

DataEng: Data Storage Activity

This week you'll gain experience with various ways to load data into a Postgres database.

Make a copy of this document and use it to record your results. Store a PDF copy of the document in your git repository along with any needed code before submitting for this week.

The data set for this week is US Census data from 2015 and 2017. The United States conducts a full census of every household every 10 years (we just finished one last year), but much of the detailed census data comes during the intervening years when the Census Bureau conducts its detailed American Community Survey (ACS) of a randomly selected sample of approximately 3.5 million households each year. The resulting data gives a more detailed view of many factors of American life and the composition of households.

[ACS Census Tract Data for 2015](#)

[ACS Census Tract Data for 2017](#)

Your job is to load these two data sets (approximately 74000 rows each) such that they can be queried together. You'll configure a postgres DBMS on a new GCP virtual machine, and then load the data **five different ways**, comparing the cost of each method.

We hope that you make it all the way through to the end, but regardless, use your time wisely to gain python programming experience and learn as much as you can about bulk loading of data. Note that the goal here is not to achieve the fastest load times. Instead, **your goal should be to gain knowledge about how a data storage server (such as PostgreSQL) works and why various data loading approaches produce differing performance results.**

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A. Configure Your Database

1. Create a new GCP virtual machine for this week's work (medium size or larger).

Answer:

Done

2. Follow the steps listed in the [Installing and Configuring and PostgreSQL server](#) instructions provided for project assignment #2. To keep things separate from your project work we suggest you use a separate vm, separate database name, separate user name, etc. Then each/all of these can then be updated or deleted whenever you need without affecting your project.

Answer:

Done

3. Also the following commands will help to configure the python module “psycopg2” which you will use to connect to your postgres database:

```
sudo apt install python3 python3-dev python3-venv
sudo apt-get install python3-pip
pip3 install psycopg2-binary
```

Answer:

Done

B. Connect to Database and Create Your Main Data Table

1. Copy/upload your data to your VM and uncompress it

Answer:

Done

2. Create a small test sample by running a linux command similar to the following. The small test sample will help you to quickly test any code that you write before running your code with the full dataset.

```
head -1 acs2015_census_tract_data.csv > Oregon2015.csv
grep Oregon acs2015_census_tract_data.csv >> Oregon2015.csv
```

The first command copies the headers to the sample file and the second command appends all of the Oregon 2015 data to the sample file. This should produce a file with approximately 800 records which is a bit more than 1% of the 2015 data set.

Answer:

Done

3. Write a python program that connects to your postgres database and creates your main census data table. Start with this example code: [load_inserts.py](#). If you want to run load_inserts.py, then run it with -d <data file> -c -y 2015 Note that you must input a year value because the census data does not explicitly include the calendar year within each data file.

Answer:

```
shengjia@datastorage:~$ python3 load_inserts.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 1.249 seconds
```

C. Baseline - Simple INSERT

The tried and true SQL command [INSERT INTO ...](#) is the most basic way to insert data into a SQL database, and often it is the best choice for small amounts of data, production databases and other situations in which you need to maintain performance and reliability of the updated table.

The `load_inserts.py` program shows how to use simple INSERTs to load data into a database. It is possibly the slowest way to load large amounts of data. For me, it takes approximately 1 second for the Oregon sample and nearly 120 seconds for either of the full acs data sets.

Take the program and try it with both the Oregon sample and the full data sets. Fill in the appropriate table rows below.

Answer:

```
shengjia@datastorage:~$ python3 load_inserts.py -d acs2015_census_tract_data.csv -c -y 2015
readdata: reading from File: acs2015_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 108.1 seconds
```

```
shengjia@datastorage:~$ python3 load_inserts.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 1.249 seconds
```

```
shengjia@datastorage:~$ python3 load_inserts.py -d acs2017_census_tract_data.csv -c -y 2017
readdata: reading from File: acs2017_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 102.5 seconds
```

```
shengjia@datastorage:~$ python3 load_inserts.py -d Oregon2017.csv -c -y 2017
readdata: reading from File: Oregon2017.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 1.026 seconds
```

D. The Effects of Indexes and Constraints

You might notice that the `CensusData` table has a composite Primary Key constraint and an additional index on the state name column. Indexes and constraints are helpful for query performance, but do not work well for load performance.

Try delaying the creation of these constraints/indexes until after the load of the first data set is loaded. Then loading the next increment of data (e.g., when loading the ACS 2017 data), try **dropping the constraint and index**, then load the new increment of data, and then re-apply the constraint and index. Enter the resulting load times into the results table. Did this technique improve load performance?

Answer:

```
shengjia@datastorage:~$ python3 partD.py -d acs2017_census_tract_data.csv -c -y 2017
readdata: reading from File: acs2017_census_tract_data.csv
Created CensusData
Loading 74000 rows
Add index and constraint
Finished Loading. Elapsed Time: 71.97 seconds
```

```
shengjia@datastorage:~$ python3 partD.py -d Oregon2017.csv -c -y 2017
readdata: reading from File: Oregon2017.csv
Created CensusData
Loading 836 rows
Add index and constraint
Finished Loading. Elapsed Time: 1.028 seconds
```

```
shengjia@datastorage:~$ python3 partD.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Add index and constraint
Finished Loading. Elapsed Time: 1.276 seconds
```

```
shengjia@datastorage:~$ python3 partD.py -d acs2015_census_tract_data.csv -c -y 2015
readdata: reading from File: acs2015_census_tract_data.csv
Created CensusData
Loading 74000 rows
Add index and constraint
Finished Loading. Elapsed Time: 72.47 seconds
```

E. The Effects of Logging

By default, RDBMS tables incur overheads of write-ahead logging (WAL) such that the database logs extra metadata about each update to the table and uses that WAL data to recover the contents of the table in case of RDBMS crash. **This is a great feature but can get in your way when trying to bulk load data into the database.**

Try loading to a “staging” table, a table that is [declared as UNLOGGED](#). This staging table should have no constraints or indexes. Then use a SQL query to append the staging data to the main CensusData table.

By the way, you might have noticed that the load_inserts.py program sets autocommit=True on the database connection. This makes loaded data available to DB queries immediately after each insert. But it also implies a great amount of transaction overhead. It also allows readers of the database to view an incomplete set of data during the load. How does load performance change if you do not set autocommit=True and instead explicitly commit all of the loaded data within a transaction?

Answer:

```
shengjia@datastorage:~$ python3 partE.py -d Oregon2017.csv -c -y 2017
readdata: reading from File: Oregon2017.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.1303 seconds
```

```
shengjia@datastorage:~$ python3 partE.py -d acs2017_census_tract_data.csv -c -y 2017
readdata: reading from File: acs2017_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 15.17 seconds
```

```
shengjia@datastorage:~$ python3 partE.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.1738 seconds
```

```
shengjia@datastorage:~$ python3 partE.py -d acs2015_census_tract_data.csv -c -y 2015
readdata: reading from File: acs2015_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 14.81 seconds
```

F. Temp Tables and Memory Tuning

Next compare the above approach with loading the data to [a temporary table](#) (and copying from the temporary table to the CensusData table). Which approach works best for you.

The amount of memory used for temporary tables is default configured to only 8MB. Your VM has enough memory to allocate much more memory to temporary tables. Try allocating 256 MB (or more) to temporary tables. So update the XYZ parameter to allow the database to use more memory for your temporary table. Rerun your load experiments. Did it make a difference?

Answer:

Used 8MB:


```
shengjia@datastorage:~$ python3 partF.py -d Oregon2017.csv -c -y 2017
readdata: reading from File: Oregon2017.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.2477 seconds
```

```
shengjia@datastorage:~$ python3 partF.py -d acs2017_census_tract_data.csv -c -y 2017
readdata: reading from File: acs2017_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 19.44 seconds
```

```
shengjia@datastorage:~$ python3 partF.py -d acs2015_census_tract_data.csv -c -y 2015
readdata: reading from File: acs2015_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 20.37 seconds
```

```
shengjia@datastorage:~$ python3 partF.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.178 seconds
```

Used 128MB: Since the us-west1-b zone only has the maximum memory 128MB

```
shengjia@datastorage:~$ python3 partF.py -d acs2017_census_tract_data.csv -c -y 2017
readdata: reading from File: acs2017_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 12.34 seconds
```

```
shengjia@datastorage:~$ python3 partF.py -d Oregon2017.csv -c -y 2017
readdata: reading from File: Oregon2017.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.1327 seconds
```

```
shengjia@datastorage:~$ python3 partF.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.1264 seconds
```

```
shengjia@datastorage:~$ python3 partF.py -d acs2015_census_tract_data.csv -c -y 2015
readdata: reading from File: acs2015_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 12.83 seconds
```

Based on the above screenshots, using the huge memory can load dataset quickly.

G. Batching

So far our load performance has been held back by the fact we are using individuals calls to the DBMS. As with many Computer Systems situations we can improve performance by batching operations. [Haki Benita's great article about fast loading to Postgres](#) notes that use of psycopg2's `execute_batch()` method can increase load rate by up to two orders of magnitude. The blog provides sample code, time measurements and memory measurements. Adapt his code to your case, rerun your experiments and note your results in the table below.

Answer:

```
shengjia@datastorage:~$ python3 partG.py -d acs2017_census_tract_data.csv -c -y 2017
readdata: reading from File: acs2017_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 11.89 seconds
```

```
shengjia@datastorage:~$ python3 partG.py -d Oregon2017.csv -c -y 2017
readdata: reading from File: Oregon2017.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.1354 seconds
```

```
shengjia@datastorage:~$ python3 partG.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.1353 seconds
```

```
shengjia@datastorage:~$ python3 partG.py -d acs2015_census_tract_data.csv -c -y 2015
readdata: reading from File: acs2015_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 11.79 seconds
```

H. Built In Facility (copy_from)

The number one rule of bulk loading is to pay attention to the native facilities provided by the DBMS system implementers. As we saw with Jjoy Victor's presentation last week, the DBMS vendors often put great effort into providing purpose-build loading mechanisms that achieve great speed and scalability.

With a simple, one-server Postgres database, that facility is known as COPY, \copy, or for python programmers [copy_from](#). Haki Benita's blog shows how to use **copy_from** to achieve another order of magnitude in load performance. Adapt Haki's code to your case, rerun your experiments and note your results in the table.

Answer:

```
shengjia@datastorage:~$ python3 partH.py -d acs2015_census_tract_data.csv -c -y 2015
readdata: reading from File: acs2015_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 1.08 seconds
```

```
shengjia@datastorage:~$ python3 partH.py -d Oregon2015.csv -c -y 2015
readdata: reading from File: Oregon2015.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.01863 seconds
```

```
shengjia@datastorage:~$ python3 partH.py -d acs2017_census_tract_data.csv -c -y 2017
readdata: reading from File: acs2017_census_tract_data.csv
Created CensusData
Loading 74000 rows
Finished Loading. Elapsed Time: 1.093 seconds
```

```
shengjia@datastorage:~$ python3 partH.py -d Oregon2017.csv -c -y 2017
readdata: reading from File: Oregon2017.csv
Created CensusData
Loading 836 rows
Finished Loading. Elapsed Time: 0.02048 seconds
shengjia@datastorage:~$
```

I. Results

Use this table to present your results. We are not asking you to do a sophisticated performance analysis here with multiple runs, warmup time, etc. Instead, do a rough measurement using timing code similar to what you see in the load_inserts.py code. Record your results in the following table.

Method	Code Link	acs2015	acs2017
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Simple inserts	load_inserts.py	Sample: 1.249 s Full: 108.1 s	Sample: 1.026 s Full: 102.5 s
Drop Indexes and Constraints	partD.py	Sample: 1.276 s Full: 72.47 s	Sample: 1.028 s Full: 71.97 s
Use UNLOGGED table	partE.py	Sample: 0.1738 s Full: 14.81 s	Sample: 0.1303 s Full: 15.17 s
Temp Table with memory tuning	partF.py	8 MB: Sample: 0.178 s Full: 20.37 s 128 MB: Sample: 0.1264 s Full: 12.83 s	8 MB: Sample: 0.2477 s Full: 19.44 s 128 MB: Sample: 0.1327 s Full: 12.34 s
Batching	partG.py	Sample: 0.1353 s Full: 11.79 s	Sample: 0.1354 s Full: 11.89 s
copy_from	partH.py	Sample: 0.01863 s Full: 1.08 s	Sample: 0.02048 s Full: 1.093 s

J. Observations

Use this section to record any observations about the various methods/techniques that you used for bulk loading of the USA Census data. Did you learn anything about how and RDBMS functions and why various loading approaches produce varying performance results?

Answer:

After doing the whole experiment, I found using the 'copy_from' method is the fastest way to load data. The 'copy_from' method uses the iterate method and I think this is the reason why this method is the fastest way to load data.

I think the 'batching' method probably uses the parallel computing idea to implement. Thus, using this method can also increase the loading speed.

Using the huge memory can increase the speed of loading the dataset.

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