Lab 8: Creating Prep Flows in Various Business Scenarios

In this lab, we will cover the following exercises:

- Creating a flow for transaction analytics
- Creating a call center flow for instant analysis

Technical requirements

To follow along with the exercises in this lab, you will require Tableau Prep Builder.

The exercises in this lab use sample data files that you can download from the course GitHub repository at https://github.com/fenago/tableau-data-prep.

Creating a flow for transaction analytics

In this exercise, we'll create a data pipeline, or flow, for analytics. In this scenario, we'll assume that we are an analyst for a fictive department store with multiple physical stores, as well as an online store front. We will be presented with multiple data sources that need to be combined, cleaned, and transformed so that we can output a clean and reliable dataset of all transactions that occurred in the first six months of 2020. This is a common scenario in most industries and is the perfect use case for Tableau Prep.

Getting ready

To follow along with this exercise, download the **Sample Files 8.1** folder from this course's GitHub repository. In here you'll find various data files. Several of these files originate from disparate systems and we'll need to employ Tableau Prep to provide a single, holistic output of all transactions.

The contents of the files are as follows:

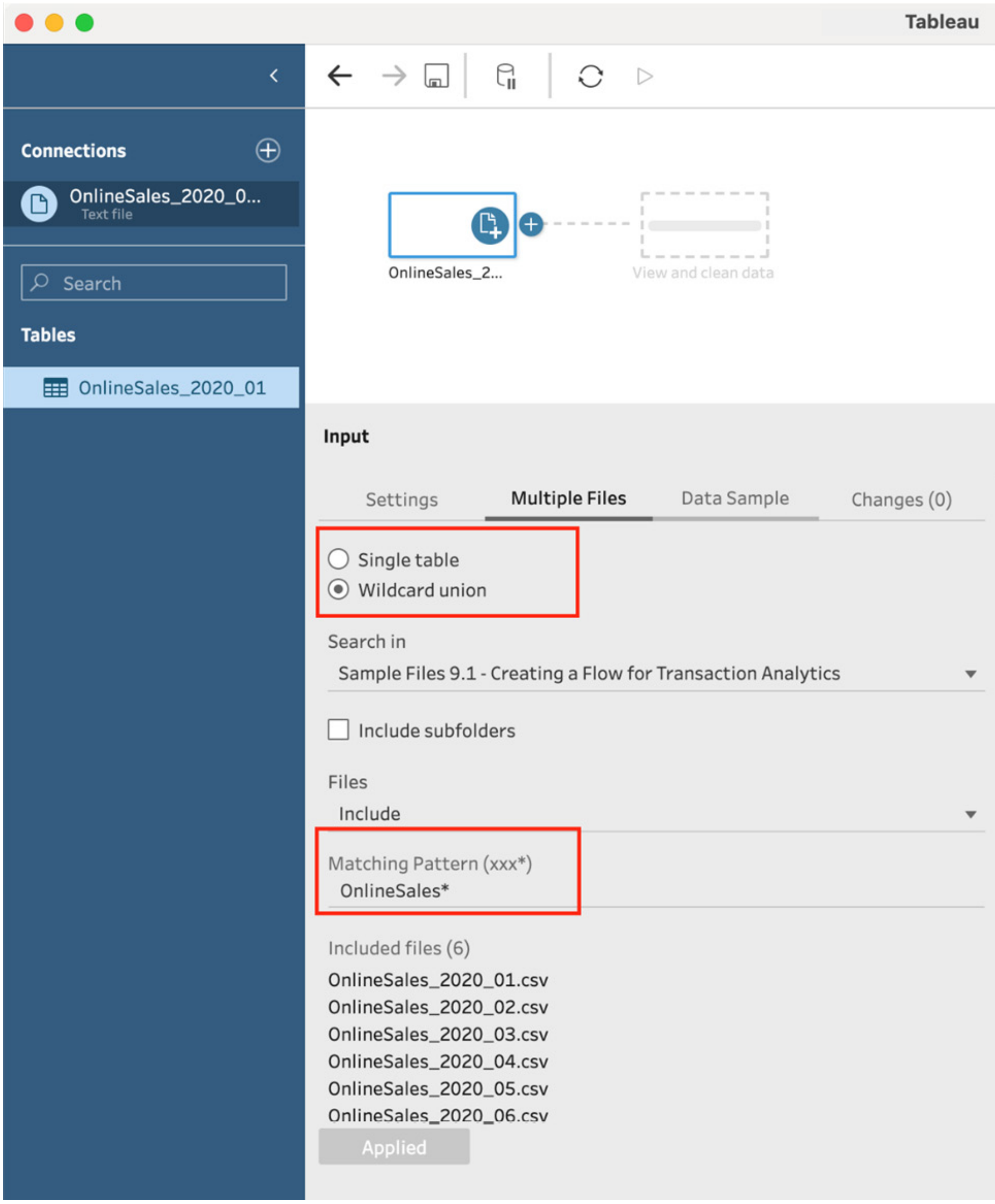
- Files starting with **OnlineSales** contain sales information for transactions made through the company website. There is one file per calendar month, and so we must combine six files to get the full dataset we need for the first six months of 2020.
- **STORE_SALES_EXPORT.xlsx** contains sales data from physical stores. The stores sell the same products as the online storefront. However, the data format is different as the stores use a different point-of-sale system. This data export contains all store sales for the six-month period we need, from January to June 2020.
- **Products.csv** contains descriptive product information, such as the product name and category. We will need to join this to the sales data so that the new dataset is easier to understand, as the sales data only includes product IDs.
- **ShippingData.hyper** is a Tableau Hyper extract prepared by our analyst colleague who works in the shipping department. The data contains product shipping information for those products that were sold online. The company does not provide a delivery service for products bought in their physical stores.
- **CustomerList.csv** contains our customer information for those customers who have created an account with the company. Let's assume that creating a customer account for online transactions is mandatory. However, in-store transactions only have a customer ID if the customer uses their optional loyalty card.
- **returns_h1_2020.csv** contains product return information.

In this exercise, we're going to combine all of these datasets using a number of techniques we've learned in this course. The output of our flow will be a comprehensive dataset that can be easily understood and used for downstream analysis purposes.

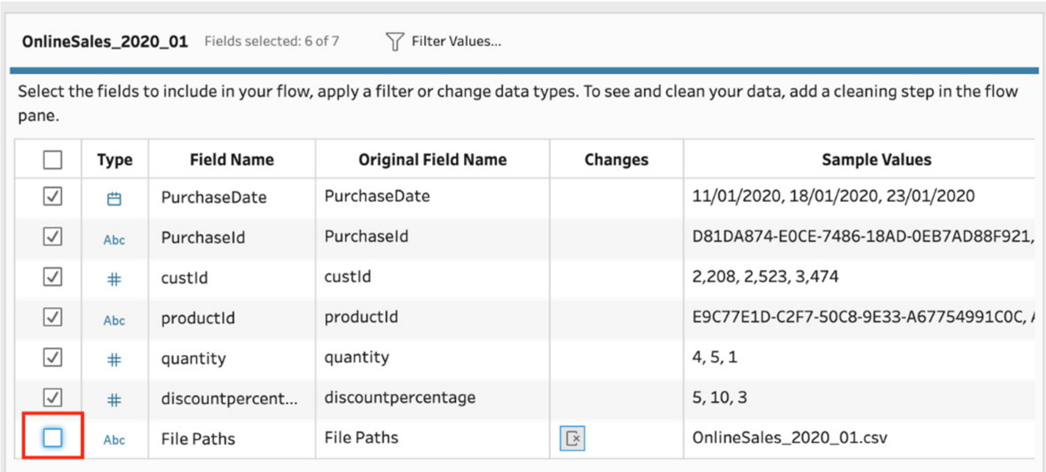
How to do it...

Start by opening up Tableau Prep and connect to the **OnlineSales_2020_01.csv** file from the **Sample Files 8.1** folder in Tableau Prep. Then, perform the following steps:

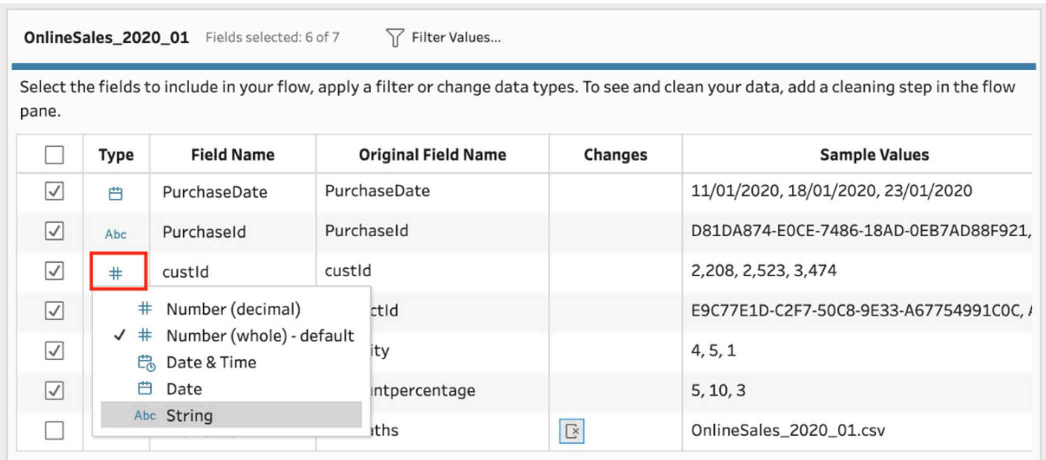
1. This dataset contains data for a single month. Specifically, the month of January, as indicated by the last two numbers in the filename. The format of all files starting with **OnlineSales** are the same, and so we can combine these files using the **UNION** functionality with the input step. To do this, select the **Multiple Files** tab in the **Input** settings and select **Wildcard union**. Then, set the matching pattern to **OnlineSales***. This will instruct Tableau Prep to union all files starting with **OnlineSales**. Make sure to click **Applied** to save your settings:



2. As a result of our union action, Tableau Prep has automatically added the **File Paths** field, to indicate where each row of data originated. As we won't require this information for any type of analysis, we can remove it here simply by unchecking the box in the field list:



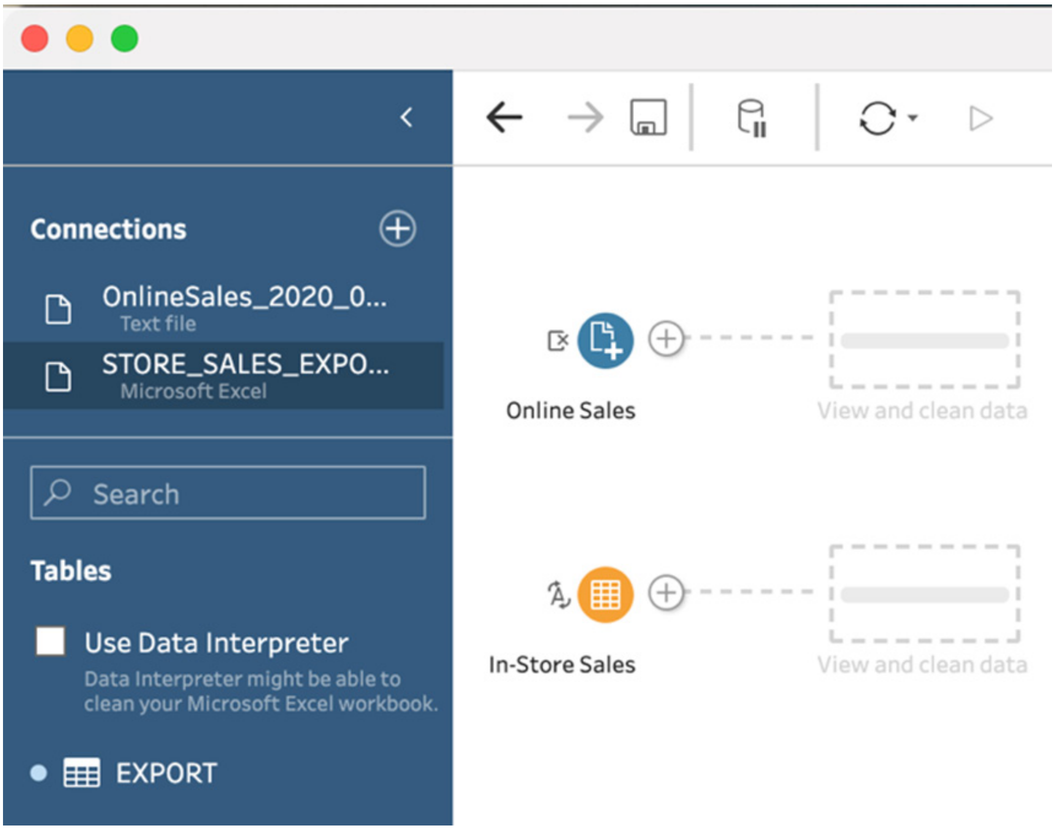
3. Observe the field list and note how Tableau Prep has wrongly assigned a numeric data type to the **custId** field. This field represents the customer ID and although it consists of numbers, it will not be used as such in any calculation. Correct the data type by clicking the data type icon **#** and select **String** instead:



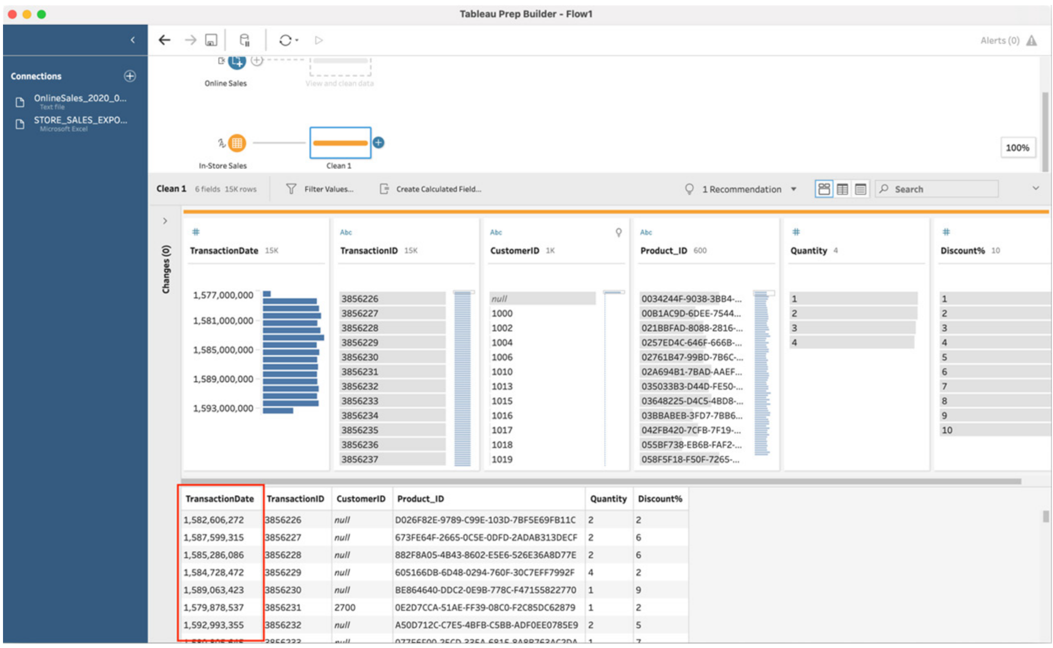
4. Next, let's add the sales data for our physical stores. Use the Connect to Excel functionality and select the **STORE_SALES_EXPORT.xlsx** file provided in the sample files folder. Unlike the online sales data we have worked with so far, this dataset contains data for the full 6 months, so we don't have to perform a union here.

5. With the new input selected, correct the data type for the **TransactionID** and **CustomerID** fields by changing the type to **String**. This is the same solution we applied in *Step 3*, and something that occurs frequently in real-world scenarios when your data contains numeric IDs.

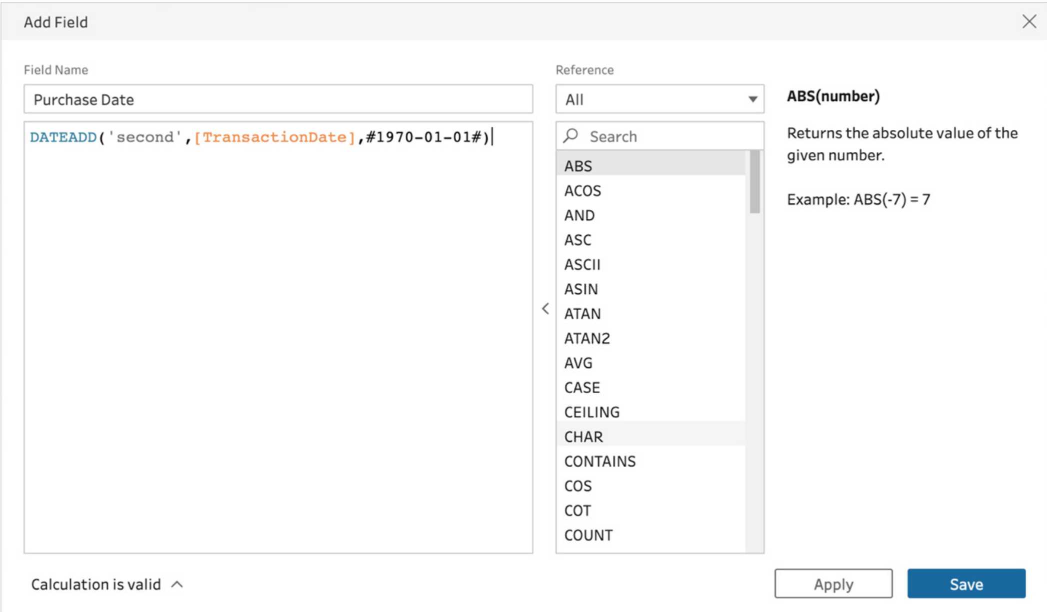
6. Before we continue, let's name the steps in our flow. As we'll build out a relatively large flow, naming your steps is useful for ensuring that your flow remains easy to understand. Rename the **OnlineSales_2020_01** input step by double-clicking its name and changing the name to **Online Sales**. Then, rename the second dataset to **In-Store Sales**:



7. Click the **+** icon besides the **In-Store Sales** input and then select **Clean Step**. Observe the **TransactionDate** field values, as highlighted in the following screenshot. Each value here seems to be a number and not a date. This is because the input data has been formatted as a **UNIX TIMESTAMP**. This type of data issue is not uncommon, and we need to create a simple calculated field to convert this value to a date, as Tableau Prep cannot automatically convert this source field to a date:



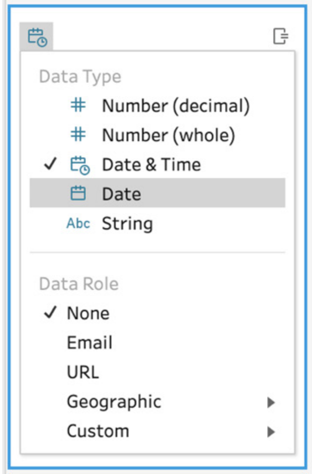
8. With **Clean Step** still selected, click on **Create Calculated Field...**. Name the new field **Purchase Date** and set the expression to **DATEADD('second',[TransactionDate],#1970-01-01#)**, which is the expression to convert a Unix timestamp to a regular datetime format. Click **Save** when done to apply your new calculation:



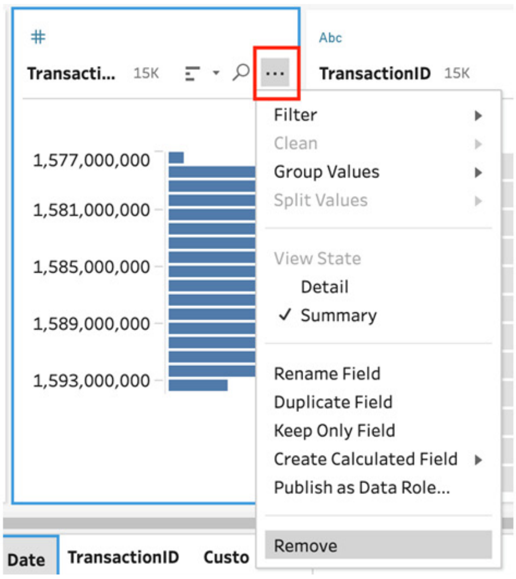
Observe the outcome and ensure that the format is indeed date and time, as shown in the following screenshot:

Purchase Date	TransactionDate
25/02/2020, 04:51:12	1,582,606,272
22/04/2020, 23:48:35	1,587,599,315
27/03/2020, 05:14:46	1,585,286,086
20/03/2020, 18:21:12	1,584,728,472
09/05/2020, 22:30:23	1,589,063,423
24/01/2020, 15:08:57	1,579,878,537
24/06/2020, 10:09:15	1,592,993,355

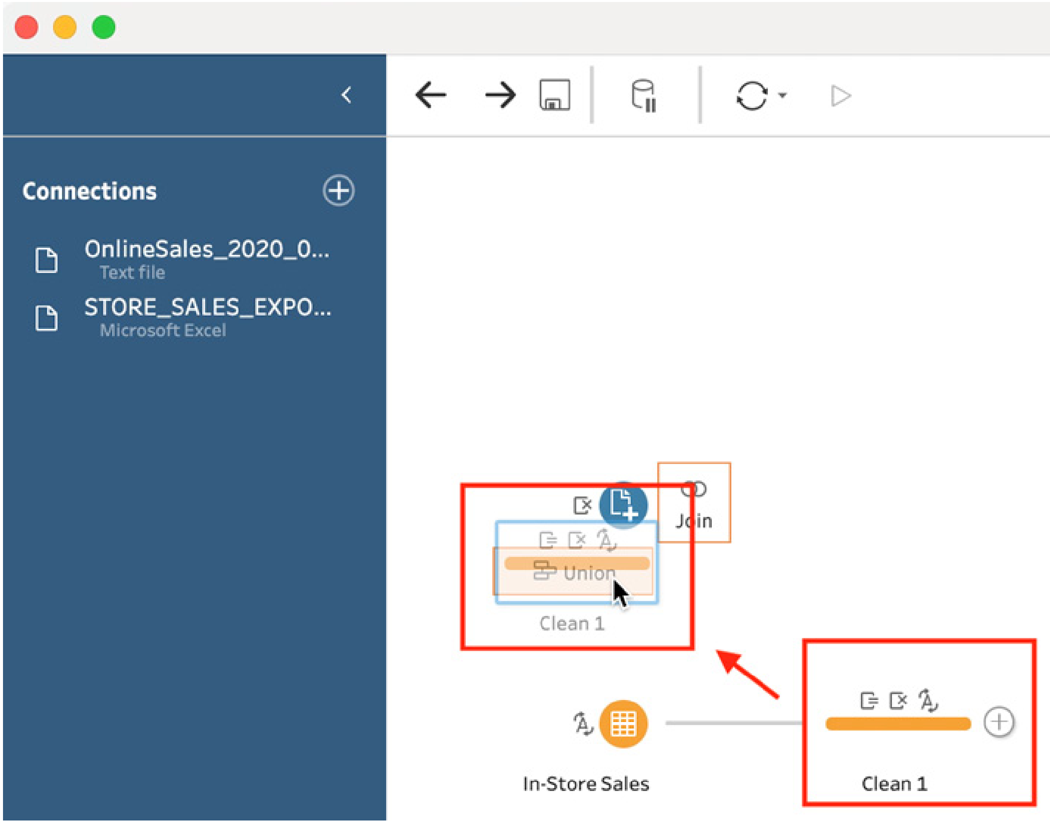
9. We won't need the specific time for the purchase date, so let's change the data type from **Date & Time** to **Date** by clicking the data type icon in the field list and then selecting **Date**, as shown in the following screenshot:



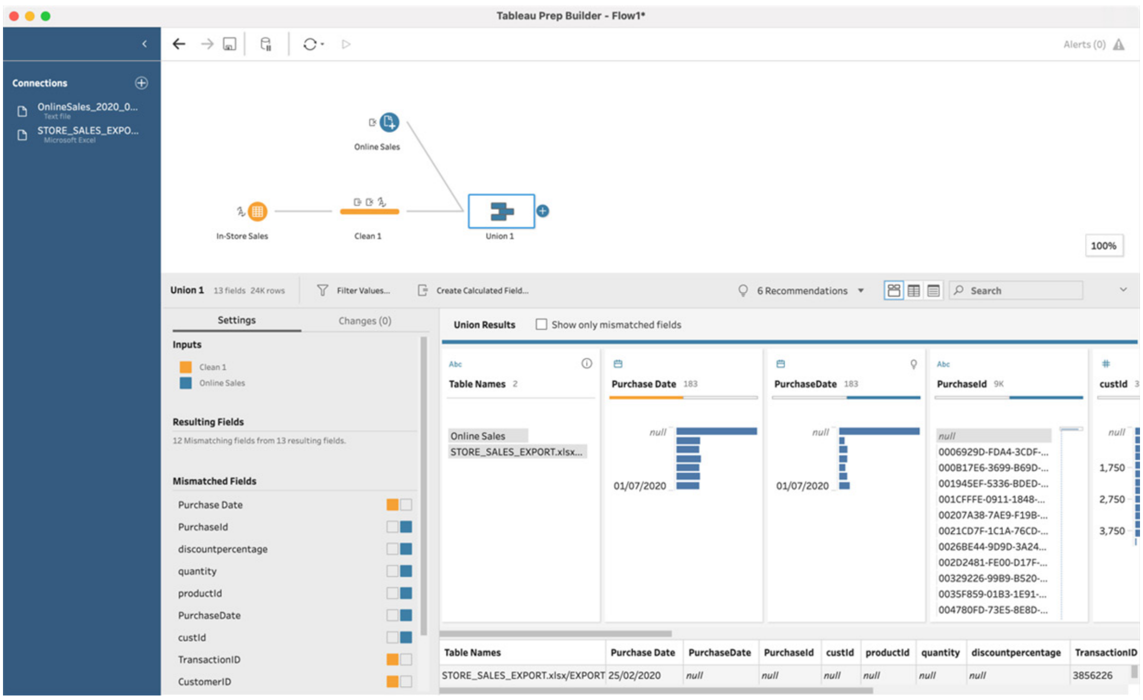
10. We also no longer require the original **TransactionDate** field. To remove this field using the clean step, click the context menu next to the field name and then select **Remove**, as shown in the following screenshot:



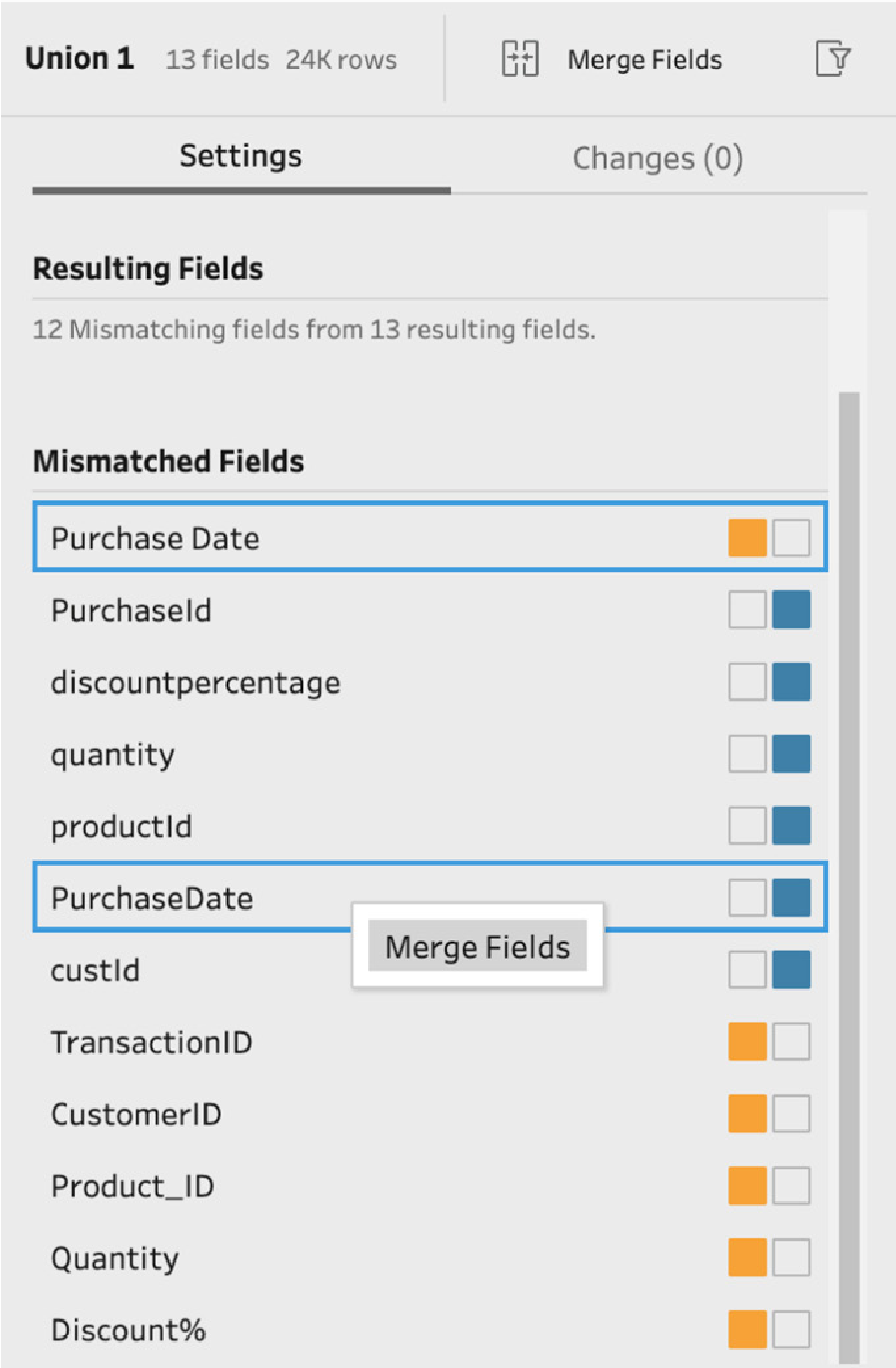
11. Next, we're going to combine the online sales data with our in-store sales data. To do this, we need to perform a union. Drag and hover **Clean Step** on top of the **Online Sales** input. Then, from the options that appear, hover over **Union** and release, as shown in the following screenshot:



This will automatically create a **Union** step and your screen should look like the following screenshot:



12. In the bottom left of the window, we can see that there are quite a few **Mismatched Fields** options. This is to be expected when you combine data from different sources, as we have just done. Fortunately, both our sources include fields with a similar meaning and they just have different field names, which prevents Tableau Prep from automatically aligning them. To resolve this, click the field pairs that represent the same information (hold the *Command* or *CTRL* key to select the second field), and then right-click and select **Merge Fields**, as shown in the following screenshot for the **Purchase Date** and **PurchaseDate** fields. Note that the newly merged field will take the name of the field you right-clicked:

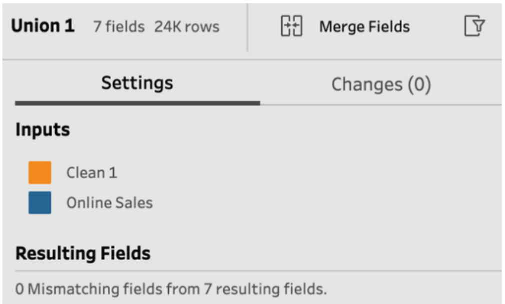


Perform this **Merge Fields** action for the field pairs listed here:

- **Purchase Date** and **PurchaseDate**

- **PurchaseId** and **TransactionID**
- **discountpercentage** and **Discount%**
- **quantity** and **Quantity**
- **productId** and **Product_ID**
- **custId** and **CustomerID**

When you've completed all the merges, your **Settings** tab should look like the following screenshot:

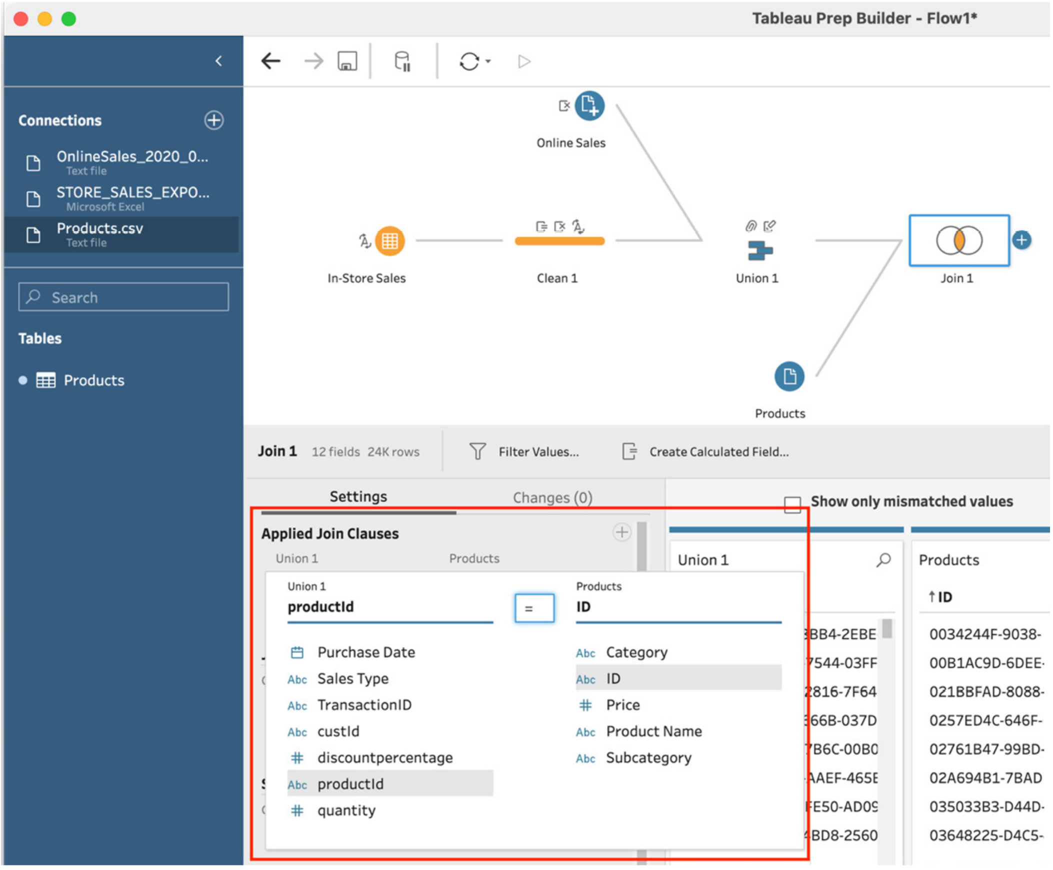


1. With the **Union** step still selected, notice that a new field has appeared in the **Union Results** field list, named **Table Names**. This field indicates where each row originated, that is, from our online sales dataset or the in-store dataset. This field may come in handy for downstream analysis, so let's rename the value **STORE_SALES_EXPORT.xlsx/EXPORT** to **In-Store Sales** and the field name itself to **Sales Type**, as shown in the following screenshot:

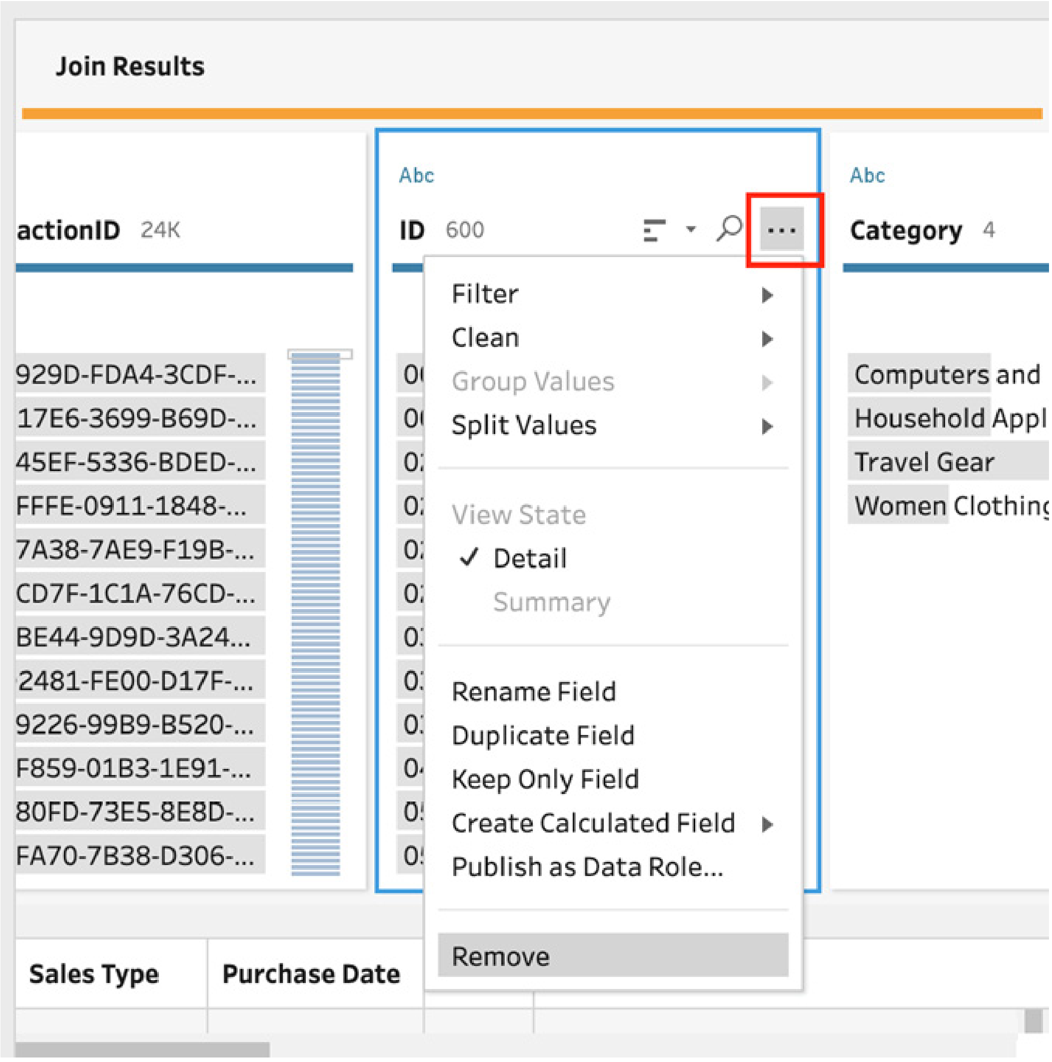
2. Next, create another data connection, this time to the **Products.csv** file, provided in the sample files with this lesson.

3. This **Products.csv** file we just added contains descriptive product information. For example, instead of using a product ID such as *1931E212-FF85-3A36-620A-8C56D1C6B605*, we can get a name such as *Modern Utility Laptop Messenger Bag*. To add this information to our existing dataset as additional columns, we need to perform a join. To do this, drag the input on top of the **Union** step. When the **Union** and **Join** options appear, drop the input on top of the **Join** option to instantly add a join step.

4. Configure the join by specifying a common field between the two datasets, in this case, **productId** and **ID**, as shown in the following screenshot. The default join type, inner, can be left as-is:

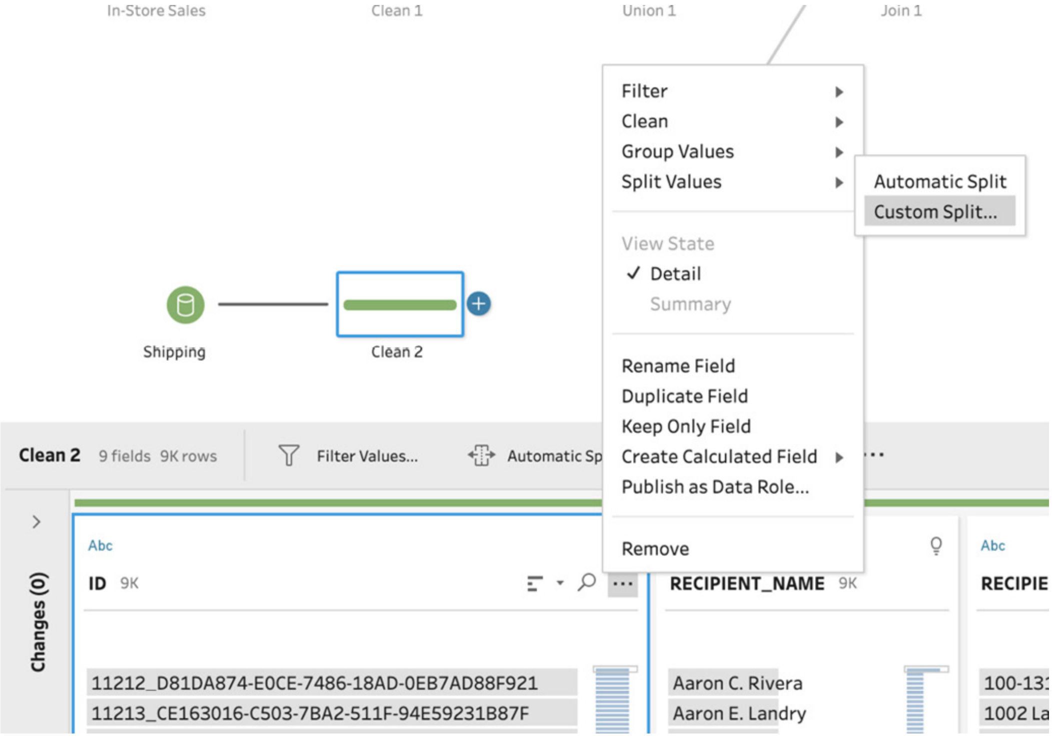


5. As is typical with a join, we now have a redundant field for product ID. Remove the **ID** field from the field list by selecting **Remove** from the field context menu. This way, we only have the **productId** field as the identifier:



6. Add another data source, this time a Tableau extract named **ShippingData.hyper**. This data is provided by our shipping department and contains shipping information for sales completed online. Rename the step **Shipping**.

7. Add a clean step to the **Shipping** input and observe the field named **ID**. The shipping ID here is made up of two identifiers; first, the shipping department's ID, followed by an underscore symbol and then the purchase ID. We need to split this field so that these values are stored separately. To do this, select **Custom Split...** from the context menu for the **ID** field:



- Configure the split to use the underscore (_) symbol as a

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separator and split the first **2** fields, as shown in the
following screenshot:
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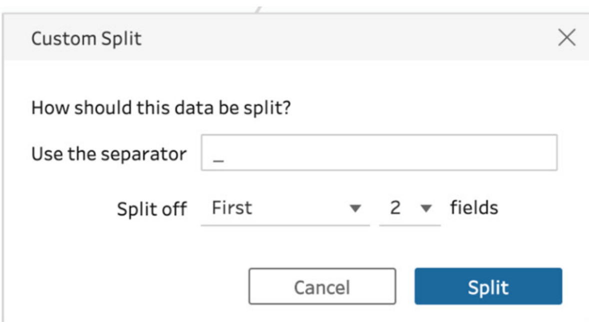
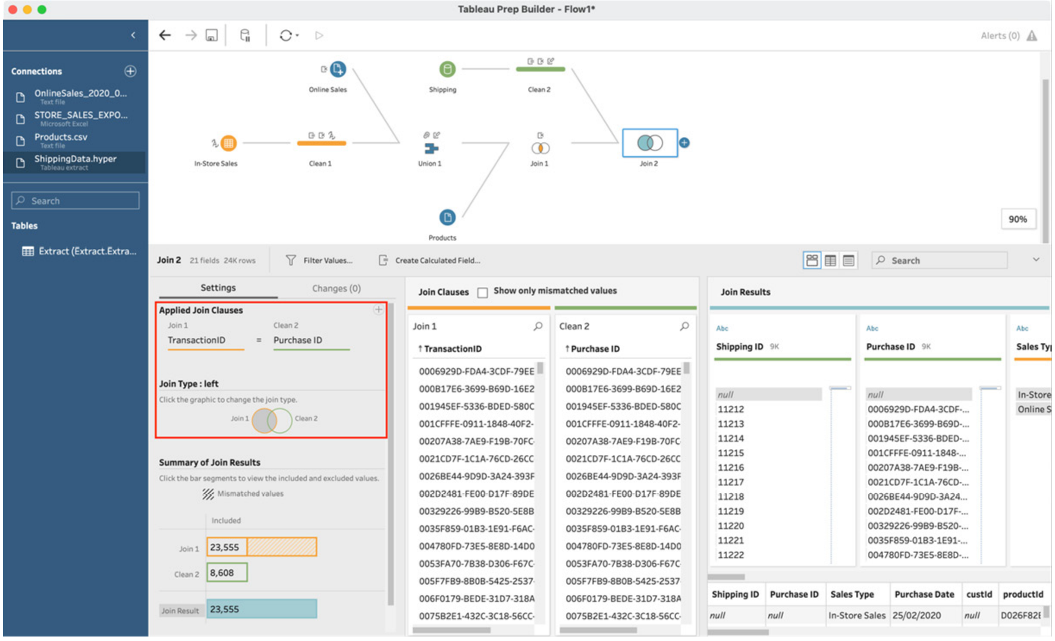


- When you're ready, click **Split**. This will then split the ID field into two new fields, named **ID - Split 1** and **ID - Split 2**:

1. Rename the **ID - Split 1** field to **Shipping ID** and the **ID - Split 2** field to **Purchase ID**.
2. We will no longer need the original **ID** field, so use the context menu to remove it from the dataset.
3. Drop the **Shipping** input on top of the existing join in order to create another **Join** step. Configure the join clause to use the **TransactionID** and **Purchase ID** fields to perform the join. Because only sales are shipped, the shipping data does not contain information for store sales. As such, we need to set this join to a left join type. A left join will result in including all data from the left dataset, which is our main flow, and any matching data from the right dataset, which is our shipping data. Set **Join Type** to **left** by selecting the left circle in the Venn diagram. Your flow and join settings should look like those in the following screenshot:



4. Delete the now redundant **Purchase ID** field. We still have the **TransactionID** field to identify a given row of data.

5. Add your fifth data connection to this flow. This time, select the **CustomerList.csv** text file. This input contains information about our customers, such as their full name. Rename the input step to **Customers**.

6. The **Customers** data includes an **ID** field, which has been incorrectly set to a numeric format by Tableau Prep. Click the data type icon for the **ID** field and change the type to **String**.

7. Join the **Customers** data to the existing flow by dropping it on the **Join 2** step. Configure the join clause to join on the **custId** and **id** fields. Because in-store checkouts do not always involve a customer loyalty card, the customer ID is not always known. Given the missing customer IDs, set the join type to **left** using the Venn diagram so that all rows are included from our main flow, including those for which we do not have customer details.

8. Delete the redundant customer ID field, named **id**, which originated from the **Customers** data.

9. Add our final data connection, the text file named **returns_h1_2020.csv**, and rename the step to **Returns**.

10. Correct the data type for the **return_id** field by setting it to **String**.

11. Rename the **status** field to **Return Status** so that we don't mix it up later with the existing status fields from the **Shipping** and **Customer** data.

12. Join the **Returns** step with the main flow by dropping it on top of **Join 3** to create a new join. Configure the join clause to use the **TransactionID** and **purchase_id** fields. Once more, use the Venn diagram to set the join type to **left**. Not all customers are returns, so we want to return all transactions and any matched rows from the **Returns** dataset.

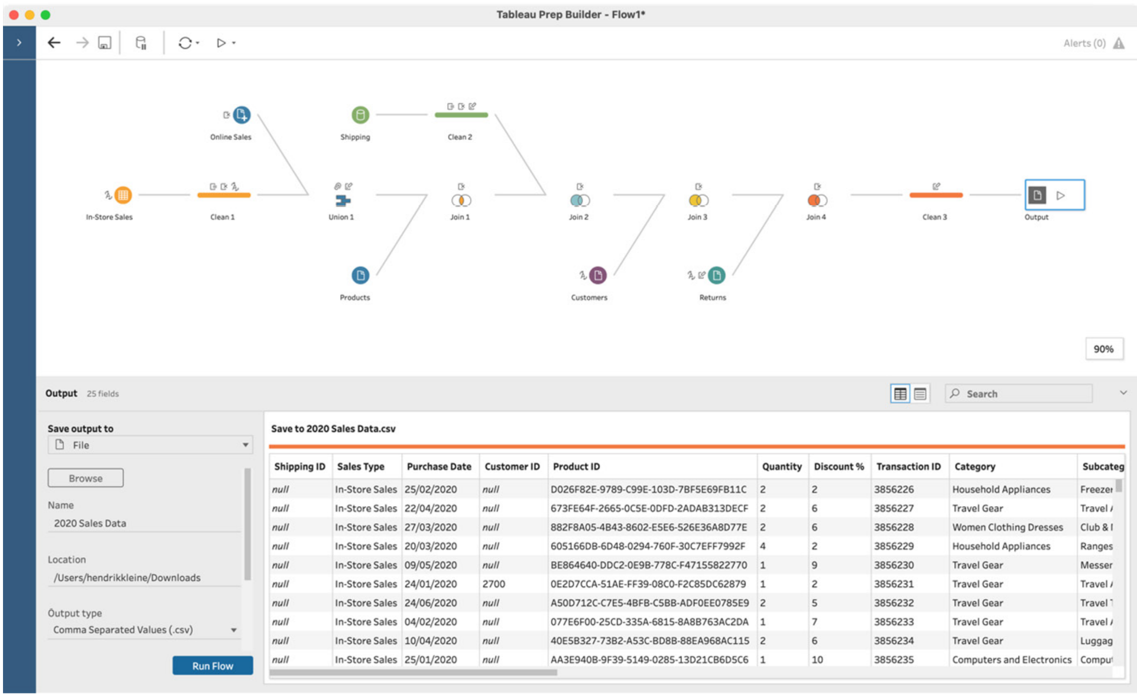
13. Remove the redundant **purchase_id** field from the dataset.

14. Click the **+** icon on the last join and add a **Clean** step. Using the **Clean** step, rename the fields as follows:

- **custId** to **Customer ID**

- **productId** to **Product ID**
- **quantity** to **Quantity**
- **discountpercentage** to **Discount %**
- **TransactionID** to **Transaction ID**
- **RECIPIENT_NAME** to **Recipient Name**
- **RECIPIENT_STREET** to **Recipient Street**
- **RECIPIENT_CITY** to **Recipient City**
- **RECIPIENT_POSTAL** to **Recipient Postal**
- **RECIPIENT_REGION** to **Recipient Region**
- **SHIPMODE** to **Shipping Mode**
- **TRACEID** to **Shipping Courier Tracking ID**
- **STATUS** to **Shipping Status**
- **name** to **Customer Name**
- **surname** to **Customer Surname**
- **status** to **Customer Membership Status**
- **return_id** to **Return ID**

15. As a final step, we need to add an output step to our flow. Click the **+** icon on the **Clean** step and select **Output**. Configure the output to write to a location of your choosing and set the filename to **2020-H1 Sales Data.csv** and the **Output** type to **CSV**. Your final flow should look like the following screenshot:



With these steps completed, you've finished this exercise and successfully created a comprehensive sales flow. If you wish, you can run the flow and analyze your data further in an application such as **Tableau Desktop**.

How it works...

In this exercise, we learned to combine multiple different tools and functions in Tableau Prep to create a comprehensive flow that provides a clean data output that can be used for downstream analysis. We leveraged different methods of input, cleaning, pivoting, union, join, calculated fields, and aggregation to create the ideal dataset and even perform quick analysis in Tableau Prep. This combination of tools is very common in flows and offers significant added value to companies who want to combine data from disparate systems into a single, holistic view.

Creating a call center flow for instant analysis

In this exercise, we'll explore another typical real-world example. In the previous exercise, *Creating a flow for transaction analytics*, our focus was to provide a new data *output* that could be used for further analytical purposes. In contrast, in this exercise, we'll leverage Tableau Prep to investigate data in order to answer a business question. That is, our objective is to find the answer using Tableau Prep itself. You're likely to find similar use cases in any industry, where your leadership relies on you not only preparing data but investigating that data and elaborating on things such as business performance using key metrics or performing a deep dive analysis for a specific scenario.

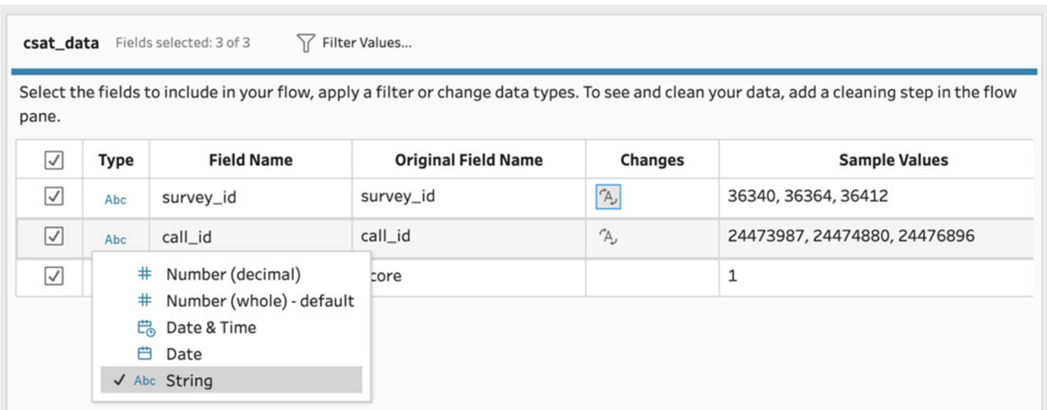
Getting ready

To follow along with this exercise, download the **Sample Files 8.2** folder from this course's GitHub repository. The files here contain information from a call center for a company selling laptops and desktop PCs. There are data files included for the month of January 2021 that include call information, case data from a CRM system, and an extract from a **Customer Satisfaction** (**CSAT**) survey. The CSAT survey is an optional survey sent to customers following a call and asks them to rate their satisfaction with the interaction on a scale of 1 to 10, where 1 is very dissatisfied and 10 is very satisfied. Let's assume that recently, the **Customer Satisfaction Score**, also known as the **CSAT Score**, has decreased and your leadership has tasked you with investigating why that may be. Using Tableau Prep, we're going to investigate the data available in order to identify some clues as to what may be affecting the drop in CSAT.

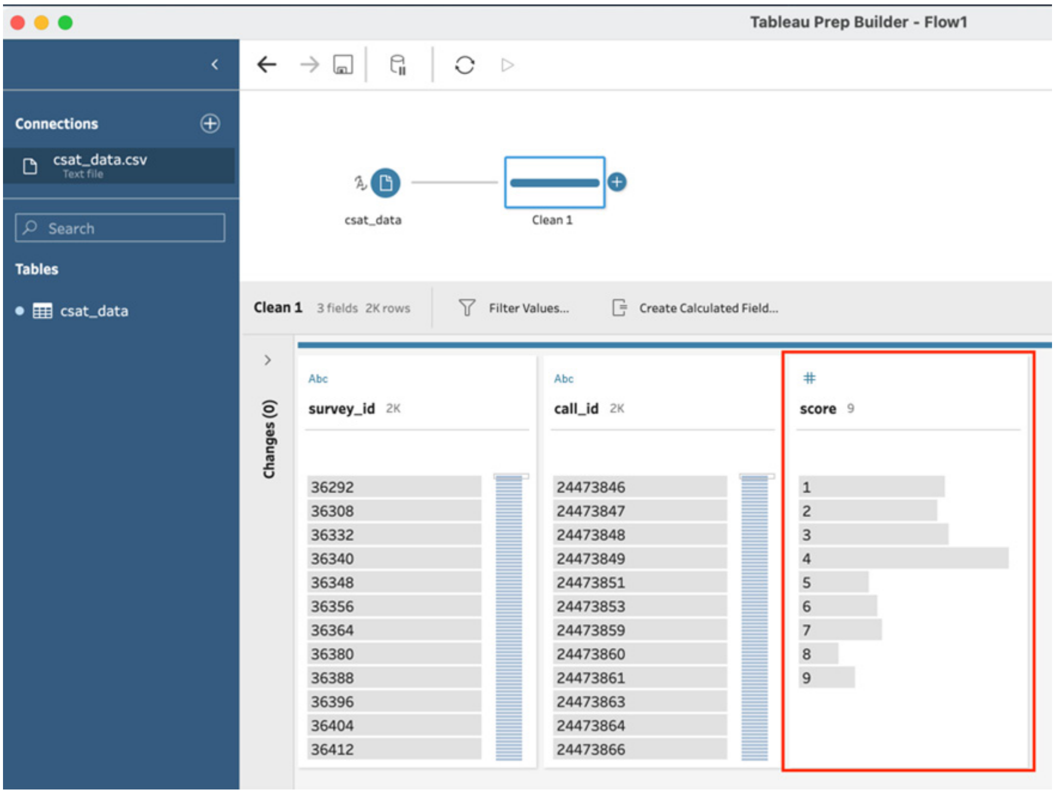
How to do it...

Let's start looking at the customer satisfaction data. Open a new Tableau Prep instance and connect to the **csat_data.csv** file from the **Sample Files 8.2** folder. Then, perform the following steps:

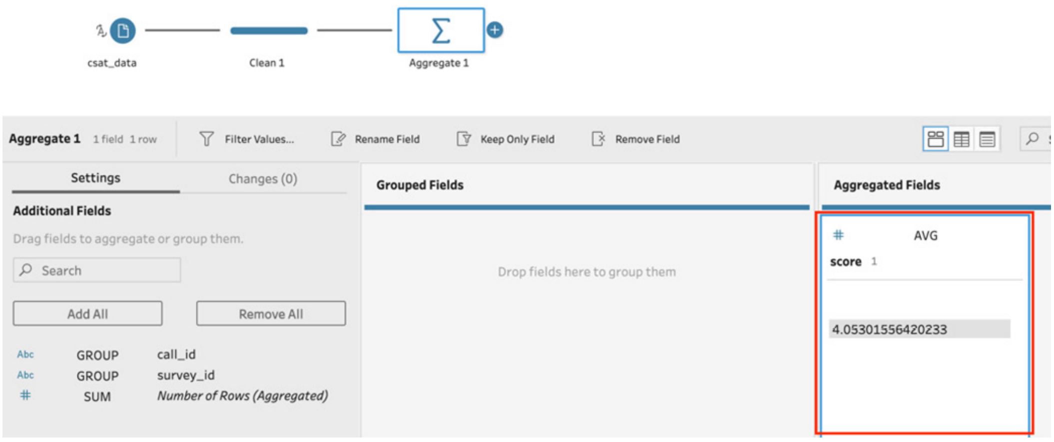
1. Start off by correcting the data types. Change **survey_id** to **String** and amend **call_id** to **String** as well:



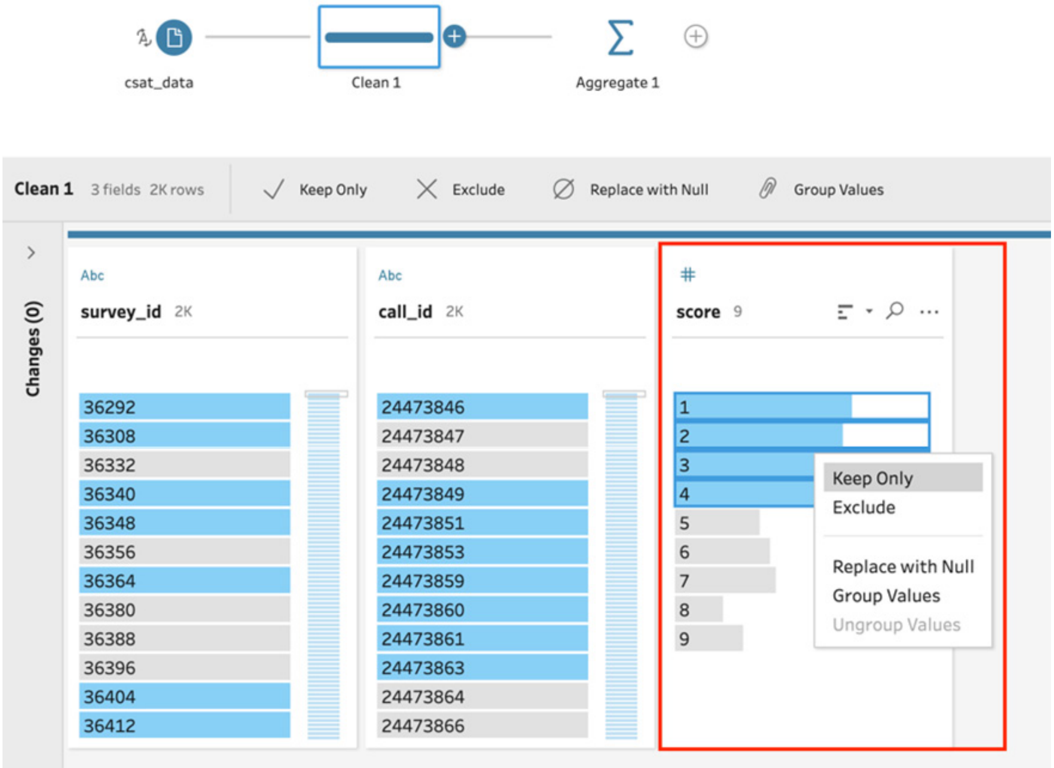
2. Next, click the **+** icon and add a **Clean** step to your flow. Observe the data profile and you will notice that the distribution of the survey score is skewed toward the lower end, as shown in the following screenshot. This is expected as we're investigating the reason behind the business's low survey score:



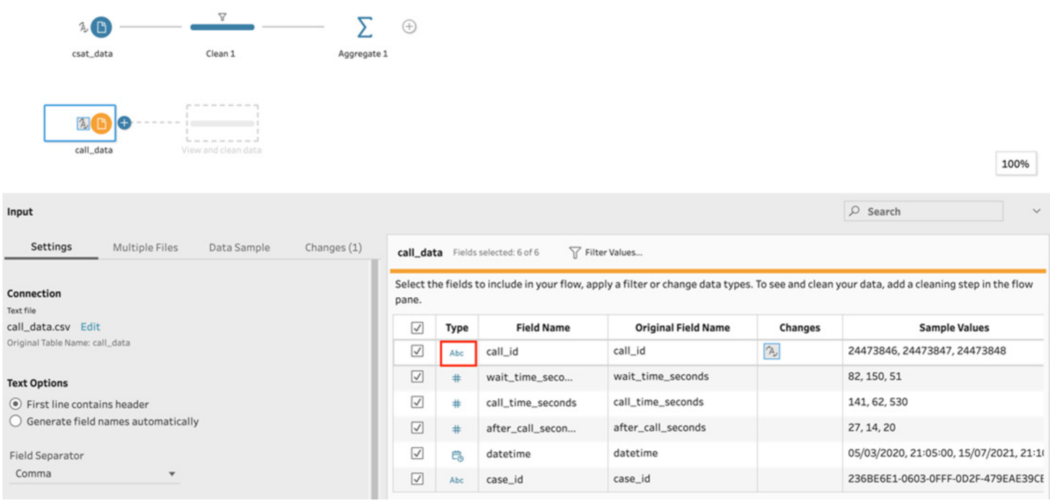
3. Let's now get the average score by adding an **Aggregate** step. In the step configuration, drag and drop the **score** field to the **Aggregated Fields** section, and click **SUM**, followed by **Average**, to get the average score across all surveys. Here, we can see that our average score is 4.05, as shown in the following screenshot:



4. Now that we know the average score, let's narrow our dataset to surveys where the customer scored between 1 and 4. To do this, select the **Clean** step, select the score values **1**, **2**, **3**, and **4** (use the *Command* or *CTRL* key to multi-select), and then right-click and select **Keep Only**. This will filter our survey data for scores 1-4 only:

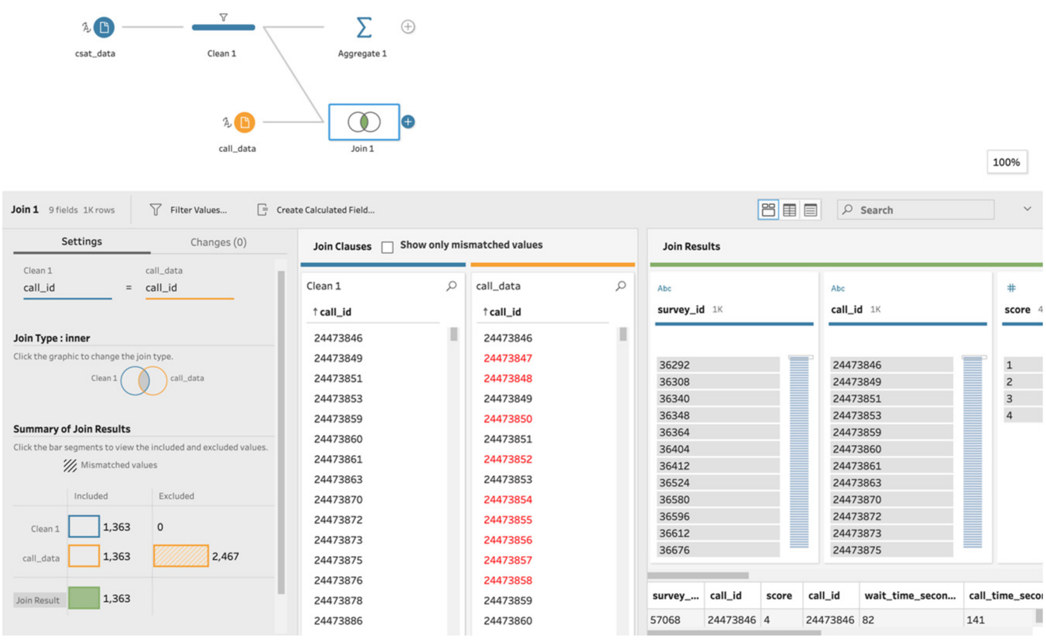


5. Let's see what we can find out from the call data for these surveys. Add another data connection, this time to the file **call_data.csv**. This dataset contains information about the date the call was made, how long the customer had to wait before being connected to a customer service agent (the **wait_time_seconds** field), the duration of the conversation with the agent (**call_time_seconds**), and the time the agent spent updating the case management system after the call ended (**after_call_seconds**). Before you continue, correct the **call_id** field data type by setting it to **String**, as shown in the following screenshot:



6. Let's join this data with our survey data. To do this, drag the **call_data** step on top of the **Clean** step and select **Join** to instantly add the **Join** step. Notice how Tableau Prep seamlessly branches our flow (the

original branch ending with **Aggregate**), as shown in the following screenshot. Since our two datasets contain the same field name, **call_id**, Tableau Prep automatically configures **Join Clauses** to use that field, which is appropriate. We can leave the **Join Type** default set to **Inner**, which ensures that only calls matching our filtered survey data come through:

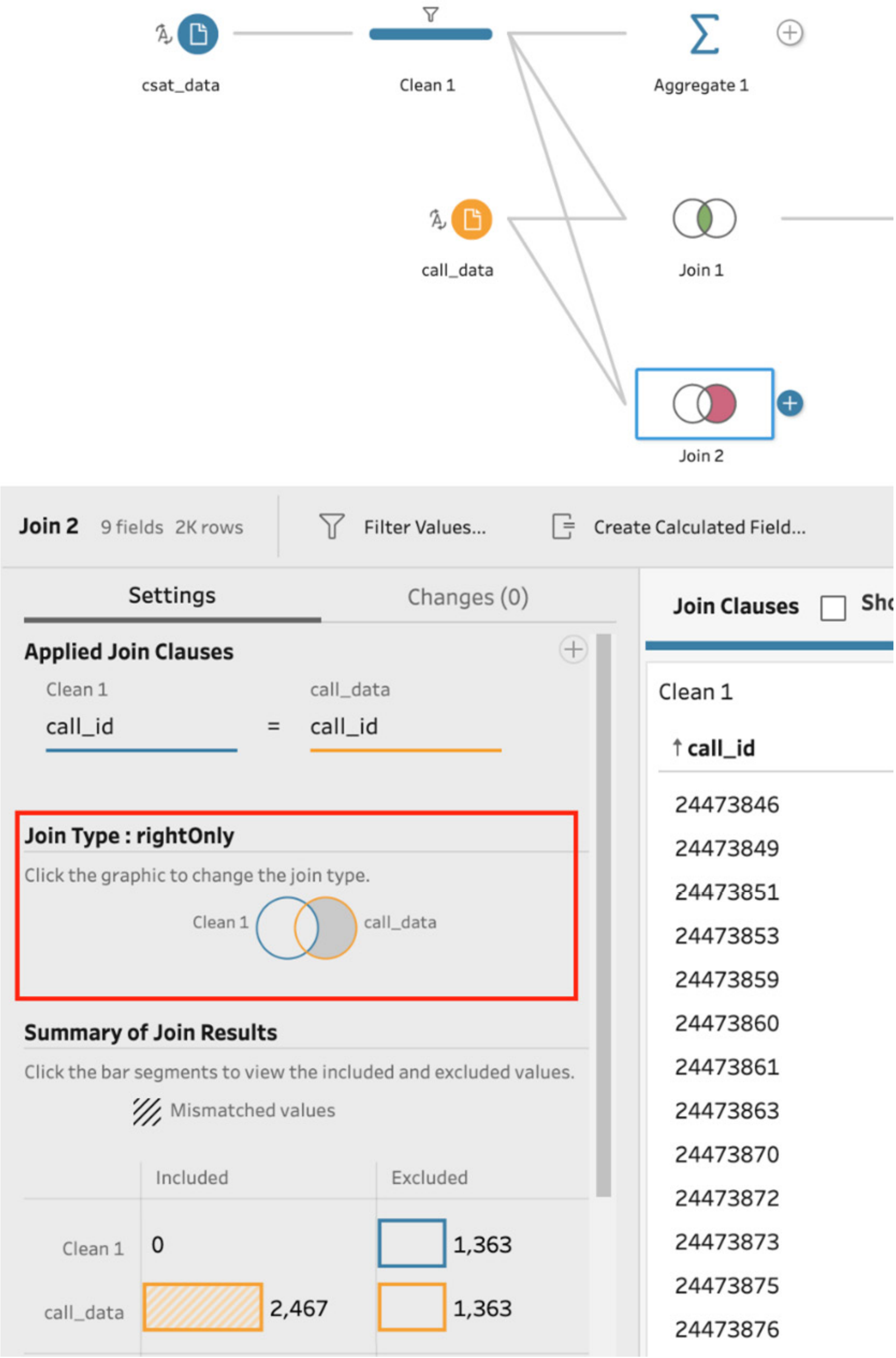


7. To keep your dataset lean, add a new **Clean** step after **Join** and remove the duplicate field, **call_id-1**.

8. Let's pull up the average call times next. Add a new **Aggregate** step after **Join** and drag the **wait_time_seconds**, **call_time_seconds**, and **after_call_seconds** fields to the **Aggregated Fields** section and change the aggregate for all fields from **SUM** to **Average**. In order to easily view the results, add a **Clean** step after **Aggregate**, as shown in the following screenshot:

We will need to compare this information to calls with a higher survey score, that is, calls with a score of between 5 and 10. We'll proceed to do so in the next step.

9. Go ahead and, once again, join the **call_data** field with the first **Clean** step, resulting in a third branch in our flow. This time, we are only interested in calls where the user had either no survey score at all (which is possible, because the survey is optional), or a score higher than 4. To do this, configure **Join Type** to **rightOnly** using the Venn diagram illustration. This will result in returning all data from the right side, which is the call data that does not match any data in the filtered clean step (which is filtered for results with a score of 1-4 only):



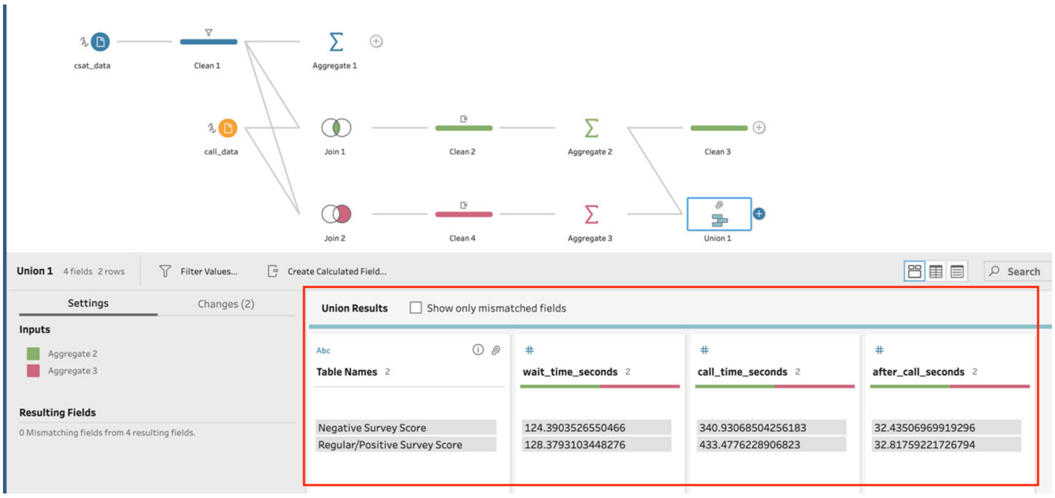
10. To keep our data tidy, add a **Clean** step and remove the duplicate **call_id** field, keeping **call_id-1**.

Important note

In this exercise, we're using the Clean step function to remove fields from the dataset that have become redundant following a Join step. It should be noted that the same action, removing a field, can be performed in the Join step itself, even if that field is part of the Join clause. It's a personal preference related to how you wish to visually organize your flow.

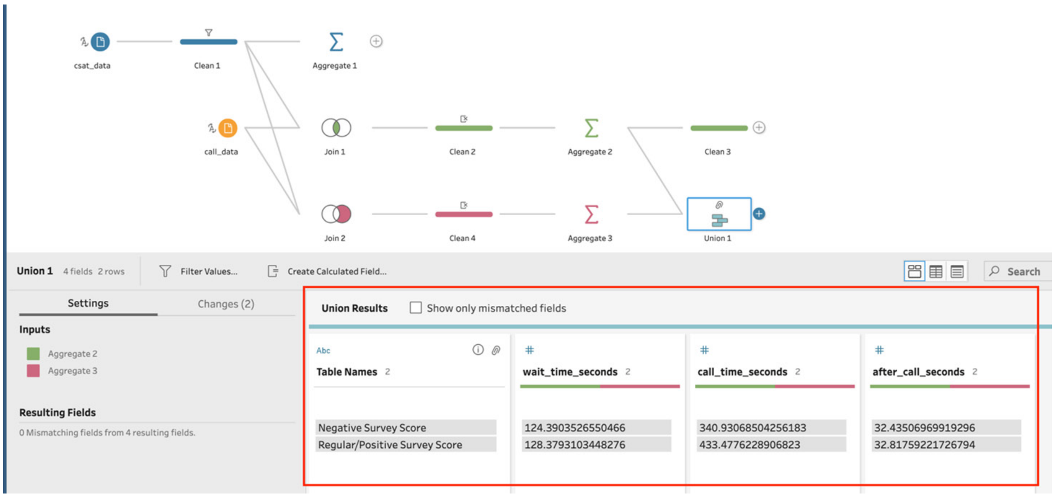
11. Now that our new, third branch only contains positive survey data (assuming positive is no score, or a score of between 5-10), let's perform the same aggregate analysis we did previously, that is, add a new **Aggregate** step after **Join** and drag the **wait_time_seconds**, **call_time_seconds**, and **after_call_seconds** fields to the **Aggregated Fields** section, and then change the aggregate for all fields from **SUM** to **Average**.

12. To easily compare this result with our previous aggregate result for negative survey call data, drag the step marked **Aggregate 3** on top of **Aggregate 2** and select **Union** to add a **Union** step. In the **Union** step, double-click the **csat_data.csv,call_data.csv** value in the table names field and rename it **Regular/Positive Survey Score**. Then, rename the **call_data.csv-1,csat_data.csv-1** value to **Negative Survey Score**, as shown in the following screenshot:



In the **Union Results** view, we can now easily compare the call data. While the **wait_time_seconds** and **after_call_seconds** values are relatively similar, we can see a significant difference in **call_time_seconds**. In fact, it's roughly **27%** (433/349) higher than calls that resulted in a positive feedback score.

13. It might be interesting to see what percentage of callers experienced this higher call time and left a negative score. We can easily go back to any step in our flow and make changes to their configurations, something that is very typical in an ad hoc analysis such as this. Return to both the **Aggregate 2** and **Aggregate 3** steps and add the **Number of Rows** field to the **Aggregated Fields** section. The **Number of Rows** field is automatically generated in the aggregate step and lets us know the row count for the step. When done, return to the **Union** step, as shown in the following screenshot:



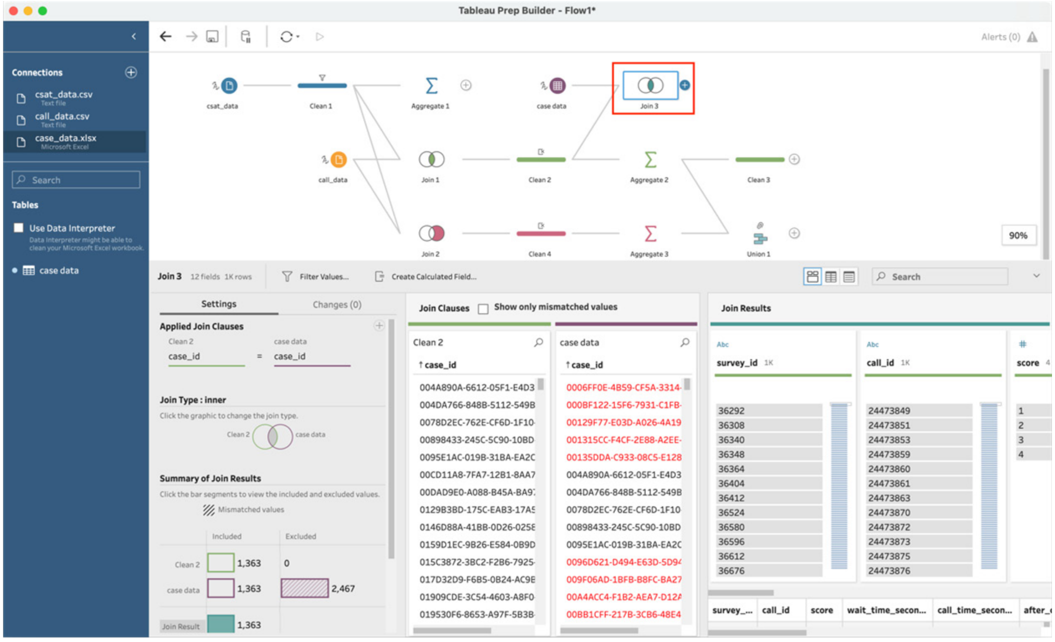
Notice that **1,363** customers out of a total of 3,830 (**1,363**+**2,467**) customers experienced a higher call time, at least on average, and left a negative survey score. That equates to 36% of all callers.

Important note

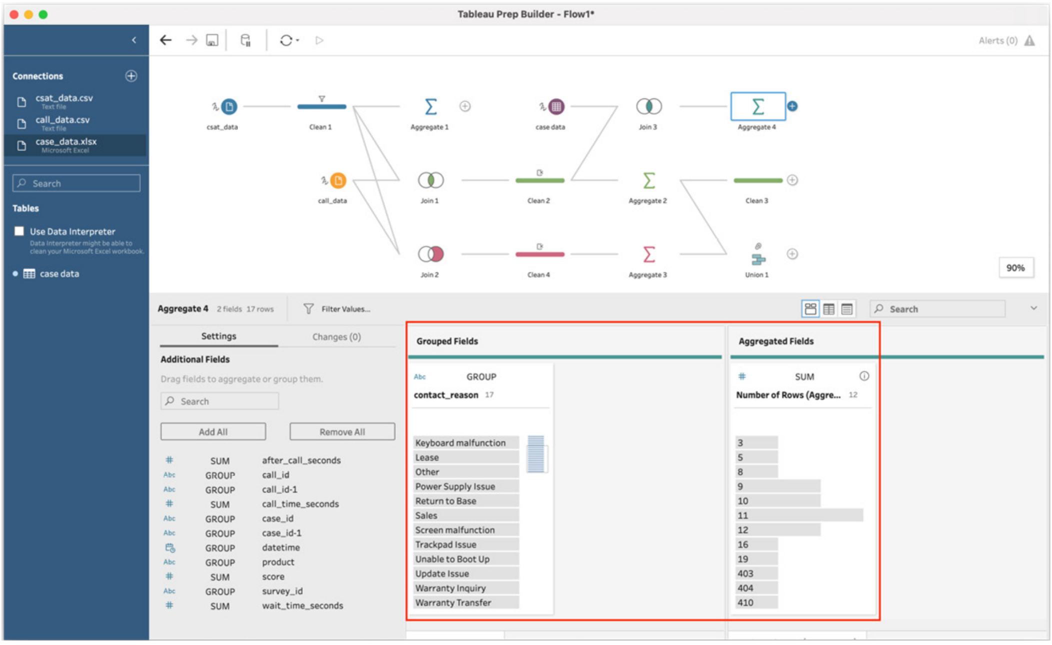
Don't forget your plain old calculator. Oftentimes, simple quick calculations during an ad hoc analysis, such as determining the percentage difference in this step, are done faster on a simple calculator. If you do not need to recalculate this value again or do not intend to run your flow against new data, this simple tip can often save you time.

14. The datasets supplied also include a case data file. This data contains an extract from the call center case management system and records the purpose of the call, as well as the related product. Add a third data connection to your flow for the Excel file, **case_data.xlsx**. In the connection settings, correct the data type for the **call_id** field to **String**.

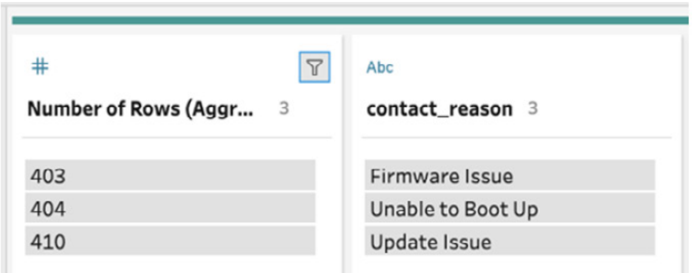
15. Join the newly added case data with the **Clean 2** step by dragging and dropping the **Case Data** step on top of the **Clean 2** step. The **Clean 2** step contains all the data we have used so far for customers who left a rating of between 1 and 4. By joining it with the case data, we can start identifying the reasons these customers called in. Leave the automatically detected **Join Clause** set to **case_id** and **Join Type** as **inner**, as shown in the following screenshot:



16. Add an **Aggregate** step after the newly added **Join 3** and then add **contact_reason** to the **Grouped Fields** section, and **Number of Rows** to the **Aggregated Fields** section, as shown in the following screenshot:



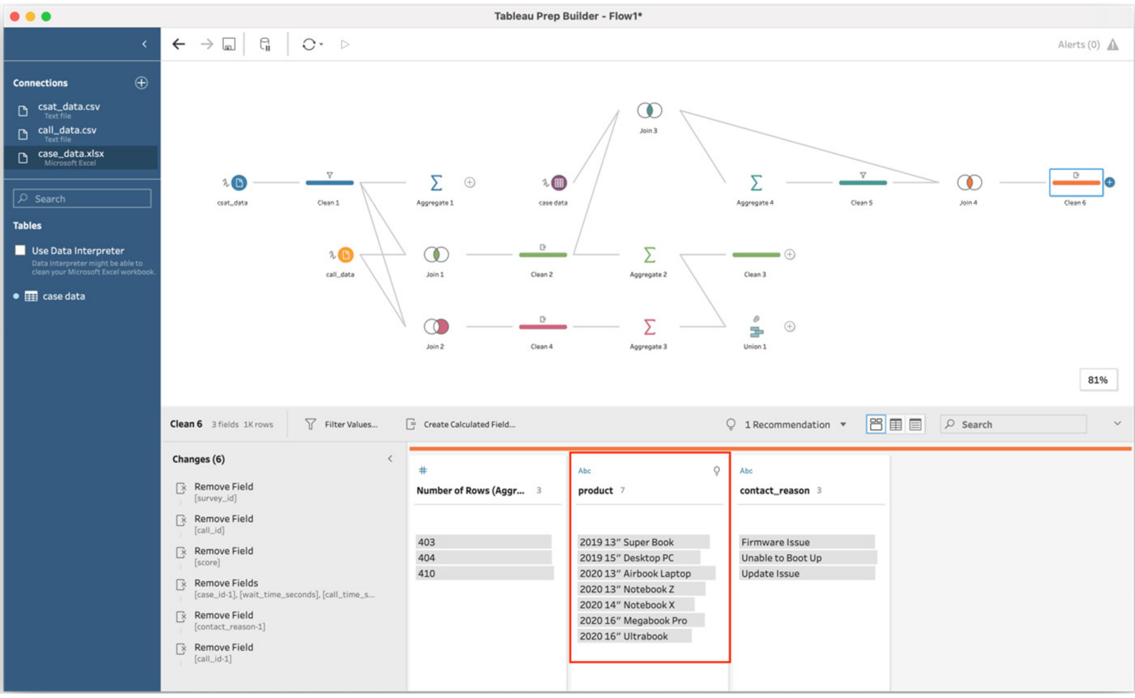
17. Next, add a **Clean** step and observe the number of rows by **contact_reason**. It's quite obvious that three numbers stand out from the rest: **403**, **404**, and **410** are significantly higher than the other row counts. Select the three numbers, right-click, and select **Keep Only** to filter the data to just these three values. In doing so, we quickly see the three main reasons why people called in: **Firmware Issue**, **Unable to Boot Up**, and **Update Issue**, as shown in the following screenshot:



18. To ascertain the percentage of calls routed to these three reasons, click the **Join 3** step to see the number of rows in this branch listed under **Join Result** in the configuration. The number of rows here, **1,363**, is the number of surveys with a score of 4 or lower. With the information collected in *Step 17*, we can calculate the percentage of calls within this subset that are related to one of the three key categories, that is, (403+404+410)/1363 = *89%*.

19. **case data** also includes the **product** per case. Let's see which products are affected by the three case reasons we've identified in *Step 17*. To do this, join **Join 3** with **Clean 5**. Leave the default configurations set, with **Join Clause** on **contact_reason** and **Join Type inner**.

20. Finally, add a **Clean** step after the newly added join and remove all fields with the exception of **Number of Rows**, **product**, and **contact_reason**. Now we can clearly see the affected products in the product file, as shown in the following screenshot:



With these steps completed, you've successfully performed an ad hoc analysis in Tableau Prep itself. We could summarize our findings in a report to the requestor as follows:

- The average customer satisfaction score for January 2021 is **4.05** (out of 10).
- More than a third, **36%**, of customers rated their level of satisfaction as 4 or lower.

- On average, customers who left negative feedback typically experienced call times **27% longer** compared to call times for customers who left positive feedback.
- Out of **1,363** calls related to negative feedback (4 or lower), **1,217 (89%)** were related to issues with regard to **Firmware, Updates or Booting up**. The products that these calls and issues relate to are the following:

  2019 13" Super Book

  2019 15" Desktop PC

  2020 13" Airbook Laptop

  2020 13" Notebook Z

  2020 14" Notebook X

  2020 16" Megabook Pro

  2020 16" Ultrabook

How it works...

In this exercise, we learned to use Tableau Prep as a data investigation tool. We were presented with data and a business question, and we merged different data sources and tools in order to find the answer. This use case presents the incredible value Tableau Prep has to offer as a data analysis tool in its own right. Oftentimes, it can be faster to perform analysis like we did in this exercise, in Tableau Prep itself, rather than performing the additional steps of writing outputs and then continuing the work in a visualization tool.