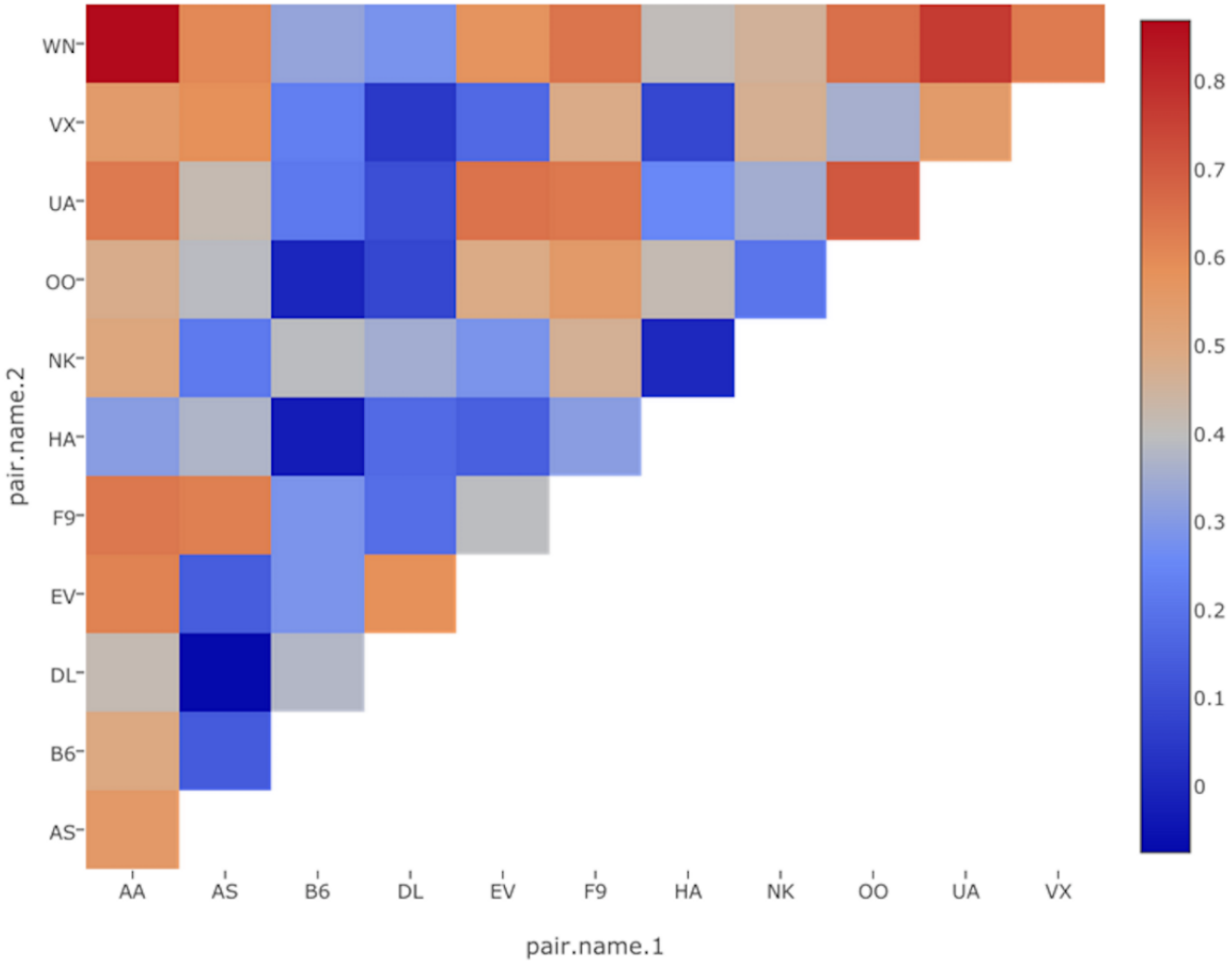


Exploratory Data Analysis for Amazon Redshift with R & dplyr

Kan Nishida Follow
Aug 10, 2016 · 9 min read

Many of our Exploratory users store data in Amazon Redshift database for variety of reasons, but one thing in common among them is the need for quickly exploring the data to uncover patterns and trends that were unknown before. And true data exploration often involves transforming (or wrangling) the data, visualizing the data,

building statistical models, and testing with statistical tools, not in a sequential way, but in a very iterative way going back and forth among those tasks at the speed of our thoughts.

Writing SQL queries is hard and slow if you want to go beyond counting rows. And what you can do with SQL is too limited for a practical exploratory data analysis. So why not extracting the data into R so that you can explore the data in a super fast and iterative way with all the statistical tools R offers? And that's many of our users have already been doing, and I wanted to share how you, too, can do to take advantage of R to discover more about your data that is stored in Redshift database.

I'm going to demonstrate it by using dplyr commands inside Exploratory Desktop. dplyr is kind of like SQL but it's way more powerful and capable than that. It provides a set of the 'easy-to-read' grammar based commands to do data wrangling and analysis in a super fast and the most effective way in R.

hadley/dplyr

dplyr - Dplyr: A grammar of data manipulation

github.com

Exploratory

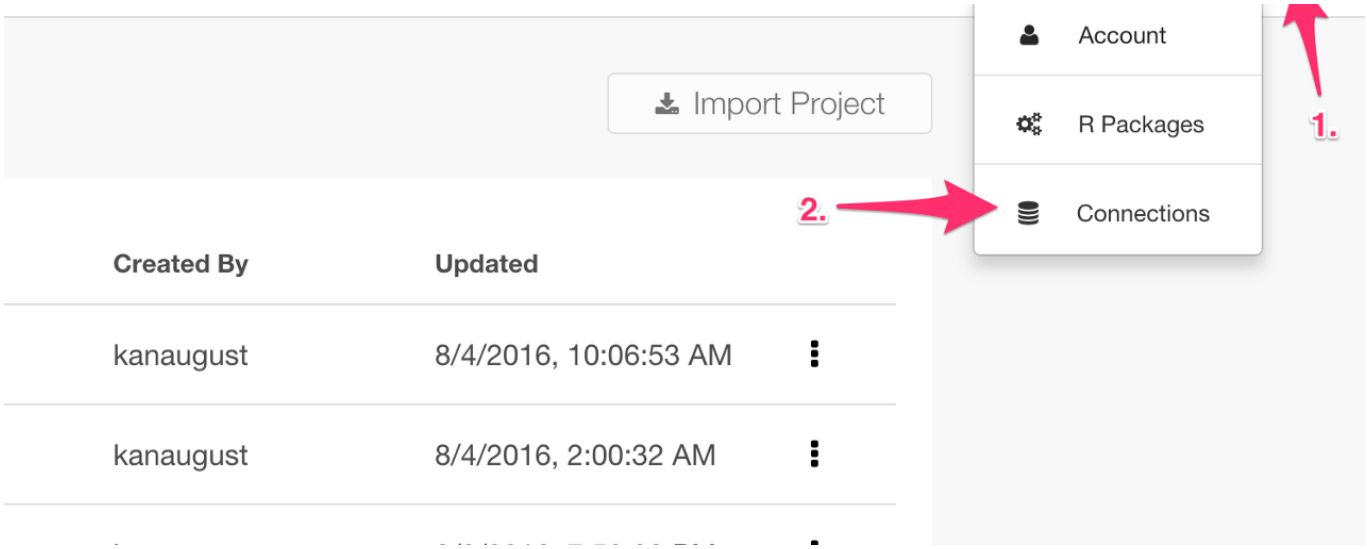
Most of the data is sitting outside of the traditional databases today. You can quickly extract data from various data...

exploratory.io

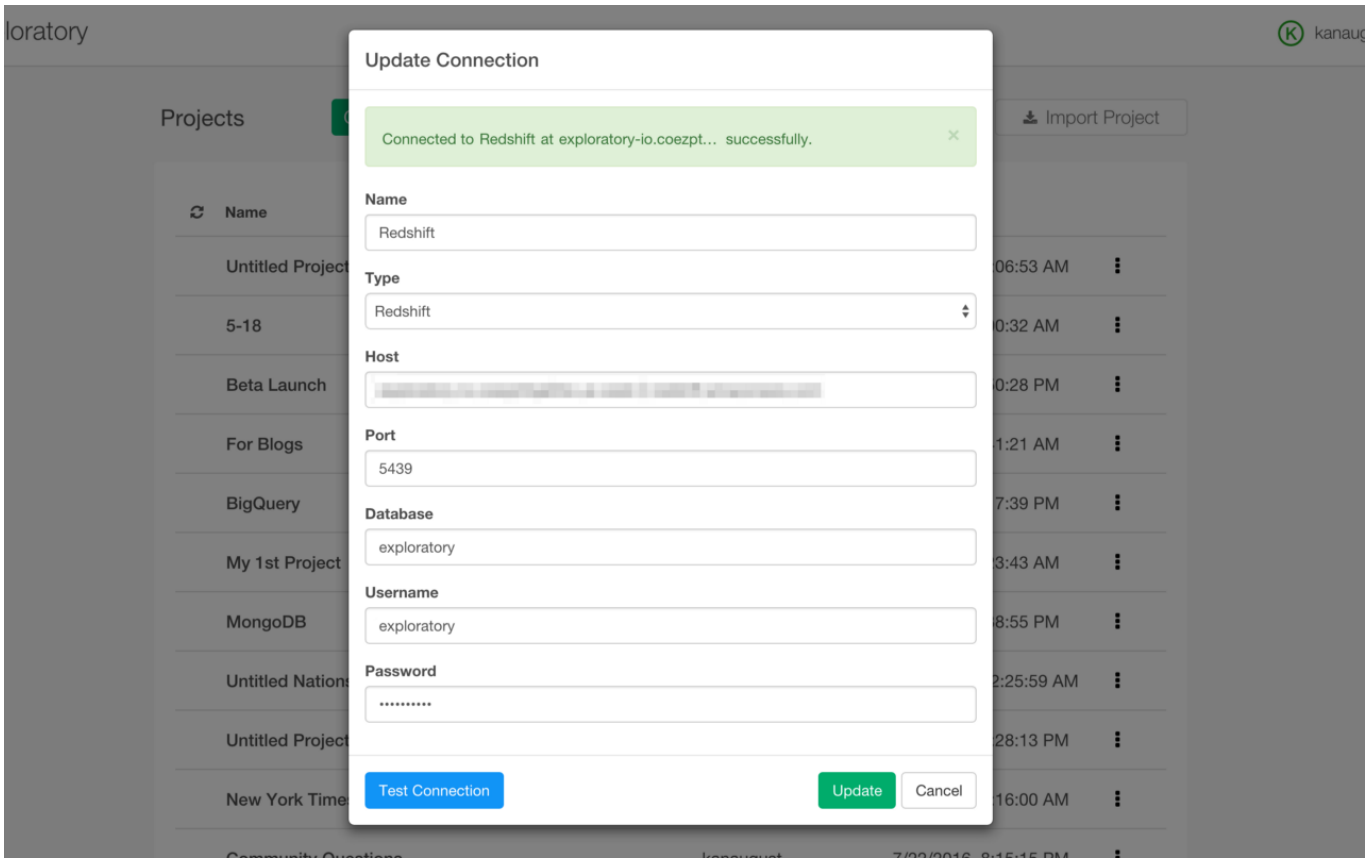
Import Data from Amazon Redshift

Create Connection

First, you want to create a connection for Amazon Redshift database in Project List page in Exploratory Desktop.



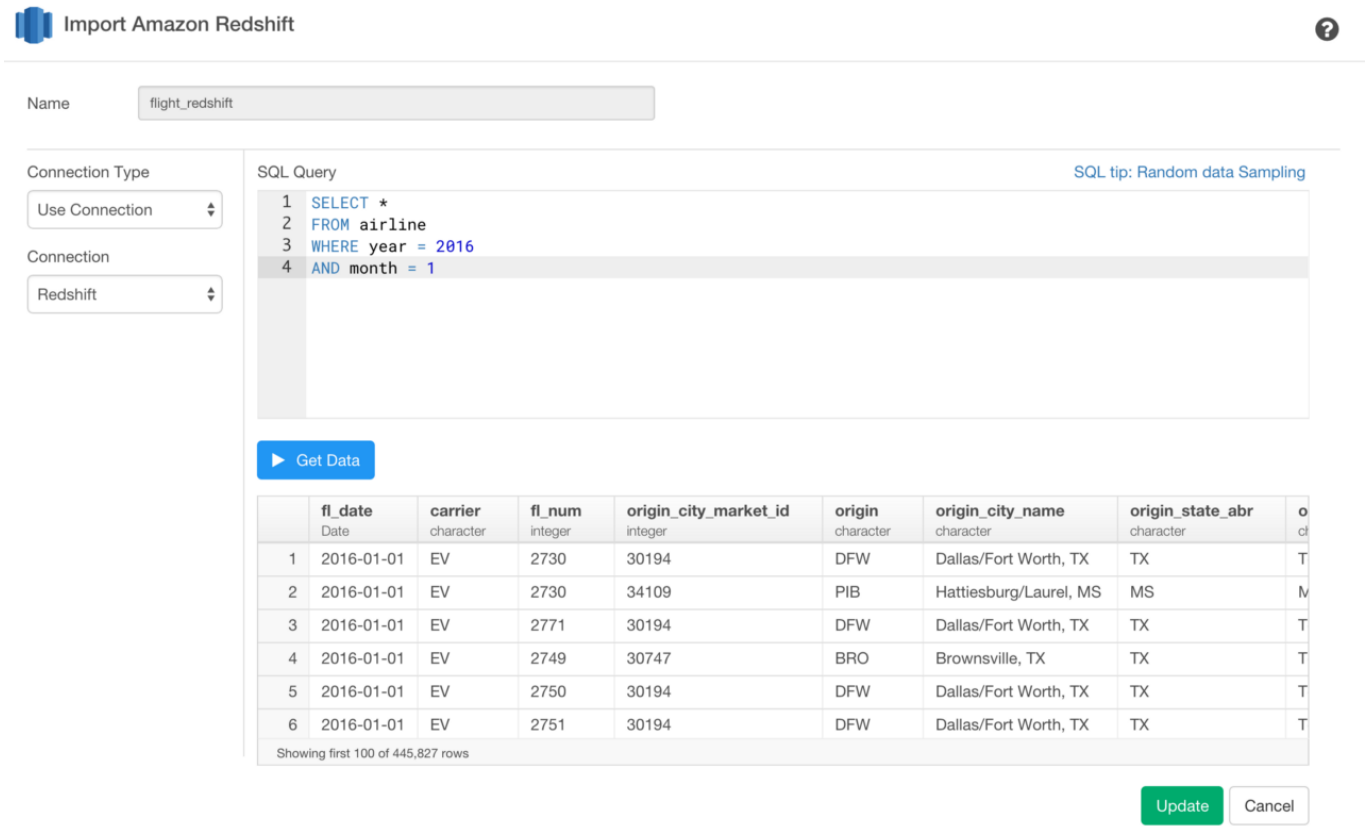
After filling the database information, click 'Test Connection' button to make sure that the information you have typed is correct, before you save it.



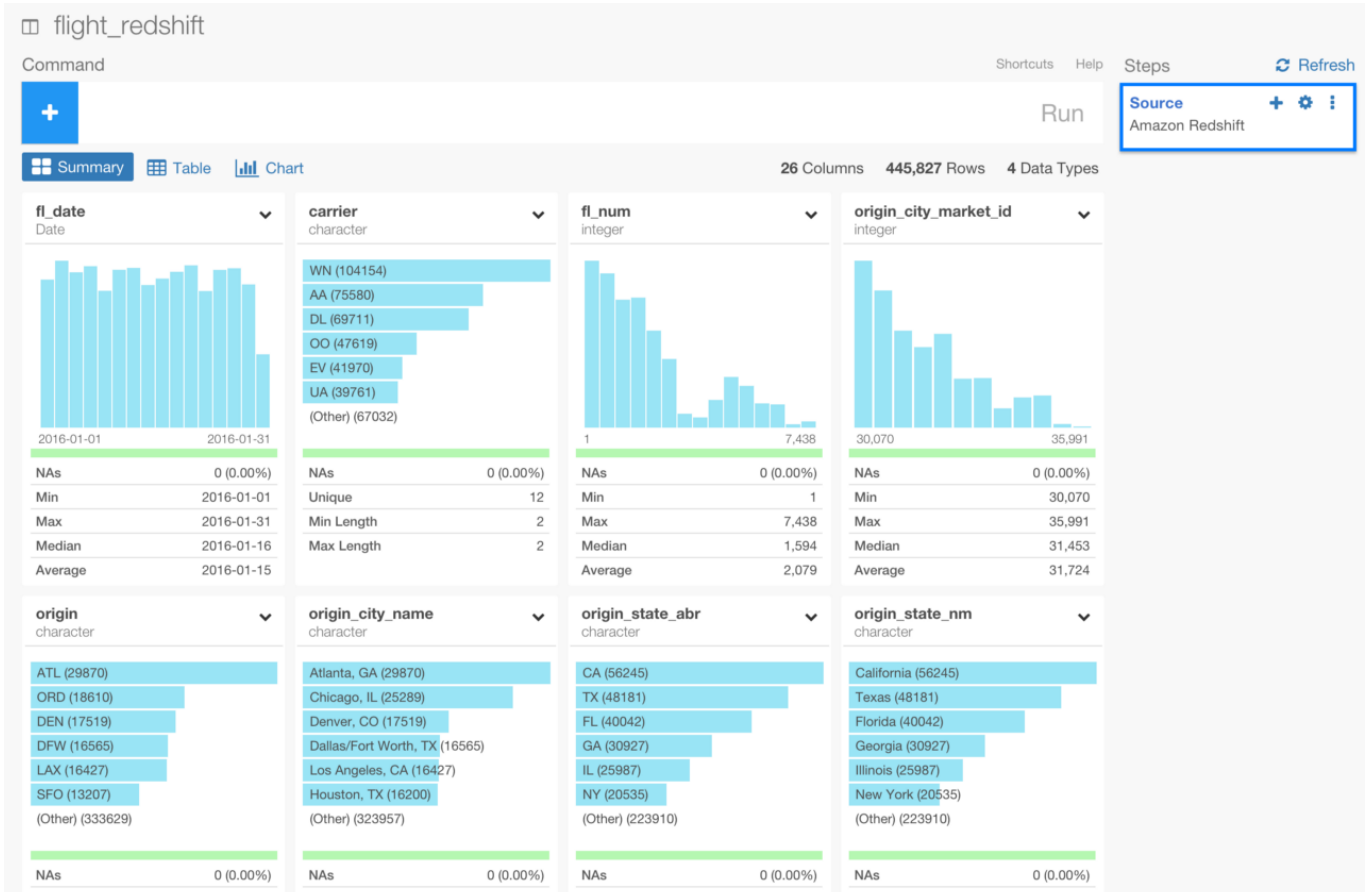
Import data with SQL Query

Inside the project, you can select Amazon Redshift from Remote Data selection dialog.

Select the connection you created from Connection dropdown at left hand side and start typing SQL query in 'SQL Query' input field and click 'Get Data' button.



After confirming that the data looks ok, click on 'Save' button to import. Then you will get this nice Summary view of your data from Redshift quickly!



Random Sample Data

Instead of filtering or aggregating the data, you might want to take a random sample of the data that would be reasonable size for your data analysis.

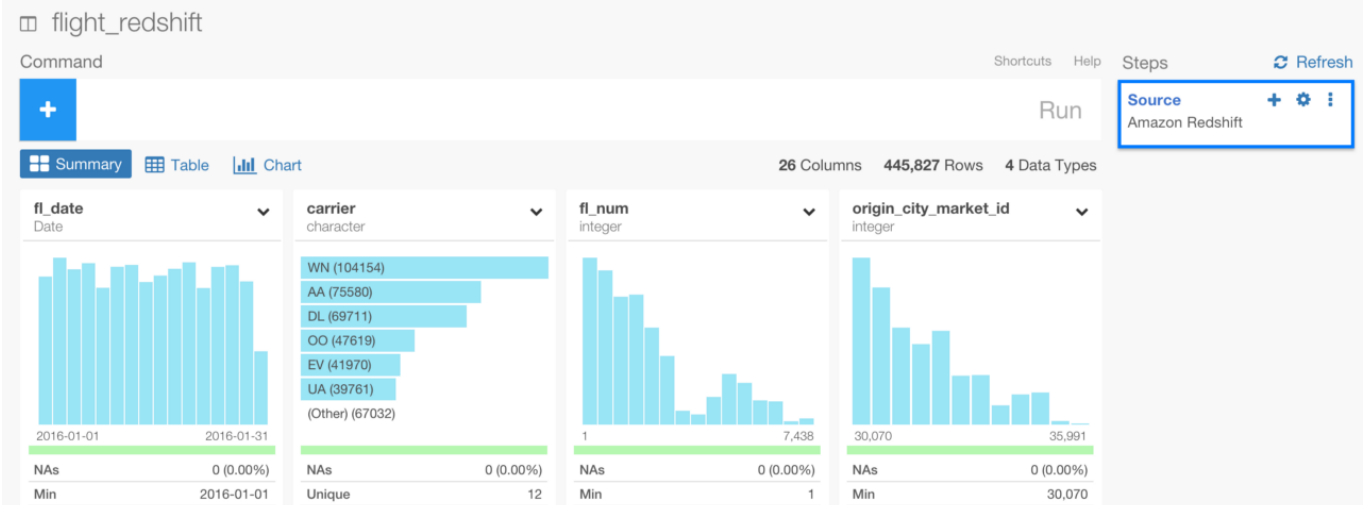
You can use 'md5' function, which returns hash code for a given text. Basically this function generates hash codes generated based on the actual data values so you can use it in ORDER BY clause to sort the data based on this hash code and limit to the first n numbers of rows, which would essentially return a random sample of the data while it would return a same set of the data every time you run the query.

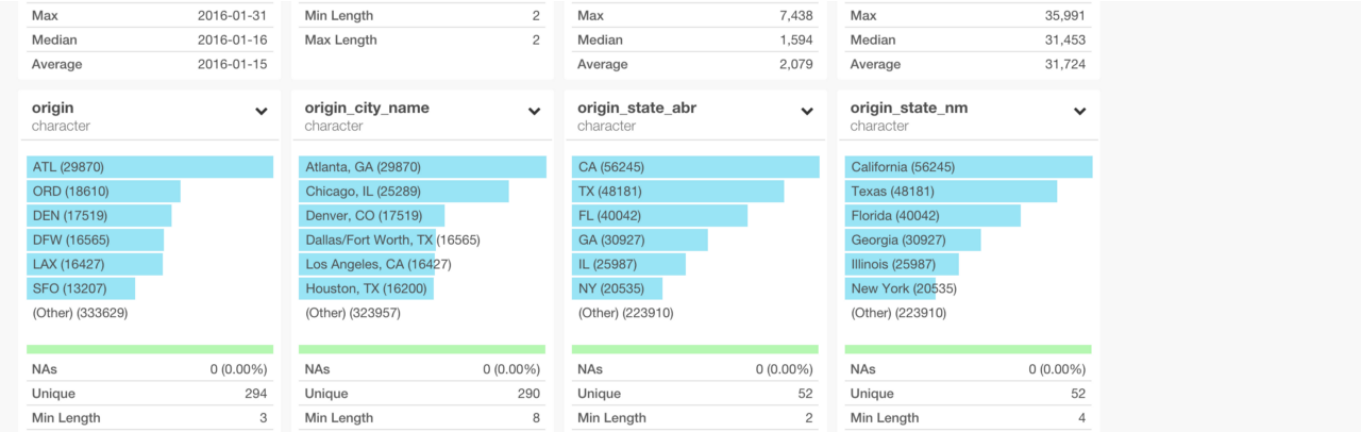
```
SELECT *
   FROM airline_2016_01
   ORDER BY md5('randomSeed' || flight_num)
   LIMIT 100000
```

Thanks to Sébastien for giving us a great guidance for how to effectively get the sample data from Redshift!

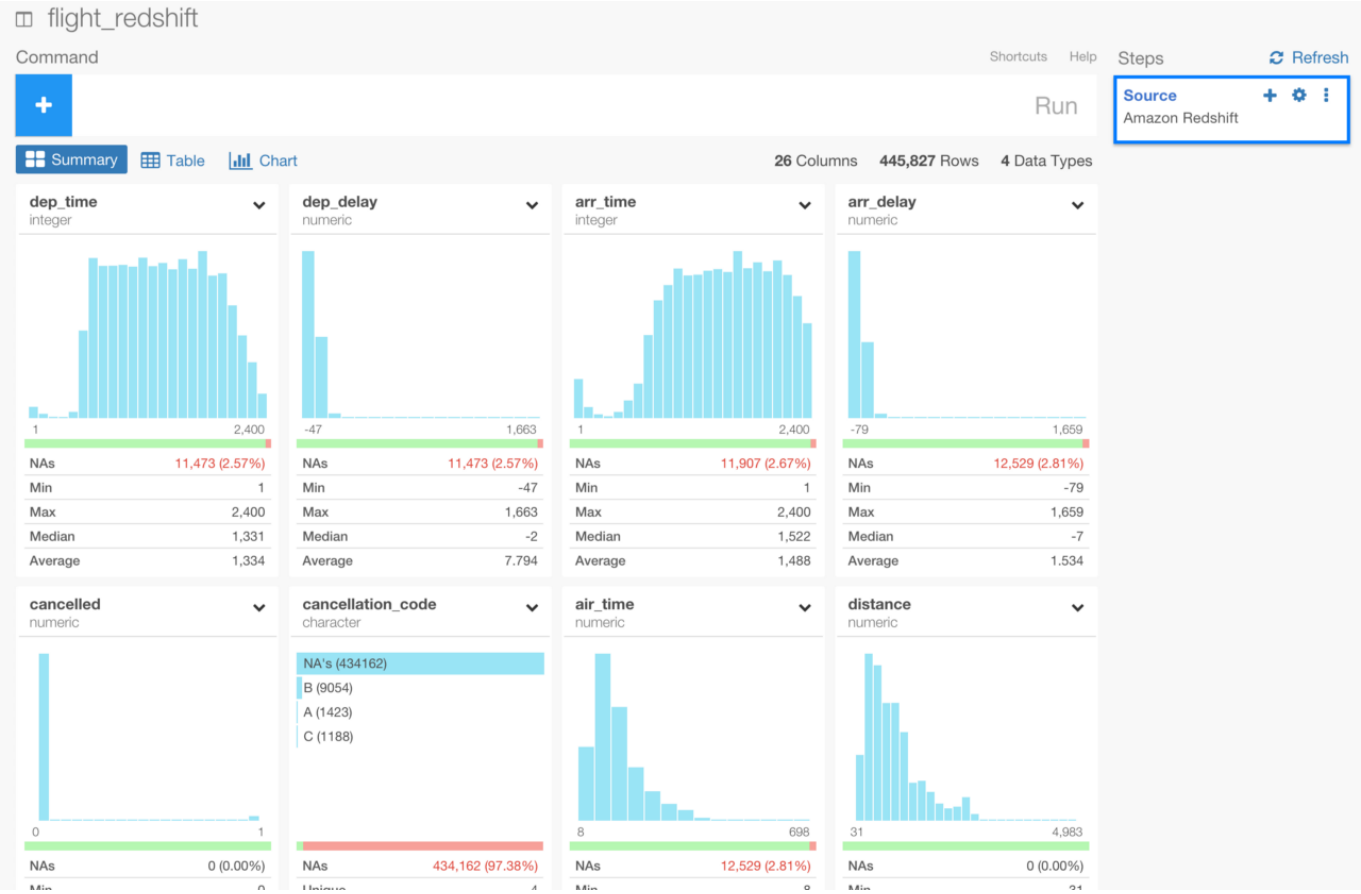
Exploratory Data Analysis

Just by importing the data you can quickly see the summary information for each column. For example, with this flight delay data, we can see 'carrier' column is 'character' data type and the top 6 carrier names along with the number of the rows for each carrier, and there are 12 carrier names in this data set.



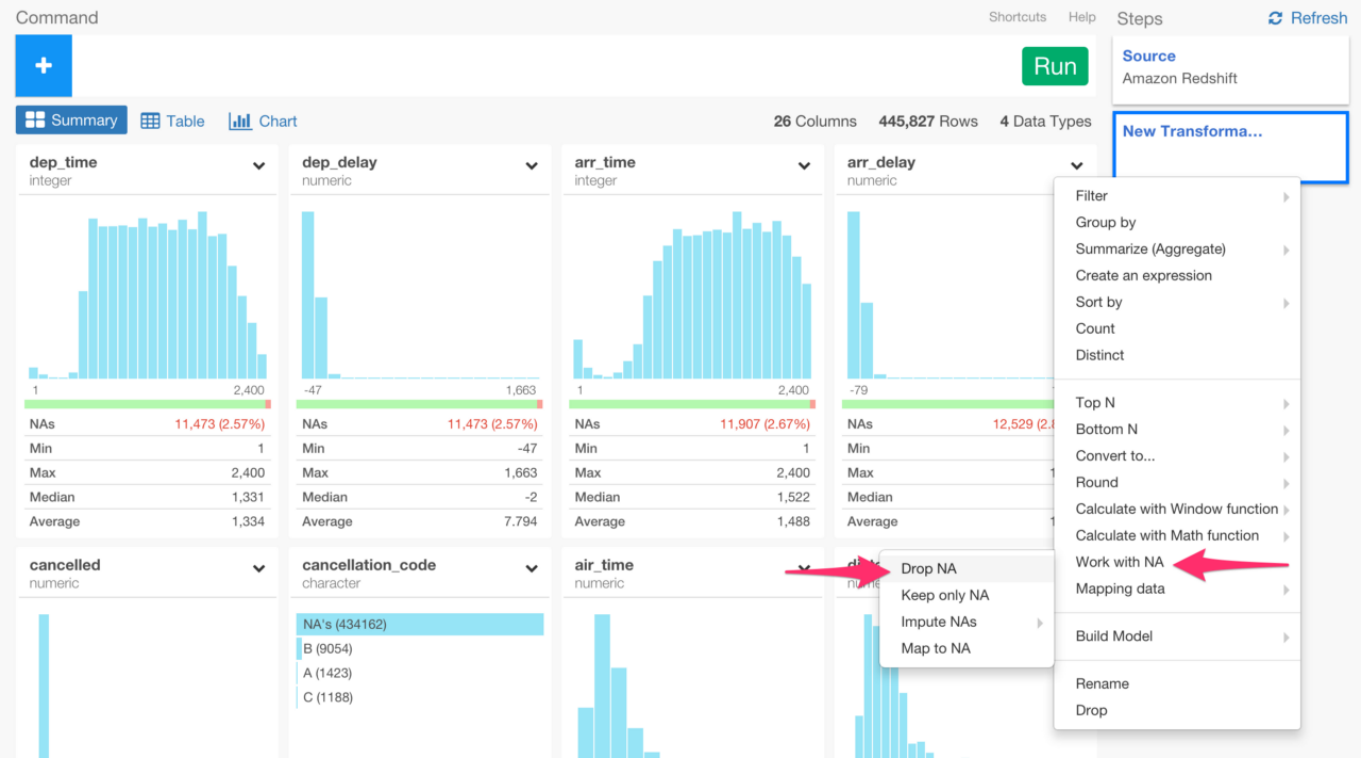


When I scroll down a bit, I can see other columns like 'arr_delay', which is 'numeric' data type, 2.81% of the data is NA. The average value is 1,534, but the median value is -7. When you look at the histogram you can see most of the data is skewed towards to the smaller values, and this is why 'median' value is more useful than 'average' value in this kind of scenario.



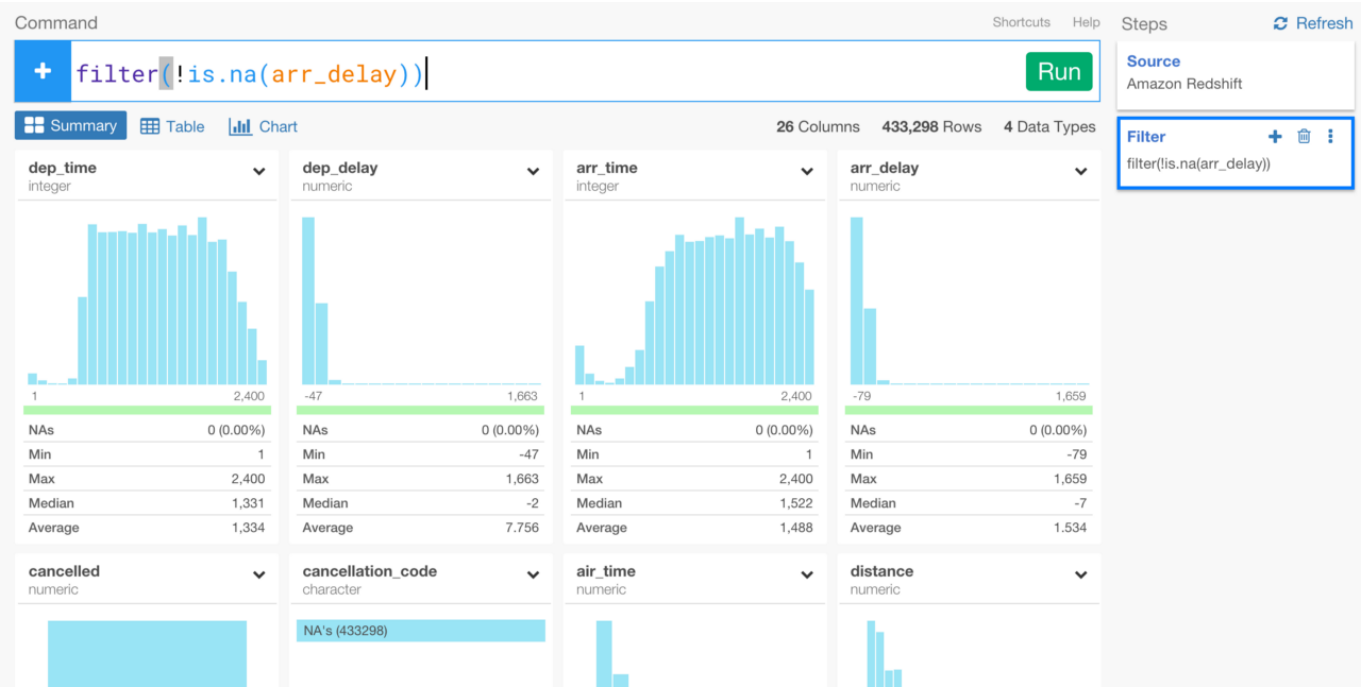
Remove NA

You can remove NA values for 'arr_delay' column by selecting 'Drop NA' under 'Work with NA' menu.



This will build a dplyr command automatically, I can click on Run button to execute.

```
filter(!is.na(arr_delay))
```



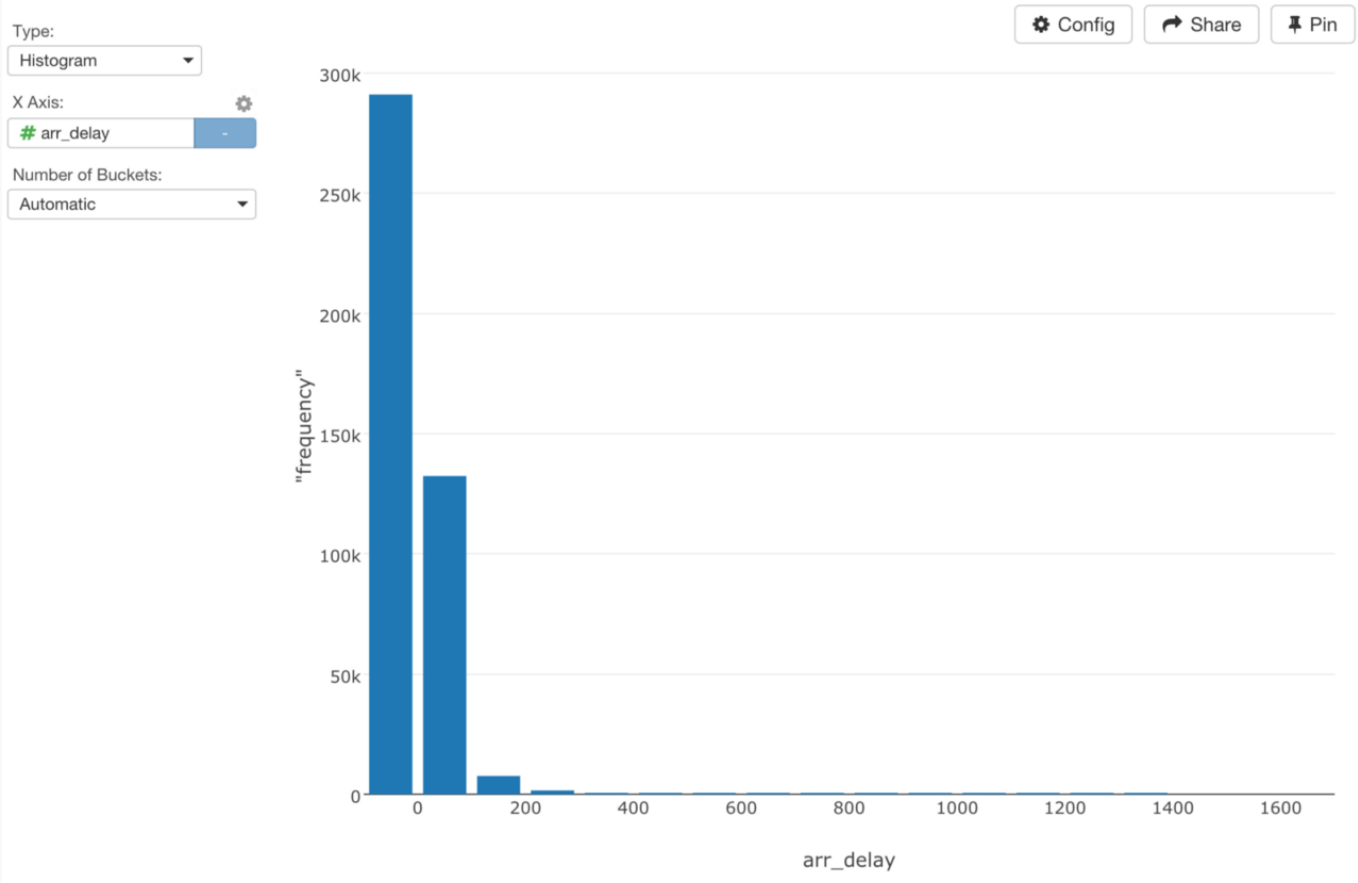
In case you are not familiar with R, the '!' (exclamation mark) is to reverse the effect of the function right after it. 'is.na(arr_delay)' would return TRUE if a given value is NA, but combined with '!' mark, it would return TRUE when the value is **not** NA. So 'filter' command would keep only the rows whose 'arr_delay' is **not** NA.

Visual Exploration

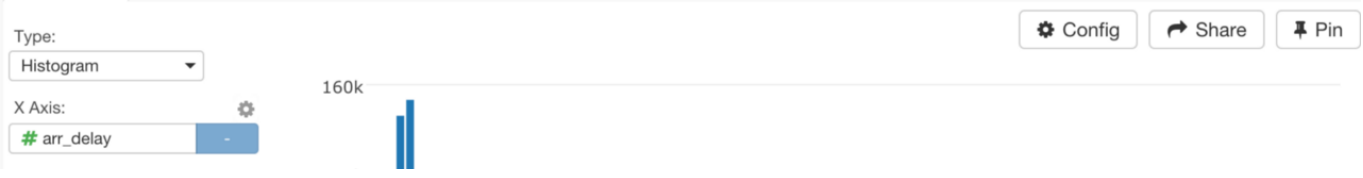
You can use Chart view to explore the data further by visualizing it.

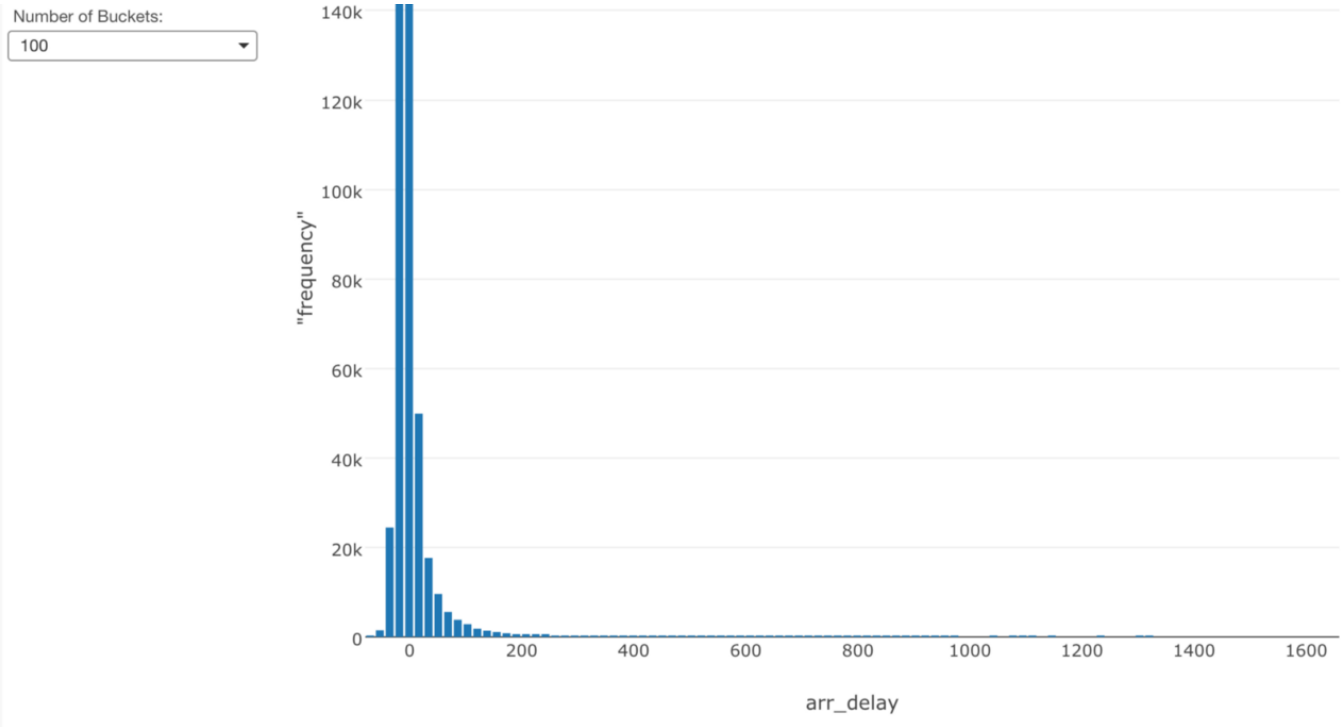
Histogram

By assigning 'arr_delay' column to X-Axis for Histogram chart type, we can see how the values for arrival delay time are distributed.

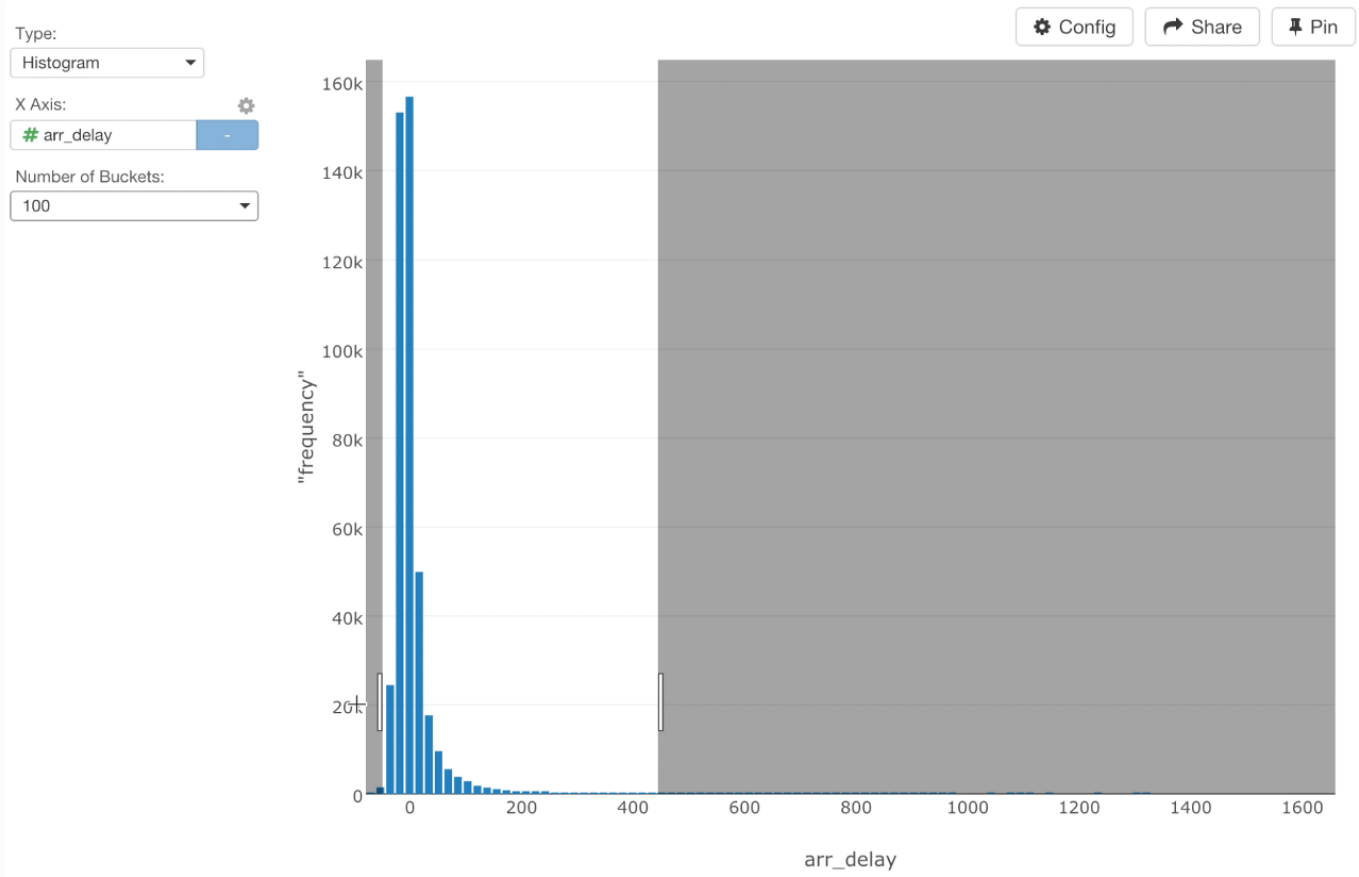


As you can see, the data is skewed highly towards to the smaller values. you can change "Number of Buckets' to 100 to see more detail level distribution.



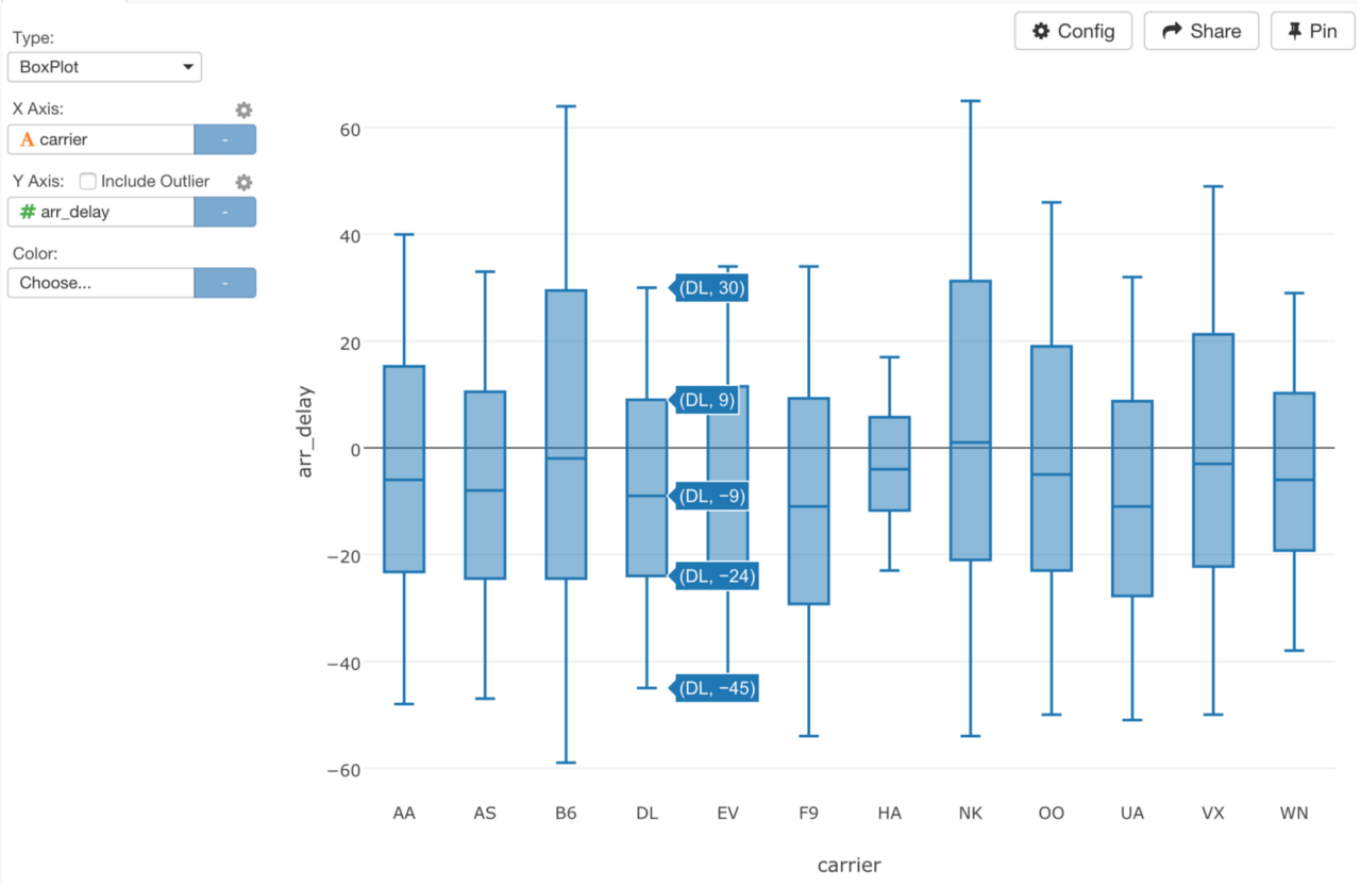


You can always zoom into a certain range of data by dragging the mouse cursor over the area you want to zoom in.



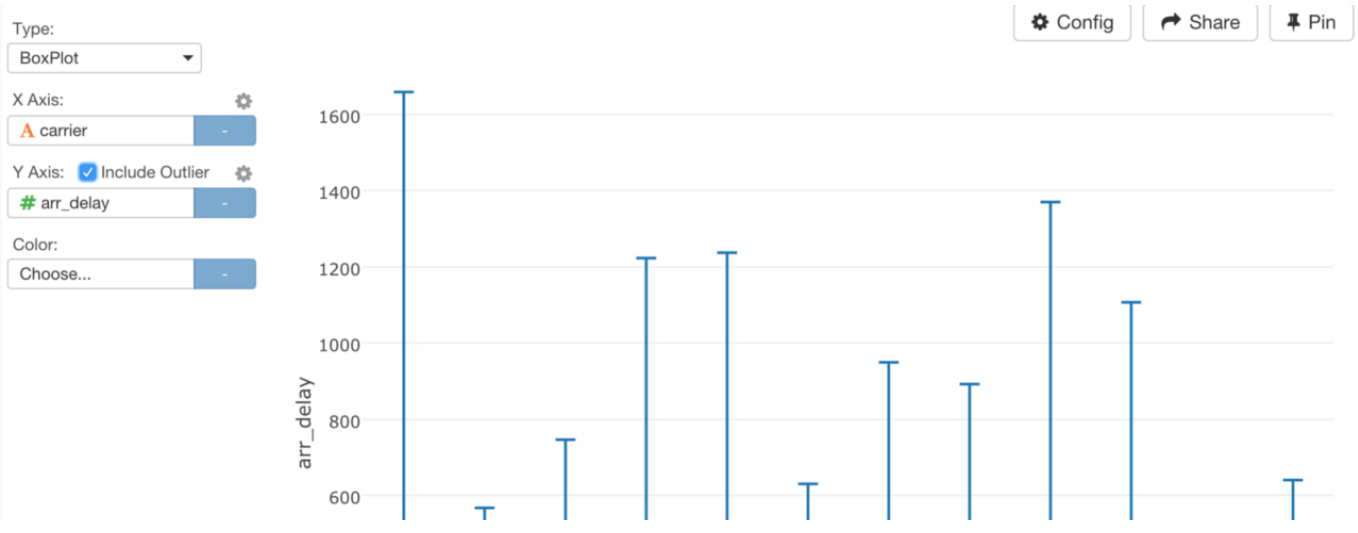
Boxplot

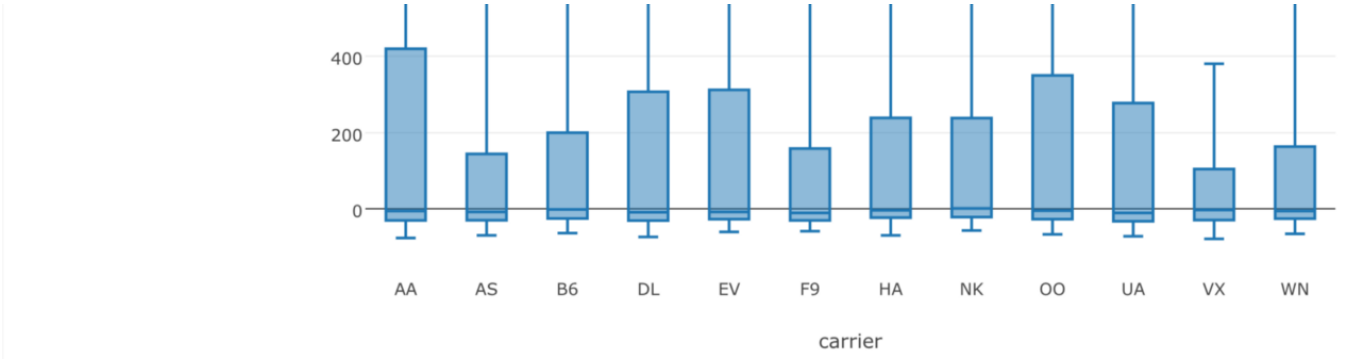
If you want to see how the data is distributed by categorical columns like 'carrier', Boxplot chart would be a good help.



It not only shows the data distribution for each carrier visually but also gives you Max, Min, Median, 1st Quartile, and 3rd Quartile values.

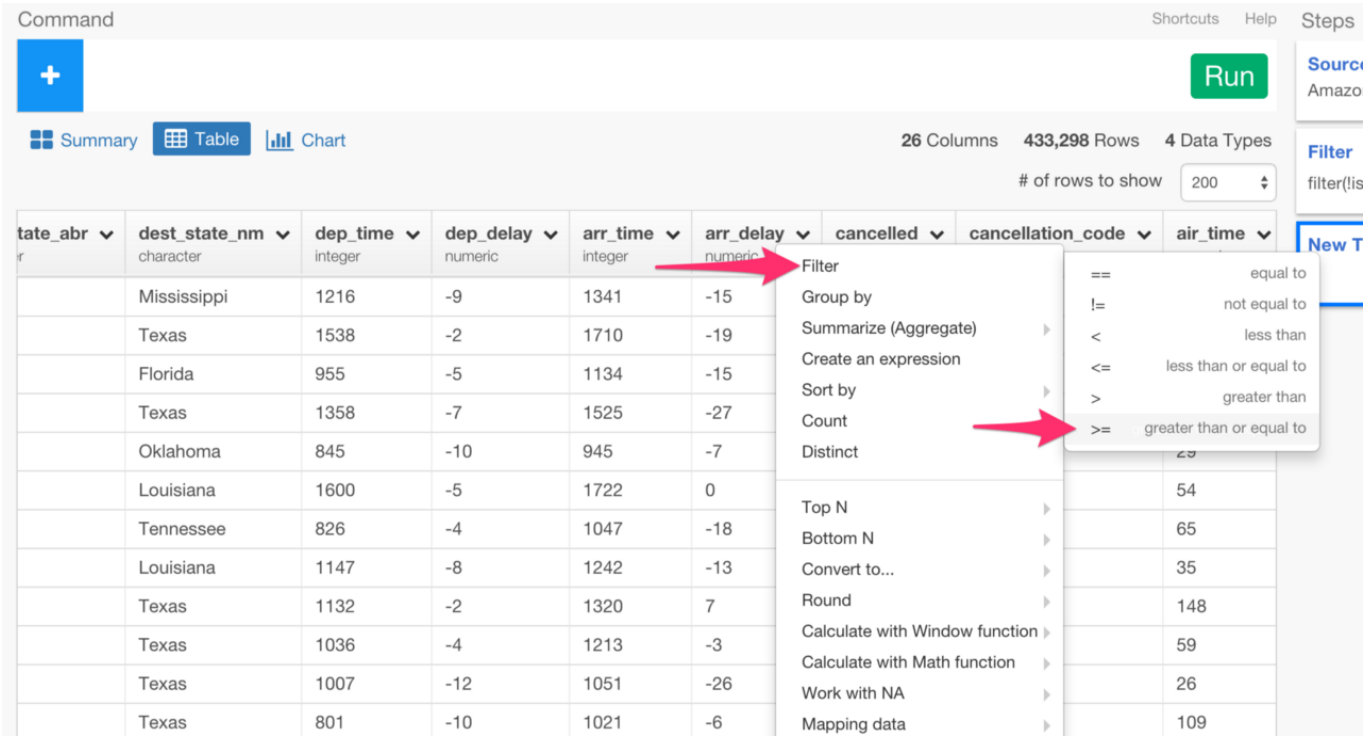
It excludes the outlier values as default, but you can include them by clicking on 'Include Outlier' checkbox if you like.



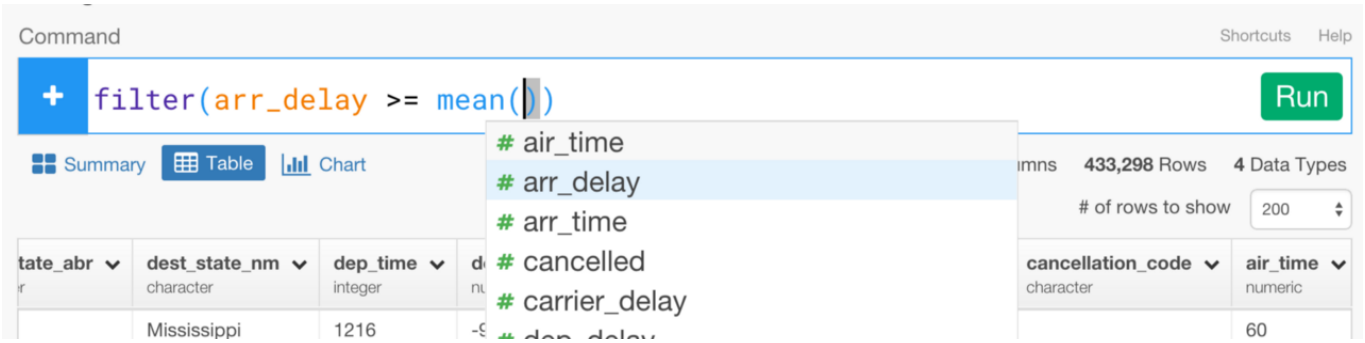


Above Average — Filter with Aggregate Function

Let's say you want to see only the flights whose arrival delay times are worse than the average. You can go back to Table view (or Summary view) and select 'Filter / greater than' menu from the column header dropdown.

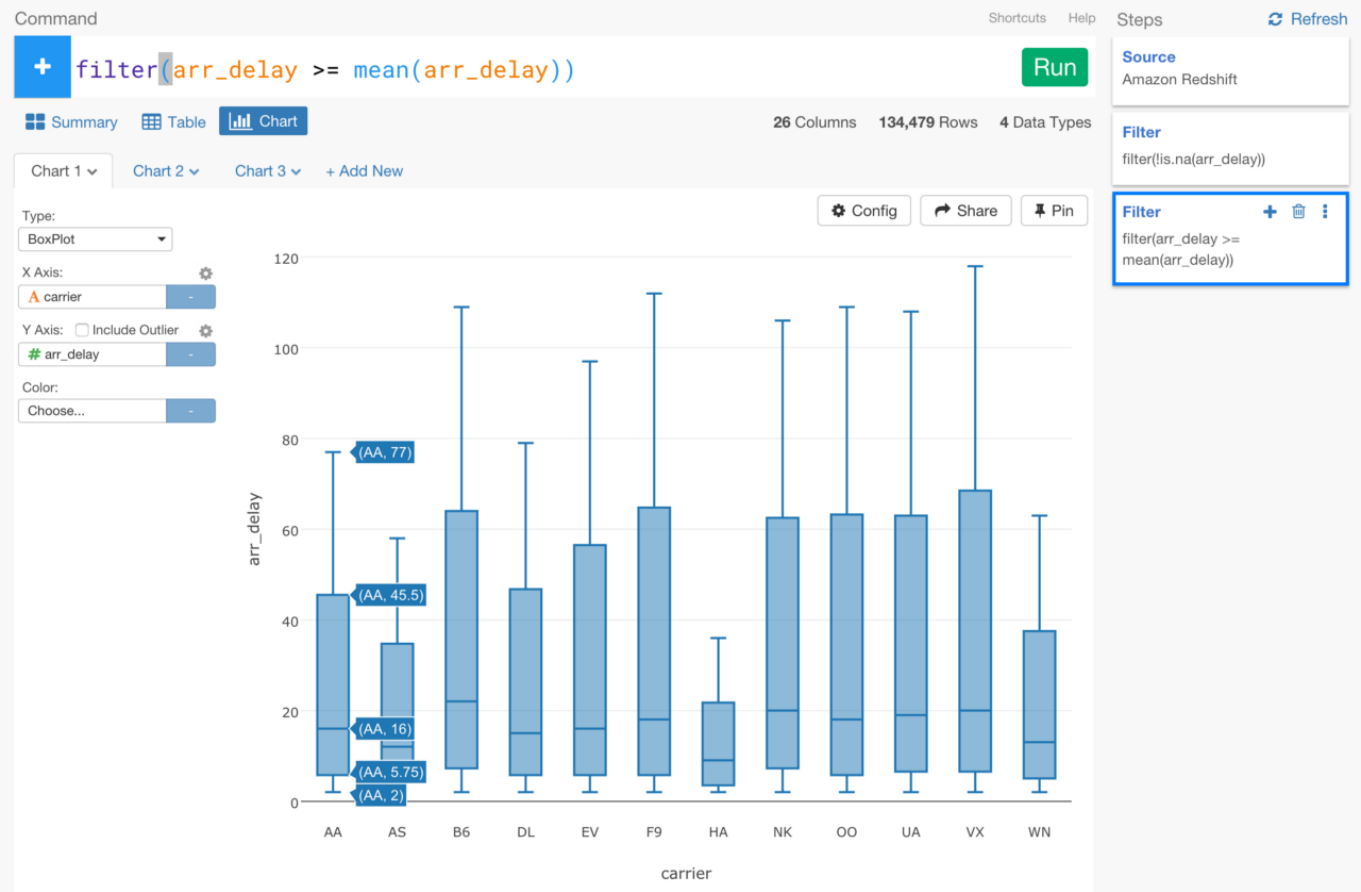


You can type 'mean' and select 'arr_delay' column from the suggested list.



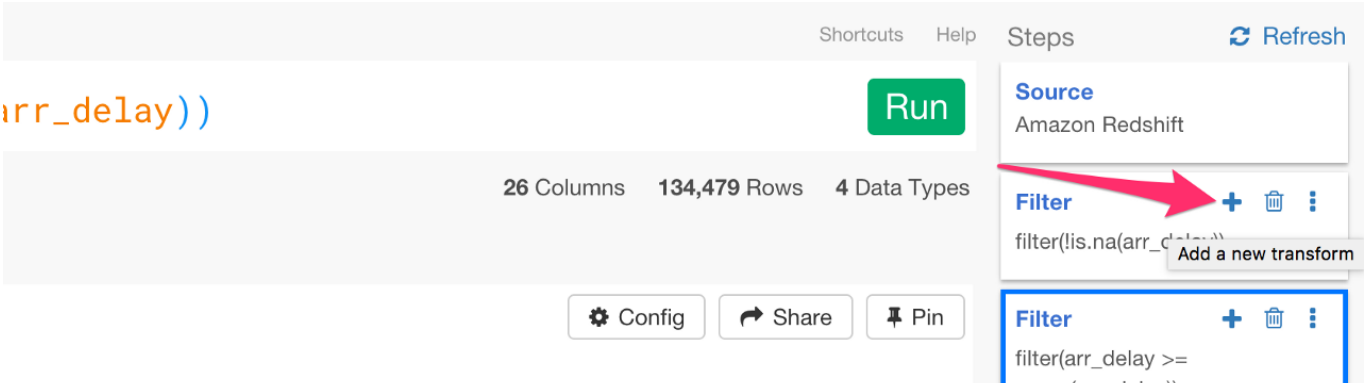
	Texas	1538	# dep_delay # dep_time # distance		79
	Florida	955			80

When you go back to Chart view you can see all the legs are starting from the average value of 2.



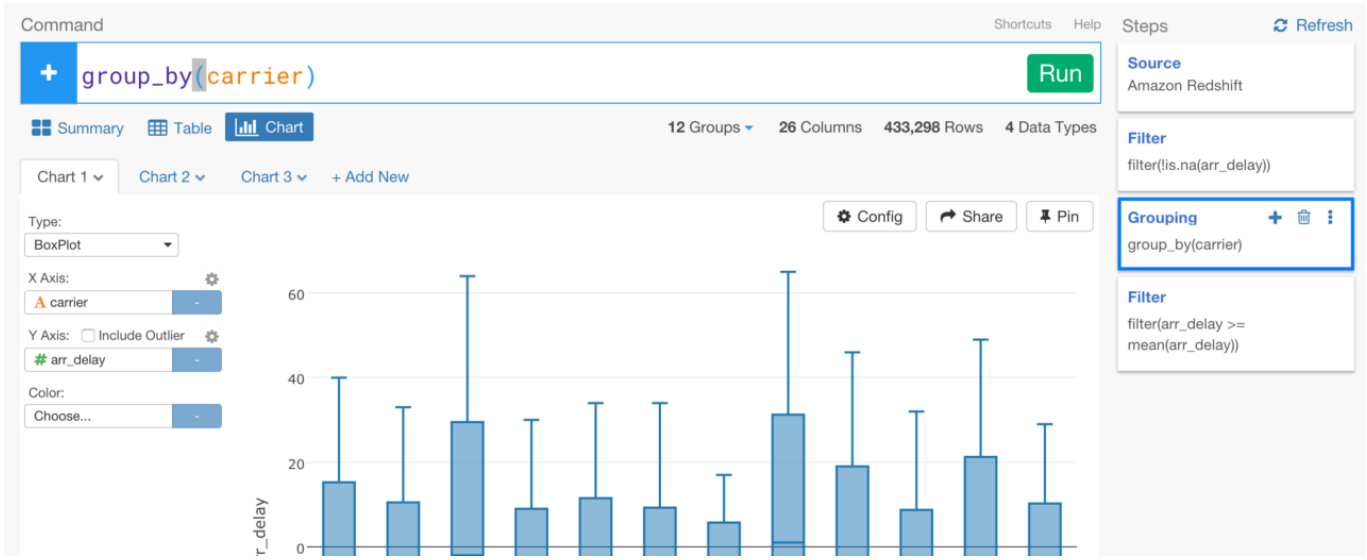
Keep Only Above Average of Each Carrier, not of All

What if you want to filter the data by using average values for each carrier instead of the entire data? It's actually super simple with dplyr. All you need to do is to add a grouping step with 'group_by' command right before the 'Filter' step.

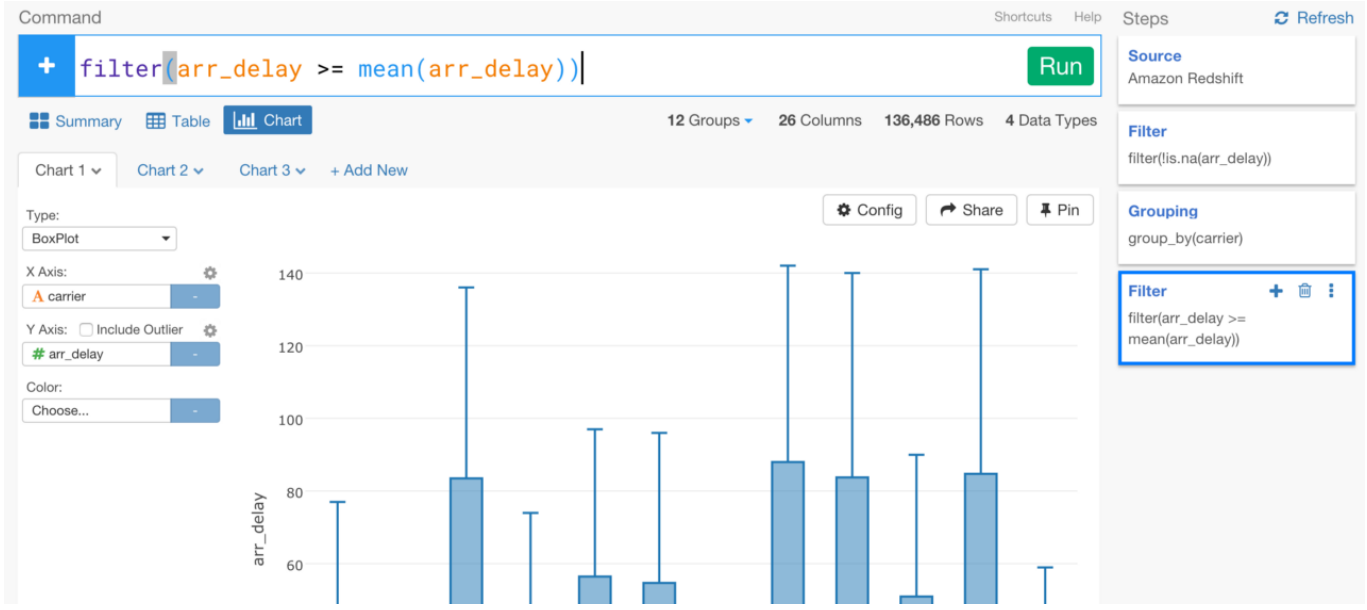


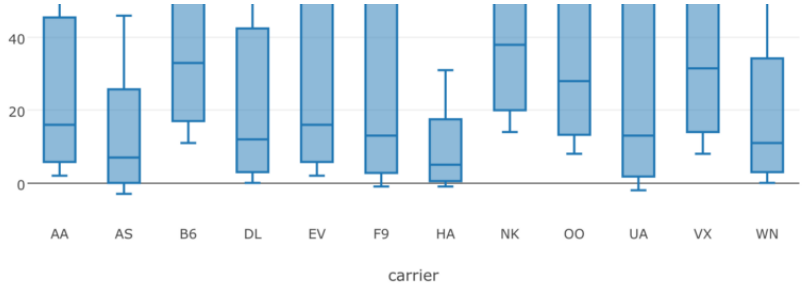
And type the following.

```
group_by(carrier)
```



Now you can go back to the last step and see that each boxplot leg is starting from each carrier's average arrival delay time.





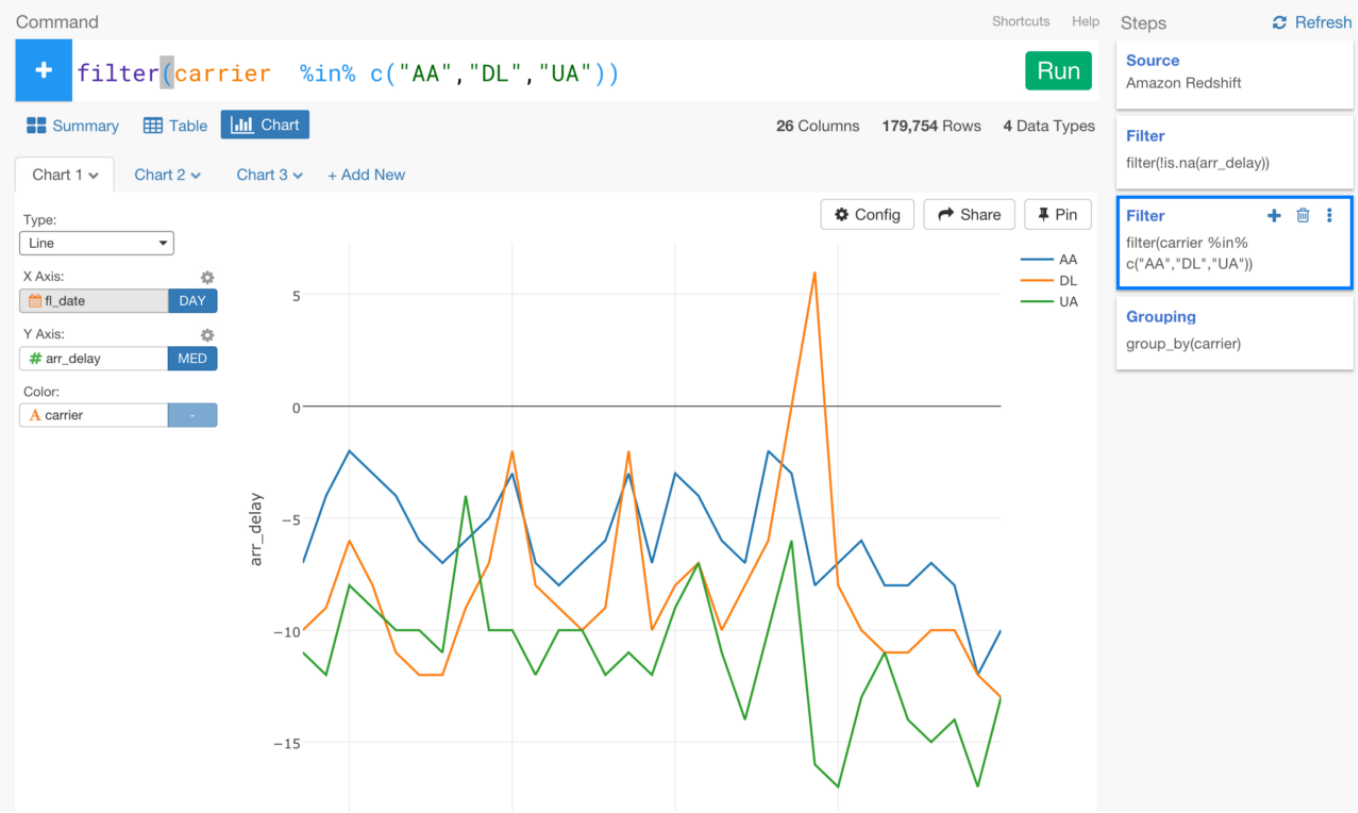
Time Series Analysis

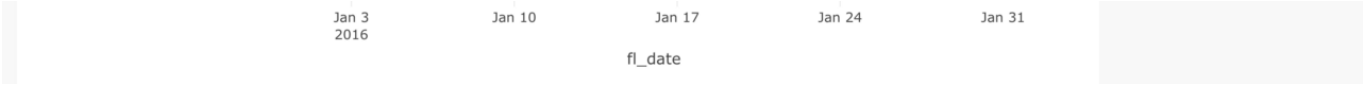
You can find the trend of the arrival delay for each carrier by using Line chart.

I'm adding another Filter step after the first 'Filter' step to keep only 'American Airline (AA)', 'United Airline (UA)', and 'Delta Airline (DL)' to make it simple for this demonstration like below.

```
filter(carrier  %in% c("AA","UA","DL"))
```

Change the chart type to Line and assign 'fl_date' to X-Axis, 'arr_delay' to Y-Axis, and 'carrier' to Color. Also, you can select 'Day' as the aggregation level for X-Axis and 'Median' as the aggregation function for Y-Axis.





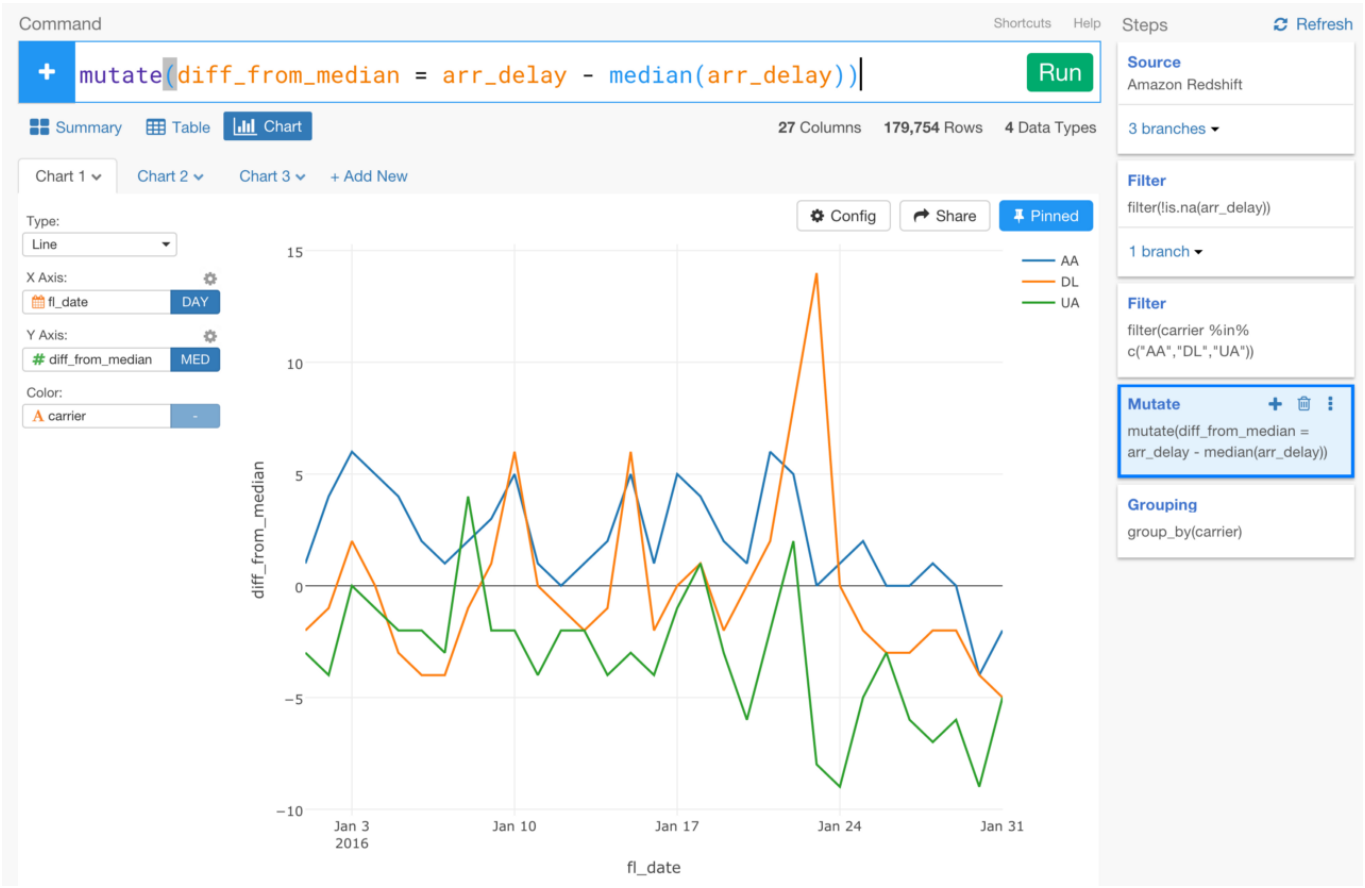
If we look at the median values of each carrier by day, they are mostly negative delay times, which means they are not delayed. But, is this really useful insight? What if all the other carriers also have not delayed? Don't we want to see how these three carriers are doing in a comparison to others?

Well, you can quickly change the baseline. you can use 'mutate' command to create a new column with an expression. In this case you can calculate the difference between the arrival delay time and the median of arrival_delay times of all.

```
mutate(diff_from_median = arr_delay - median(arr_delay))
```

Make sure you add this step before 'Grouping' step, otherwise the 'median' function would do the calculation for each group, which we don't want for this time.

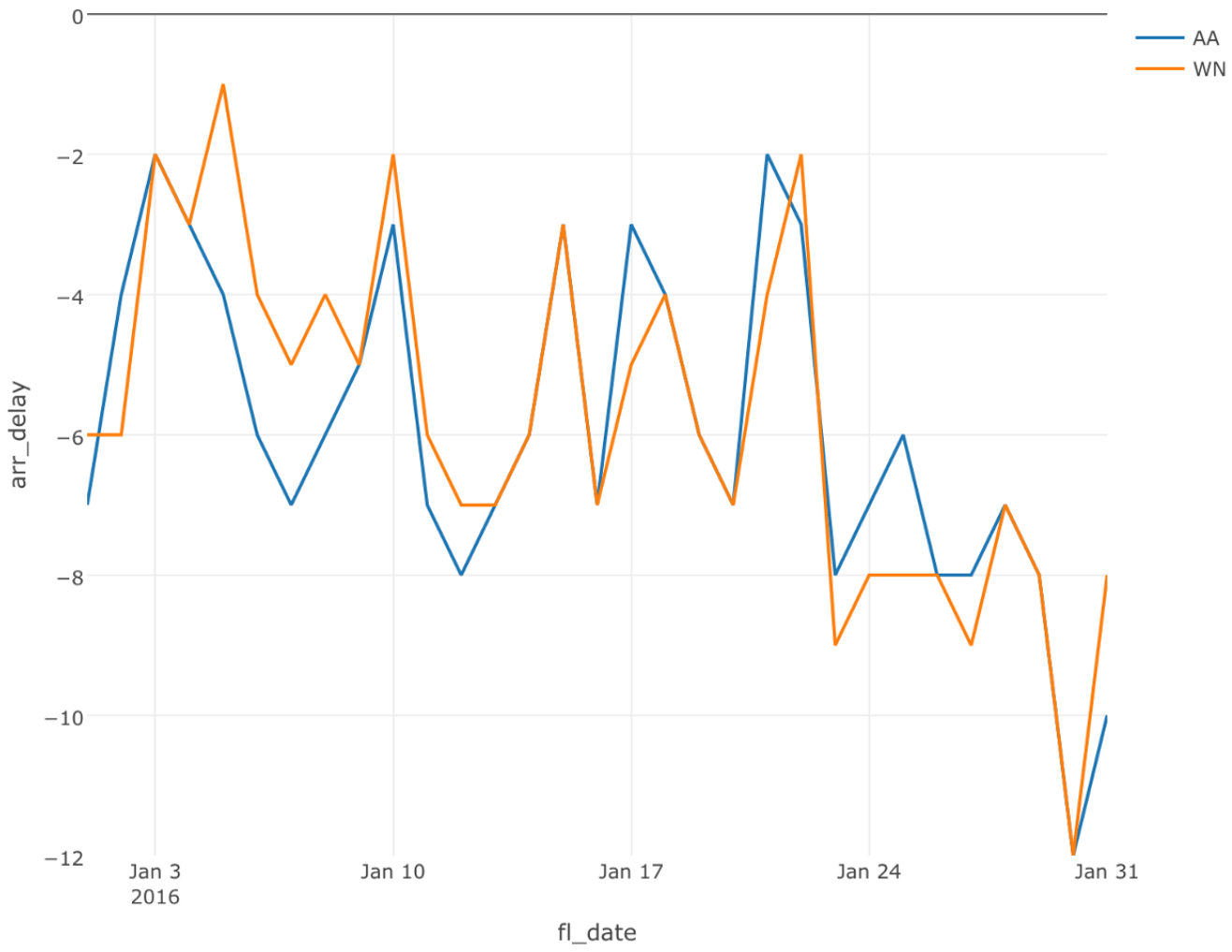
Assign this newly created column 'diff_from_median' to Y-Axis.



Now, we can see a slight different view here. For example, American Airline is mostly worse than the overall median arrival delay time while United Air is mostly better than the overall median.

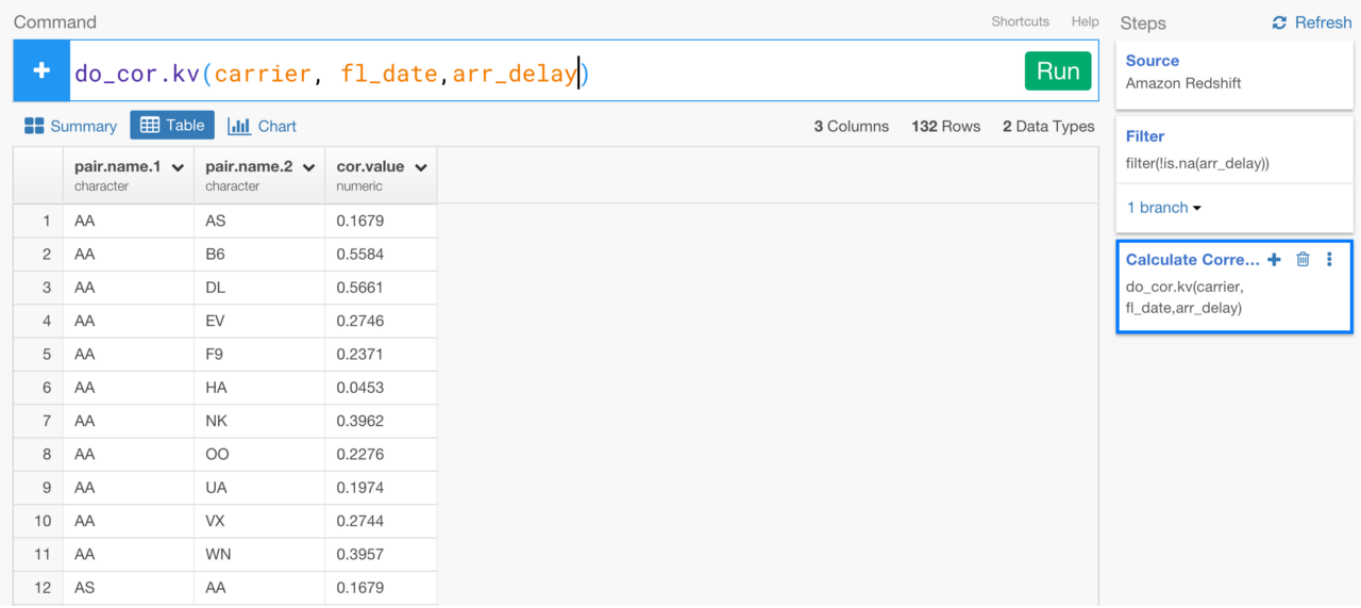
Statistical Data Analysis — Correlation

Let's say we want to find which airline carriers are closely correlated based on the daily arrival delay trend. For example, if we see the trend lines for two carriers like below, then we consider them as highly correlated.



Instead of using our eyes on the visualization to see how the carriers are corrrelated to one another we can let the machine figure it all out automatically by applying the correlation algorithm.

```
do_cor.kv(carrier, fl_date, arr_delay)
```

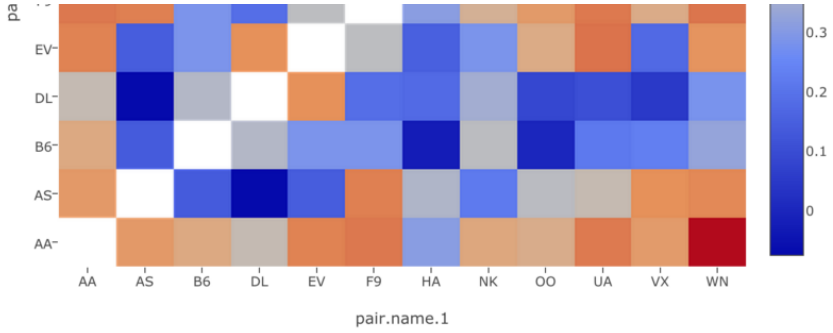


	pair.name.1 character	pair.name.2 character	cor.value numeric
1	AA	AS	0.1679
2	AA	B6	0.5584
3	AA	DL	0.5661
4	AA	EV	0.2746
5	AA	F9	0.2371
6	AA	HA	0.0453
7	AA	NK	0.3962
8	AA	OO	0.2276
9	AA	UA	0.1974
10	AA	VX	0.2744
11	AA	WN	0.3957
12	AS	AA	0.1679

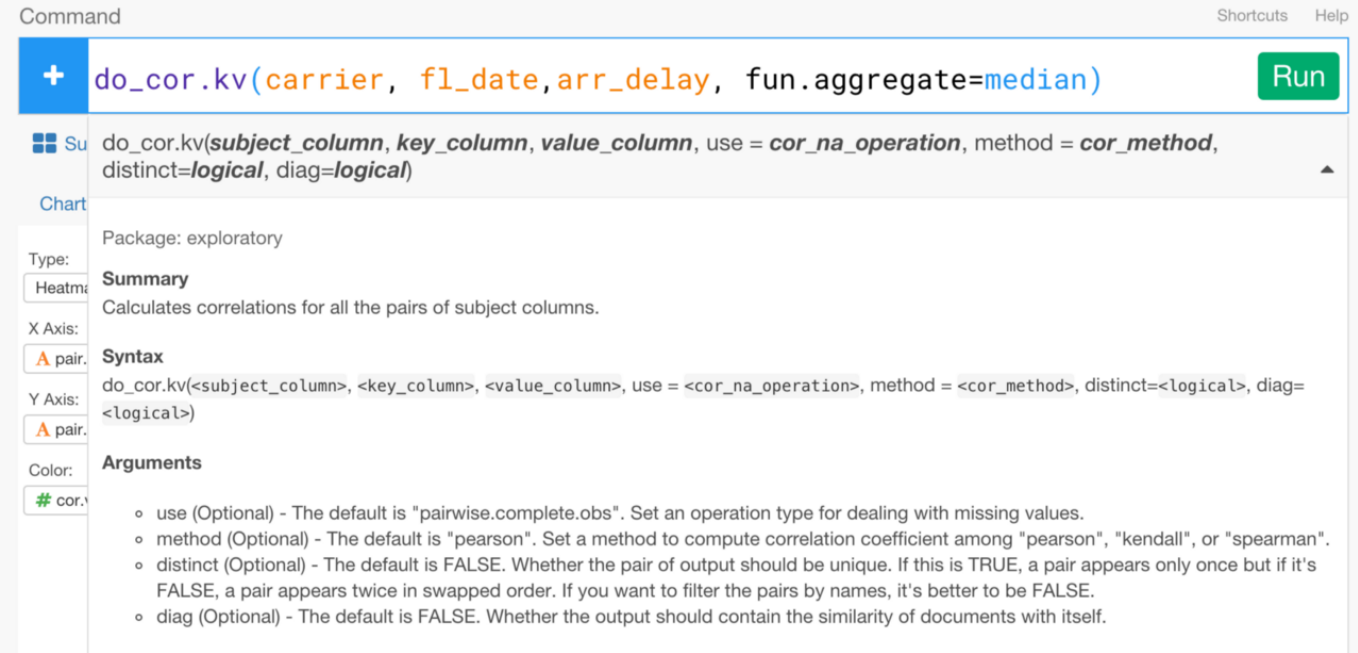
This 'do_cor.kv' function calculates the correlation for every single pair of the carriers based on how the arrival delay values (arr_delay) are for each flight date (fl_date). It aggregates the values at carrier and flight date level by using 'mean' function as default, but you can change this by using 'fun.aggregate' function. For example, I'm setting it to 'median' below.

```
do_cor.kv(carrier, fl_date, arr_delay, fun.aggregate=median)
```

We can go to Chart view and visualize the result to see the correlation among the carriers better. The darker the red color is the higher they are correlated, such as AA and WN.

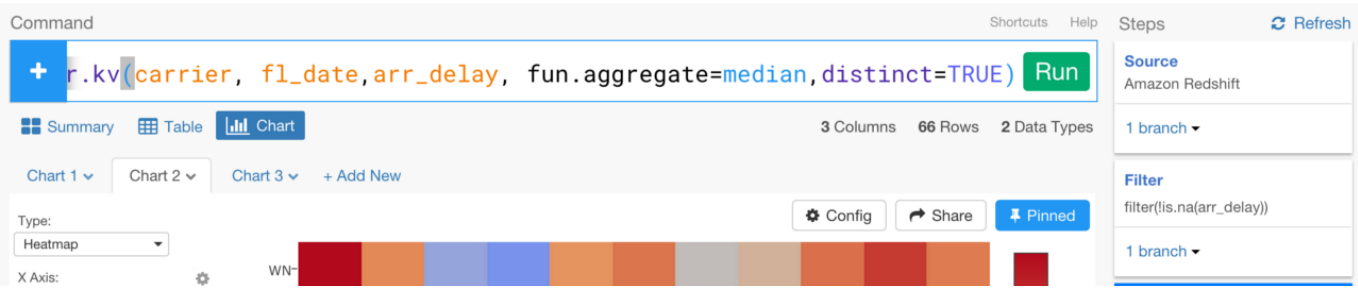


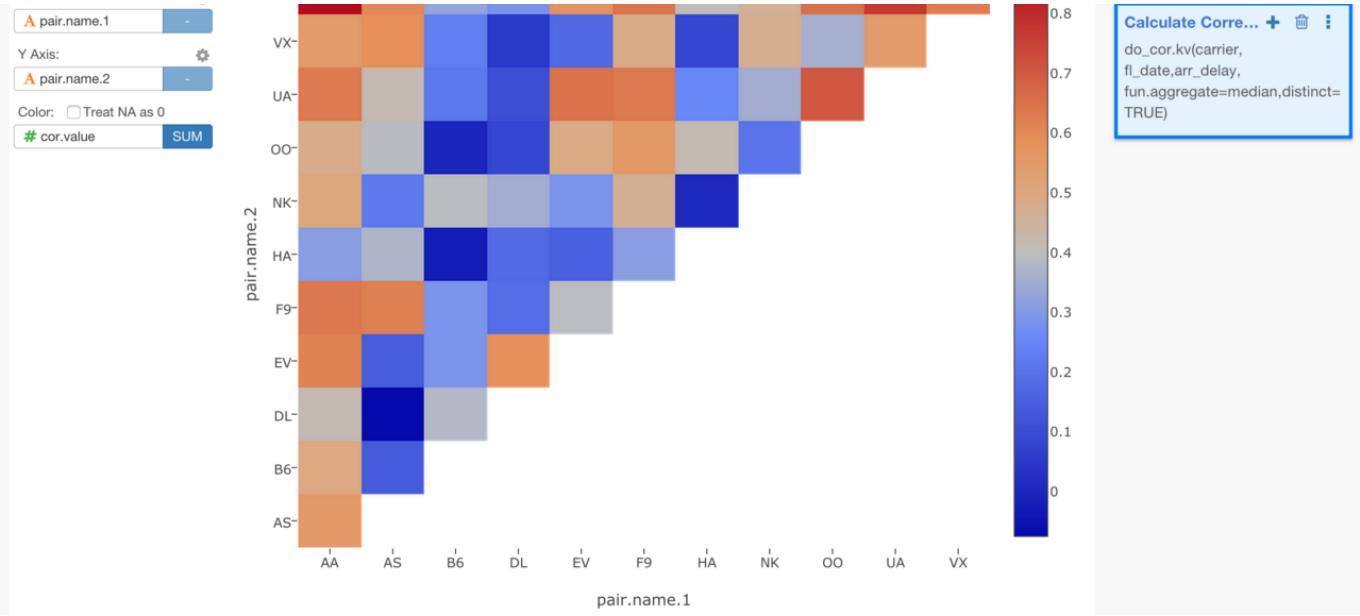
When you click inside the function you can always see what the function does and how it works. Or, you can always see the reference document for all the functions.



As you can see there are other arguments you can try it out. For example, if you don't want to see the duplicated pairs, you can set 'distinct' argument to TRUE.

```
do_cor.kv(carrier, fl_date, arr_delay, fun.aggregate=median,
distinct=TRUE)
```





As you have seen, with Exploratory you can quickly bring your data in Amazon Redshift database into R and start exploring the data interactively and iteratively with various visualization types and with so many R's algorithms.

If you would like to try it out quickly you can sign up for Exploratory Desktop beta from here for free!

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Amazon Redshift support could not have been done without helps from the community. Special thanks to Sébastien for his advise on the random sampling and variable support!

. . .

R packages used in this post

hadley/dplyr

dplyr - Dplyr: A grammar of data manipulation

github.com

exploratory-io/exploratory_func

exploratory_func - R functions for Exploratory

github.com

Thanks to hide kojima, Kei Saito, and Hideaki Hayashi.

Data Science Big Data Data Visualization Redshift