603 West Kirkland..	East Northport	NY	11731

## Week 2: Data Warehousing and Python Programming



**Firstly**

# **Data Warehousing**

# Medallion Architecture
















# Bronze pipeline



From the source to the bronze

# Bronze Schema



- ▼  bronze
  - ▼  Tables
    - >  brands
    - >  categories
    - >  customer
    - >  interactions
    - >  new\_order\_items
    - >  new\_orders
    - >  products
    - >  staffs
    - >  stocks ...
    - >  stores
    - >  transactions

From the source to the bronze



# Silver Schema

## ✓ Tables






- >  customers
- >  dim\_order\_items
- >  dim\_orders
- >  dim\_stores
- >  dim\_transactions
- >  interactions
- >  products

## Stored procedures to transfer data to the Silver Schema

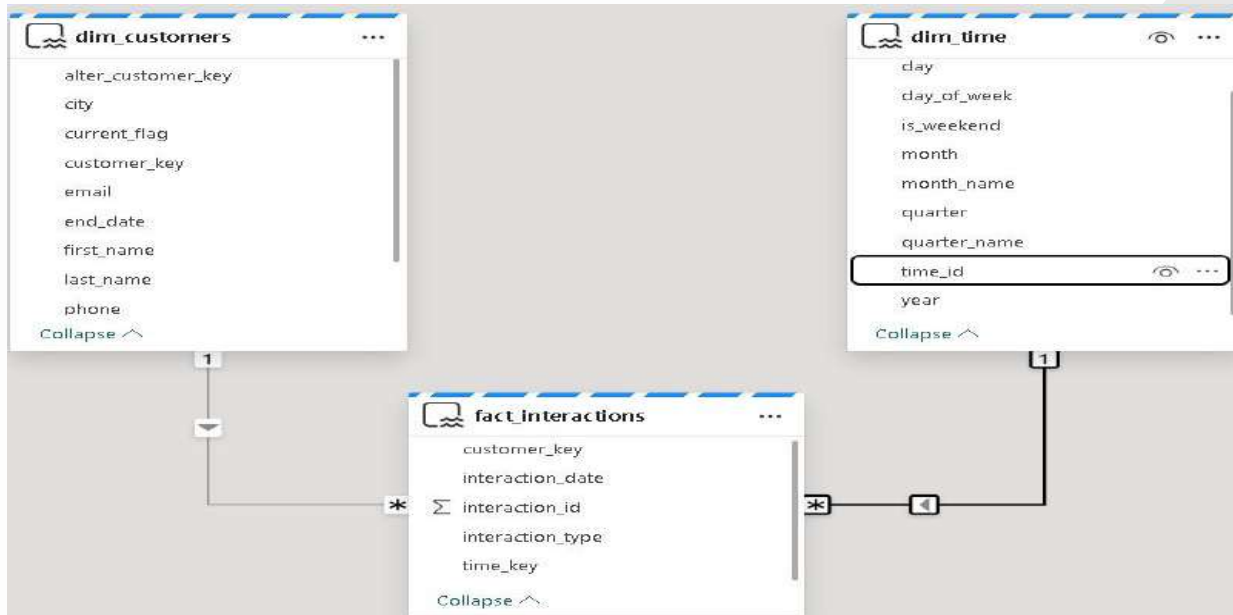
### Stored Procedures

- UPDATE\_customer
- INSERT\_customer
- UPDATE\_transactions
- INSERT\_transactions
- UPDATE\_interactions
- INSERT\_interactions
- UPDATE\_silver\_schema
- UPDATE\_product\_silver
- UPDATE\_dim\_orders\_silver
- copy\_transactions\_from\_bro...
- UPDATE\_stores
- UPDATE\_order\_item\_silver

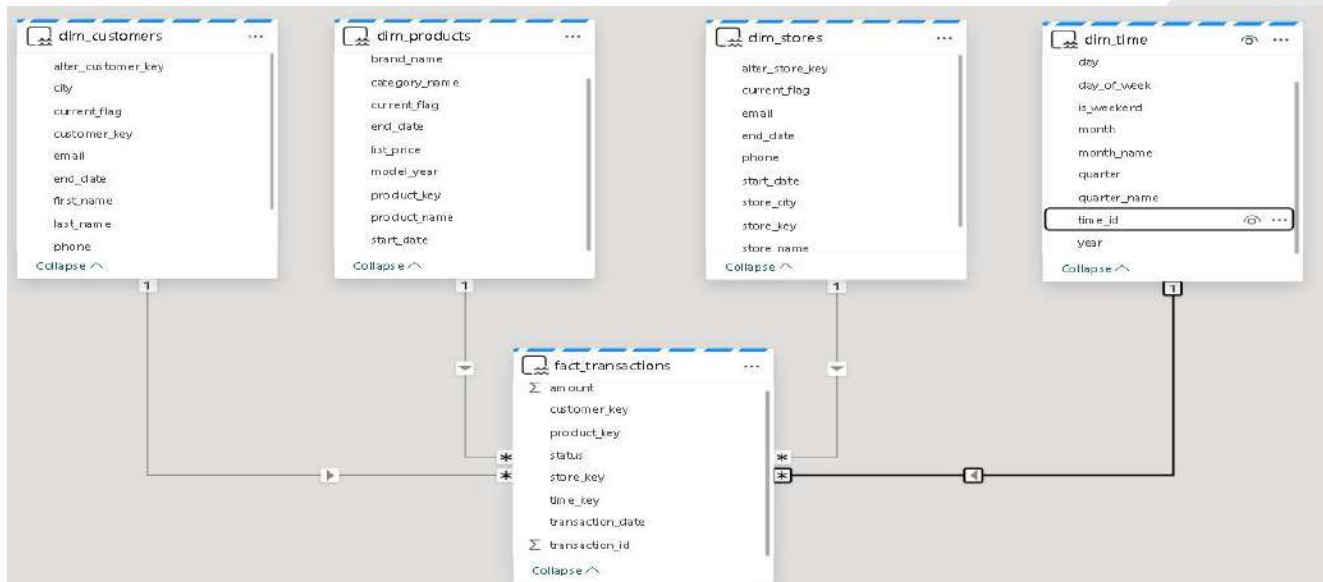
# Gold Schema

- ▼  gold
  - ▼  Tables
    - >  dim\_customers
    - >  dim\_order\_items
    - >  dim\_products
    - >  dim\_stores
    - >  dim\_time
    - >  fact\_interactions
    - >  fact\_orders
    - >  fact\_transactions

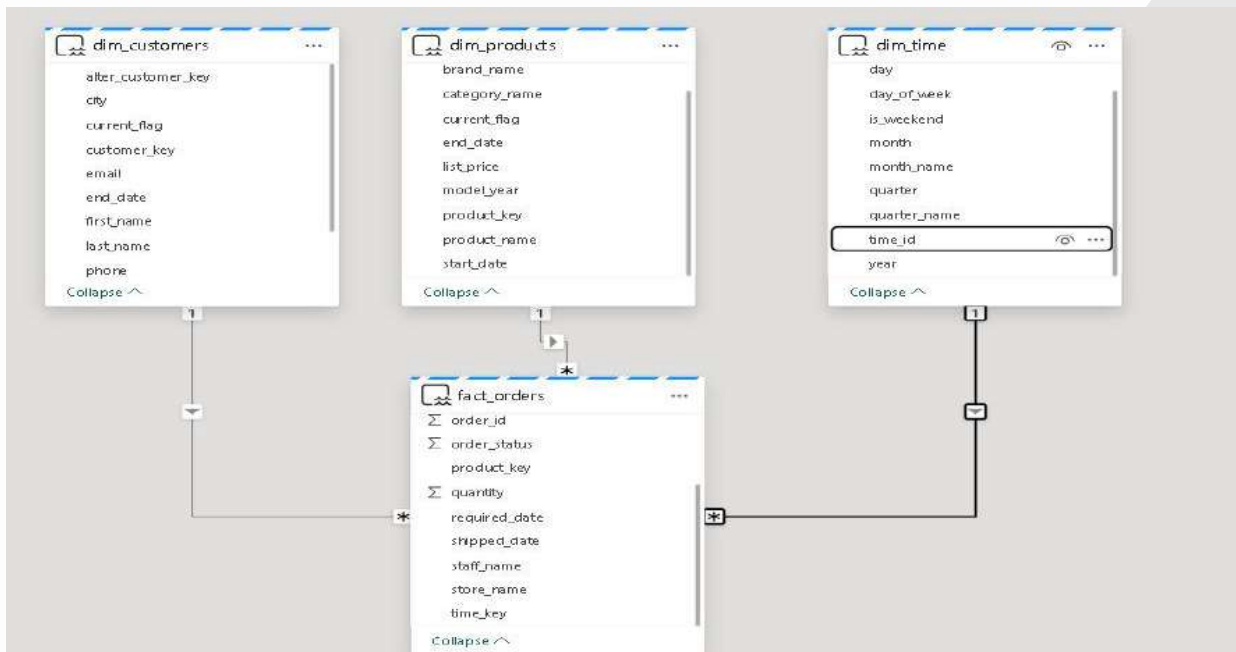
# Gold Schema









# Gold Schema



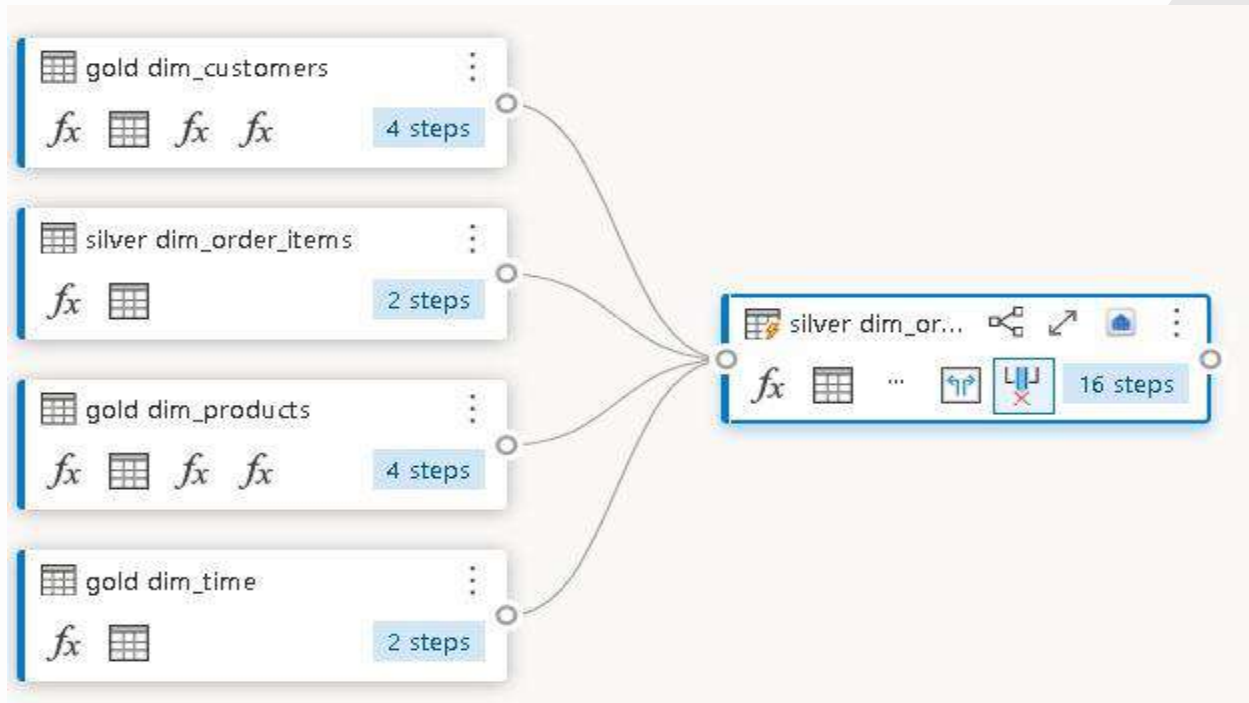
# Gold Schema



# Stored procedures to update gold schema

- ▼  Stored Procedures
  -  UPDATE customer\_dim
  -  UPDATE gold schema
  -  UPDATE dim\_stores
  -  UPDATE dim\_products
  -  UPDATE dim\_order\_items

# Fact table by dataflow gen 2





# Data preview

Data preview - dim\_stores

Showing 1000 rows

Search

	123 store_key	123 alter_store_key	ABC store_name	ABC phone	ABC_email	ABC_store_city	ABC_store_state	📅 start_date	📅 end_date	0/1 current_flag
1	4	2	Baldwin Bikes	99639	baldwin@bikes.shop	Baldwin	NY	2024-10-07	NULL	1
2	1	1	Santa Cruz Bikes	(831) 476-4321		Santa Cruz	CA	2024-09-30	NULL	1
3	3	3	Rowlett Bikes	(972) 530-5555	rowlett@bikes.shop	Rowlett	TX	2024-09-30	NULL	1
4	2	2	Baldwin Bikes	(516) 379-8888	baldwin@bikes.shop	Baldwin	NY	2024-09-30	2024-10-07	0

**secondly**

# **Python programming**

# Python

```
1  # Customer interaction report
2  customer_interaction_df = spark.sql("""
3      SELECT
4          dc.customer_key,
5          dc.first_name,
6          dc.last_name,
7          fi.interaction_type,
8          COUNT(fi.interaction_id) AS total_interactions,
9          MIN(fi.interaction_date) AS first_interaction_date,
10         MAX(fi.interaction_date) AS last_interaction_date
11     FROM fact_interactions fi
12     JOIN dim_customers dc ON fi.customer_key = dc.customer_key
13     GROUP BY dc.customer_key, dc.first_name, dc.last_name, fi.interaction_type
14 """)
15
16 # Displaying the customer interaction report
17 customer_interaction_df.show()
18
```

✓ - Command executed in 3 sec 560 ms by Suez Gahar on 2:59:43 AM, 10/07/24

customer_key	first_name	last_name	interaction_type	total_interactions	first_interaction_date	last_interaction_date
673	Adam	Henderson	Complaint	1	2024-08-09 00:00:00	2024-08-09 00:00:00
1045	Pasquale	Hogan	Complaint	1	2024-07-01 00:00:00	2024-07-01 00:00:00
1361	Destiny	Goodman	Complaint	1	2024-02-04 00:00:00	2024-02-04 00:00:00
651	Laure	Pena	Complaint	1	2024-01-16 00:00:00	2024-01-16 00:00:00
1268	Sung	Chambers	Review	1	2023-09-23 00:00:00	2023-09-23 00:00:00
504	Tiana	Henderson	Review	1	2024-09-14 00:00:00	2024-09-14 00:00:00
855	Lean	Stark	Inquiry	1	2023-09-30 00:00:00	2023-09-30 00:00:00
253	Maurice	Norton	Inquiry	1	2024-07-07 00:00:00	2024-07-07 00:00:00
1299	Shauna	Edwards	Inquiry	2	2024-01-13 00:00:00	2024-05-24 00:00:00
124	Jeni	Booker	Inquiry	1	2024-09-02 00:00:00	2024-09-02 00:00:00
887	Graig	Cannon	Inquiry	1	2024-01-27 00:00:00	2024-01-27 00:00:00
794	Donette	McCarthy	Complaint	1	2024-06-24 00:00:00	2024-06-24 00:00:00

# Python

```
1 # Customer transaction report
2 customer_transaction_df = spark.sql("""
3     SELECT
4         dc.customer_key,
5         dc.first_name,
6         dc.last_name,
7         COUNT(ft.transaction_id) AS total_transactions,
8         SUM(ft.amount) AS total_amount_spent,
9         AVG(ft.amount) AS avg_transaction_value,
10        MIN(ft.transaction_date) AS first_transaction_date,
11        MAX(ft.transaction_date) AS last_transaction_date
12    FROM fact_transactions ft
13    JOIN dim_customers dc ON ft.customer_key = dc.customer_key
14    GROUP BY dc.customer_key, dc.first_name, dc.last_name
15 """)
16
17 # Displaying the customer transaction report
18 customer_transaction_df.show()
19
```

[8] ✓ - Command executed in 3 sec 498 ms by Suez Gahar on 2:59:47 AM, 10/07/24

customer_key	first_name	last_name	total_transactions	total_amount_spent	avg_transaction_value	first_transaction_date	last_transaction_date
1393	Vivian	Deleon	1	1678.46	1678.46	2024-05-21 00:00:00	2024-05-21 00:00:00
32	Araceli	Golden	2	2063.76	1031.88	2024-02-06 00:00:00	2024-02-06 00:00:00
1321	Shantel	Gregory	3	3964.63	1321.5433333333333	2024-02-18 00:00:00	2024-07-19 00:00:00
334	Somer	Jordan	2	2860.83	1430.415	2024-08-10 00:00:00	2024-09-05 00:00:00
857	Inga	Koch	2	1965.3899999999999	982.6949999999999	2024-04-01 00:00:00	2024-07-12 00:00:00
53	Saturnina	Ganner	3	8591.380000000001	2863.7933333333335	2023-09-26 00:00:00	2024-06-27 00:00:00
34	Brittney	Woodward	2	3196.7400000000002	1598.3700000000001	2023-10-19 00:00:00	2023-11-07 00:00:00
146	Stefany	Potter	3	1768.55	589.5166666666667	2024-01-26 00:00:00	2024-05-04 00:00:00
990	Casimira	Chapman	4	8302.87	2075.7175	2024-03-01 00:00:00	2024-06-28 00:00:00
15	Linnie	Branch	3	5529.76	1843.2533333333333	2023-10-16 00:00:00	2024-04-29 00:00:00
385	Rochelle	Ward	2	4946.93	2473.465	2023-12-29 00:00:00	2024-04-09 00:00:00
1268	Sung	Chambers	3	2525.14	841.7133333333333	2023-11-01 00:00:00	2023-12-24 00:00:00

# Python

```
1 # Top selling products report
2 top_selling_products_df = spark.sql("""
3     SELECT
4         dp.product_key,
5         dp.product_name,
6         COUNT(ft.transaction_id) AS total_sales,
7         SUM(ft.amount) AS total_revenue,
8         AVG(ft.amount) AS avg_sale_price
9     FROM fact_transactions ft
10    JOIN dim_products dp ON ft.product_key = dp.product_key
11    GROUP BY dp.product_key, dp.product_name
12    ORDER BY total_sales DESC
13    LIMIT 10
14 """)
15
16 # Displaying the top selling products report
17 top_selling_products_df.show()
18
```

[41] ✓ - Command executed in 1 sec 508 ms by Suez Gahar on 2:59:49 AM, 10/07/24

product_key	product_name	total_sales	total_revenue	avg_sale_price
100	Haro Shredder Pro...	53	63996.240000000005	1207.4762264150945
99	Haro Shredder Pro...	53	63996.240000000005	1207.4762264150945
197	Trek Lift+ Lowste...	31	64769.610000000002	2089.342258064517
196	Trek Lift+ Lowste...	31	64769.610000000002	2089.342258064517
328	Electra Townie Or...	30	45086.290000000001	1502.8763333333336
302	Electra Sweet Rid...	28	34393.500000000001	1228.339285714286
303	Electra Sweet Rid...	28	34393.500000000001	1228.339285714286
41	Haro Flightline T...	28	47656.020000000004	1702.0007142857144
46	Trek Fuel EX 9.8 ...	24	17392.41	724.68375
301	Electra Sweet Rid...	22	35061.870000000002	1593.7213636363645

# Python

```
1  # Top customers by sales
2  top_customers_df = spark.sql("""
3      SELECT
4          dc.customer_key,
5          dc.first_name,
6          dc.last_name,
7          SUM(ft.amount) AS total_spent
8      FROM fact_transactions ft
9      JOIN dim_customers dc ON ft.customer_key = dc.customer_key
10     GROUP BY dc.customer_key, dc.first_name, dc.last_name
11     ORDER BY total_spent DESC
12     LIMIT 10
13 """)
14
15 # Displaying the top customers by sales
16 top_customers_df.show()
17
```

[6] ✓ - Command executed in 1 sec 483 ms by Suez Gahar on 2:59:53 AM, 10/07/24

customer_key	first_name	last_name	total_spent
875	Tanesha	Sawyer	14009.699999999999
1283	Mica	Barry	13533.36
399	Bart	Hess	12508.850000000002
286	Virgil	Frost	12160.31
366	Lavonne	Anderson	11928.689999999999
267	Angelina	Lloyd	11881.369999999999
206	Stephaine	Riddle	11723.289999999999
1183	Kim	Clark	11428.079999999998
376	Elanor	Patrick	11383.580000000002
1190	Romeo	Steele	11249.46

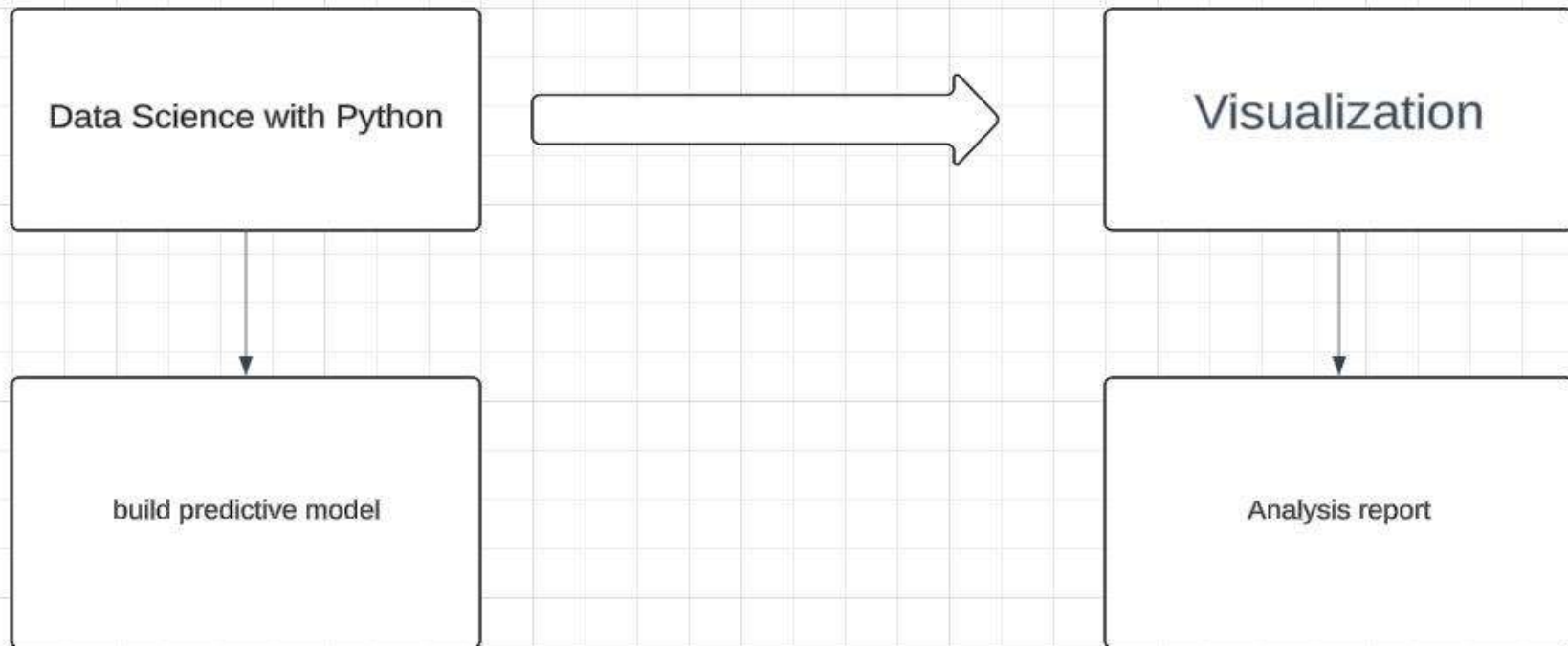
# Python

```
1 # Top selling products report
2 top_selling_products_df = spark.sql("""
3     SELECT
4         dp.product_key,
5         dp.product_name,
6         COUNT(ft.transaction_id) AS total_sales,
7         SUM(ft.amount) AS total_revenue,
8         AVG(ft.amount) AS avg_sale_price
9     FROM fact_transactions ft
10    JOIN dim_products dp ON ft.product_key = dp.product_key
11    GROUP BY dp.product_key, dp.product_name
12    ORDER BY total_sales DESC
13    LIMIT 10
14 """)
15
16 # Displaying the top selling products report
17 top_selling_products_df.show()
18
```

[41] ✓ - Command executed in 1 sec 508 ms by Suez Gahar on 2:59:49 AM, 10/07/24

product_key	product_name	total_sales	total_revenue	avg_sale_price
100	Haro Shredder Pro...	53	63996.240000000005	1207.4762264150945
99	Haro Shredder Pro...	53	63996.240000000005	1207.4762264150945
197	Trek Lift+ Lowste...	31	64769.610000000002	2089.342258064517
196	Trek Lift+ Lowste...	31	64769.610000000002	2089.342258064517
328	Electra Townie Or...	30	45086.290000000001	1502.8763333333336
302	Electra Sweet Rid...	28	34393.500000000001	1228.339285714286
303	Electra Sweet Rid...	28	34393.500000000001	1228.339285714286
41	Haro Flightline T...	28	47656.020000000004	1702.0007142857144
46	Trek Fuel EX 9.8 ...	24	17392.41	724.68375
301	Electra Sweet Rid...	22	35061.870000000002	1593.7213636363645

## Week 3: Data Science





**Firstly**

**Data  
science**

# methods



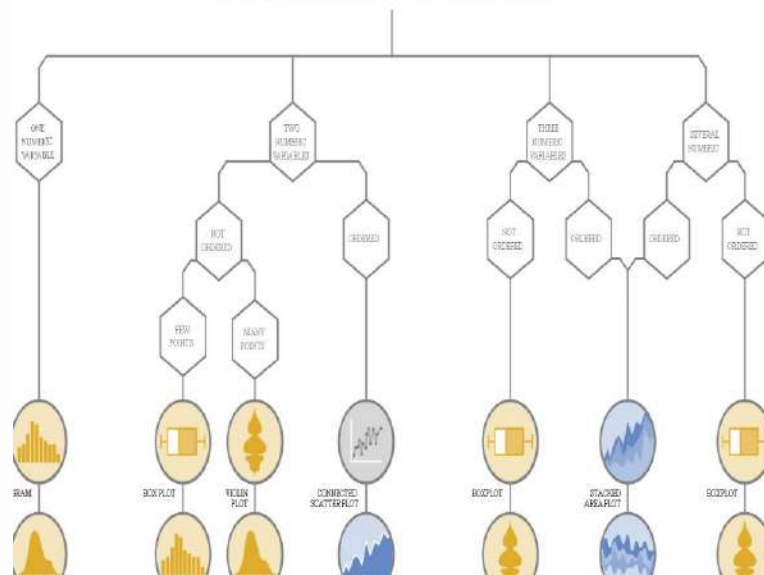
from Data to Viz

From Data to Viz leads you to the most appropriate graph for your data. It links to the code to build it and lists common caveats you should avoid.

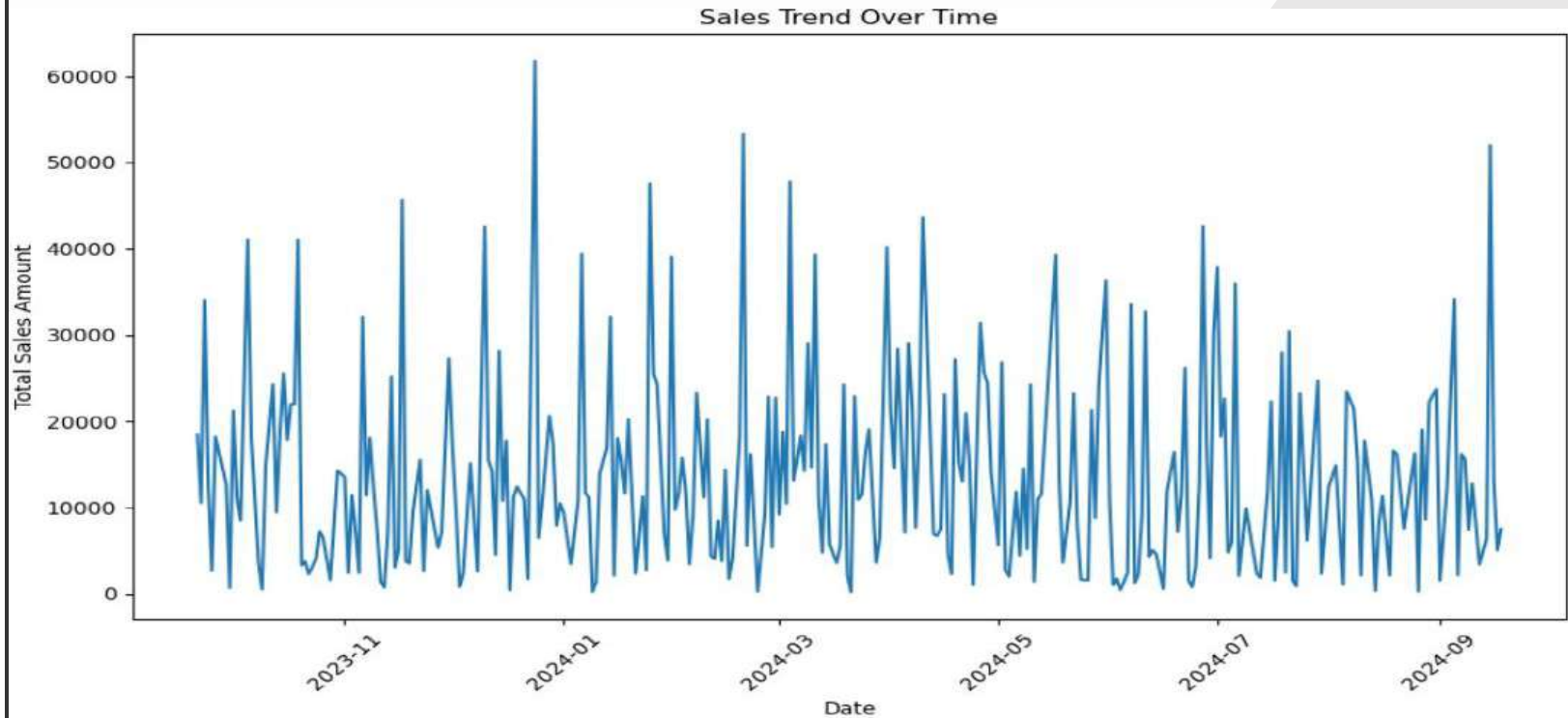
EXPLORE

SEE POSTER

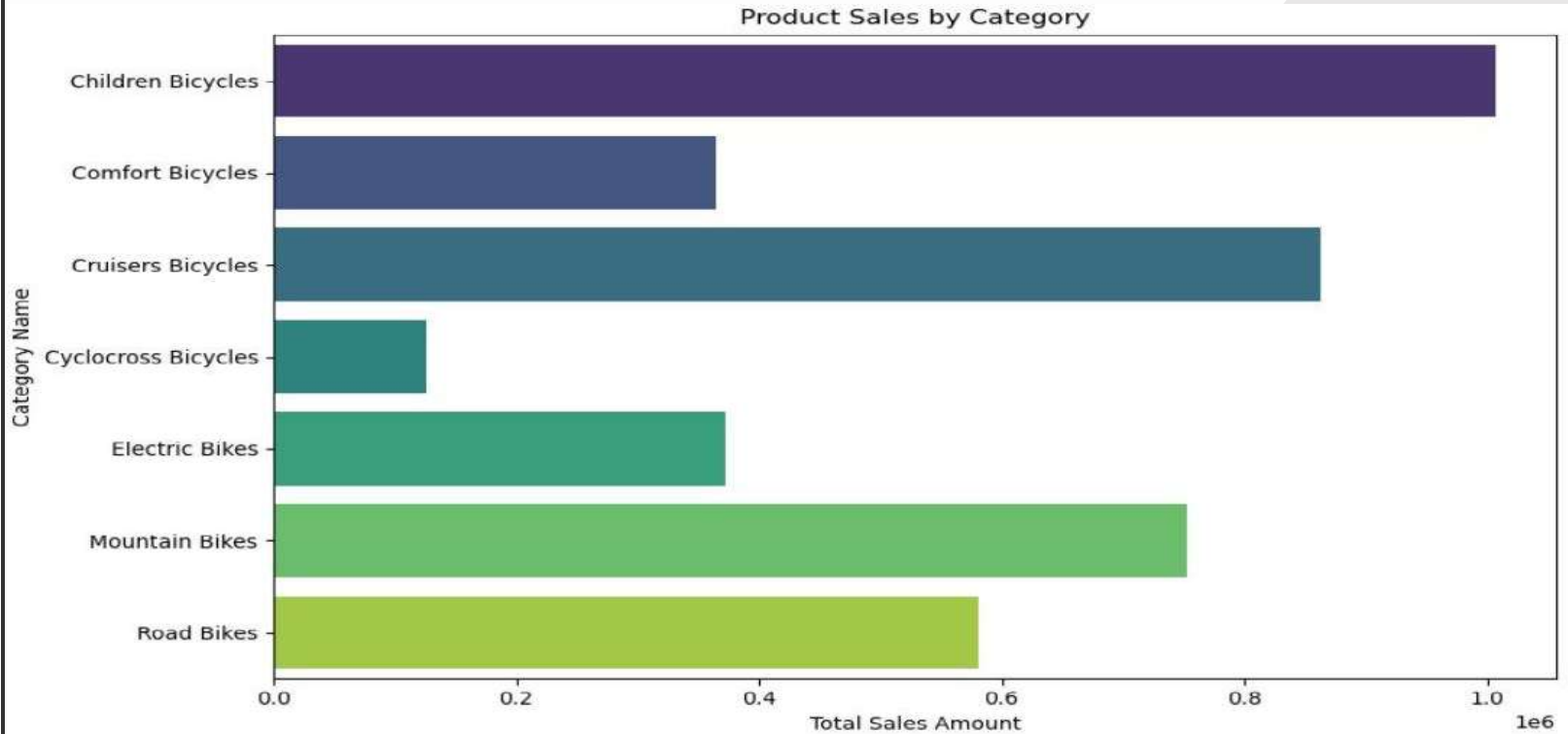
What kind of data do you have? Pick the main type using the buttons below. Then let the decision tree guide you toward your graphic possibilities. Alternatively, check the [complete decision tree](#).



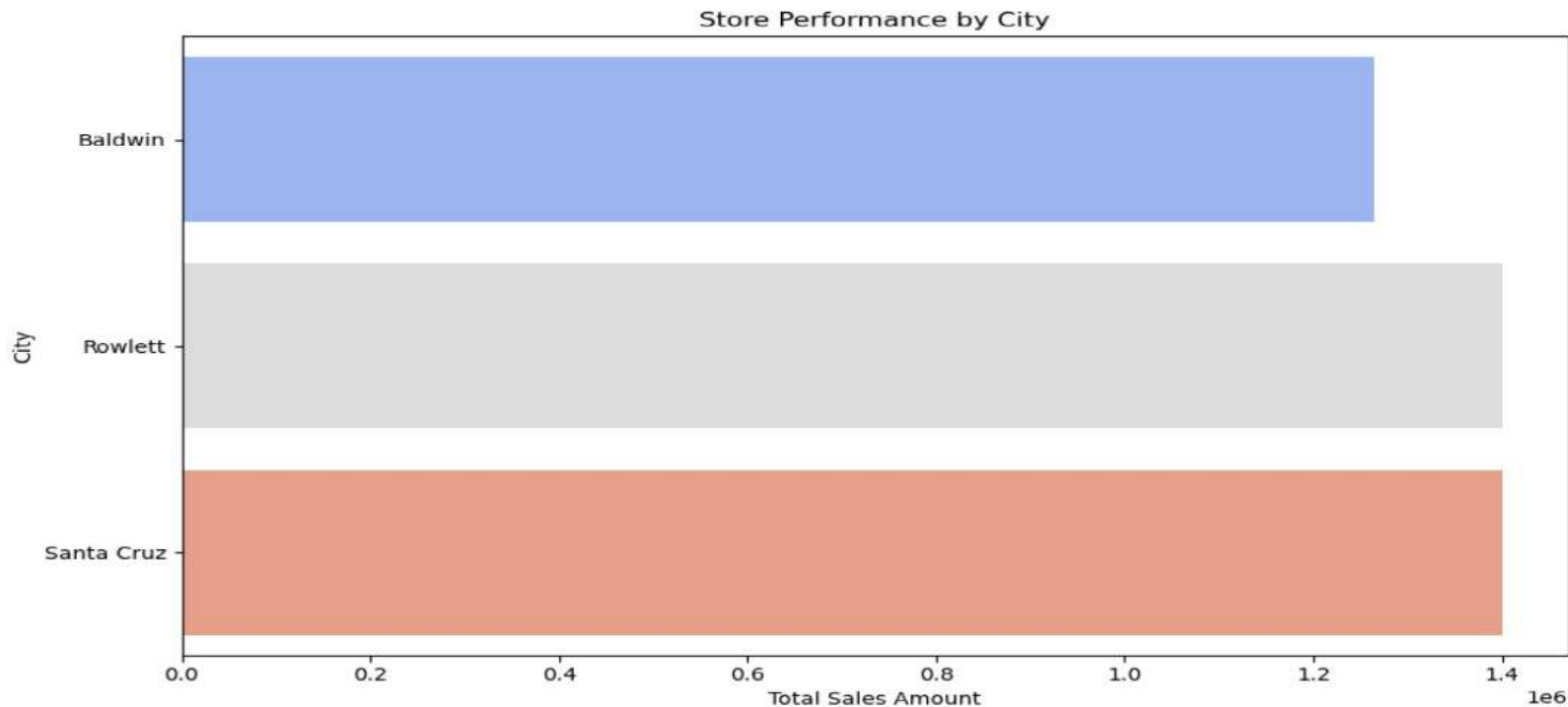
# Examples for visualization



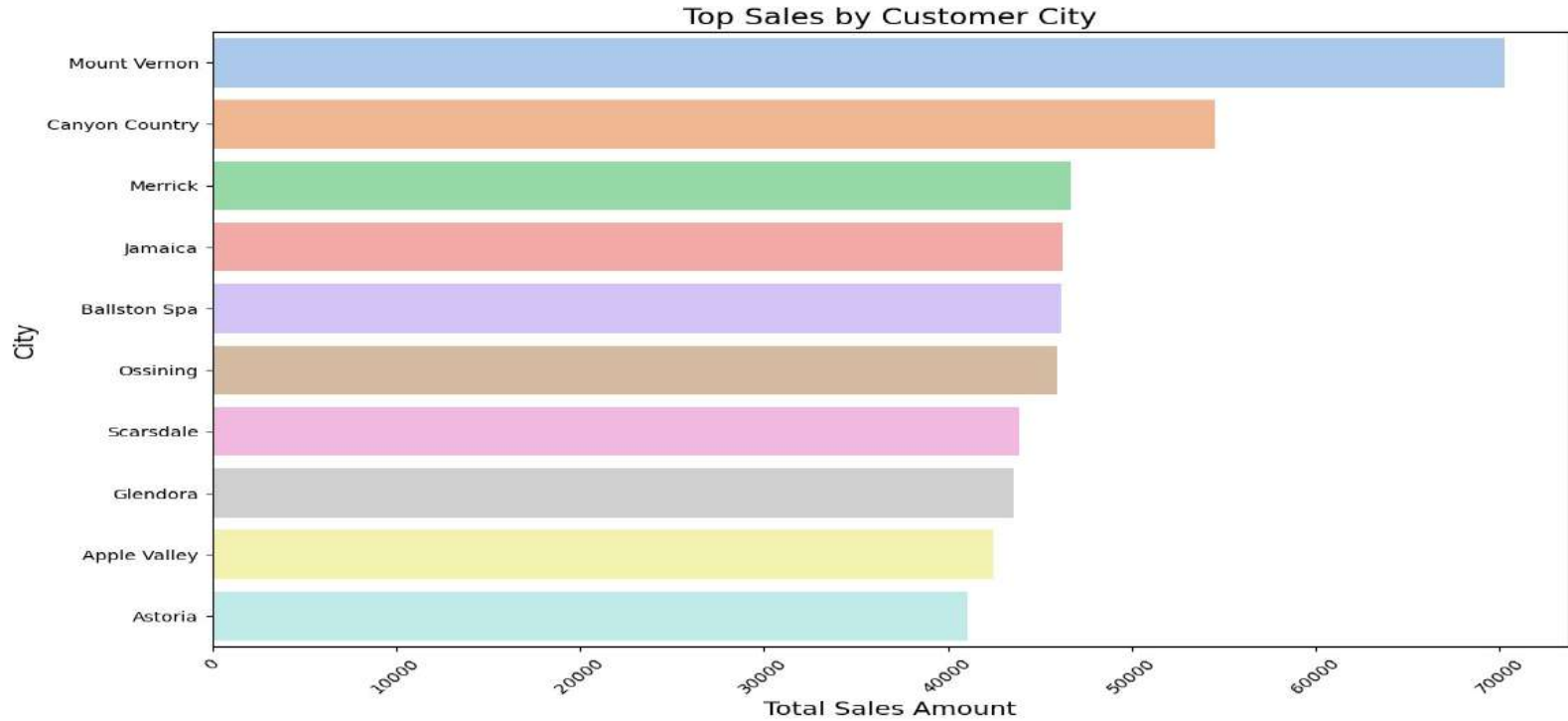
# Examples for visualization



# Examples for visualization

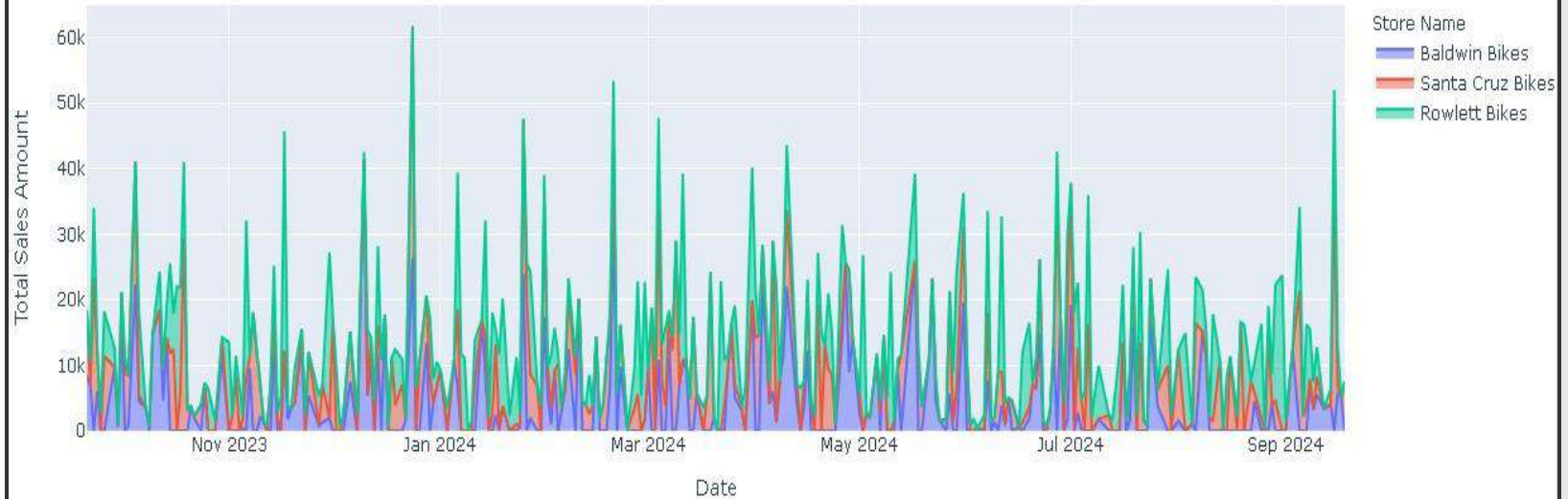


# Examples for visualization



# Examples for visualization

Sales Over Time by Store



**secondly**

**Model  
building**



## Important libraries & loading the data (table reading)

```
1  from pyspark.ml.classification import RandomForestClassifier
2  from pyspark.ml.feature import VectorAssembler
3  from pyspark.ml.evaluation import BinaryClassificationEvaluator
4  from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
5  from pyspark.sql import functions as F
6  from pyspark.ml import Pipeline
7
8  # قراءة الجداول
9  df_customers = spark.read.table('dim_customers')
10 df_products = spark.read.table('dim_products')
11 df_time = spark.read.table('dim_time')
12 df_stores = spark.read.table('dim_stores')
13 df_interactions = spark.read.table('fact_interactions')
14 df_transactions = spark.read.table('fact_transactions')
15 df_orders = spark.read.table('fact_orders')  # تم تعديل هذا الجزء
16
```

## Merging specific data

```
# دمج البيانات اللازمة
df_churn = df_customers \
    .join(df_interactions, 'customer_key', 'left') \
    .join(df_transactions, 'customer_key', 'left') \
    .join(df_orders, 'customer_key', 'left') # تم تعديل هذا الجزء
```

# Creating new features

```
# إنشاء ميزات جديدة
df_churn = df_churn \
    .groupBy('customer_key') \
    .agg(
        F.count('order_id').alias('total_orders'),
        F.count('interaction_id').alias('total_interactions'),
        F.sum('amount').alias('total_spent'),
        F.max('interaction_date').alias('last_interaction_date'),
        F.min('interaction_date').alias('first_interaction_date')
    )
```

# Calculating relation time

# حساب مدة العلاقة

```
df_churn = df_churn \
    .withColumn('customer_lifetime', F.datediff(F.current_date(), 'first_interaction_date')) \
    .withColumn('churned', F.when(F.datediff(F.current_date(), 'last_interaction_date') > 30, 1).otherwise(0))
```

# Removing empty values

```
# إزالة القيم الفارغة  
feature_columns = ['total_orders', 'total_interactions', 'total_spent', 'customer_lifetime']  
df_churn_cleaned = df_churn.na.drop(subset=feature_columns)
```

# Splitting the data into train and test

```
# تقسيم البيانات  
train_data, test_data = df_churn_cleaned.randomSplit([0.8, 0.2], seed=1234)
```

Train : 80%

Test : 20%

## Creating Vector assembler , Randomforest , Grid search , Cross-Validation

# للميزات VectorAssembler إنشاء الـ

```
assembler = VectorAssembler(inputCols=feature_columns, outputCol='features', handleInvalid='skip')
```

# RandomForestClassifier إنشاء

```
rf = RandomForestClassifier(labelCol='churned', featuresCol='features')
```

# Grid Search إعداد شبكة المعلومات لـ

```
paramGrid = (ParamGridBuilder()  
              .addGrid(rf.numTrees, [50, 100, 150])  
              .addGrid(rf.maxDepth, [5, 10, 15])  
              .addGrid(rf.maxBins, [32, 64])  
              .build())
```

# مع 5 طبقات Cross-Validation إعداد

```
evaluator = BinaryClassificationEvaluator(labelCol="churned", rawPredictionCol="rawPrediction", metricName="areaUnderROC")
```

```
crossval = CrossValidator(estimator=rf,  
                           estimatorParamMaps=paramGrid,  
                           evaluator=evaluator,  
                           numFolds=5)
```

# Pipeline إنشاء

```
pipeline = Pipeline(stages=[assembler, crossval])
```

# Model Training & Prediction

```
# تدريب النموذج  
cvModel = pipeline.fit(train_data)  
  
# التنبؤ على مجموعة الاختبار  
predictions = cvModel.transform(test_data)
```



# Model Evaluation

```
75 # تقييم النموذج باستخدام AUC
76 auc = evaluator.evaluate(predictions)
77 print(f"Area Under ROC: {auc}")
78
79 # استخراج أهمية الميزات من أفضل نموذج
80 best_rf_model = cvModel.stages[-1].bestModel # استرجاع أفضل نموذج RandomForest
81 importances = best_rf_model.featureImportances
82 print(f"Feature Importances: {importances}")
83
```

```
feature_columns = ['total_orders', 'total_interactions', 'total_spent', 'customer_lifetime']
```

# Results

Feature Importances: (4,[0,1,2,3],[0.18801491955270033,0.11321680322382169,0.24472010817663795,0.4540481690468401])

## Run metrics (2)

areaUnderROC_test_data	0.8337325349301397
accuracy_test_data	0.9340659340659341

## Week 4: Using predictive model and Final Presentation

Customer Churn Prediction



Final Presentation

Providing the model with inputs,  
and it gives the prediction

Project Summary Over the Past  
Weeks

# Prediction according to input

```
2 input_data = spark.createDataFrame([
3     (26, 5000.00, 20, 30) # customer_lifetime, total_spent, total_orders, total_interactions
4 ], ["customer_lifetime", "total_spent", "total_orders", "total_interactions"])
5
6 predictions = model.transform(input_data)
7 predictions.show()
8
```

✓ - Command executed in 830 ms by Suez Gahar on 11:29:44 AM, 10/09/24

customer_lifetime	total_spent	total_orders	total_interactions	features	rawPrediction	probability	prediction
26	5000.0	20	30	[20.0,30.0,5000.0...]	[28.3826676907322...]	[0.56765335381464...]	0.0

```
2 input_data = spark.createDataFrame([
3     (300, 15000.00, 30, 50) # customer_lifetime, total_spent, total_orders, total_interactions
4 ], ["customer_lifetime", "total_spent", "total_orders", "total_interactions"])
5
6 predictions = model.transform(input_data)
7 predictions.show()
8
```

✓ - Command executed in 900 ms by Suez Gahar on 11:22:51 AM, 10/09/24

customer_lifetime	total_spent	total_orders	total_interactions	features	rawPrediction	probability	prediction
300	15000.0	30	50	[30.0,50.0,15000.0...]	[5.59409381457472...]	[0.11188187629149...]	1.0

# Prediction according to input

```
4 import mlflow
5 model_uri = "runs:/d8f40238-e76d-4b60-9f55-2a251854c0c3/model"
6 model = mlflow.spark.load_model(model_uri)
7
8 # تمرير بيانات متنوعة للنموذج
9 input_data = spark.createDataFrame([
10     (50, 5000.75, 15, 20), # مثال 1: العميل قضى 50 يومًا، أنفق 5000.75 دولار، قدم 15 طلبًا، وشارك في 20 تفاعل
11     (120, 25000.99, 50, 100), # مثال 2: العميل قضى 120 يومًا، أنفق 25000.99 دولار، قدم 50 طلبًا، وشارك في 100 تفاعل
12     (30, 1500.25, 8, 15), # مثال 3: العميل قضى 30 يومًا، أنفق 1500.25 دولار، قدم 8 طلبات، وشارك في 15 تفاعل
13     (200, 50000.00, 100, 250), # مثال 4: العميل قضى 200 يومًا، أنفق 50000 دولار، قدم 100 طلب، وشارك في 250 تفاعل
14     (10, 100.50, 2, 5) # مثال 5: العميل قضى 10 أيام، أنفق 100.50 دولار، قدم طلبين، وشارك في 5 تفاعلات
15 ], ["customer_lifetime", "total_spent", "total_orders", "total_interactions"])
16
17 # إجراء التنبؤات باستخدام النموذج
18 predictions = model.transform(input_data)
19 predictions.show()
20
```

✓ - Command executed in 20 sec 103 ms by Suez Gahar on 11:16:19 AM, 10/09/24

PySpark (Python) ✓

2024/10/09 08:15:51 INFO mlflow.spark: 'runs:/d8f40238-e76d-4b60-9f55-2a251854c0c3/model' resolved as 'sds://onelakenortheurope.pbidedicated.windows.net/2d498147-60d2-487b-8282-34b25813be4e/c13b5d78-500f-4567-919a-d0227f829292/d8f40238-e76d-4b60-9f55-2a251854c0c3/artifacts/model'

Downloading artifacts: 100%  1/1 [00:00<00:00, 11.80it/s]

Downloading artifacts: 100%  28/28 [00:00<00:00, 493.06it/s]

2024/10/09 08:15:52 INFO mlflow.store.artifact.artifact\_repo: The progress bar can be disabled by setting the environment variable MLFLOW\_ENABLE\_ARTIFACTS\_PROGRESS\_BAR to false

2024/10/09 08:15:53 INFO mlflow.spark: File 'runs:/d8f40238-e76d-4b60-9f55-2a251854c0c3/model/sparkml' not found on DFS. Will attempt to upload the file.

2024/10/09 08:15:55 INFO mlflow.spark: Copied SparkML model to Files/tmp/mlflow/f527c2f7-84d9-4ca6-80a1-179ca57996b5

customer_lifetime	total_spent	total_orders	total_interactions	features	rawPrediction	probability	prediction
50	5000.75	15	20	[15.0,20.0,5000.7...	[5.60334545080591...	[0.11206690901611...	1.0
120	25000.99	50	100	[50.0,100.0,25000...	[6.36641919680480...	[0.12732838393609...	1.0
30	1500.25	8	15	[8.0,15.0,1500.25...	[19.6641018507174...	[0.39328203701434...	1.0
200	50000.0	100	250	[100.0,250.0,5000...	[3.12654755055833...	[0.06253095301115...	1.0
10	100.5	2	5	[2.0,5.0,100.5,10...	[19.4713650457543...	[0.38942730091508...	1.0