Prepare Training Data for Machine Learning with Minimal Code

TUTORIAL

Overview

In this tutorial, you will learn how to prepare data for machine learning (ML) using Amazon SageMaker Data Wrangler.

Amazon SageMaker Data Wrangler reduces the time it takes to aggregate and prepare data for ML from weeks to minutes. Using SageMaker Data Wrangler, you can simplify the process of data preparation and feature engineering and complete each step of the data preparation workflow, including data selection, cleansing, exploration, and visualization from a single visual interface.

In this tutorial, you will use Amazon SageMaker Data Wrangler to prepare dat
prediction model. You will use a version of the Brazil house rental dataset found in the Kaggle

data for bias, and lastly save the output to Amazon S3 to be used later for ML training.

What you will accomplish

In this guide, you will:

- Visualize and analyze data to understand key relationships
- Apply transformations to clean up the data and generate new features
- Automatically generate notebooks for repeatable data preparation workflows

Prerequisites

Before starting this tutorial, you will need:

- **An AWS account:** If you don't already have an account, follow the Setting Up Your AWS Environment getting started guide for a quick overview.

AWS experience
Beginner

Minimum time to complete
30 minutes

Cost to complete
See Amazon SageMaker pricing to estimate cost for this tutorial.

Requires
You must be logged into an AWS account.

Services used
Amazon SageMaker Data Wrangler

Last updated
March 7, 2023

Step 1: Set up your Amazon SageMaker Studio domain

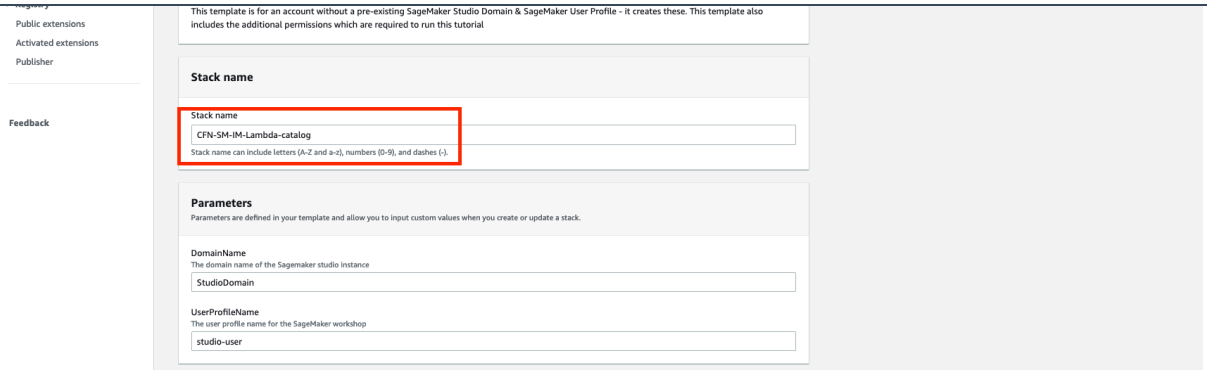
With Amazon SageMaker, you can deploy a model visually using the console or programmatically using either SageMaker Studio or SageMaker notebooks. In this tutorial, you deploy the model programmatically using a SageMaker Studio notebook, which requires a SageMaker Studio domain.

An AWS account can have only one SageMaker Studio domain per Region. If you already have a SageMaker Studio domain in the US East (N. Virginia) Region, follow the SageMaker Studio setup guide to attach the required AWS IAM policies to your SageMaker Studio account, then skip Step 1, and proceed directly to Step 2.

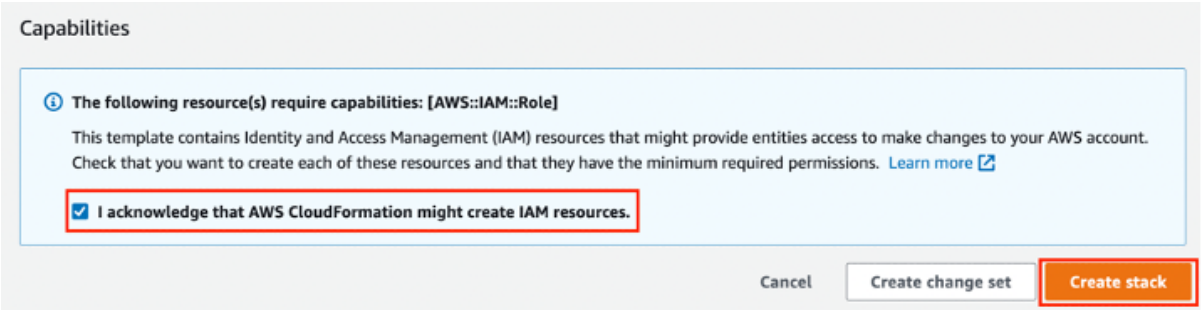
If you don't have an existing SageMaker Studio domain, continue with Step 1 to run an AWS CloudFormation template that creates a SageMaker Studio domain and adds the permissions required for the rest of this tutorial.

Choose the **AWS CloudFormation stack** link. This link opens the AWS CloudFormation console and creates your SageMaker Studio domain and a user named *studio-user*. It also adds the required permissions to your SageMaker Studio account. In the CloudFormation console, confirm that **US East (N. Virginia)** is the **Region** displayed in the upper right corner. **Stack name** should be **CFN-SM-IM-Lambda-catalog**, and should not be changed. This stack takes about 10 minutes to create all the resources.

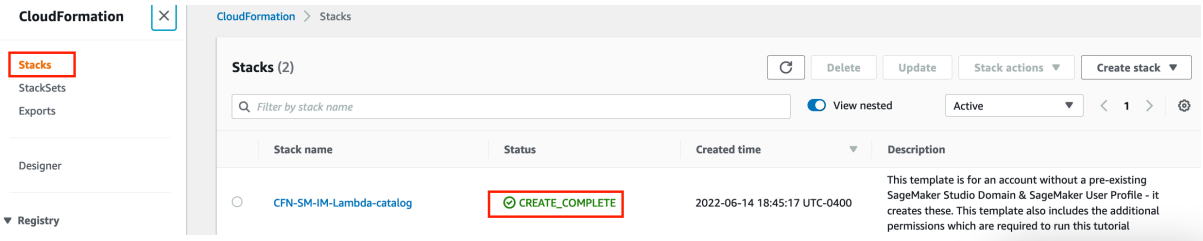
This stack assumes that you already have a public VPC set up in your account. If you do not have a public VPC, see VPC with a single public subnet to learn how to create a public VPC.



Select **I acknowledge that AWS CloudFormation might create IAM resources**, and then choose **Create stack**.



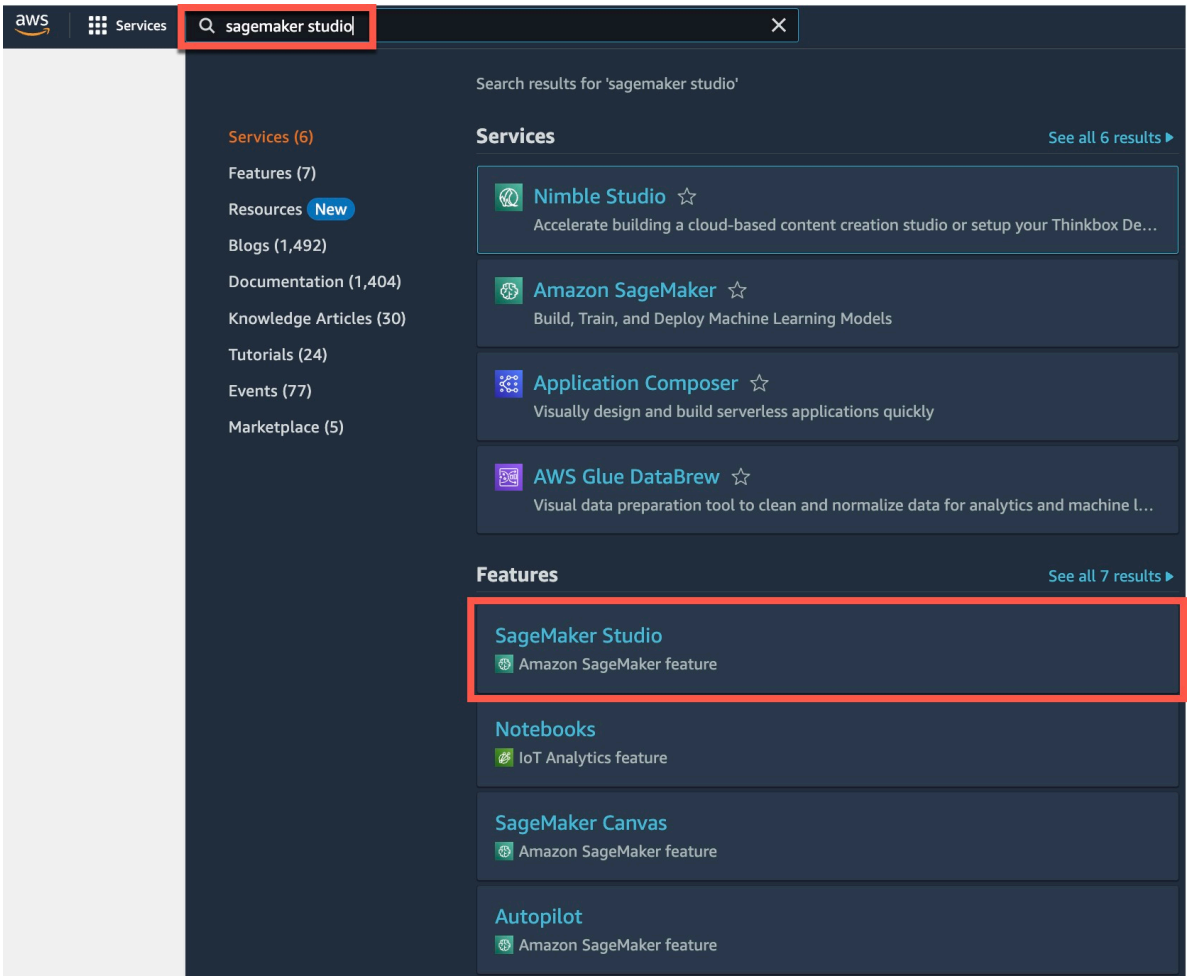
On the **CloudFormation** pane, choose **Stacks**. It takes about 10 minutes for the stack to be created. When the stack is created, the status of the stack changes from **CREATE_IN_PROGRESS** to **CREATE_COMPLETE**.



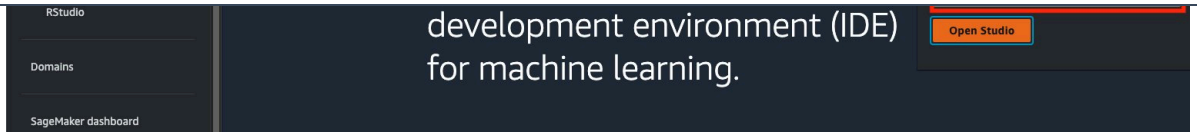
Step 2: Create a new SageMaker Data Wrangler flow

information about homes along with a target column indicating the rental amount of the property.

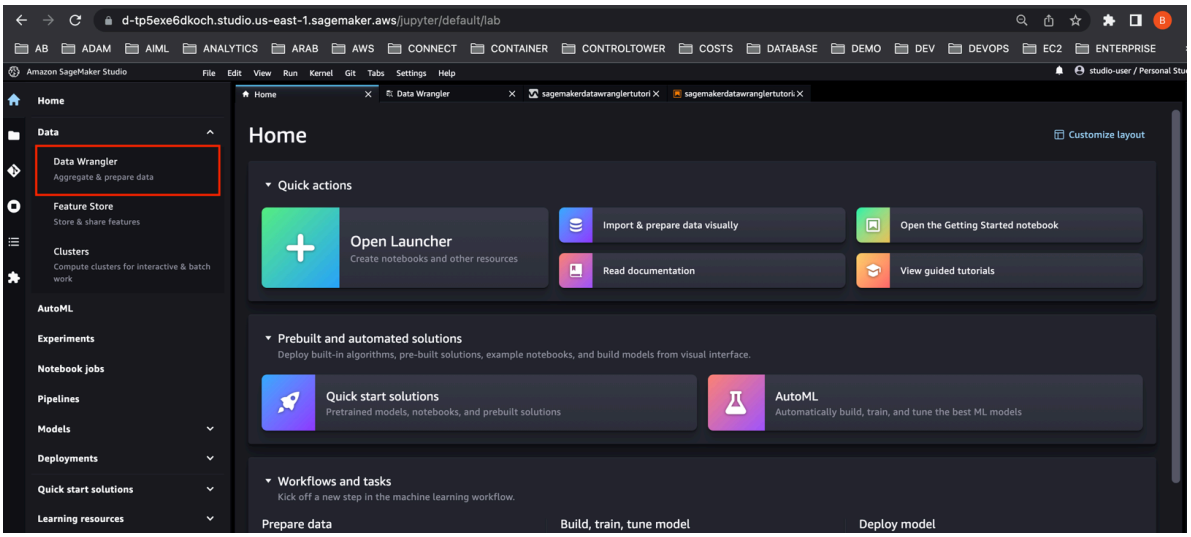
Enter **SageMaker Studio** into the console search bar, and then choose **SageMaker Studio**.



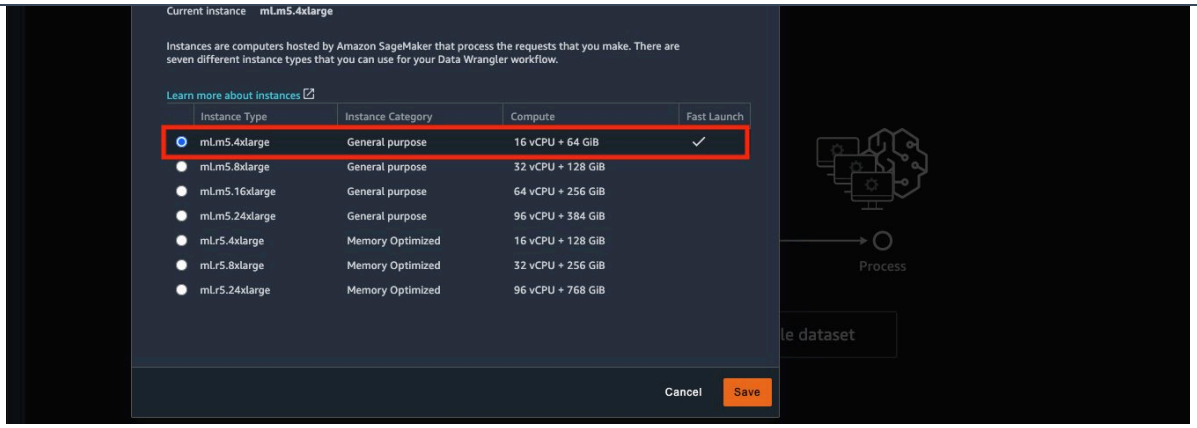
Choose **US East (N. Virginia)** from the Region dropdown list on the upper right corner of the SageMaker console. Browse to the **Getting Started** sect left-hand navigation and then choose **Studio**. Then select the studio and then choose the **Open Studio** button.



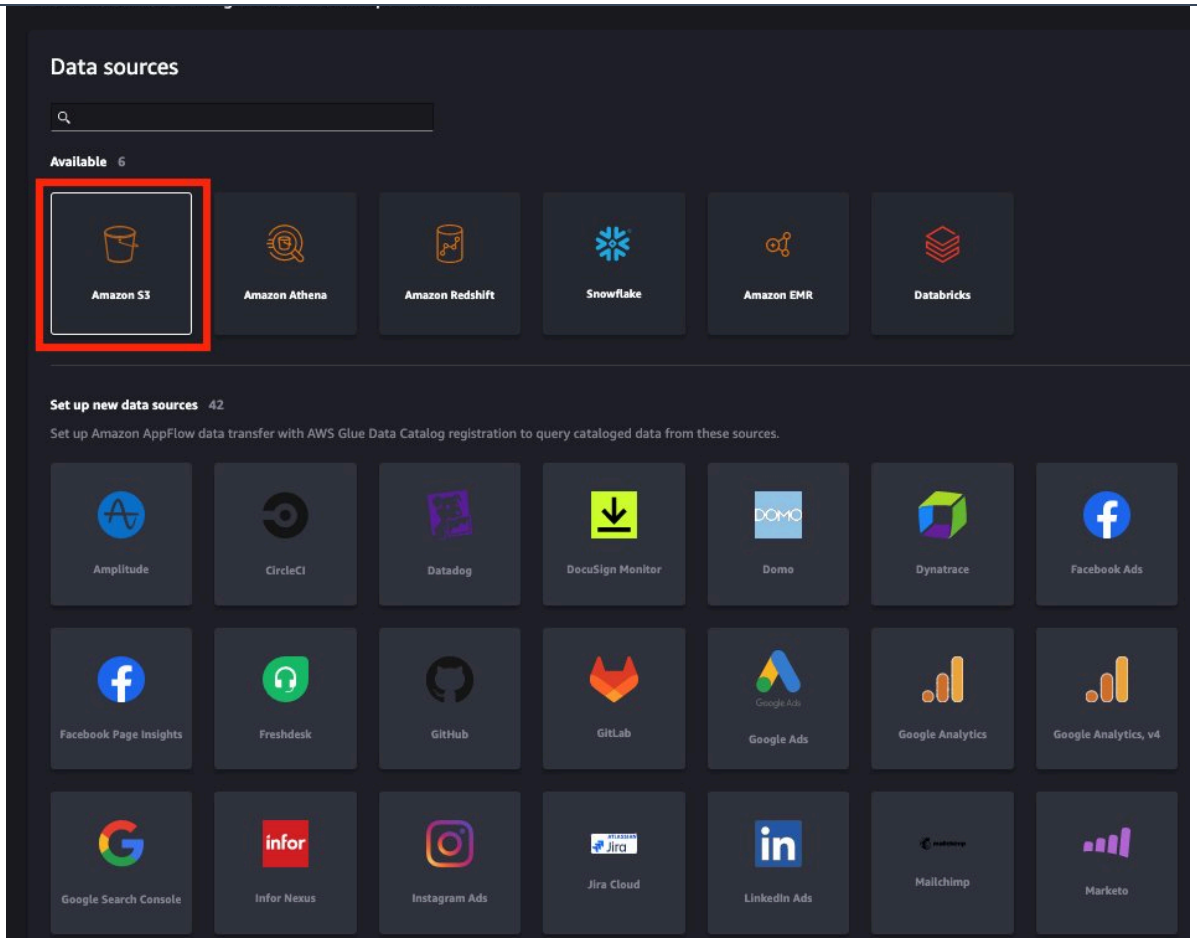
Open the **SageMaker Studio** interface. On the navigation bar, choose **Data Wrangler** on the left-hand side, and then choose the **Import Data** button.



Note that you can change the Flow's compute instance type using the upper right button showing the current Compute instance. You may decide to change the compute instance type based on your scenario's dataset size and can scale it up or down when your requirements change. For the purposes of this tutorial, you can use the default **ml.m5.4xlarge**.

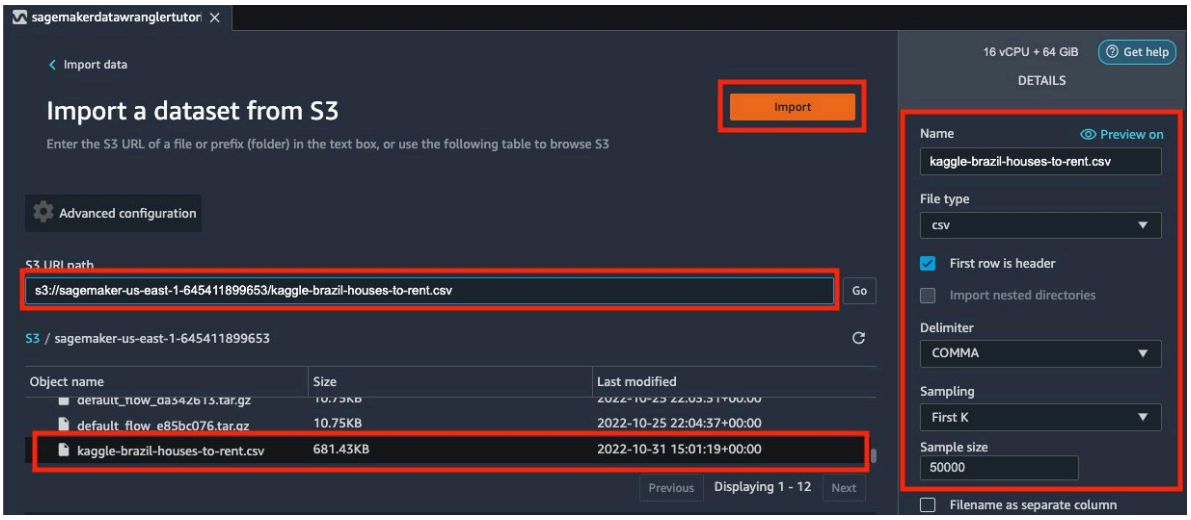


In the **Data Import** tab, under **Import** data, choose **Amazon S3.**



In the S3 URI Path field, enter **s3://sagemaker-sample-files/datasets/tabular/brazil_houses/kaggle_brazil_houses_rental_data.csv**, and then choose **Go**. Under **Object name**, select **kaggle_brazil_houses_rental_data.csv.**

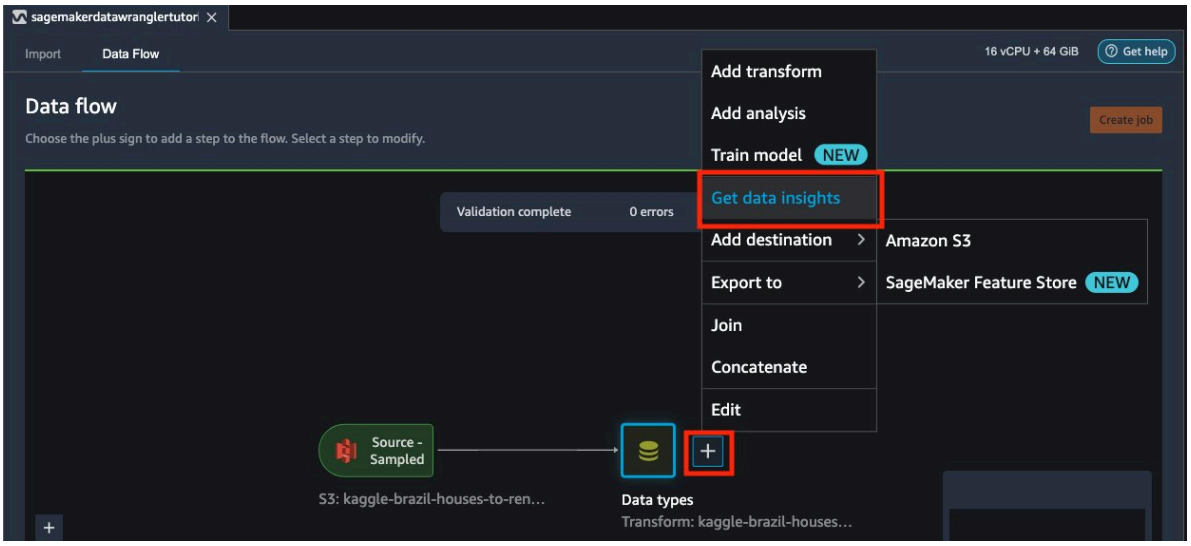
In the S3 import details panel, note that you can change the default delimiter and the sampling method when necessary. For the purposes of this tutorial, you can use the default **comma delimiter** and **First K sampling method**. Then choose **Import**.



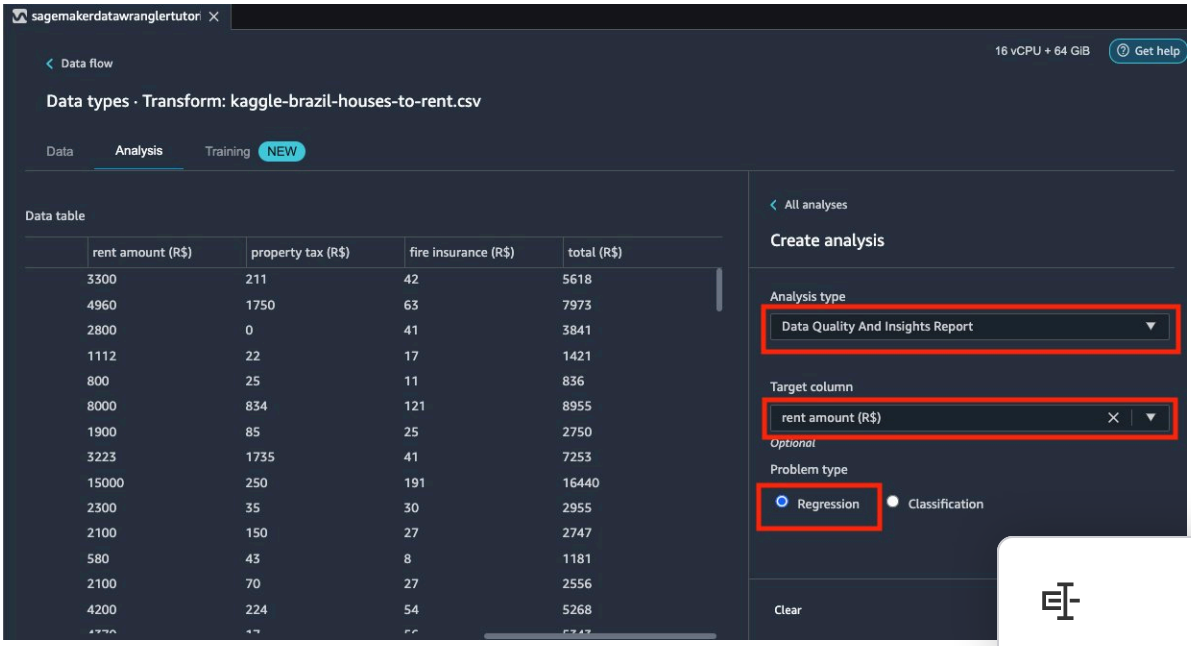
Step 3: Explore the data

In this step, you use SageMaker Data Wrangler to assess and explore the quality of the training dataset for building machine learning models. Use the Data Quality and Insights report feature to understand your dataset quality, and then use the Quick Model feature to estimate the expected prediction quality and the predictive power of the features in your dataset.

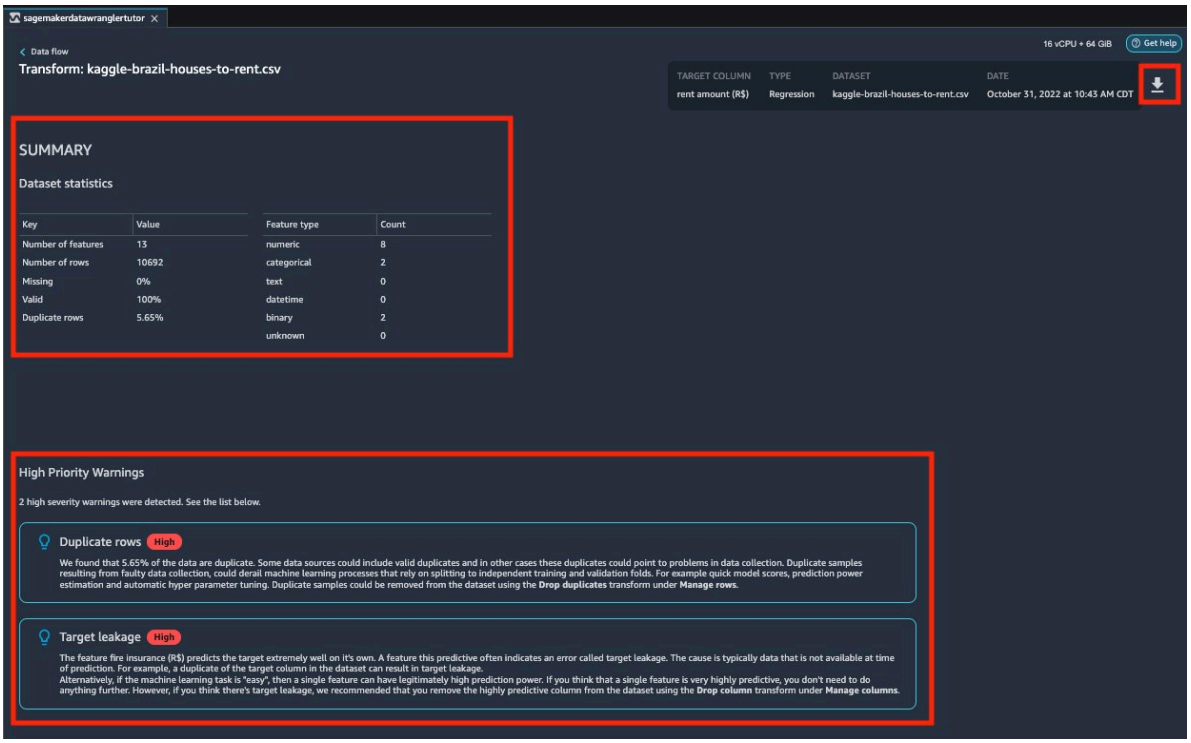
your attention on the most important areas to improve the data. On the **Data flow** tab, in the data flow diagram, choose the **+** icon, then choose **Add analysis.** Then choose **Get data insights.**



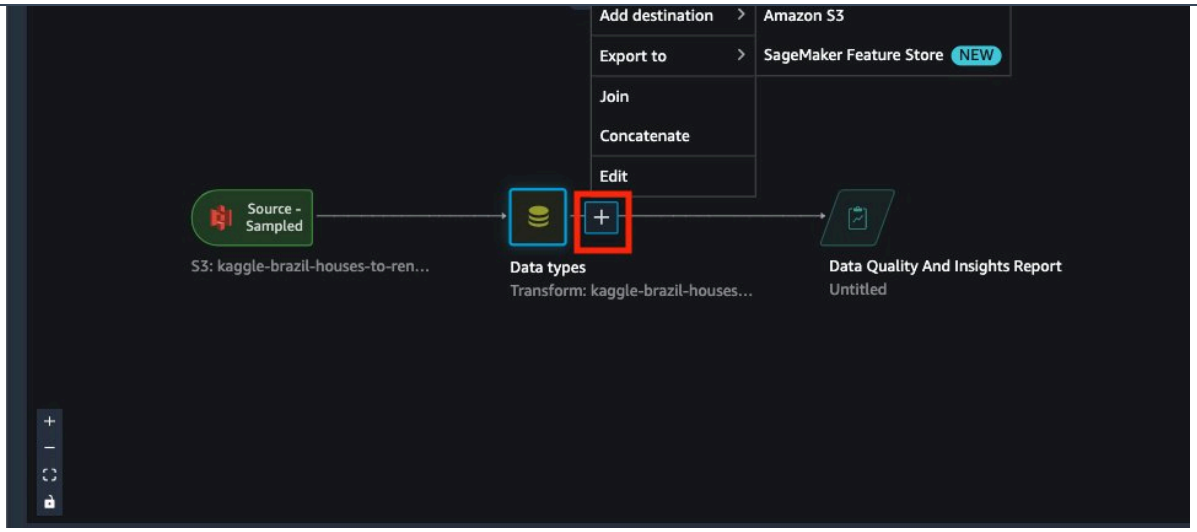
From the **Data Insights** pane, choose **rent amount** as the **Target column.** Then choose **Regression** as the **Problem type**. Then choose **Create**.



further before building the ML model. For this specific dataset, the Data Insights report has highlighted two possible issues: the first is related to **duplicate rows** in the dataset and the second is related to possible **target leakage** such that one feature is highly correlated with the output and may indicate a duplicate of the target **rent** column. The report can also be downloaded to a PDF file and shared with colleagues on your team.



For further data analysis and exploration, you can create additional analytical artifacts including correlation matrices, histograms, scatter plots, and summary statistics as well as custom visualizations. For example, choose the **+** icon, then choose **Add analysis.**

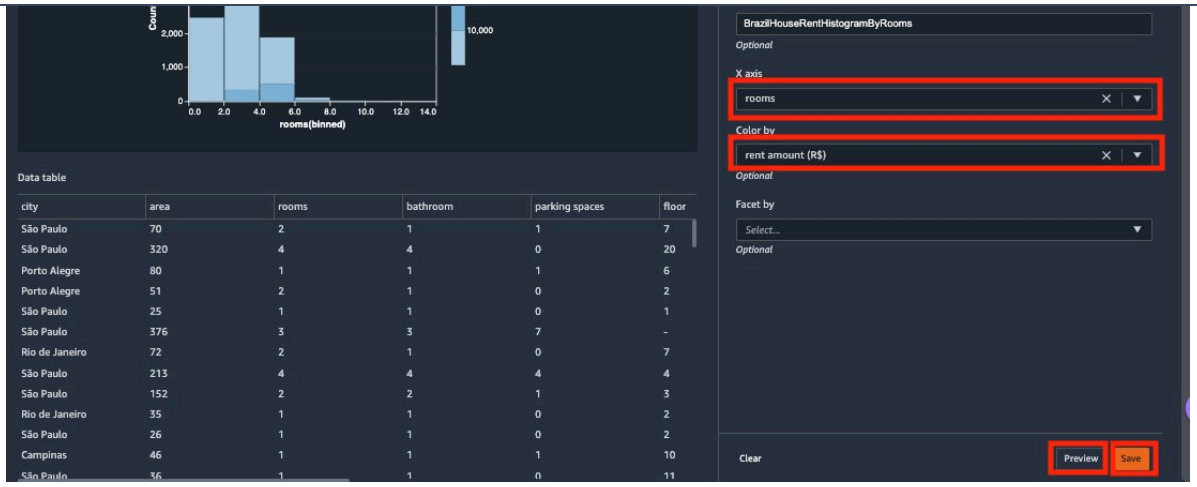


Under the **Create analysis** panel, for **Analysis type**, select **Histogram** and name it **RentHistogramByRooms**. For **X axis**, select **rooms**.

For **Color by,** select **Rent amount.**

Choose **Preview** to generate a **histogram** of the **rent amount** field, color-coded by the **rooms** variable.

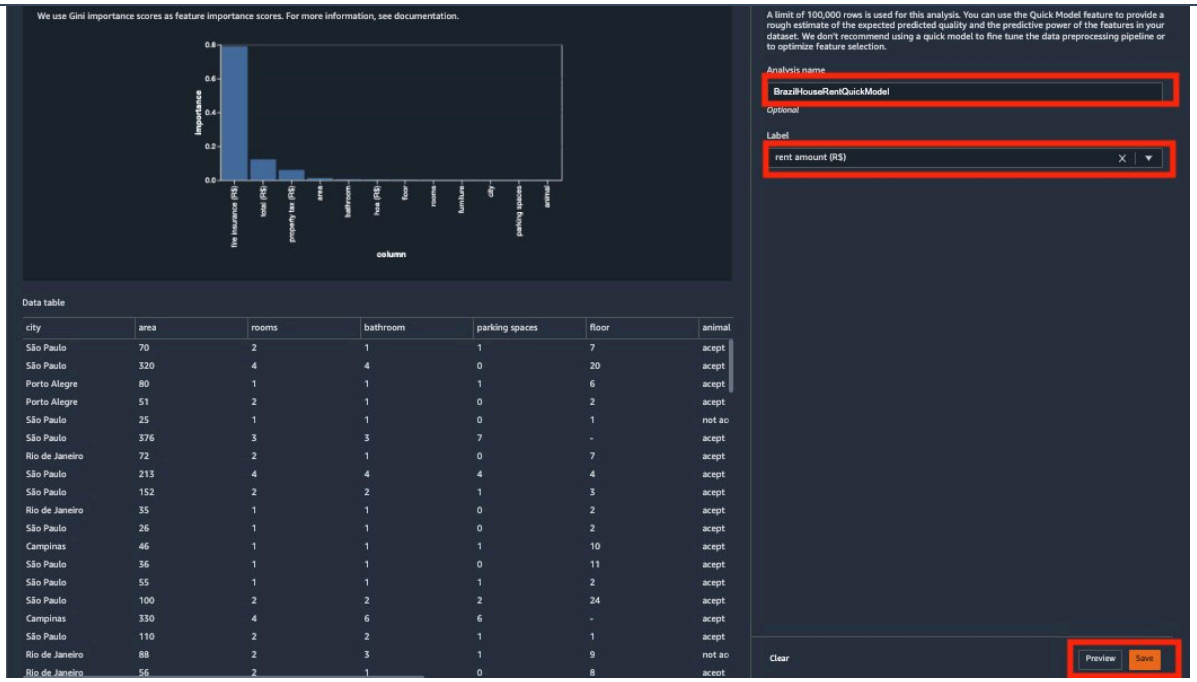
Choose **Save** to save this analysis to the data flow.



Next, to gain higher confidence that the underlying data has some predictive power, we are going to create a Quick Model. Under the **Create analysis** pane, for **Analysis type,** choose **Quick Model** and name it **RentQuickModel**.

Then for **Label**, select **rental amount** and then choose **Preview**.

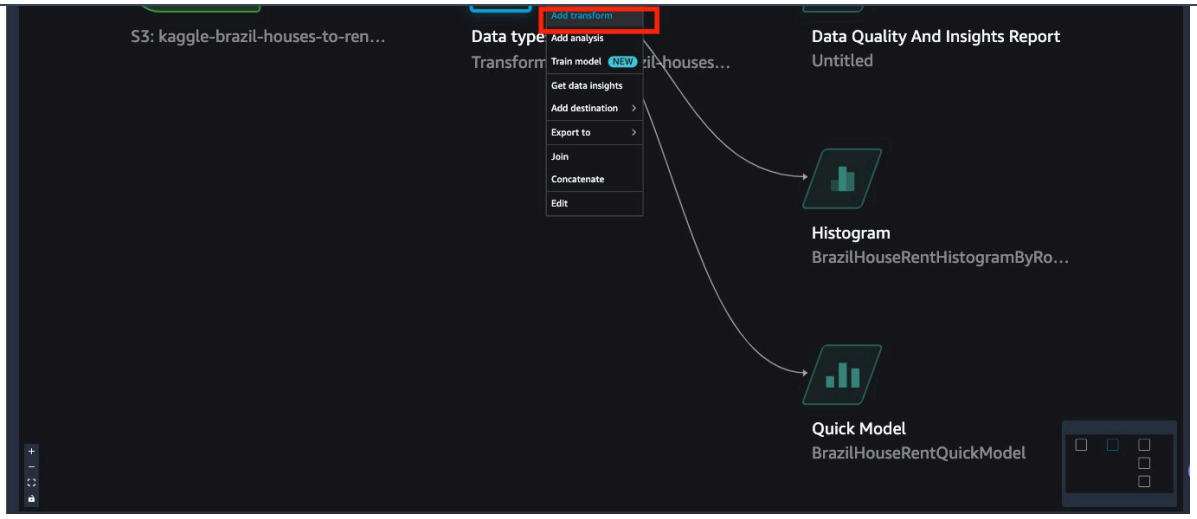
The **Quick Model** may take several minutes to complete, then the pane shows a brief overview of the Random Cut Forest model built and trained with default hyperparameters. The model generated also displays some statistics, including the Mean Square Error (MSE) score and feature importance to help you evaluate the quality of the dataset. Choose **Save**.



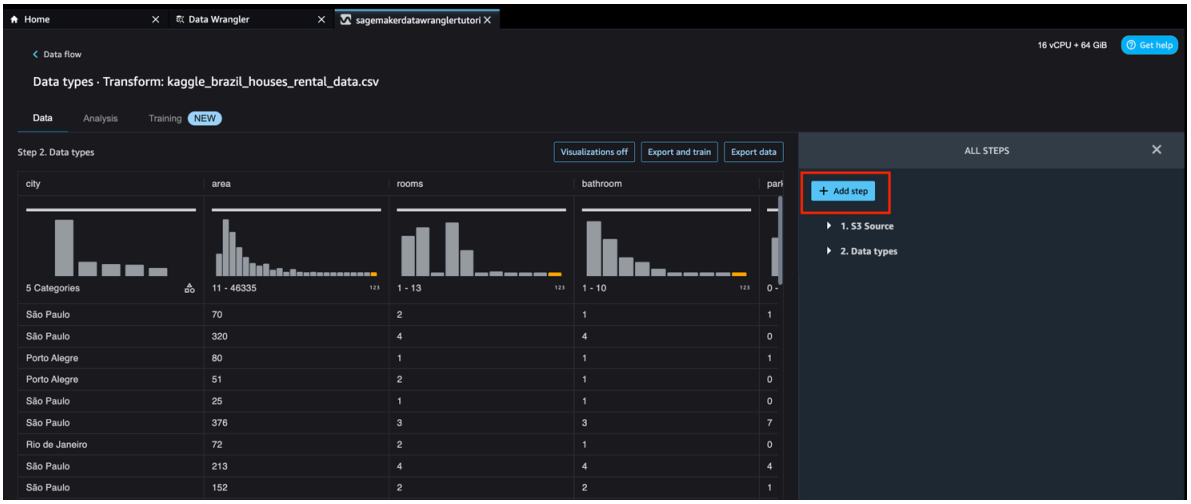
Step 4: Add transformations to the data flow

SageMaker Data Wrangler simplifies data processing by providing a visual interface with which you can add a wide variety of pre-built transformations. You can also write your custom transformations when necessary using SageMaker Data Wrangler. In this step, you change the type of a string column, rename columns, and drop unnecessary columns using the visual editor.

To navigate to the data flow diagram, choose **Data flow**. On the data flow diagram, choose the **+** icon, then **Add transform**

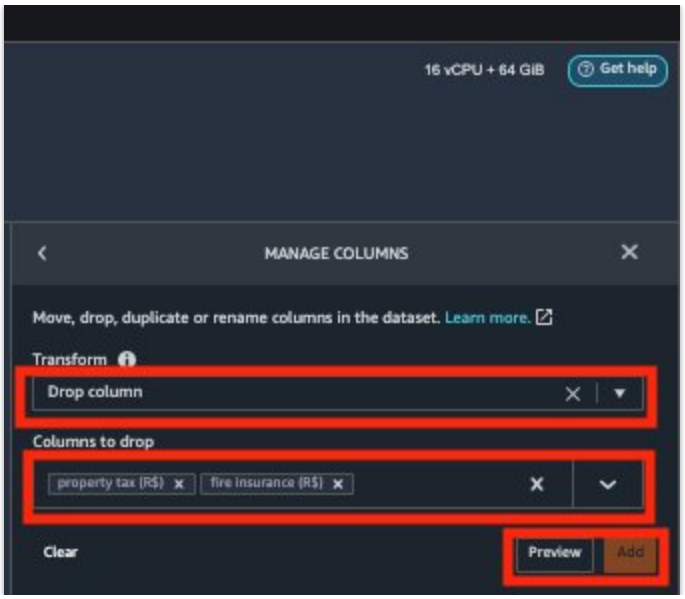


Under the **ALL STEPS** pane, choose **Add step.**



The first step is following the Data Insights Report recommendations regarding high risk items and removing the duplicate rows. So as the first transf choose **Manage Rows,** and then select the **Drop duplicates** operatio choose **Preview** and **Save**.

Second, we are going to remove the dataset features highlighted as possible sources of target leakage and not appropriate for a machine learning model predicting the rental amount. From the **ADD TRANSFORM** list, choose **Manage columns.** Then choose **Drop column** and choose **property tax** and **fire insurance.** Choose **Preview** then **Save**.



Next, change the data type of the **floor** column from **string** to **long**. Machine learning models can benefit from using numerically typed columns and this step will allow us to perform further processing later on.

Then rename several columns to improve the readability of the input data set and later analysis.

From the **ADD TRANSFORM** list, choose **Manage columns.** Then choose **Rename column.** Then choose **bathroom** as the input column and **bathrooms** as the output column. Choose **Preview** then **Save**.

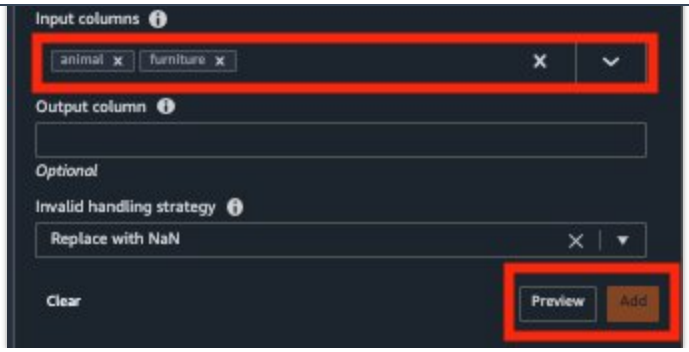
Repeat this renaming column process for **hoa** [originally from **hoa (R$)**], **rent** [originally from **rent amount (R$)**], and **total** [originally from **total (R$)**].

Step 5: Add categorical encoding and numeric scaling transformations to data flow

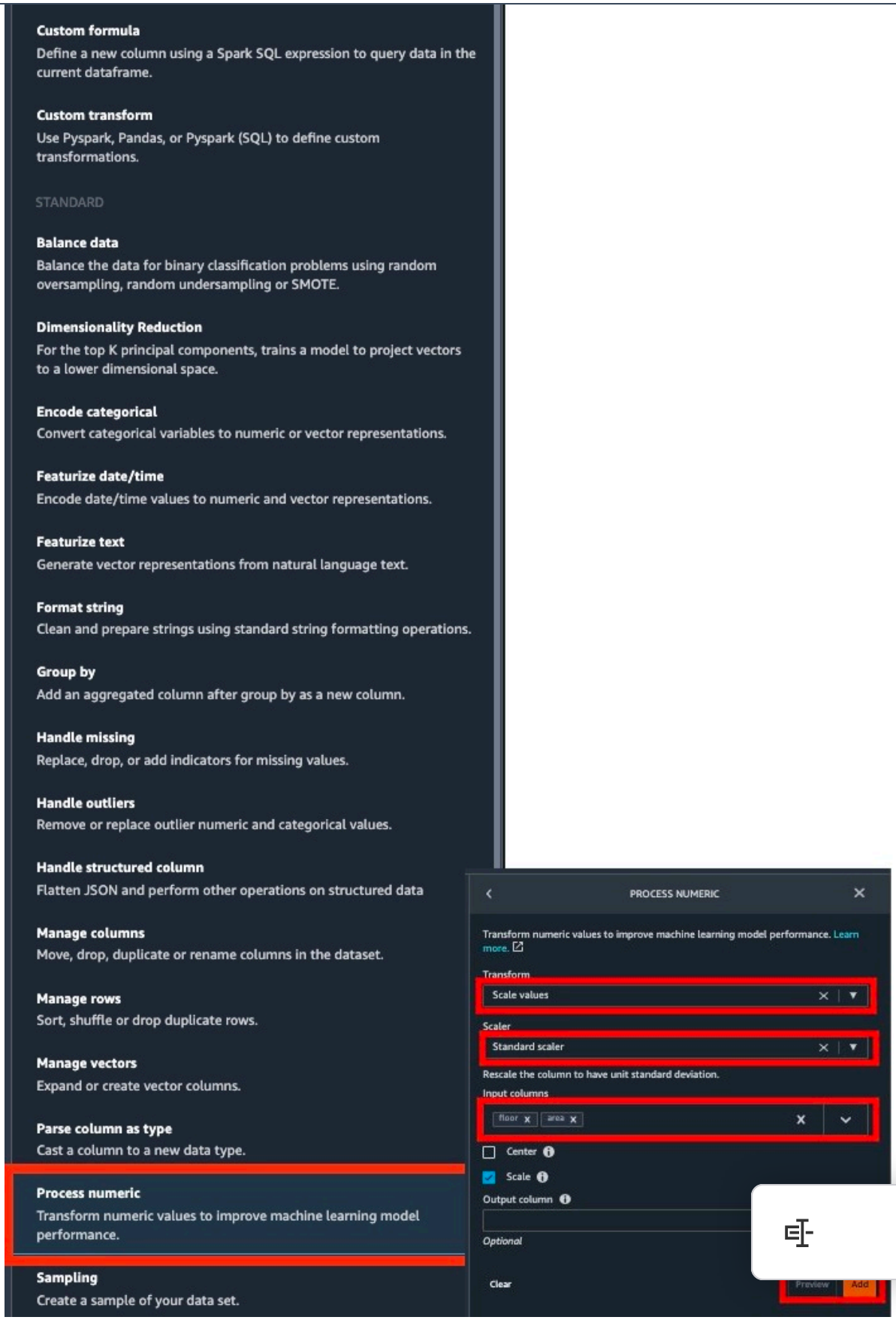
In this step, you encode categorical variables and scale numerical variables. Categorical encoding transforms string data type categories into numerical features. It's a common preprocessing task because the numerical features can be used in a wide variety of machine learning model types.

In the dataset, the rental property's **animal** and **furniture** classification is represented by various strings. In this step, you convert these string values to a binary representation, 0 or 1.

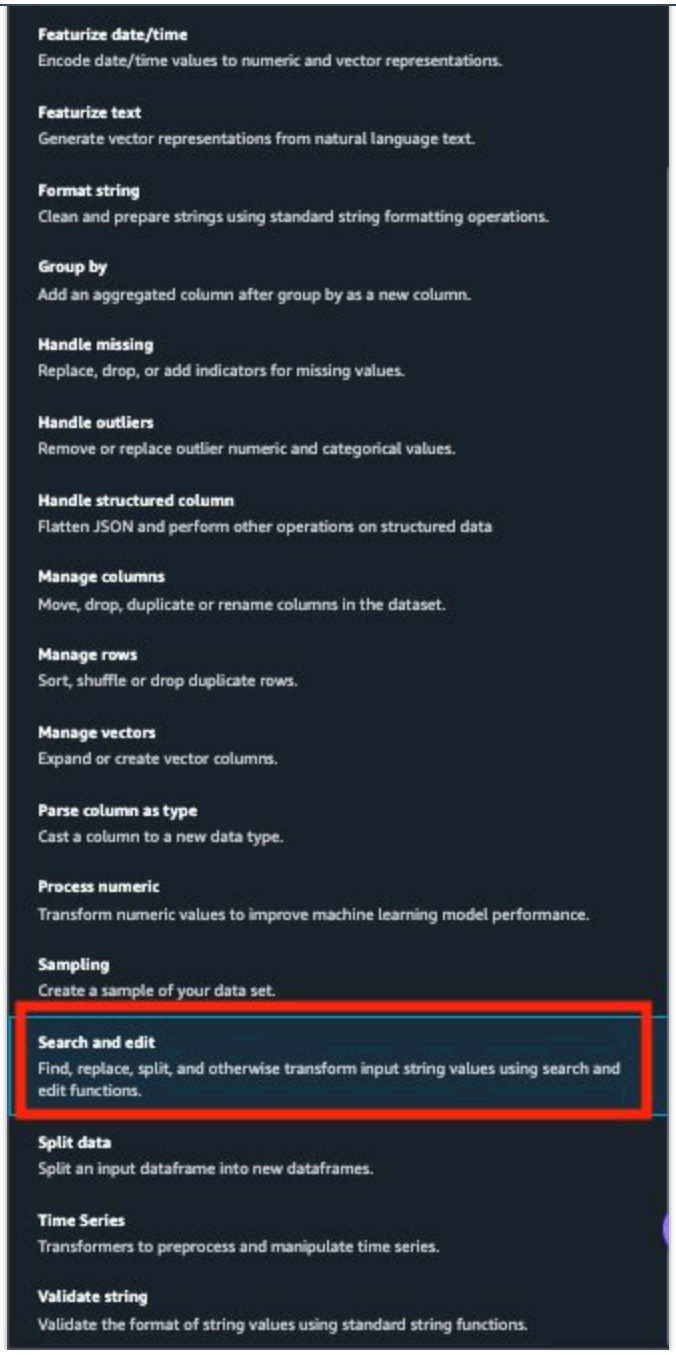
Under the **ALL STEPS** pane, choose **+ Add step**. From the **ADD TRANSFORM** list, choose **Encode categorical.** SageMaker Data Wrangler provides three transformation types: Ordinal encode, One hot encode, and Similarity encode. Under the **ENCODE CATEGORICAL** pane, for **Transform,** use the default **Ordinal encode**. For **Input** columns, select **animal** and **furniture**. Ignore the **Invalid handling strategy** box for this tutorial. Choose **Preview**, then **Add**.



To scale the numerical columns **area** and **floor**, apply a scaler transformation to normalize the distribution of the data in these columns: Under the **ALL STEPS** pane, Choose **+ Add step**. From the **ADD TRANSFORM** list, choose **Process numeric**. For **Scaler,** select the default option **Standard scaler**. For **Input** columns, select **area** and **floor**. Choose **Preview**, and then **Add**.


Custom formula
Define a new column using a Spark SQL expression to query data in the current dataframe.
Custom transform
Use Pyspark, Pandas, or Pyspark (SQL) to define custom transformations.
STANDARD
Balance data
Balance the data for binary classification problems using random oversampling, random undersampling or SMOTE.
Dimensionality Reduction
For the top K principal components, trains a model to project vectors to a lower dimensional space.
Encode categorical
Convert categorical variables to numeric or vector representations.
Featurize date/time
Encode date/time values to numeric and vector representations.
Featurize text
Generate vector representations from natural language text.
Format string
Clean and prepare strings using standard string formatting operations.
Group by
Add an aggregated column after group by as a new column.
Handle missing
Replace, drop, or add indicators for missing values.
Handle outliers
Remove or replace outlier numeric and categorical values.
Handle structured column
Flatten JSON and perform other operations on structured data
Manage columns
Move, drop, duplicate or rename columns in the dataset.
Manage rows
Sort, shuffle or drop duplicate rows.
Manage vectors
Expand or create vector columns.
Parse column as type
Cast a column to a new data type.
Process numeric
Transform numeric values to improve machine learning model performance.
Sampling
Create a sample of your data set.
PROCESS NUMERIC
Transform numeric values to improve machine learning model performance. Learn more.
Transform
Scale values
Scaler
Standard scaler
Rescale the column to have unit standard deviation.
Input columns
floor
area
Center
Scale
Output column
Optional
Clear
Preview
Add

Finally, we will follow another recommendation from the Data Insight report and replace the 0s in the Home Owner Association (*hoa*) feature with **NaN** because they indicate missing data and should not be treated as valid inputs that might skew the model. Under the **ALL STEPS** pane, choose **+ Add step**. From the **ADD TRANSFORM** list, choose **Search and edit** and then **Convert regex to missing**. Choose **hoa** as the **Input column**, specify **0** as the **Pattern**. Click **Preview**, and then choose **Add**.


Featurize date/time
Encode date/time values to numeric and vector representations.
Featurize text
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Replace, drop, or add indicators for missing values.
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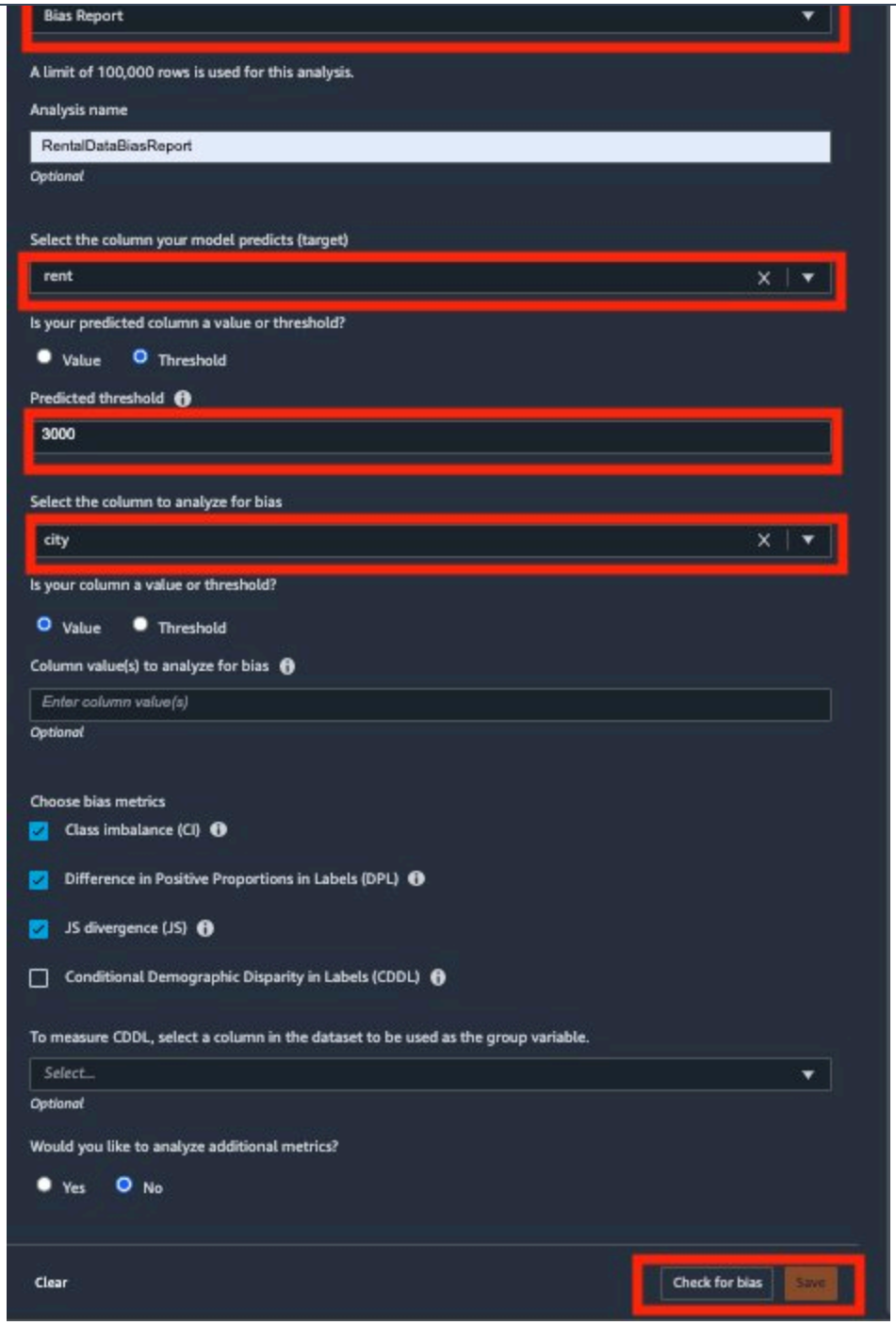
Flatten JSON and perform other operations on structured data
Manage columns
Move, drop, duplicate or rename columns in the dataset.
Manage rows
Sort, shuffle or drop duplicate rows.
Manage vectors
Expand or create vector columns.
Parse column as type
Cast a column to a new data type.
Process numeric
Transform numeric values to improve machine learning model performance.
Sampling
Create a sample of your data set.
Search and edit
Find, replace, split, and otherwise transform input string values using search and edit functions.
Split data
Split an input dataframe into new dataframes.
Time Series
Transformers to preprocess and manipulate time series.
Validate string
Validate the format of string values using standard string functions.

Step 6: Check for data bias

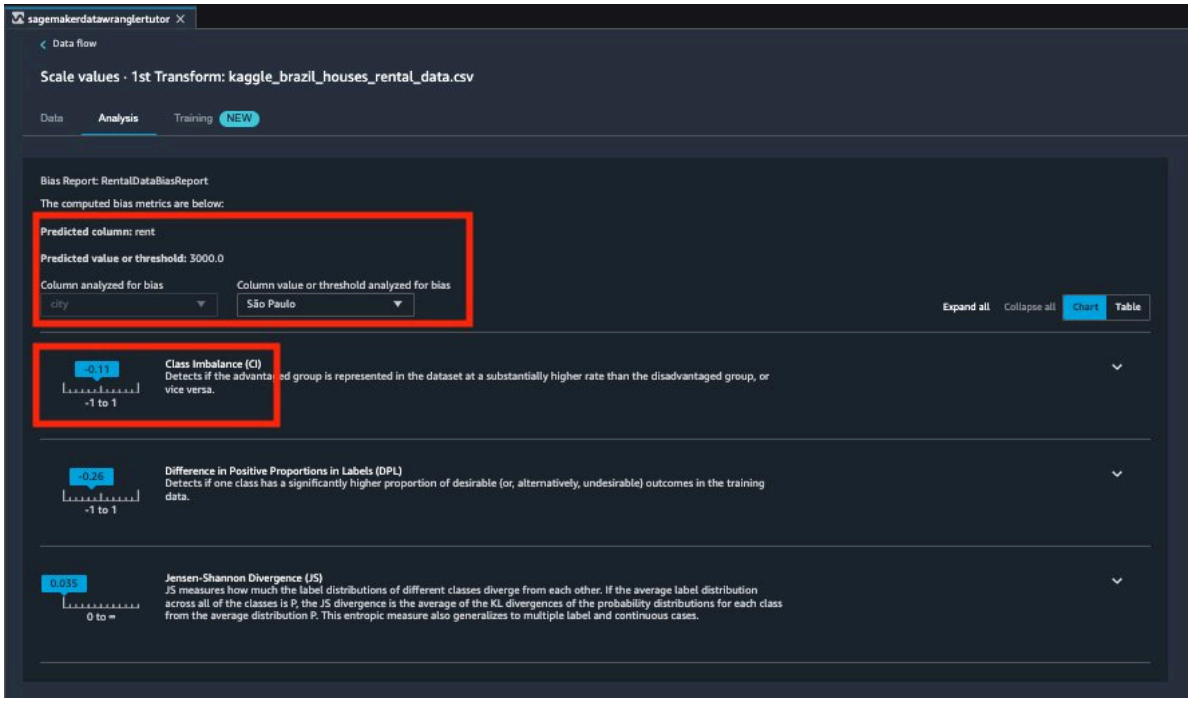
In this step, check your data for bias using Amazon SageMaker Clarify, which provides you with greater visibility into your training data and models so you can identify and limit bias and better explain predictions.

Choose **Data flow** in the upper left to return to the data flow diagram. Choose the **+** icon**, Add analysis**. In the **Create analysis** pane, for **Analysis** type, select **Bias Report**. For **Analysis name,** enter **RentalDataBiasReport**. For **Select the column your model predicts (target)**, select **rent**. Then select **Threshold** as the predicted column type since this is a regression problem. Specify **3000** as the **predicted threshold** which corresponds to the average of the **rent** column in the dataset. Then select **city** as the column to analyze for bias because we are interested in whether the dataset is imbalanced and over-represents some cities instead of others. Then for **Choose bias metrics**, keep the default selections. Then choose **Check for bias** and then **Save.**



After several seconds, SageMaker Clarify generates a report, which sh
the target and feature columns score on a number of bias-related metrics

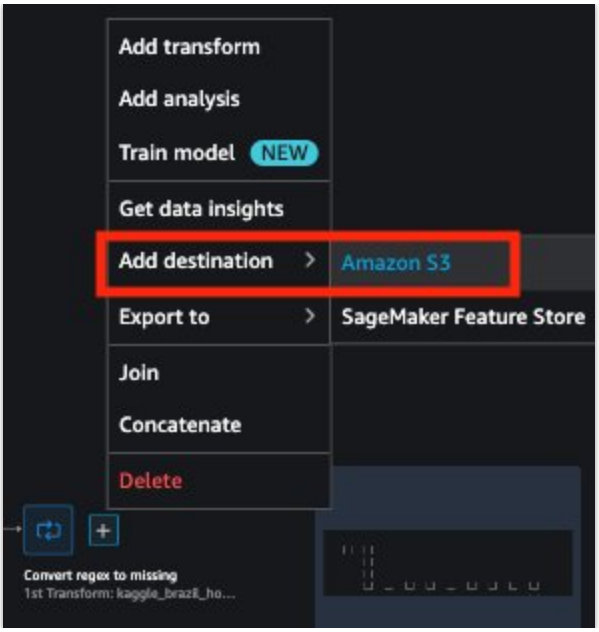
consider a bias remediation method, such as using SageMaker Data Wrangler's built-in SMOTE transformation. For the purpose of this tutorial, skip the remediation step. Choose **Save** to save the bias report to the data flow.



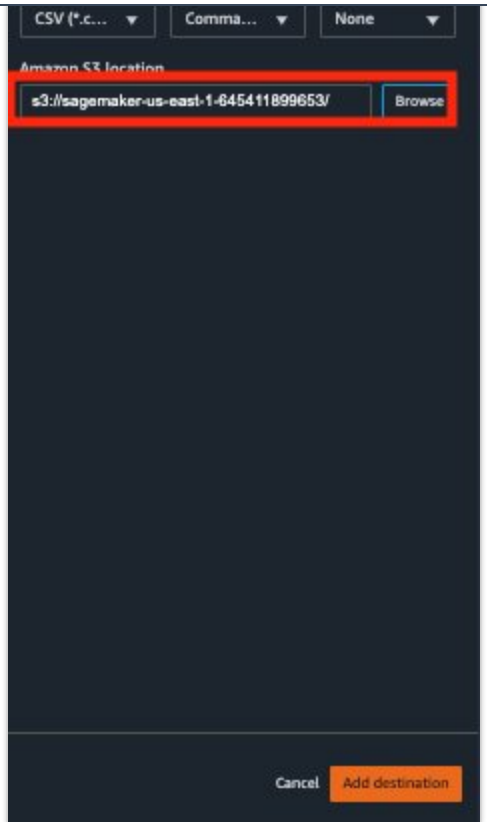
Step 7: Review, integrate, and export your data flow

From the **Data Flow** tab, review your end-to-end data flow graph including the data source, analytical artifacts, and data transformations. You can easily navigate, view, modify, and delete data flow steps iteratively.

Data Wrangler further streamlines the automation process of exporting the output of the data flow to a persistent destination and can orchestrate the schedule of the flow's execution. First, set the storage destination to Amazon S3.

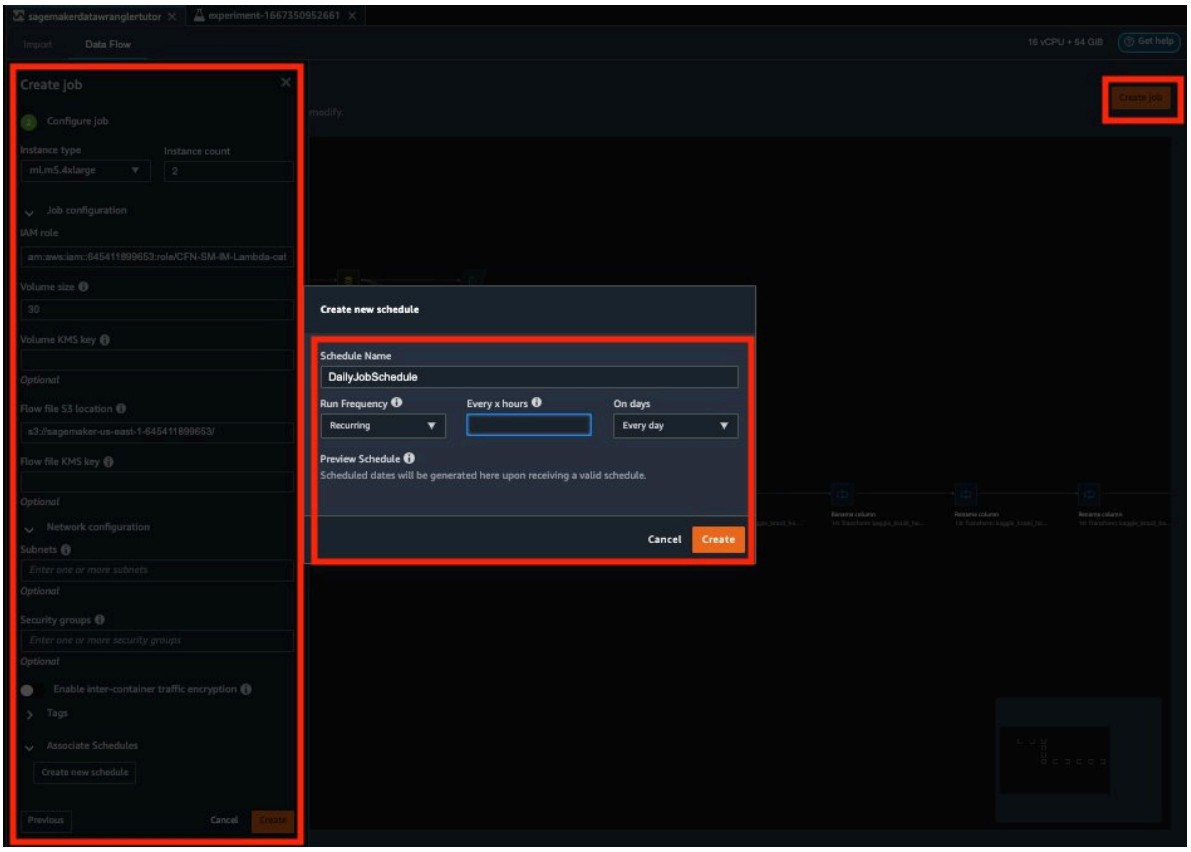


Then specify the output dataset name **(kaggle_brazil_houses_rental_data_dw_processed.csv)** and the Am
location as your preferred S3 bucket. Then choose **Add destination.**



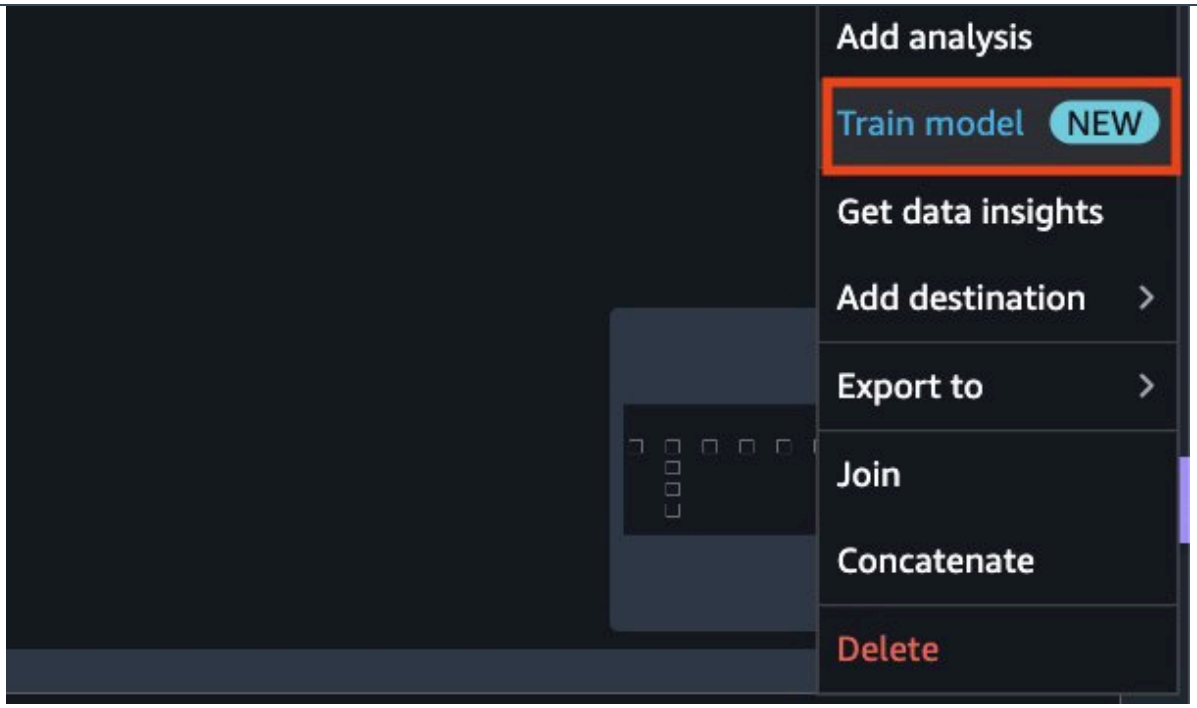
Lastly, create the scheduled job that will export the data flow output to Amazon S3 by choosing the **Create job** button from the **Data Flow** diagram pane, and then choosing **Configure job.**

Then you can decide on the job instance type, instance count, the job's IAM security role, and the job schedule.



SageMaker Autopilot Integration

You can also integrate your data flow with SageMaker Autopilot which automates key tasks of training and deploying a machine learning model. From the **Data Flow** tab, choose the **+** icon and then choose **Train model.**



Choose **Export and Train** to export the Data Wrangler flow and associate its output with the Autopilot Experiment input.

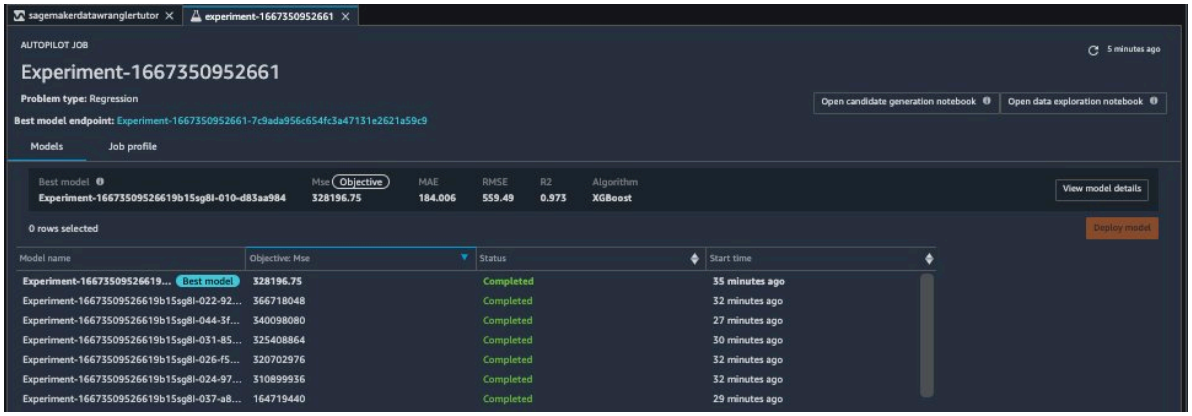
Choose the **S3 location** where the Data Wrangler flow saved the processed input dataset and specify the **target** column as **rent** for the Autopilot model.

Specify the Autopilot **Training method.** You can choose Ensembling, Hyperparameter Optimization, or Auto. For the purposes of this tutorial, choose **Auto**.

For **Deployment,** select the machine learning problem type as **Regression** with the object metric as **MSE**.

Confirm the Autopilot Experiment deployment settings and then choose **Create experiment.** This action launches a SageMaker Autopilot job that ins
input data, generates and evaluates multiple ML models, and then se
best model for subsequent deployment according to the desired perf

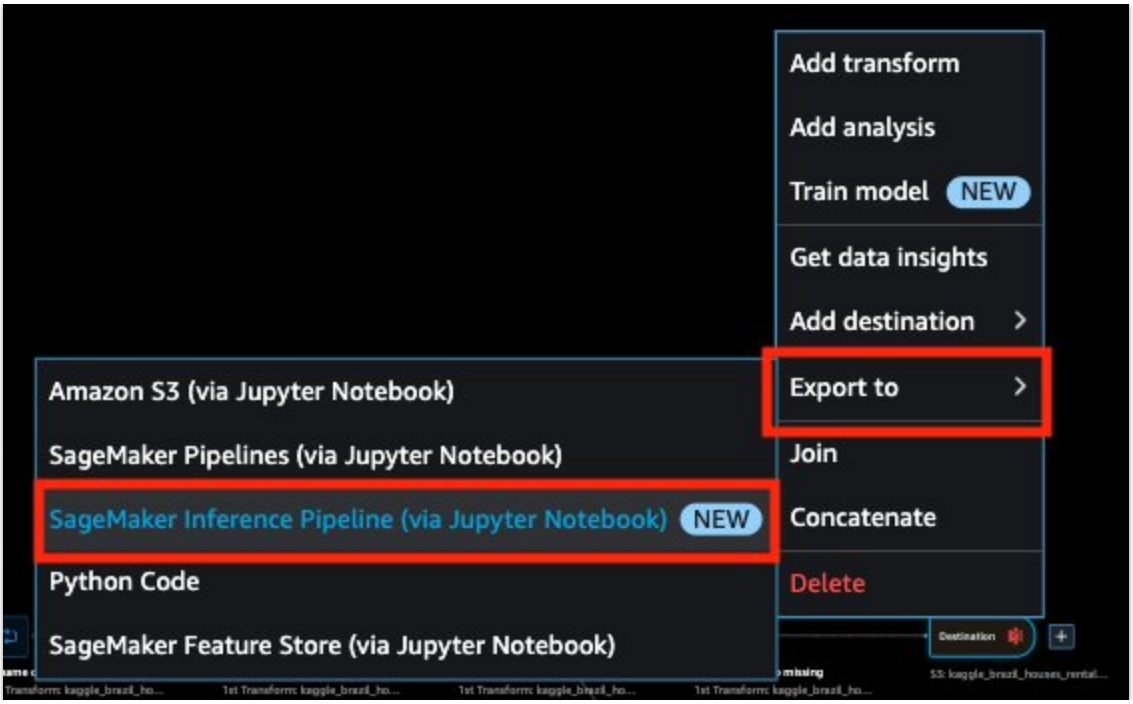
attribution and explainability statistics using SageMaker Clarify.



SageMaker Pipeline Integration

Data Wrangler can also be integrated with SageMaker Inference Pipelines to process data at the time of inference, thereby streamlining the steps between data processing and model inference. When you export one or more steps from the data flow to an inference endpoint, Data Wrangler creates a Jupyter notebook that you can use to define, instantiate, customize, run, and manage the inference pipeline. To create the inference endpoint, choose the **+** next to the final transformation step (Convert regex to missing) and choose **Export to,** and then choose **SageMaker Inference Pipeline (via Jupyter Notebook).** Then inspect and run that Jupyter notebook.

You can optionally export your Data Wrangler data flow to a Jupyter notebook to run the flow steps as a SageMaker Processing job.



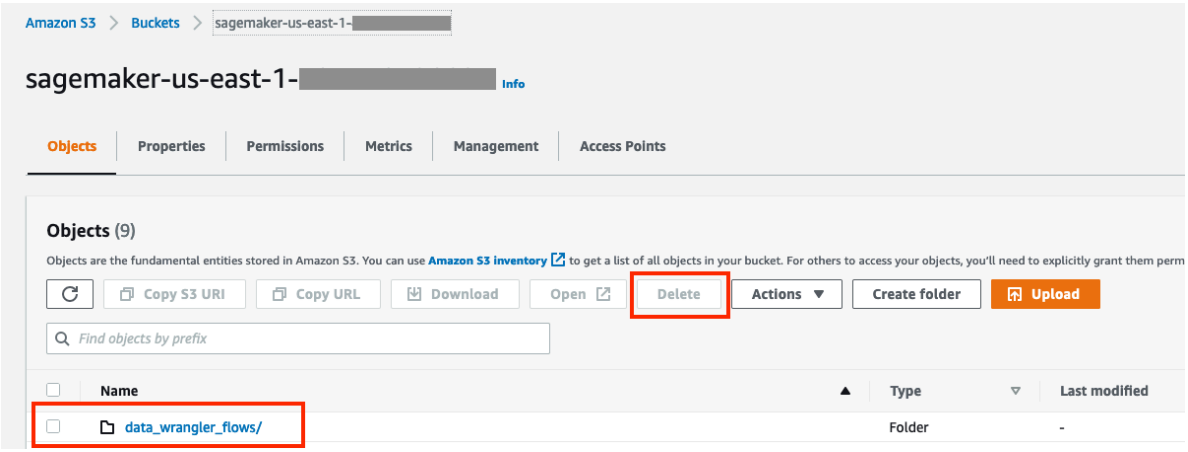
Step 8: Clean up resources

It is a best practice to delete resources that you are no longer using so that you don't incur unintended charges.

To delete the S3 bucket, do the following:

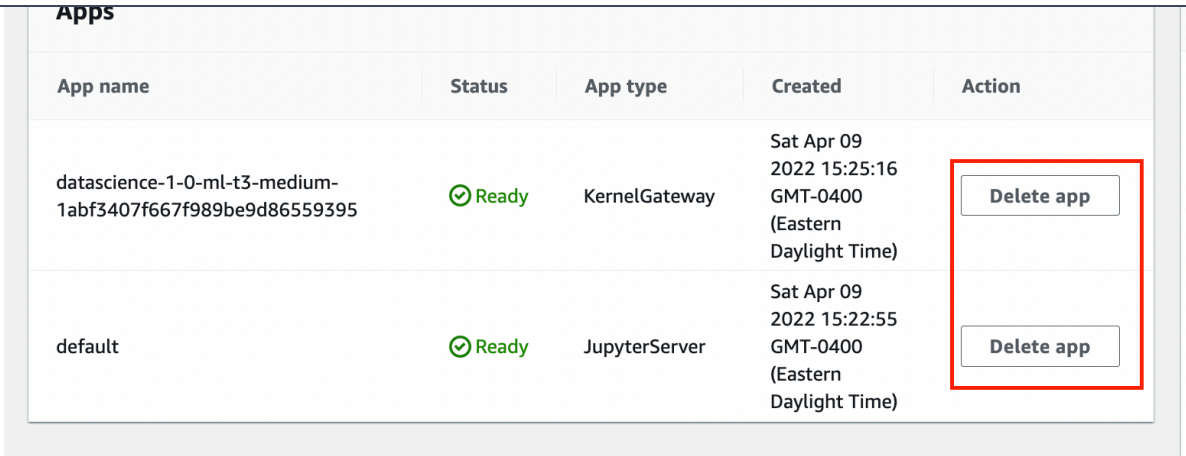
object to delete and enter **permanently delete** into the **Permanently delete objects** confirmation box.

- Once this is complete and the bucket is empty, you can delete the ***sagemaker-<your-Region>-<your-account-id>*** bucket by following the same procedure again.



The Data Science kernel used for running the notebook image in this tutorial will accumulate charges until you either stop the kernel or perform the following steps to delete the apps. For more information, see Shut Down Resources in the *Amazon SageMaker Developer Guide.*

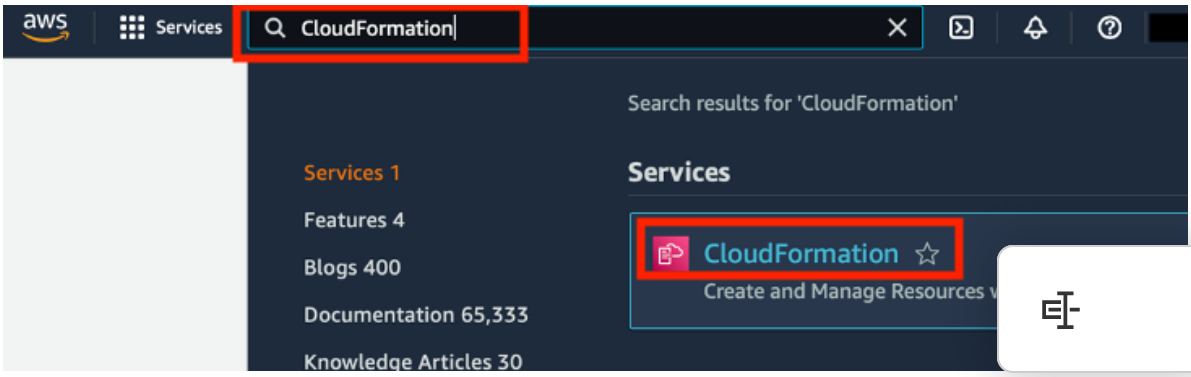
To delete the SageMaker Studio apps, do the following: On the SageMaker Studio console, choose **studio-user**, and then delete all the apps listed under **Apps** by choosing **Delete app**. Wait until the **Status** changes to **Deleted**.



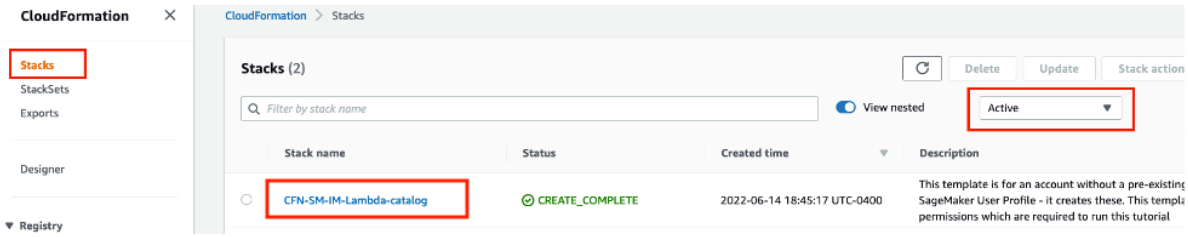
If you used an existing SageMaker Studio domain in Step 1, skip the rest of Step 8 and proceed directly to the conclusion section.

If you ran the CloudFormation template in Step 1 to create a new SageMaker Studio domain, continue with the following steps to delete the domain, user, and the resources created by the CloudFormation template.

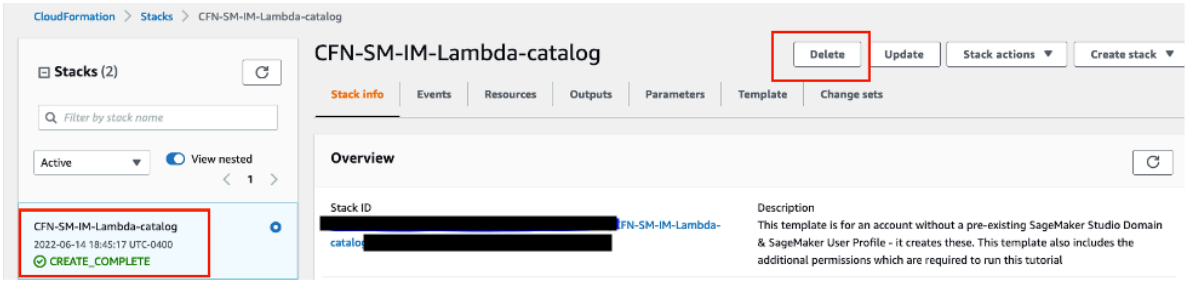
To open the CloudFormation console, enter **CloudFormation** into the AWS console search bar, and choose **CloudFormation** from the search results.



In the **CloudFormation** pane, choose **Stacks**. From the status dropdown list, select **Active**. Under **Stack name,** choose **CFN-SM-IM-Lambda-catalog** to open the stack details page.



On the **CFN-SM-IM-Lambda-catalog** stack details page, choose **Delete** to delete the stack along with the resources it created in Step 1.



Conclusion

Congratulations! You have completed the **Prepare Training Data for Machine Learning with Minimal Code** tutorial.

You have successfully used Amazon SageMaker Data Wrangler to prepare dat machine learning model. SageMaker Data Wrangler offers 300+ preconfigure transformations, such as convert column type, one-hot encoding, impute mis mean

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