Cloud Data Warehouse

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1. Overview

The main activity is to implement a basic ETL(Extract, Transform, Load) pipeline to handle data integration for a sample database. Using Apache Hop, Oracle Cloud, and SQL queries, I developed processes to load dimension and fact tables. This report summarizes the design choices, database schema, and major steps involved in creating the pipeline, along with insights into potential improvements

2. ETL Pipeline Design and Database Diagram

The ETL pipeline was created in Apache Hop to enable the seamless movement of data from multiple sources into a consolidated database. A diagram of the database schema was generated, showing key entities such as **Dim_Date, Dim_Product, Dim_Customer, and the main fact table.** This schema aimed to support typical analytical queries, with each dimension table containing relevant details about dates, products, and customers.

3. Process Steps and Key Components

- Loading Dimension Tables:
    - Dim_Date: Rows were loaded by executing SQL queries to retrieve relevant date information.
    - Dim_Product: Rows were inserted using DDL, and screenshots of successful SQL executions are attached.
    - Dim_Customer: Rows were inserted using DDL, with attached screenshots of successful SQL executions, and output was verified to ensure accurate data capture.
- Pipeline Execution and Validation:
    - Apache Hop Pipeline: Configured using necessary transformations, each validated through visual monitoring in Apache Hop. A screenshot of the pipeline setup is attached to show the flow and data processing steps.
    - Oracle Cloud Validation: SQL queries were run to validate the data in Oracle Cloud, with screenshots confirming the correct loading of data.
- Fact Table Integration:

  For the fact table, a stream connector was used to link data from multiple sources effectively. Screenshots of the entire flow, including the stream connector and its configuration, are included. This approach allowed seamless and efficient data integration, ensuring the fact table received up-to-date, accurate data through continuous data streams.

4. Challenges

I encountered several challenges related to modifying database parallel to the ETL pipeline. Initially, I faced an issue where the pipeline encountered errors due to table modifications in the database. To address this, I created a new database from scratch, ensuring a stable structure before implementing the pipeline.

Later in the process, after making some minor adjustments to the database schema, the pipeline again encountered issues. This time, the problem was resolved by committing the changes in the database before re-running the pipeline. This experience underscored the importance of committing schema updates consistently to avoid disruptions during ETL execution.

5. Missing Components

This database model is missing foreign keys and referential constraints between the fact and dimension tables, which are typically expected in a star schema design. These constraints ensure data integrity by linking dimension tables to the fact table through key relationships. They might be missing here to simplify the model, either to speed up data loading or because of a decision to handle integrity through ETL processes rather than within the database schema itself. Also, the database schema currently supports essential analytical functions. However, an additional dimension table, such as Dim_Location for geographical data, might enhance the system's analytical depth. These components may have been excluded due to initial scope of requirements but could add value in future expansions.

6. Conclusion

The ETL pipeline implemented in this project successfully facilitated data integration from multiple sources into a consolidated database, demonstrating the efficiency and reliability of Apache Hop and Oracle Cloud for building and maintaining data workflows. By following structured steps to load dimension and fact tables, this pipeline supported essential analytical functions, with each design choice tailored to meet the initial scope.

While the pipeline effectively handled the basic needs of the sample database, several areas for improvement have been identified. Adding foreign keys and referential constraints would strengthen data integrity, linking fact and dimension tables and ensuring consistency across the schema. Additionally, the introduction of a Dim_Location table could provide valuable insights into geographical trends, enhancing the model's analytical potential.

This project highlighted the importance of managing schema updates, committing changes carefully to avoid disruptions. It underscored how a flexible, well-structured ETL pipeline can be expanded to support more advanced analytics, with future improvements likely to enhance the system's robustness and analytical capabilities.

7. Database Diagram

Generate a diagram of the database

Figure 1 Database Diagram

- **Based on the diagram generated, what is this database missing that you'd expect to see? Why might it be missing this component?**

  This database model lacks foreign keys and referential constraints between the fact and dimension tables, which are standard elements in a typical star schema design. Such constraints are essential for maintaining data integrity by linking dimension tables (e.g., DIM_CUSTOMER, DIM_PRODUCT, DIM_DATE) to the fact table (FACT_SALES) through defined key relationships. Their absence here may be intentional, possibly to simplify the model, speed up data loading, or shift the responsibility for data integrity to the ETL processes rather than enforcing it within the database schema itself.

8. Dim_Date

```
SELECT * FROM Dim_Date;
```

Query Result | Script Output | DBMS Output | Explain Plan | Autotrace | SQL History

Download ▾ Execution time: 0.037 seconds

	DATEKEY	DATE	DAY_TIME_SPAN	DAY_END_DATE	WEEK_DAY_FULL	WEEK_DAY_SHOR	DAY_NUM_OF_WE	DAY_
2	20180102	1/2/2018, 12:00:00 A	1	1/2/2018, 12:00:00 A	Tuesday	TUE	3	
3	20180103	1/3/2018, 12:00:00 A	1	1/3/2018, 12:00:00 A	Wednesday	WED	4	
4	20180104	1/4/2018, 12:00:00 A	1	1/4/2018, 12:00:00 A	Thursday	THU	5	
5	20180105	1/5/2018, 12:00:00 A	1	1/5/2018, 12:00:00 A	Friday	FRI	6	
6	20180106	1/6/2018, 12:00:00 A	1	1/6/2018, 12:00:00 A	Saturday	SAT	7	
7	20180107	1/7/2018, 12:00:00 A	1	1/7/2018, 12:00:00 A	Sunday	SUN	1	
8	20180108	1/8/2018, 12:00:00 A	1	1/8/2018, 12:00:00 A	Monday	MON	2	

Figure 2 Dim_Date Table

9. Dim_Date Updated

The client isn't happy with the values in the date dimension table and has asked to redo the dimension table in the data warehouse to begin in January, 2016 and end in December, 2026, updated script is as follows

```
DROP TABLE DIM_DATE;

CREATE TABLE DIM_DATE AS
SELECT  TO_NUMBER(TRIM(leading '0' FROM TO_CHAR(CurrDate,'yyyymmdd'))) as DATEKEY
        ,CurrDate AS "Date"
        ,1 AS Day_Time_Span
        ,CurrDate AS Day_End_Date
        ,TO_CHAR(CurrDate,'Day') AS Week_Day_Full
        ,TO_CHAR(CurrDate,'DY') AS Week_Day_Short
        ,TO_NUMBER(TRIM(leading '0' FROM TO_CHAR(CurrDate,'D'))) AS Day_Num_of_Week
        ,TO_NUMBER(TRIM(leading '0' FROM TO_CHAR(CurrDate,'DD'))) AS Day_Num_of_Month
        ,TO_NUMBER(TRIM(leading '0' FROM TO_CHAR(CurrDate,'DDD'))) AS Day_Num_of_Year
        ,UPPER(TO_CHAR(CurrDate,'Mon') || '-' || TO_CHAR(CurrDate,'YYYY')) AS Month_ID
        ,MAX(TO_NUMBER(TO_CHAR(CurrDate, 'DD'))) OVER (PARTITION BY TO_CHAR(CurrDate,'Mon')) AS Month_Time_Span
        ,MAX(CurrDate) OVER (PARTITION BY TO_CHAR(CurrDate,'Mon')) as Month_End_Date
        ,TO_CHAR(CurrDate,'Mon') || ' ' || TO_CHAR(CurrDate,'YYYY') AS Month_Short_Desc
        ,RTRIM(TO_CHAR(CurrDate,'Month')) || ' ' || TO_CHAR(CurrDate,'YYYY') AS Month_Long_Desc
        ,TO_CHAR(CurrDate,'Mon') AS Month_Short
        ,TO_CHAR(CurrDate,'Month') AS Month_Long
        ,TO_NUMBER(TRIM(leading '0'FROM TO_CHAR(CurrDate,'MM'))) AS Month_Num_of_Year
        ,'Q' || UPPER(TO_CHAR(CurrDate,'Q') || '-' || TO_CHAR(CurrDate,'YYYY')) AS Quarter_ID
        ,COUNT(*) OVER (PARTITION BY TO_CHAR(CurrDate,'Q')) AS Quarter_Time_Span
        ,MAX(CurrDate) OVER (PARTITION BY TO_CHAR(CurrDate,'Q')) AS Quarter_End_Date
        ,TO_NUMBER(TO_CHAR(CurrDate,'Q')) AS Quarter_Num_of_Year
        ,TO_CHAR(CurrDate,'YYYY') AS Year_ID
        ,COUNT(*) OVER (PARTITION BY TO_CHAR(CurrDate,'YYYY')) AS Year_Time_Span
        ,MAX(CurrDate) OVER (PARTITION BY TO_CHAR(CurrDate,'YYYY')) Year_End_Date
FROM
(SELECT level   n
        -- Calendar starts at the day after this date.
        ,TO_DATE('31/12/2015','DD/MM/YYYY') + NUMTODSINTERVAL(level,'day') CurrDate
FROM dual
-- Change for the number of days to be added to the table.
CONNECT BY level <= 4018)
ORDER BY CurrDate
;

ALTER TABLE DIM_DATE
ADD CONSTRAINT pk_datekey PRIMARY KEY (DATEKEY);
```

Figure 3 Dim_Date DDL Updated script

```
SELECT * FROM Dim_Date;
```

Query Result | Script Output | DBMS Output | Explain Plan | Autotrace | SQL History

Download ▾ Execution time: 0.027 seconds

	DATEKEY	DATE	DAY_TIME_SPAN	DAY_END_DATE	WEEK_DAY_FULL	WEEK_DAY_SHOR	DAY_NUM_OF_WE	DAY_
1	20160101	1/1/2016, 12:00:00 A	1	1/1/2016, 12:00:00 A	Friday	FRI	6	
2	20160102	1/2/2016, 12:00:00 A	1	1/2/2016, 12:00:00 A	Saturday	SAT	7	
3	20160103	1/3/2016, 12:00:00 A	1	1/3/2016, 12:00:00 A	Sunday	SUN	1	
4	20160104	1/4/2016, 12:00:00 A	1	1/4/2016, 12:00:00 A	Monday	MON	2	
5	20160105	1/5/2016, 12:00:00 A	1	1/5/2016, 12:00:00 A	Tuesday	TUE	3	
6	20160106	1/6/2016, 12:00:00 A	1	1/6/2016, 12:00:00 A	Wednesday	WED	4	

Figure 4 Dim_Date Updated(Date ascending order)

[Worksheet]* Consumer group: LOW

Data Load

```
SELECT * FROM Dim_Date ORDER BY DATEKEY DESC;
```

Query Result | Script Output | DBMS Output | Explain Plan | Autotrace | SQL History

Download ▾ Execution time: 0.029 seconds

	DATEKEY	DATE	DAY_TIME_SPAN	DAY_END_DATE	WEEK_DAY_FULL	WEEK_DAY_SHOR	DAY_NUM_OF_WE	DAY_
1	20261231	12/31/2026, 12:00:0(	1	12/31/2026, 12:00:0(	Thursday	THU	5	
2	20261230	12/30/2026, 12:00:0	1	12/30/2026, 12:00:0	Wednesday	WED	4	
3	20261229	12/29/2026, 12:00:0	1	12/29/2026, 12:00:0	Tuesday	TUE	3	
4	20261228	12/28/2026, 12:00:0	1	12/28/2026, 12:00:0	Monday	MON	2	
5	20261227	12/27/2026, 12:00:0(	1	12/27/2026, 12:00:0(	Sunday	SUN	1	
6	20261226	12/26/2026, 12:00:0	1	12/26/2026, 12:00:0	Saturday	SAT	7	

Figure 5 Dim_Date Updated(Date descending order)

10. Dim_Customer

```
SELECT * FROM Dim_Customer;
```

Query Result | Script Output | DBMS Output | Explain Plan | Autotrace | SQL History

Download ▾ Execution time: 0.016 seconds

	CUSTOMERKEY	CNAME	BIRTHDAY	CADDRESS	CITY	STATEPROV	ZIP	ISCU
1	1	Dominic Sellitto	1/1/1956, 12:00:00 A	123 ABC St.	Buffalo	NY	14222	Y
2	2	Jeep Sellitto	2/2/1979, 12:00:00 A	123 Cool St.	Buffalo	NY	14222	Y
3	3	Sally Sallerson	3/3/1989, 12:00:00 /	415 Awesome Pl.	Rochester	NY	54321	Y

Figure 6 Dim_Customer

11. Dim_Product

Query Result | Script Output | DBMS Output | Explain Plan | Autotrace | SQL History

Download ▾ Execution time: 0.015 seconds

	PRODUCTKEY	PRODUCTNAME	CATEGORY	SUBCATEGORY	BRAND	ISCURI	PRODUCTID	SCD_START	SCD_END	VERSIONING
1	(null)	Cinnamon Bread	Wheat	Bread	Nothing Breader	Y	1	1/1/2024, 12:00:	12/31/2099, 12:C	1
2	(null)	Milk	Dairy	Liquid	Buffalo Farms	Y	2	2/1/2024, 12:00:	12/31/2099, 12:C	1
3	(null)	Chocolate Chip Cool	Candy	Cookies	Nothing Breader	Y	3	3/1/2024, 12:00	12/31/2099, 12:C	1
4	(null)	Eggs	Dairy	Solid	Rochester Farms	Y	4	4/1/2024, 12:00	12/31/2099, 12:C	1
5	(null)	Rotini	Wheat	Pasta	Buffalo Farms	Y	5	4/1/2024, 12:00	12/31/2099, 12:C	1

Figure 7 Dim_Product(without sequence)

	PRODUCTKEY	PRODUCTNAME	CATEGORY	SUBCATEGORY	BRAND	ISCU	PROI	SCD_START	SCD_END	VERSIONING
1	100	Cinnamon Bread	Wheat	Bread	Nothing Breader	Y	1	1/1/2024, 12:00:	12/31/2099, 12:00	1
2	101	Milk	Dairy	Liquid	Buffalo Farms	Y	2	2/1/2024, 12:00	12/31/2099, 12:00	1
3	102	Chocolate Chip Cool	Candy	Cookies	Nothing Breader	Y	3	3/1/2024, 12:00	12/31/2099, 12:00	1
4	103	Eggs	Dairy	Solid	Rochester Farms	Y	4	4/1/2024, 12:00	12/31/2099, 12:00	1
5	104	Rotini	Wheat	Pasta	Buffalo Farms	Y	5	4/1/2024, 12:00	12/31/2099, 12:00	1

Figure 8 Dim_Product(with Sequencing)

12. Pipeline 1- Text file output

Figure 9 Pipeline 1-Text File Output

filename.txt.txt

```
CUSTOMERKEY;CNAME;BIRTHDAY;CADDRESS;CITY;STATEPROV;ZIP;ISCURRENT;CUSTID;SCD_START;SCD_END;VERSIONING
1;Dominic Sellitto                       ;;123 ABC St.      ;Buffalo          ;NY               ;14222           ;Y               ;1.0;;;1
2;Jeep Sellitto                          ;;123 Cool St.     ;Buffalo          ;NY               ;14222           ;Y               ;2.0;;;1
3;Sally Sallerson                        ;;415 Awesome Pl.  ;Rochester        ;NY               ;54321           ;Y               ;3.0;;;1
```

Figure 10 Pipeline 1-Text File Output

13. Pipeline 2-Product Dimension Update

This pipeline flow is designed to update the product data warehouse table based on changes in an Excel file. Here, all options are set to insert new records, except for the product name, which is configured to "punch through" updates. This means that if a dimension table already contains the same combination of values for a given product name, only the existing record will be updated with the new values, effectively revising its version.

Figure 11 Pipeline 2-Product Update

	PRODUCTKEY	PRODUCTNAME	CATEGORY	SUBCATEGORY	BRAND	ISCUI	PRODUCTIC	SCD_START	SCD_END	VERSIONING
1	0	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	1
2	105	Eggs	Poultry	Solid	Rochester Farms	Y	4	11/9/2024, 4:14:57 A	12/31/2199, 11:	2
3	106	Sugary Cereal	Wheat	Cereal	Food For You	Y	6	11/9/2024, 4:14:57 A	12/31/2199, 11:	1
4	100	Cinnamon Bread Loaf	Wheat	Bread	Nothing Breader	Y	1	1/1/2024, 12:00:00 A	12/31/2099, 12	1
5	101	Milk	Dairy	Liquid	Buffalo Farms	Y	2	2/1/2024, 12:00:00 A	12/31/2099, 12	1
6	102	Chocolate Chip Cookies	Candy	Cookies	Nothing Breader	Y	3	3/1/2024, 12:00:00 A	12/31/2099, 12	1
7	103	Eggs	Dairy	Solid	Rochester Farms	N	4	4/1/2024, 12:00:00 A	11/9/2024, 4:1	1
8	104	Rotini	Wheat	Pasta	Buffalo Farms	Y	5	4/1/2024, 12:00:00 A	12/31/2099, 12	1

Figure 12 Dim_Product Updated via Apache hop flow

14. Pipeline 3-Customer Dimension Update

This pipeline flow is designed to update the customer data warehouse table based on changes in an Excel file. Here, all options are set to insert new records, except for the customer name, which is configured to "punch through" updates. This means that if a dimension table already contains the same combination of values for a given product name, only the existing record will be updated with the new values, effectively revising its version.

Figure 13 Pipeline 3-Customer Update

	CUSTOMERKEY	CNAME	BIRTHDAY	CADDRESS	CITY	STATEPROV	ZIP	ISCURRENT	CUSTID	SCD_START	SCD_END	VERSIONING
1	1	Dominic Sellitto	1/1/1956, 12:00:00 A	123 ABC St.	Buffalo	NY	14222	N	1	12/31/2021, 12:00:00 AM	11/9/2024, 4:47:46 AM	1
2	2	Jeep Sellitto	2/2/1979, 12:00:00 A	123 Cool St.	Buffalo	NY	14222	N	2	12/31/2021, 12:00:00 AM	11/9/2024, 4:47:46 AM	1
3	3	Sally Sallerson	3/3/1989, 12:00:00 A	415 Awesome Pl.	Rochester	NY	54321	Y	3	12/31/2021, 12:00:00 AM	12/31/2099, 12:00:00 AM	1
4	0	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	*(null)*	1
5	1000	Dominic Sellitto	*(null)*	123 New St.	Rochester	NY	14321	Y	1	11/9/2024, 4:47:45 AM	12/31/2199, 11:59:59 PM	2
6	1001	Jeep Jeeperson	*(null)*	123 Cool St.	Buffalo	NY	14043	Y	2	11/9/2024, 4:47:45 AM	12/31/2199, 11:59:59 PM	2
7	1002	James Bond	*(null)*	543 Bond Rd.	Buffalo	NY	14222	Y	4	11/9/2024, 4:47:45 AM	12/31/2199, 11:59:59 PM	1
8	1003	Jennifer Lopez	*(null)*	91 Perfect Ave.	Rochester	NY	14321	Y	5	11/9/2024, 4:47:45 AM	12/31/2199, 11:59:59 PM	1

Figure 14 Dim_Customer Updated via Apache hop flow

15. Pipeline 4-Fact Sales

In this workflow, we created a new pipeline in Apache Hop called "LOAD_FACT_SALES_STAGING" to load data into a fact table in the data warehouse. This process involved configuring multiple lookups for each foreign key, using a combination of CSV inputs and table lookups to match business keys with their corresponding surrogate keys from dimension tables. Through this setup, we used "Stream Lookup" nodes to retrieve current keys, ensuring accurate foreign key references in the fact table. This method streamlines data integration by maintaining continuous data flow and allowing efficient key matching across dimension and fact tables.

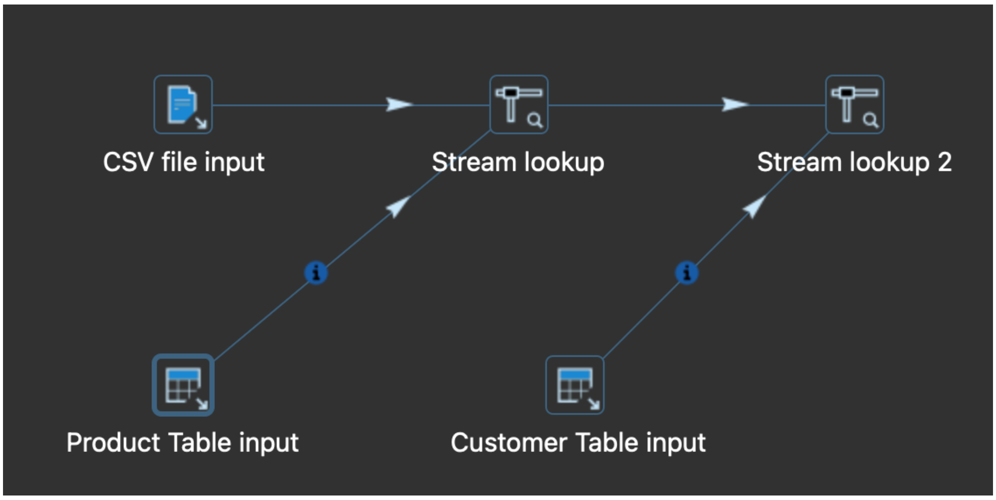


Figure 15 Pipeline 4-Fact Sales

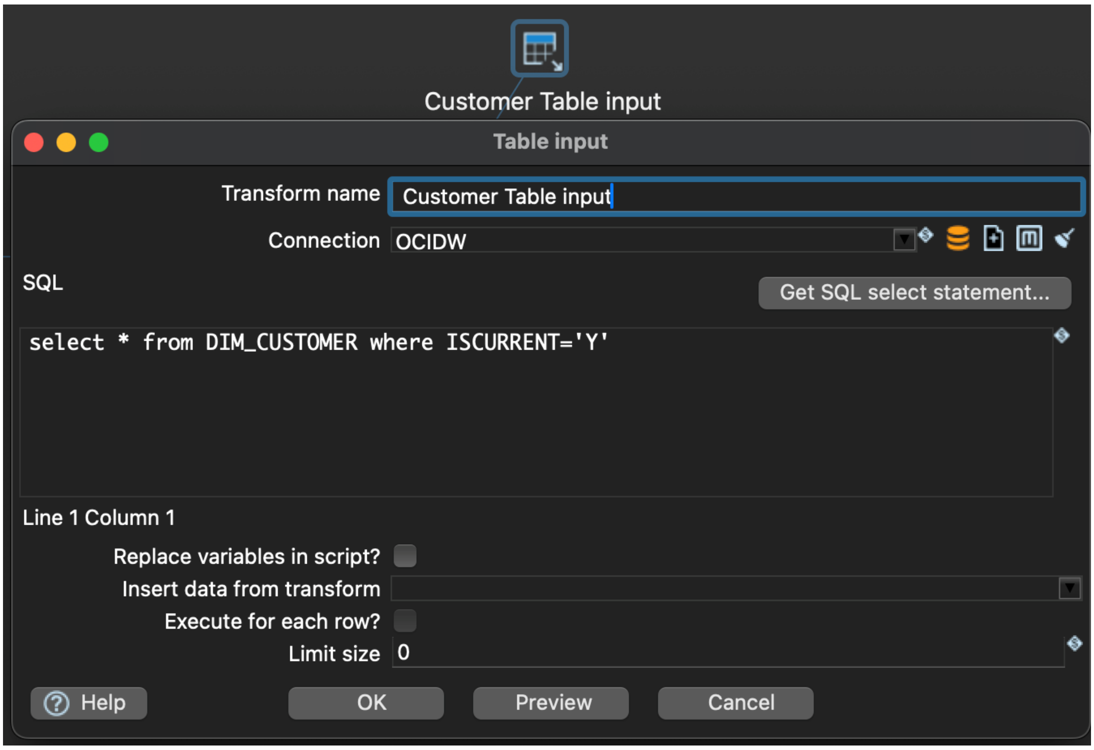


Figure 16 Pipeline 4- Fact Sales(Customer Table Input)

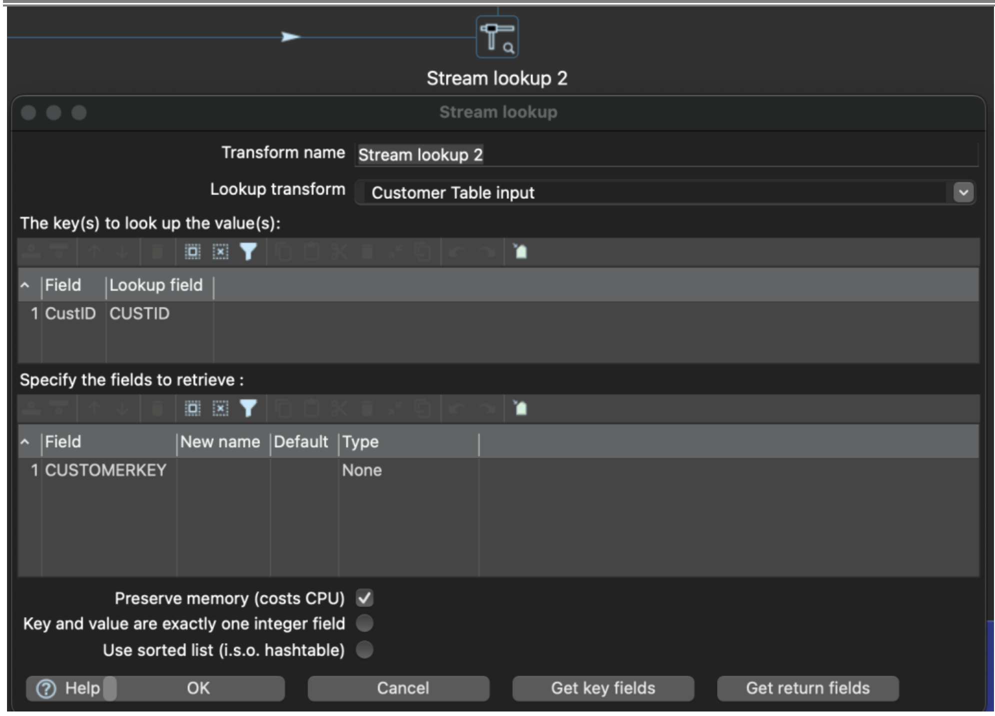


Figure 17 Pipeline 4-Fact Sales(Customer Stream Lookup)

- You might have noticed we're not doing a lookup for the date dimension, why?

A lookup for the date dimension is unnecessary because:

- **Unique DATEKEY**: The DIM_DATE table already has a unique DATEKEY that identifies each date, allowing direct joins without requiring an additional surrogate key lookup.
- **Direct Date Use in Fact Table**: The fact table can use the date value directly, referencing DATEKEY as needed. Since the date information is static and consistent, pre-joining or merging with **Dim_Date** may not be necessary at every ETL run. This avoids redundancy and simplifies the join process with the date dimension.

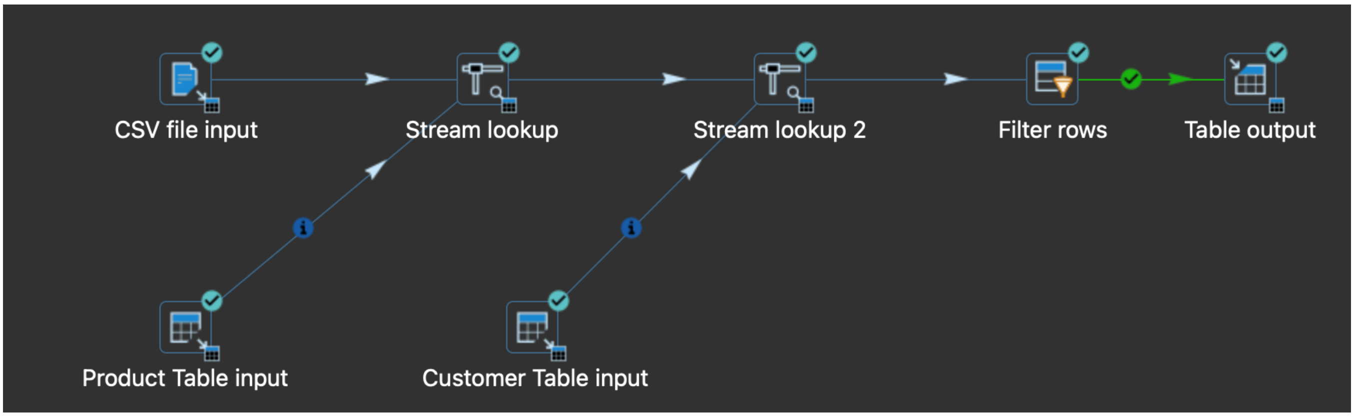


Figure 18 Pipeline 4-Fact Sales(Final Flow)

```
1   select * from FACT_SALES;
```

Query Result   Script Output   DBMS Output   Explain Plan   Autotrace   SQL History

Download   Execution time: 0.013 seconds

	SALESID	INVOICENUMBER	CUSTOMERKEY	DATEKEY	PRODUCTKEY	SALEPRICE	QUANTITY
1	1	1	3	8052018	100	19	5
2	2	2	1001	8062018	105	29	2
3	3	3	1003	8062018	105	1	2
4	4	4	3	8062018	105	8	4
5	5	5	1000	8092018	102	1	3
6	6	6	1002	8112018	104	28	2
7	7	7	1001	8122018	101	2	2
8	8	8	1003	8132018	101	8	4
9	9	9	1001	8132018	101	26	2
10	10	10	3	8142018	104	19	5
11	11	11	1003	8142018	100	28	1

Figure 19 Fact Sales(Head)

```
1   select * from fact_sales;
```

Query Result   Script Output   DBMS Output   Explain Plan   Autotrace   SQL History

Download   Execution time: 0.01 seconds

	SALESID	INVOICENUMBER	CUSTOMERKEY	DATEKEY	PRODUCTKEY	SALEPRICE	QUANTITY
989	989	989	1000	7072021	106	2	1
990	990	990	1002	7092021	100	7	1
991	991	991	1001	7102021	101	28	5
992	992	992	1002	7112021	106	17	4
993	993	993	3	7112021	102	13	2
994	994	994	1000	7122021	104	6	5
995	995	995	1001	7142021	105	1	3
996	996	996	1002	7152021	104	14	2
997	997	997	1003	7152021	105	29	2
998	998	998	1003	7152021	101	4	4
999	999	999	1002	7162021	104	27	3
1000	1000	1000	1001	7172021	104	26	5

Figure 20 Fact Sales(tail)

16. Tableau Setup and Data Connection

- Successfully installed Tableau Desktop and connected it to sample Excel data as well as our Oracle Cloud data warehouse.
- Configured the necessary Oracle Instant Client and drivers to enable seamless connectivity between Tableau and our cloud database.

17. Data Preparation and Modelling

- Explored Tableau's data preparation capabilities, including creating calculated fields and modifying data types to ensure accurate representation of our metrics.
- Leveraged Tableau's automated relationship detection to establish connections between fact and dimension tables, creating a functional star schema for analysis.

18. Visualization and Dashboard Creation

- Developed multiple chart types, including line charts for time series data, to visualize key business metrics like employment numbers and unemployment rates.
- Experimented with Tableau's forecasting functionality, applying different models to project future trends based on historical data.
  - Model Exploration: Tested various forecasting models available in Tableau, including automatic, and additive models. This allowed us to compare different approaches and understand their strengths and limitations.
  - Seasonality Analysis: By adjusting seasonal parameters, we gained insights into cyclical patterns within our data, particularly useful for metrics like employment rates that often have annual trends.
- Played with various aspects of chart creation and customization:
  - Color schemes: We explored how changing colors can affect data perception and dashboard aesthetics.
  - Axis manipulation: We learned how adjusting axis ranges can dramatically change the story a chart tells, highlighting the importance of thoughtful design choices.

  - **Filtering**: We applied date filters to focus on specific time periods, enhancing the relevance of our visualizations.

- Created a focused 1-page dashboard incorporating multiple visualizations to tell a cohesive story about our business data.

19. Key Learnings

- ✓ **Data Connectivity:** Establishing a robust connection between Tableau and cloud-based data warehouses is a critical first step. While it requires careful configuration, the resulting real-time access to business data is invaluable for timely decision-making.
- ✓ **Data Preparation:** Tableau offers powerful capabilities for data manipulation and calculated fields. These features allow us to refine and enhance our raw data, creating more meaningful metrics and enabling deeper insights.
- ✓ **Visualization Best Practices:** Creating effective dashboards involves more than just presenting data. It requires thoughtful design choices around chart types, colour schemes, and data filtering. We learned the importance of considering the end-user's perspective and the story we want our data to tell.
- ✓ **Forecasting Considerations:** Tableau's forecasting feature is powerful but requires careful application. Understanding the underlying models and the potential impacts of data anomalies is crucial for generating reliable projections. This underscores the need for domain knowledge alongside technical skills in data analysis.
- ✓ **Interactivity and User Engagement:** Tableau's interactive features, such as filters and drill-down capabilities, add significant value to dashboards. They allow users to explore data dynamically, potentially uncovering insights that might be missed in static reports.

20. Tableau Exposure

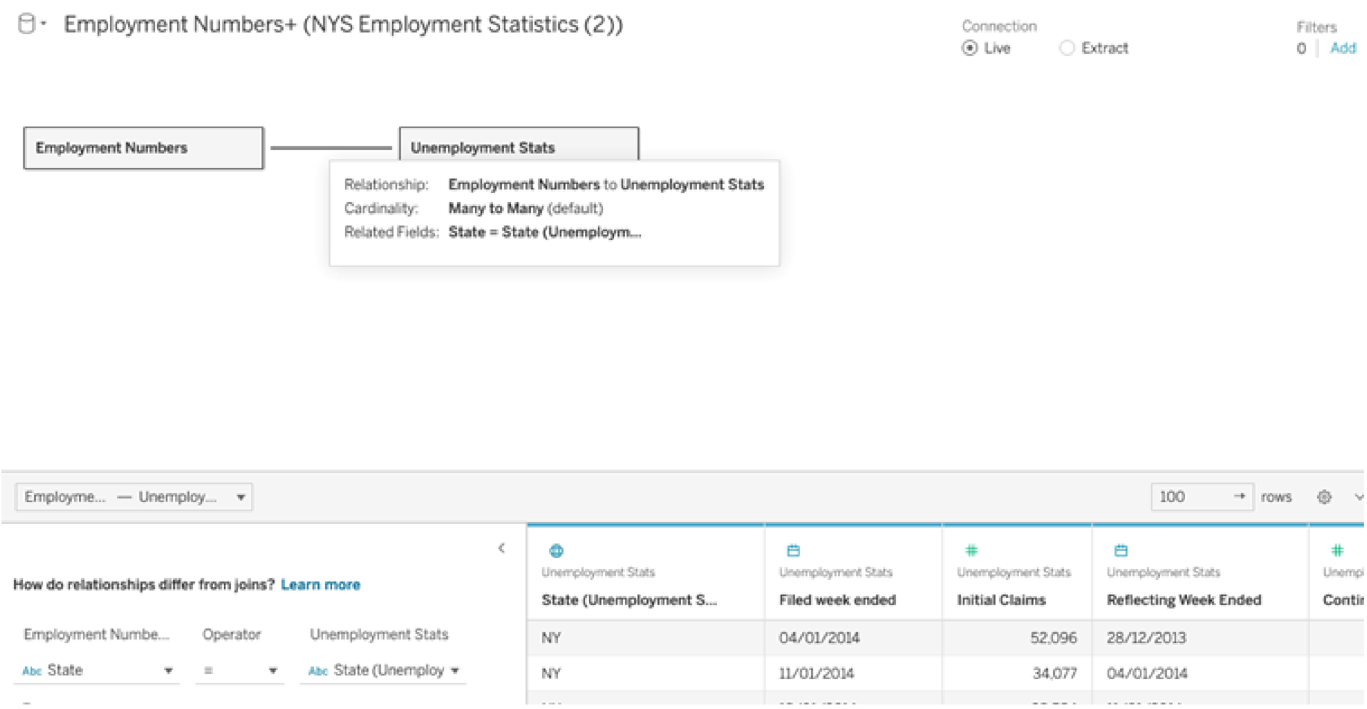


Figure 21 Tableau Data Sources Relationships

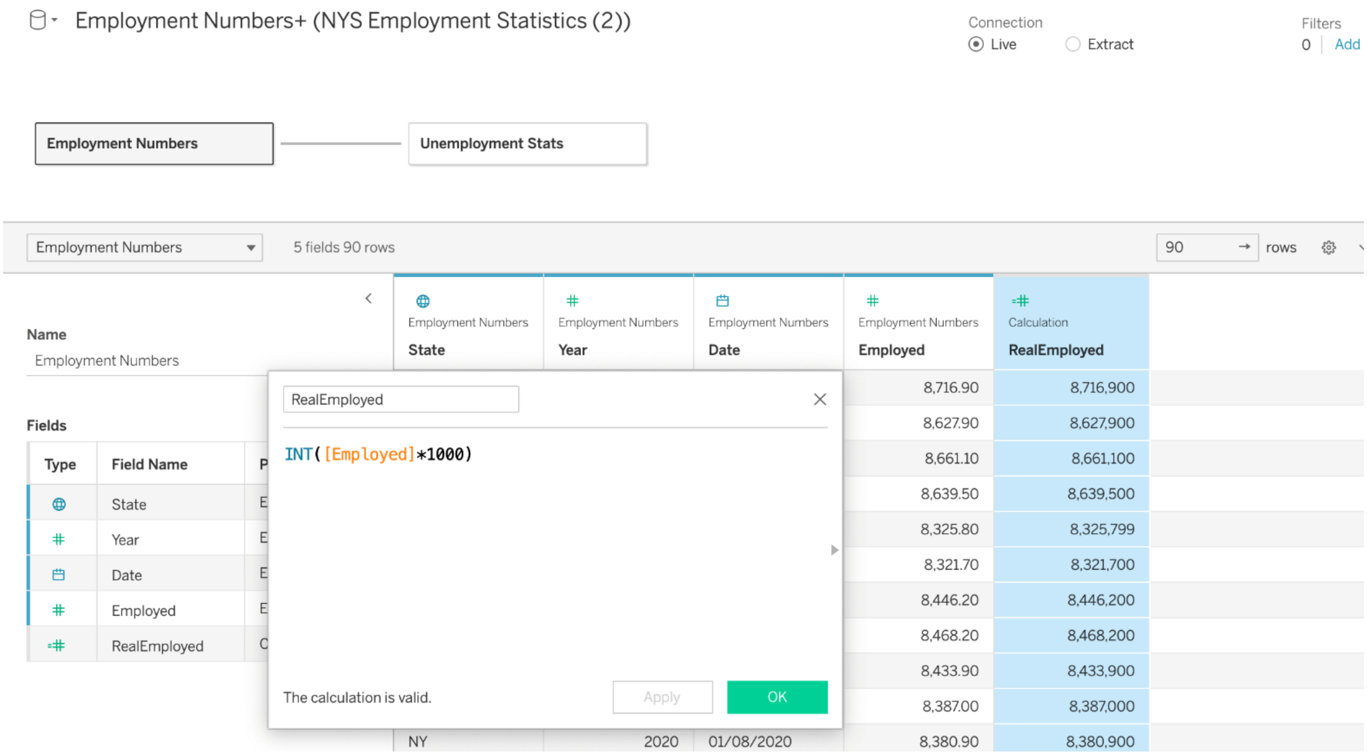


Figure 22 Modifying the Data-1

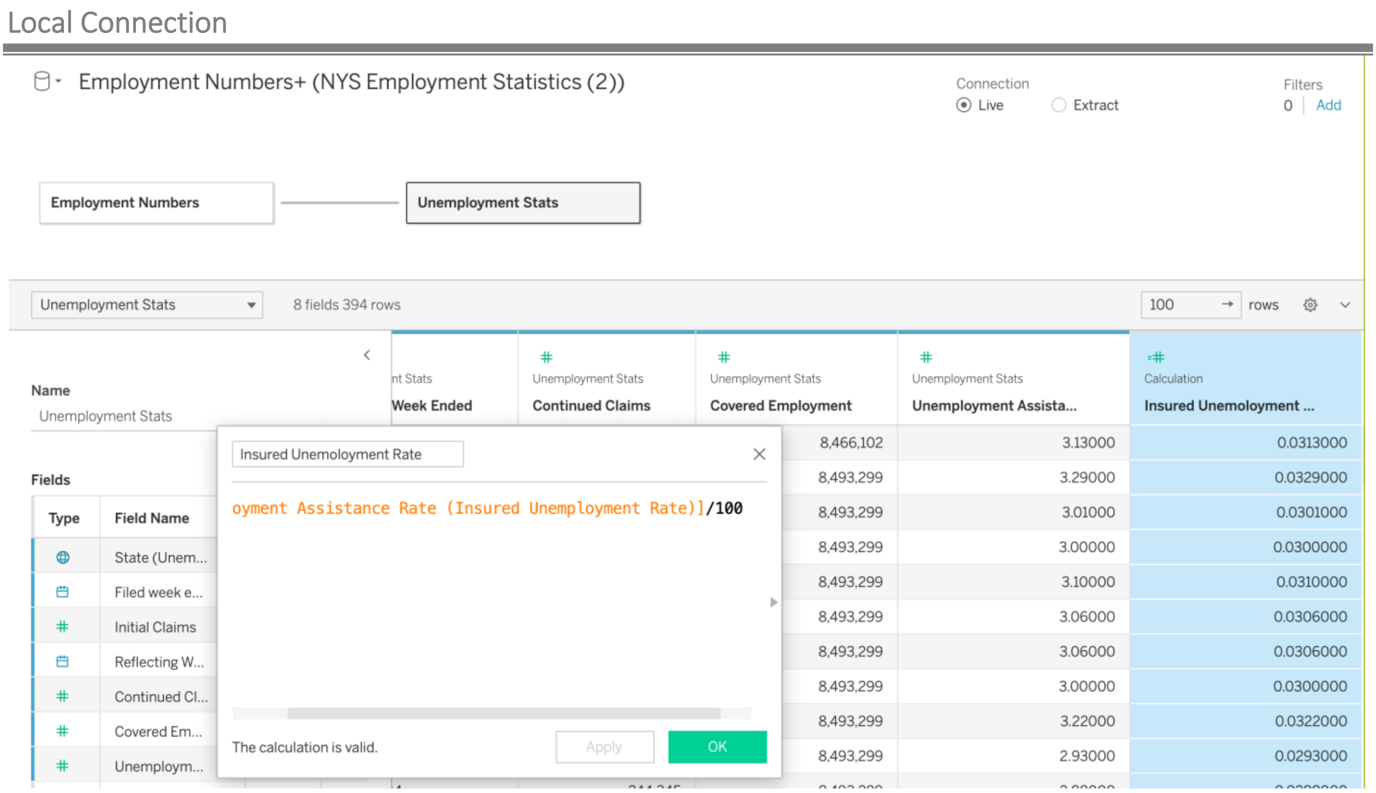


Figure 24 Modifying the data-2

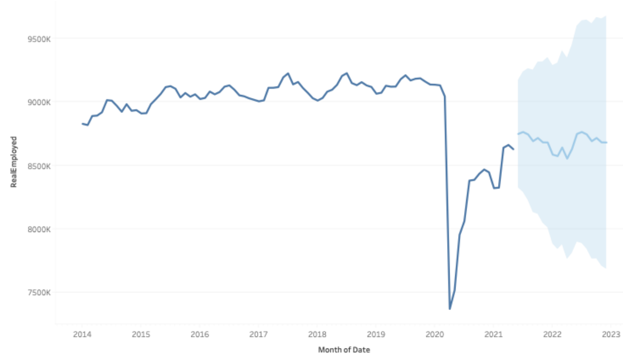


Figure 25 Forecast model default

Figure 23 Forecast model modified

The left chart shows a flat forecasted line extending into the future. This flat forecast results from using the default automatic forecast settings, the right chart shows a modified forecast with more variation, reflecting seasonal patterns in the data. This modified forecast was created by adjusting the forecast settings to use a custom model with additive seasonality. The major anomaly visible in both charts is a sharp drop in the data around 2020, which is likely due to the impact of the COVID-19 pandemic on employment numbers. This significant anomaly could be why the initial automatic forecast produced a flat line, as extreme outliers can sometimes lead forecasting algorithms to produce overly conservative predictions.

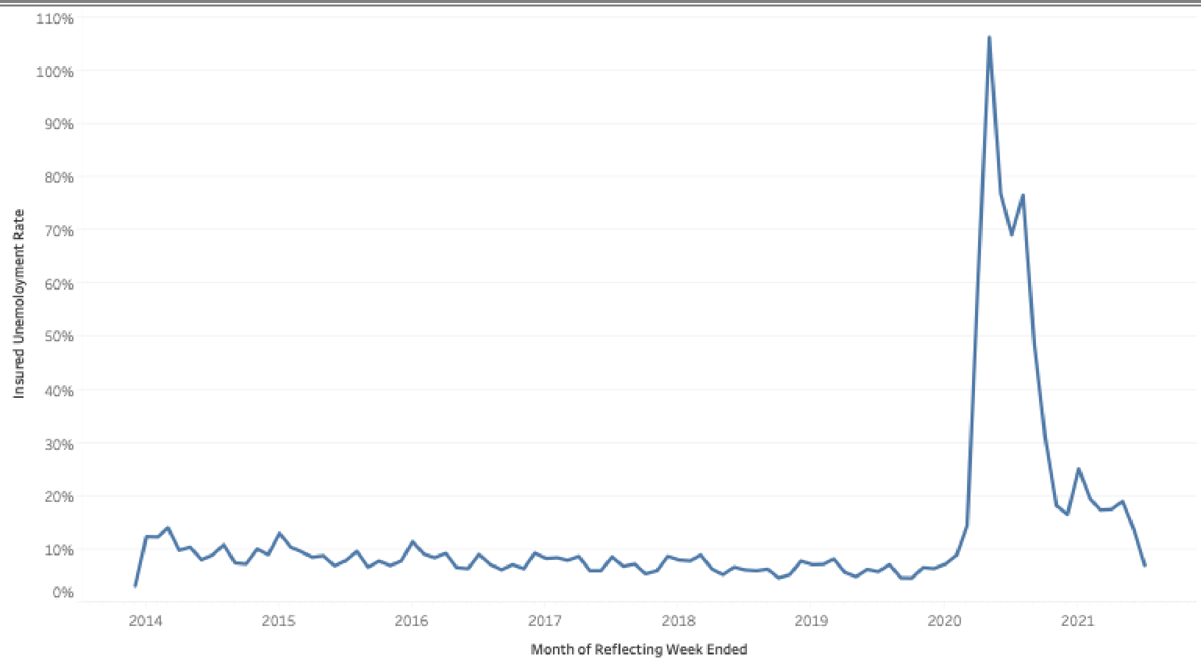


Figure 26 Line Chart from Unemployed Data(%)

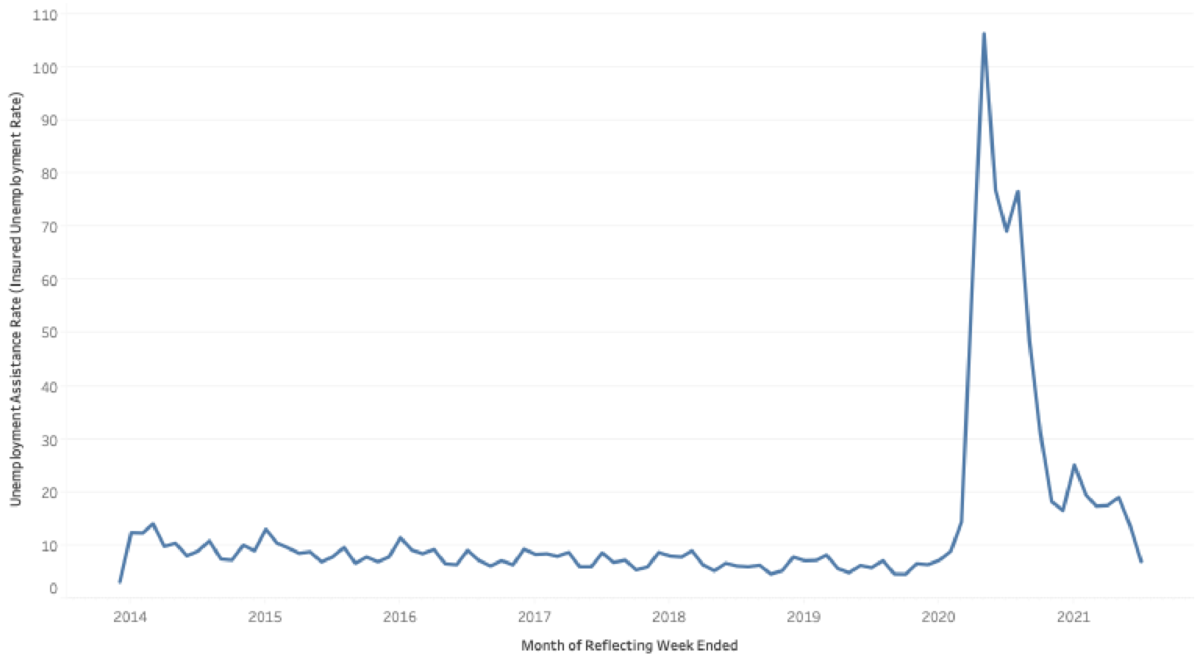


Figure 27 Line Chart from Unemployed Data

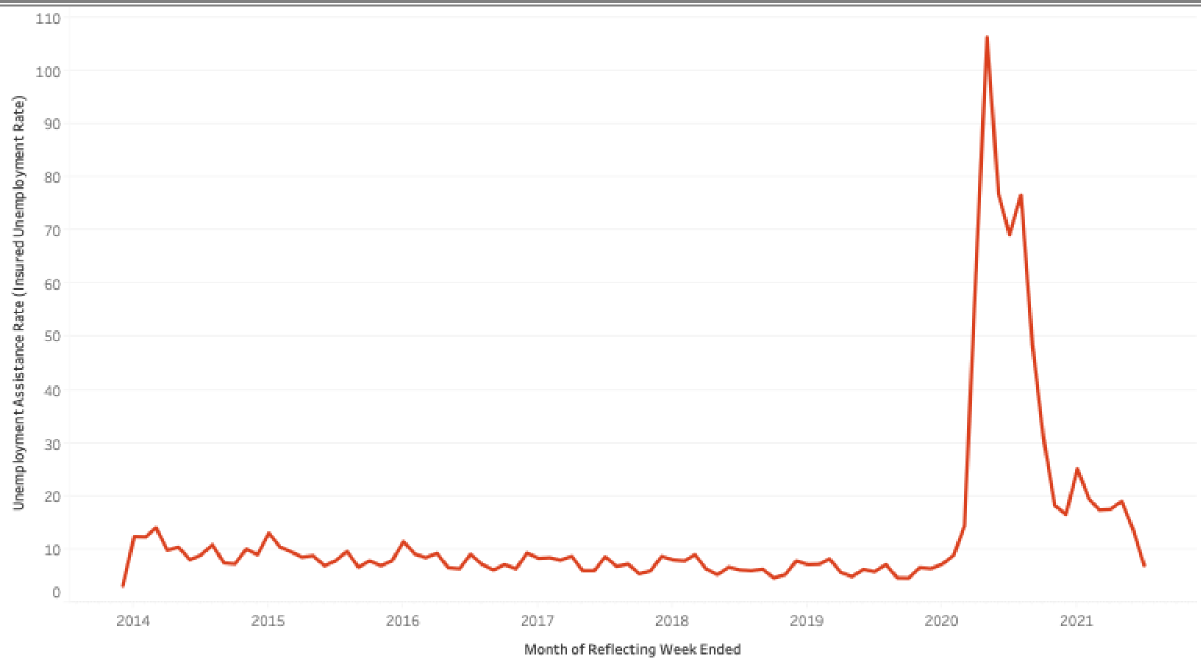
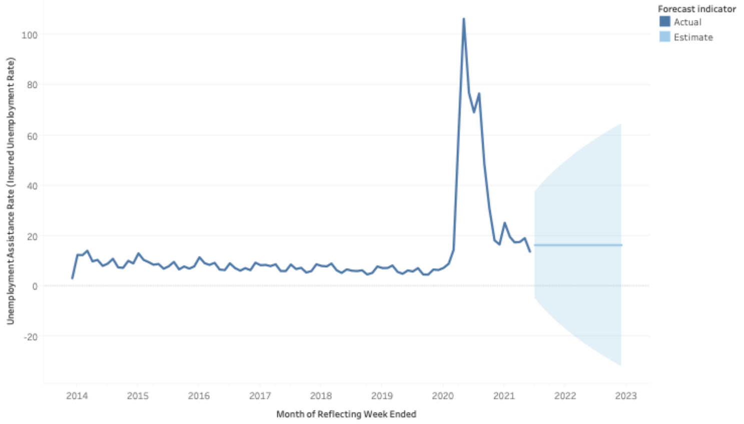


Figure 28 Same Line Chart with Modified Colour



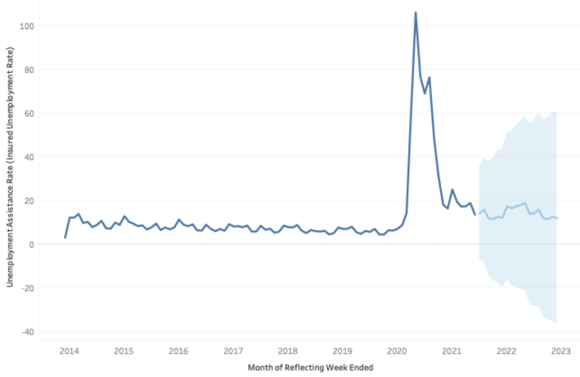


Figure 29 Default Forecast Model

Figure 30 Custom Forecast Model

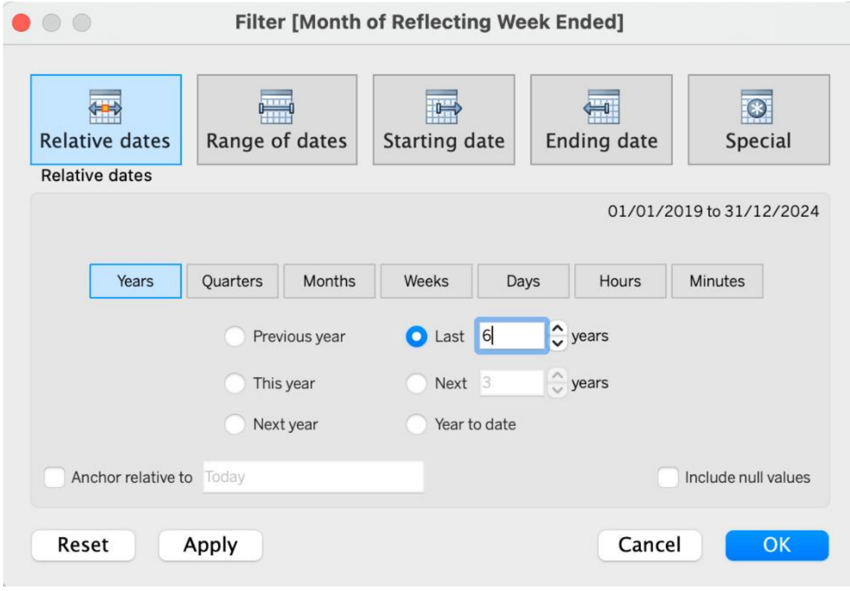


Figure 31 Relative Dates Filter

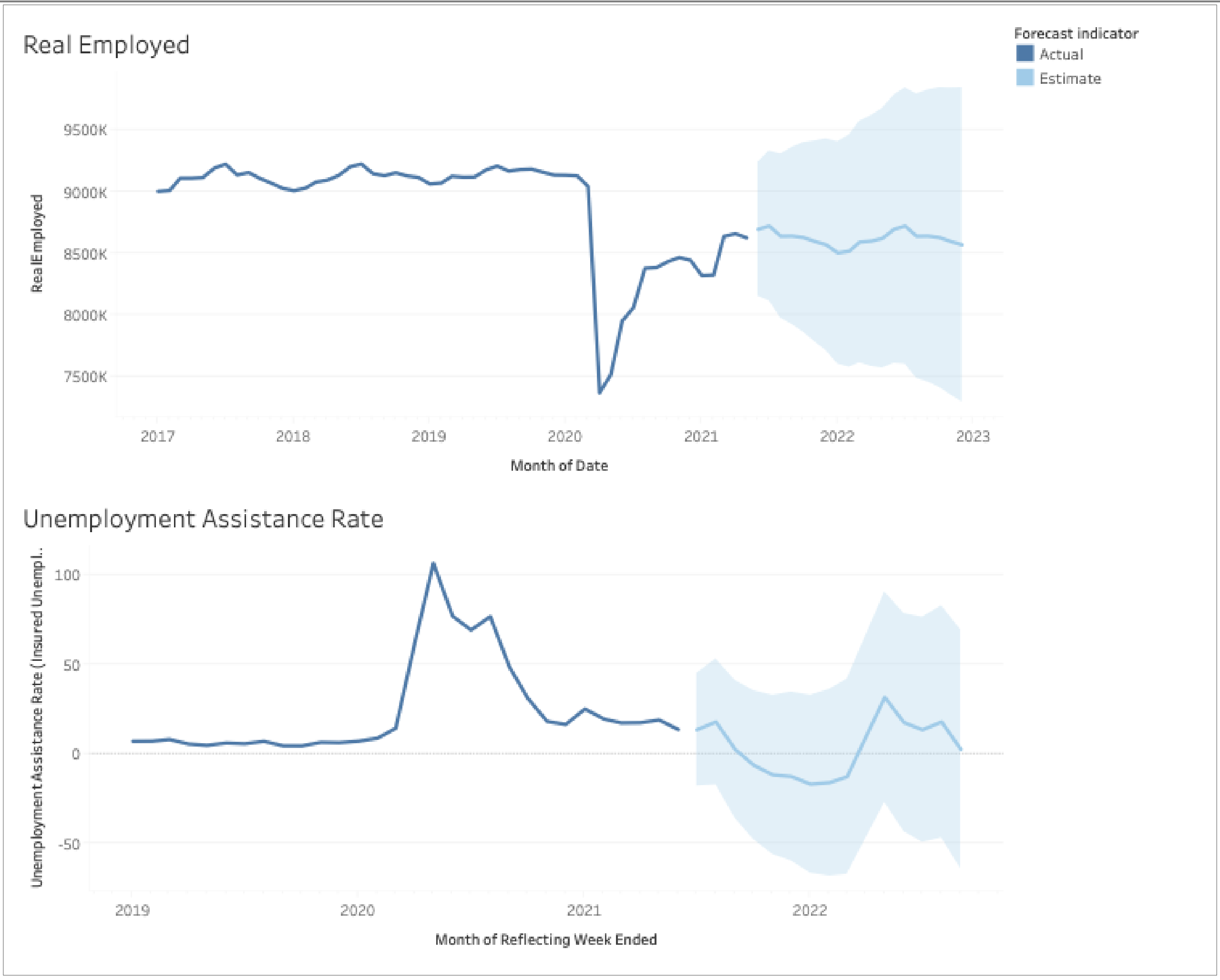


Figure 32 Dashboard View of Both The Charts

Key Insights from the dashboard

a. Both employment levels and unemployment assistance rates were relatively stable from 2017 to early 2020

b. A significant event, likely the COVID-19 pandemic, caused a dramatic shift in both metrics around early 2020. Employment levels sharply dropped while unemployment assistance rates spiked dramatically.

c. The charts show a clear inverse relationship between employment and unemployment assistance rates. As employment fell, unemployment assistance surged.

d. Both charts show signs of recovery post-2020, but neither has fully returned to pre-pandemic levels. Employment has been gradually increasing, while unemployment assistance rates have decreased from their peak but remain higher than pre-2020 levels.

e. Both charts show considerable uncertainty in their forecasts, indicated by the wide light blue areas. This suggests difficulty in predicting future trends accurately for both metrics.

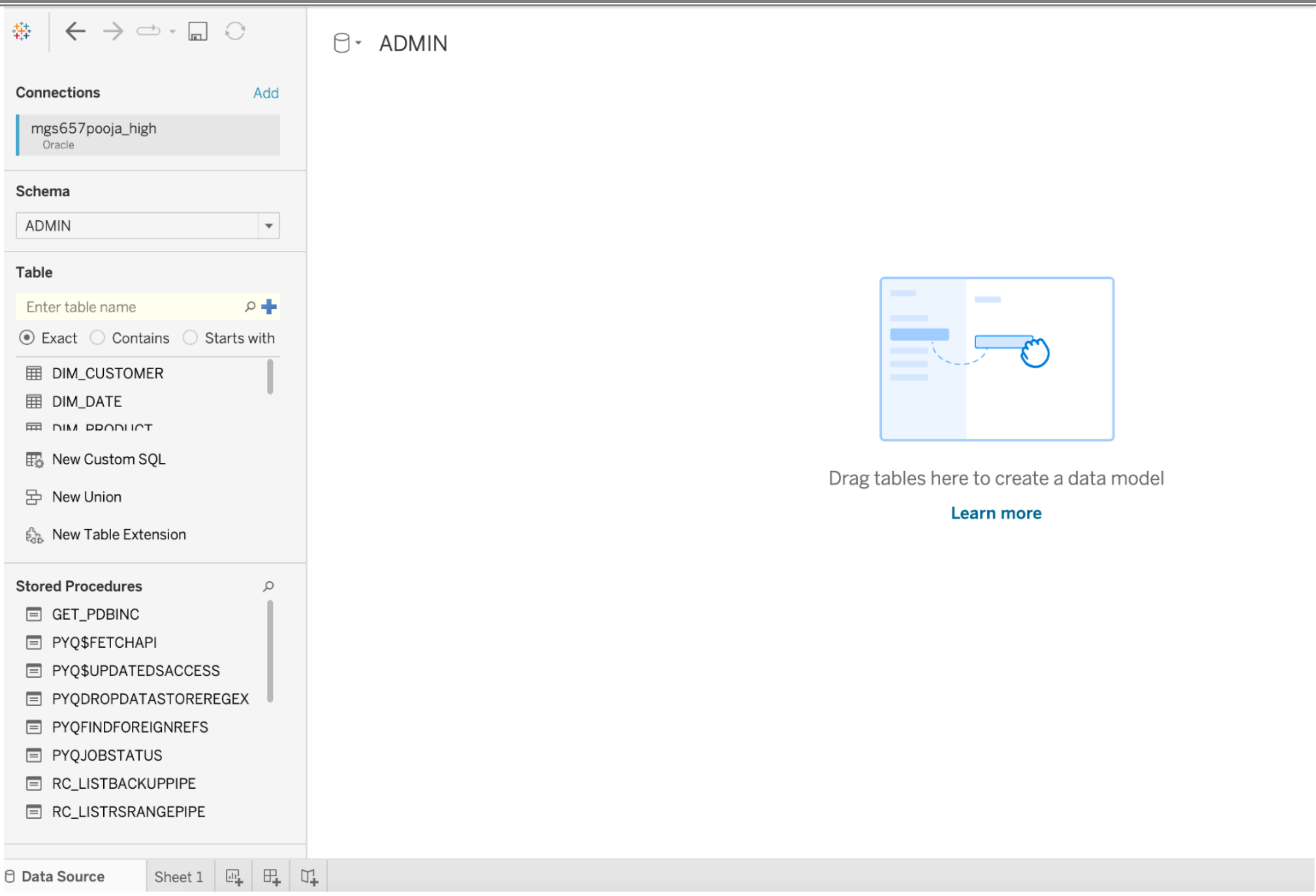


Figure 33 Successful Connection to the Oracle Datawarehouse

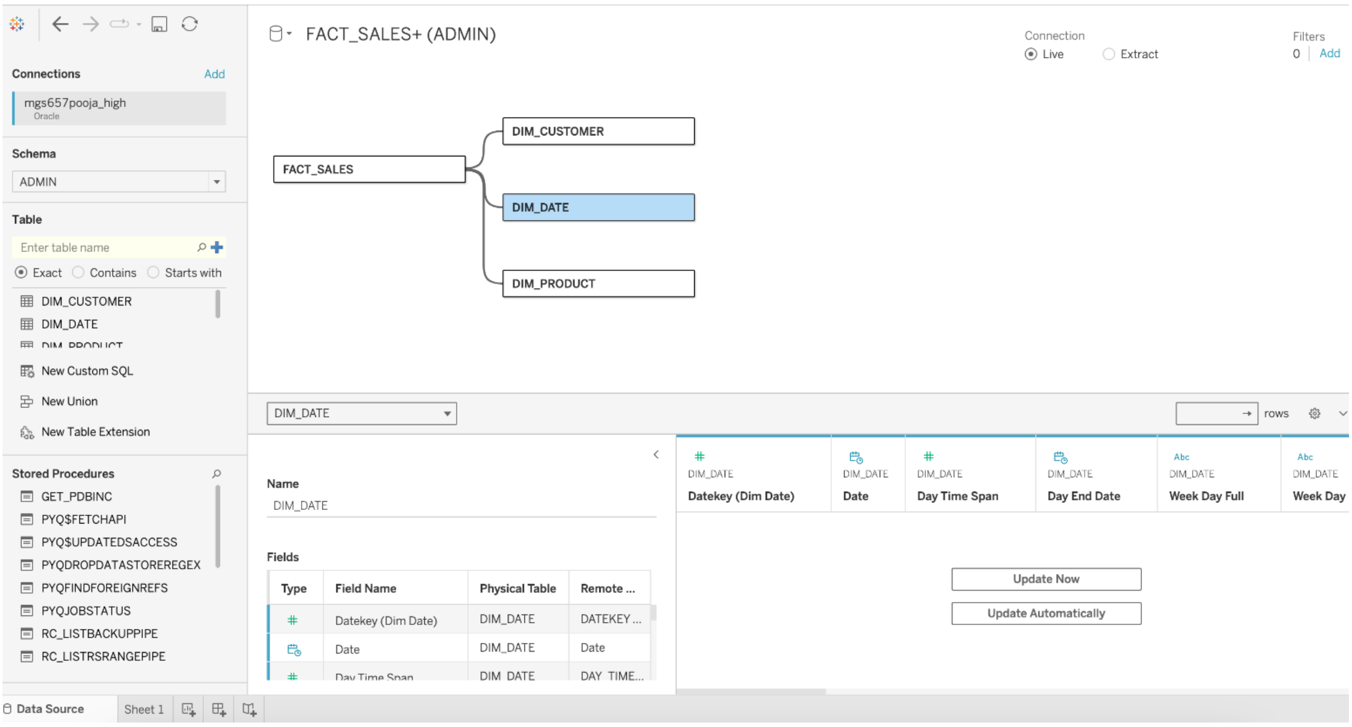


Figure 34 Pulling up the required tables for analysis.

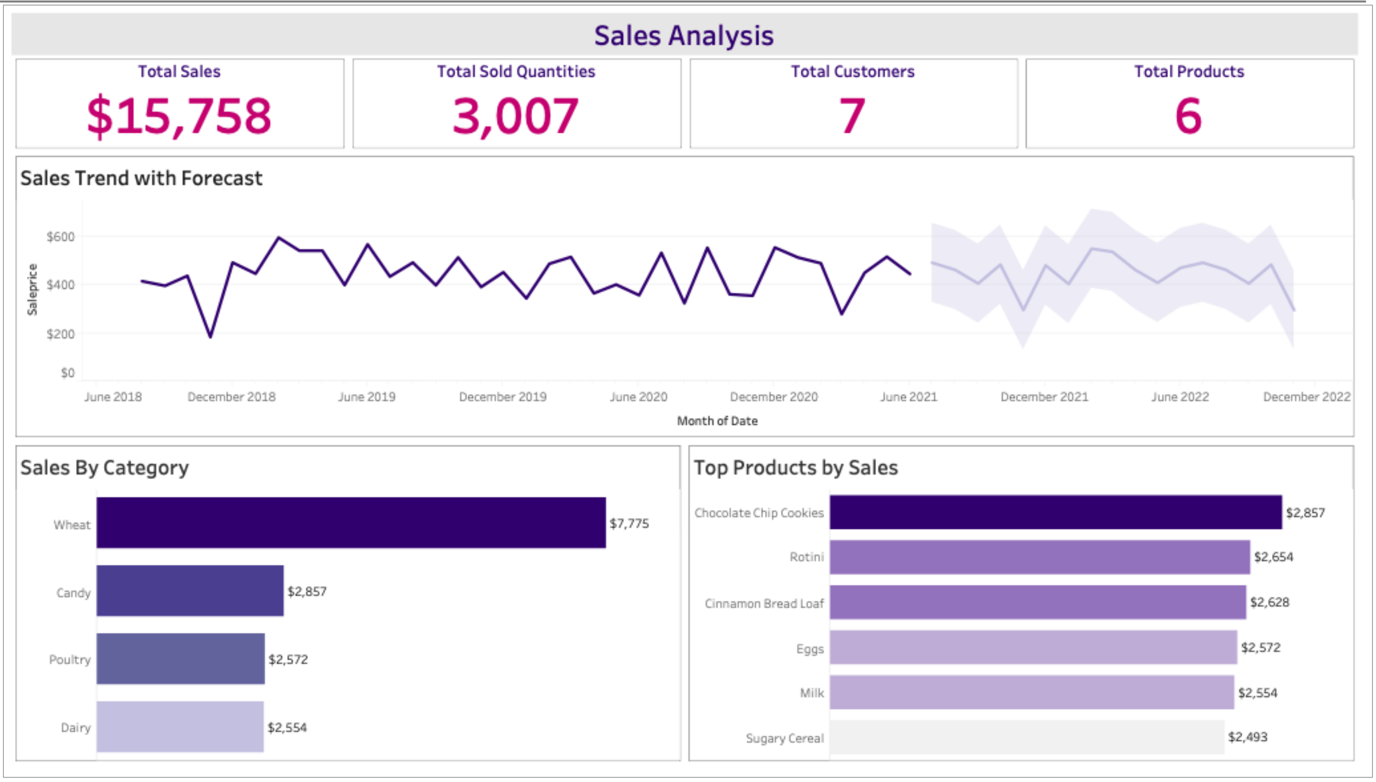


Figure 35 Sales Trend Analysis Dashboard

- The dashboard offers a comprehensive view of sales performance, focusing on total sales, customer engagement, and product performance.
- The sales trend analysis shows consistent revenue streams, with a stable outlook predicted by the forecast.
- Wheat is the most successful category, generating nearly half the revenue, while other categories like Candy and Poultry also show promise.
- On the product level, Chocolate Chip Cookies emerge as the top performer, emphasizing the popularity of sweet treats.
- Insights suggest opportunities to expand the customer base (currently only 7 customers) and capitalize on high-performing categories and products to further boost revenue.
- Overall, the dashboard provides actionable insights to refine sales strategies and target growth areas effectively.