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Using SparkSQL and Pandas to Import Data into Hive and Big Data Discovery

13 JULY 2016 on Big Data (/blog/tag/big-data/), Technical (/blog/tag/technical/), Oracle Big Data Discovery (/blog/tag/oracle-big-data-discovery/), Rittman Mead Life (/blog/tag/rittman-mead-life/), Hive (/blog/tag/hive/), csv (/blog/tag/csv/), twitter (/blog/tag/twitter/), hdfs (/blog/tag/hdfs/), pandas (/blog/tag/pandas/), dgraph (/blog/tag/dgraph/), hue (/blog/tag/hue/), json (/blog/tag/json/), serde (/blog/tag/serde/), sparksql (/blog/tag/sparksql/)

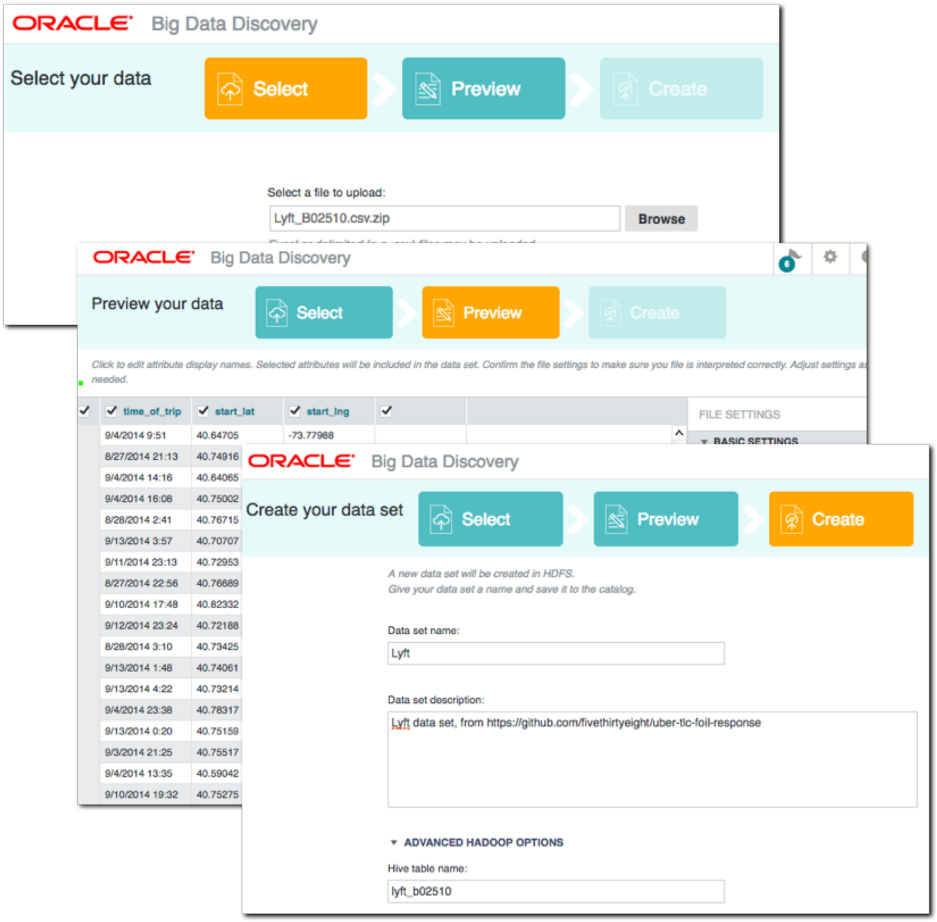
Big Data Discovery (https://www.oracle.com/big-data/big-data-discovery/index.html) (BDD) is a great tool for exploring, transforming, and visualising data stored in your organisation's Data Reservoir. I presented a workshop on it at a recent conference (https://speakerdeck.com/rmoff/unlock-the-value-in-your-big-data-reservoir-using-oracle-big-data-discovery-and-oracle-big-data-spatial-and-graph), and got an interesting question from the audience that I thought I'd explore further here. Currently the primary route for getting data into BDD requires that it be (i) in HDFS and (ii) have a Hive table defined on top of it. From there, BDD automagically ingests the Hive table, or the `data_processing_CLI` is manually called which prompts the BDD DGraph engine to go and sample (or read in full) the Hive dataset.

This is great, and works well where the dataset is vast (this is Big Data, after all) and needs the sampling that DGraph provides. It's also simple enough for Hive tables that have already been defined, perhaps by another team. But - and this was the gist of the question that I got - what about where the Hive table *doesn't* exist already? Because if it doesn't, we now need to declare all the columns as well as choose the all-important SerDe (https://cwiki.apache.org/confluence/display/Hive/SerDe) in order to read the data.

SerDes (https://cwiki.apache.org/confluence/display/Hive/SerDe) are brilliant, in that they enable the application of a schema-on-read to data in many forms, but at the very early stages of a data project there are probably going to be lots of formats of data (such as TSV, CSV, JSON, as well as log files and so on) from varying sources. Choosing the relevant SerDe for each one, and making sure that BDD is also configured with the necessary `jar`, as well as manually listing each column to be defined in the table, adds overhead to the project. Wouldn't it be nice if we could side-step this step somehow? In this article we'll see how!

Importing Datasets through BDD Studio

Before we get into more fancy options, don't forget that BDD itself offers the facility to upload CSV, TSV, and XLSX files, as well as connect to JDBC datasources. Data imported this way will be stored by BDD in a Hive table and ingested to DGraph.



This is great for smaller files held locally. But what about files on your BDD cluster, that are too large to upload from local machine, or in other formats - such as JSON?

Loading a CSV file

As we've just seen, CSV files can be imported to Hive/BDD directly through the GUI. But perhaps you've got a large CSV file sat local to BDD that you want to import? Or a folder full of varying CSV files that would be too time-consuming to upload through the GUI one-by-one?

For this we can use BDD Shell with the Python Pandas (http://pandas.pydata.org/) library, and I'm going to do so here through the excellent Jupyter Notebooks interface. You can read more about these here (http://www.rittmanmead.com/2016/06/using-jupyter-notebooks-big-data-discovery-1-2/) and details of how to configure them on BigDataLite 4.5 here (http://www.rittmanmead.com/2016/06/running-big-data-discovery-shell-jupyter-notebook-big-data-lite-vm-4-5/). The great thing about notebooks, whether Jupyter (http://jupyter.org/) or Zeppelin (https://zeppelin.apache.org/), is that I don't need to write any more blog text here - I can simply embed the notebook inline and it is self-documenting:

https://gist.github.com/76b477f69303dd8a9d8ee460a341c445 (https://gist.github.com/76b477f69303dd8a9d8ee460a341c445)

(gist link (https://gist.github.com/76b477f69303dd8a9d8ee460a341c445))

Note that at end of this we call `data_processing_CLI` to automatically bring the new table into BDD's DGraph engine for use in BDD Studio. If you've got BDD configured to automagically add new Hive tables, or you don't want to run this step, you can just comment it out.

Loading simple JSON data

Whilst CSV files are tabular by definition, JSON (http://www.w3schools.com/json/json_syntax.asp) records can contain nested objects (recursively), as well as arrays. Let's look at an example of using SparkSQL (http://spark.apache.org/docs/latest/sql-programming-guide.html#json-datasets) to import a simple flat JSON file, before then considering how we handle nested and array formats. Note that SparkSQL can read datasets from both local (`file://`) storage as well as HDFS (`hdfs://`):

https://gist.github.com/8b7118c230f34f7d57bd9b0aa4e0c34c (https://gist.github.com/8b7118c230f34f7d57bd9b0aa4e0c34c)

(gist link (https://gist.github.com/8b7118c230f34f7d57bd9b0aa4e0c34c))

Once loaded into Hive, it can be viewed in Hue:

Data sample for tmp01

	tmp01.business_id	tmp01.date	tmp01.likes	tmp01.text
1	cE27W9VPgO88Qxe4ol6y_g	2013-04-18	0	Don't waste your time.
2	mVHrayjG3uZ_RLHkLj-AMg	2013-01-06	1	Your GPS will not allow you to find this place. Put Rar
3	KayYbHCt-RkbGcPdGOThNg	2013-12-03	0	Great drink specials!
4	KayYbHCt-RkbGcPdGOThNg	2015-07-08	0	Friendly staff, good food, great beer selection, and rel

Loading nested JSON data

What's been great so far, whether loading CSV, XLS, or simple JSON, is that we've not had to list out column names. All that needs modifying in the scripts above to import a different file with a different set of columns is to change the filename and the target tablename. Now we're going to look at an example of a JSON file with nested objects - which is very common in JSON - and we're going to have to roll our sleeves up a tad and start hardcoding some schema details.

First up, we import the JSON to a SparkSQL dataframe as before (although this time I'm loading it from HDFS, but local works too):

```
df = sqlContext.read.json('hdfs:///user/oracle/incoming/twitter/2016/07/12/')
```

Then I declare this as a temporary table, which enables me to subsequently run queries with SQL against it

```
df.registerTempTable("twitter")
```

A very simple example of a SQL query would be to look at the record count:

```
result_df = sqlContext.sql("select count(*) from twitter")
result_df.show()

+----+
| _c0|
+----+
|3011|
+----+
```

The result of a `sqlContext.sql` invocation is a dataframe, which above I'm assigning to a new variable, but I could as easily run:

```
sqlContext.sql("select count(*) from twitter").show()
```

for the same result.

The sqlContext has inferred the JSON schema automagically, and we can inspect it using

```
df.printSchema()
```

The twitter schema is huge, so I'm just quoting a few choice sections of it here to illustrate subsequent points:

```
root
 |-- created_at: string (nullable = true)
 |-- entities: struct (nullable = true)
 |    |-- hashtags: array (nullable = true)
 |    |    |-- element: struct (containsNull = true)
 |    |    |    |-- indices: array (nullable = true)
 |    |    |    |    |-- element: long (containsNull = true)
 |    |    |    |-- text: string (nullable = true)
 |    |-- user_mentions: array (nullable = true)
 |    |    |-- element: struct (containsNull = true)
 |    |    |    |-- id: long (nullable = true)
 |    |    |    |-- id_str: string (nullable = true)
 |    |    |    |-- indices: array (nullable = true)
 |    |    |    |    |-- element: long (containsNull = true)
 |    |    |    |-- name: string (nullable = true)
 |    |    |    |-- screen_name: string (nullable = true)
 |-- source: string (nullable = true)
 |-- text: string (nullable = true)
 |-- timestamp_ms: string (nullable = true)
 |-- truncated: boolean (nullable = true)
 |-- user: struct (nullable = true)
 |    |-- followers_count: long (nullable = true)
 |    |-- following: string (nullable = true)
 |    |-- friends_count: long (nullable = true)
 |    |-- name: string (nullable = true)
 |    |-- screen_name: string (nullable = true)
```

Points to note about the schema:

- In the root of the schema we have attributes such as `text` and `created_at`
- There are nested elements ("**struct**") such as `user` and within it `screen_name`, `followers_count` etc
- There's also **array** objects, where an attribute can occur more than one, such as `hashtags`, and `user_mentions`.

Accessing root and *nested* attributes is easy - we just use dot notation:

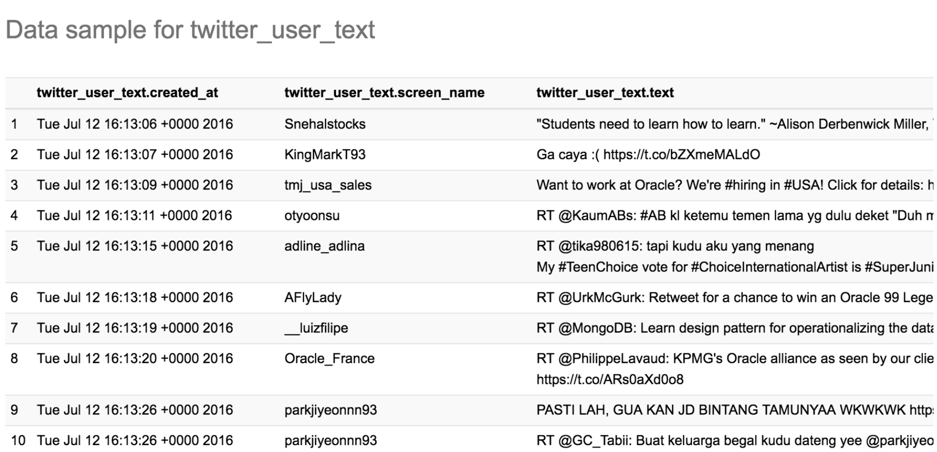
```
sqlContext.sql("SELECT created_at, user.screen_name, text FROM twitter").show()

+--------------------+--------------+--------------------+
|          created_at|   screen_name|                text|
+--------------------+--------------+--------------------+
|Tue Jul 12 16:13:...|  Snehalstocks|"Students need to...|
|Tue Jul 12 16:13:...|   KingMarkT93|Ga caya :( https:...|
```

We can save this as a dataframe that's then persisted to Hive, for ingest into BDD:

```
subset02 = sqlContext.sql("SELECT created_at, user.screen_name, text FROM twitter")
tablename = 'twitter_user_text'
qualified_tablename='default.' + tablename
subset02.write.mode('Overwrite').saveAsTable(qualified_tablename)
```

Which in Hue looks like this:



Data sample for twitter_user_text

	twitter_user_text.created_at	twitter_user_text.screen_name	twitter_user_text.text
1	Tue Jul 12 16:13:06 +0000 2016	Snehalstocks	"Students need to learn how to learn." ~Alison Derbenwick Miller,
2	Tue Jul 12 16:13:07 +0000 2016	KingMarkT93	Ga caya :(https://t.co/bZXmeMALdO
3	Tue Jul 12 16:13:09 +0000 2016	tmj_usa_sales	Want to work at Oracle? We're #hiring in #USA! Click for details: h
4	Tue Jul 12 16:13:11 +0000 2016	otyoonsu	RT @KaumABs: #AB kl ketemu temen lama yg dulu deket "Duh m
5	Tue Jul 12 16:13:15 +0000 2016	adline_adlina	RT @tika980615: tapi kudu aku yang menang My #TeenChoice vote for #ChoiceInternationalArtist is #SuperJuni
6	Tue Jul 12 16:13:18 +0000 2016	AFlyLady	RT @UrkMcGurk: Retweet for a chance to win an Oracle 99 Lege
7	Tue Jul 12 16:13:19 +0000 2016	__luizfilipe	RT @MongoDB: Learn design pattern for operationalizing the data
8	Tue Jul 12 16:13:20 +0000 2016	Oracle_France	RT @PhilippeLavaud: KPMG's Oracle alliance as seen by our clie https://t.co/ARs0aXd0o8
9	Tue Jul 12 16:13:26 +0000 2016	parkjiyeonnn93	PASTI LAH, GUA KAN JD BINTANG TAMUNYAA WKWKWK http:
10	Tue Jul 12 16:13:26 +0000 2016	parkjiyeonnn93	RT @GC_Tabii: Buat keluarga begal kudu dateng yee @parkjiyeo

DETAILED TABLE INFORMATION

Database:	default	
Owner:	oracle	
CreateTime:	Wed Jul 13 09:56:48 BST 2016	
LastAccessTime:	UNKNOWN	
Protect Mode:	None	
Retention:	0	
Location:	hdfs://bigdatalite.localdomain:8020/user/hive/warehouse/twitter_user_text	
Table Type:	MANAGED_TABLE	
Table Parameters:		
	EXTERNAL	FALSE
	spark.sql.sources.provider	org.apache.spark.sql.parquet
	spark.sql.sources.schema.numParts	1
	spark.sql.sources.schema.part.0	{\"type\":\"struct\",\"fields\":[{\"name\":\"created_at\",\" {\"name\":\"screen_name\",\"type\":\"string\",\"nullable
	transient_lastDdlTime	1468400208

STORAGE INFORMATION

SerDe Library:	org.apache.hadoop.hive.ql.io.parquet.serde.ParquetHiveSerDe	
InputFormat:	org.apache.hadoop.hive.ql.io.parquet.MapredParquetInputFormat	
OutputFormat:	org.apache.hadoop.hive.ql.io.parquet.MapredParquetOutputFormat	
Compressed:	No	
Num Buckets:	-1	
Bucket Columns:	[]	
Sort Columns:	[]	
Storage Desc Params:		
	path	hdfs://bigdatalite.localdomain:8020/user/hive/wareho
	serialization.format	1

Attributes in an *array* are a bit more tricky. Here's an example tweet with multiple `user_mentions` and a `hashtag` too:

https://twitter.com/flederbine/status/752940179569115136 (https://twitter.com/flederbine/status/752940179569115136)

Here we use the `LATERAL VIEW` (https://cwiki.apache.org/confluence/display/Hive/LanguageManual+LateralView) syntax, with the optional `OUTER` operator since not all tweets have these additional entities, and we want to make sure we show all tweets including those that don't have these entities. Here's the SQL formatted for reading:

```
SELECT id,
created_at,
user.screen_name,
text as tweet_text,
hashtag.text as hashtag,
user_mentions.screen_name as mentioned_user
from twitter
LATERAL VIEW OUTER explode(entities.user_mentions) user_mentionsTable as user_mentions
LATERAL VIEW OUTER explode(entities.hashtags) hashtagsTable AS hashtag
```

Which when run as from `sqlContext.sql()` gives us:

```
+------------------+--------------------+--------------+--------------------+-------+--------------+
|                id|          created_at|   screen_name|          tweet_text|hashtag|   screen_name|
+------------------+--------------------+--------------+--------------------+-------+--------------+
|752940179569115136|Tue Jul 12 18:58:...|    flederbine|@johnnyq72 @orcld...|ImALLin|    johnnyq72|
|752940179569115136|Tue Jul 12 18:58:...|    flederbine|@johnnyq72 @orcld...|ImALLin|     orcldoug|
|752940179569115136|Tue Jul 12 18:58:...|    flederbine|@johnnyq72 @orcld...|ImALLin|        rmoff|
|752940179569115136|Tue Jul 12 18:58:...|    flederbine|@johnnyq72 @orcld...|ImALLin|  markrittman|
|752940179569115136|Tue Jul 12 18:58:...|    flederbine|@johnnyq72 @orcld...|ImALLin|   mikedurran|
+------------------+--------------------+--------------+--------------------+-------+--------------+
```

and written back to Hive for ingest to BDD:

Data sample for twitter_user_text_hashtags

View more...

	twitter_user_text_hashtags.id	twitter_user_text_hashtags.created_at	twitter_user_text_hashtags.screen_name	twitter_user_text_hashtags.tweet_text	twitter_user_text_hashtags.hashtag	twitter_user_text_hashtag
1	752940179569115100	Tue Jul 12 18:58:22 +0000 2016	flederbine	@johnnyq72 @orcldoug @rmoff @markrittman @mikedurran #ImALLin 😊	ImALLin	johnnyq72
2	752940179569115100	Tue Jul 12 18:58:22 +0000 2016	flederbine	@johnnyq72 @orcldoug @rmoff @markrittman @mikedurran #ImALLin 😊	ImALLin	orcldoug
3	752940179569115100	Tue Jul 12 18:58:22 +0000 2016	flederbine	@johnnyq72 @orcldoug @rmoff @markrittman @mikedurran #ImALLin 😊	ImALLin	rmoff
4	752940179569115100	Tue Jul 12 18:58:22 +0000 2016	flederbine	@johnnyq72 @orcldoug @rmoff @markrittman @mikedurran #ImALLin 😊	ImALLin	markrittman
5	752940179569115100	Tue Jul 12 18:58:22 +0000 2016	flederbine	@johnnyq72 @orcldoug @rmoff @markrittman @mikedurran #ImALLin 😊	ImALLin	mikedurran

Yorkshire, UK https://www.linkedin.com/in/robinmoffatt (https://www.linkedin.com/in/robinmoffatt)

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You can use these SQL queries both for simply flattening JSON, as above, or for building summary tables, such as this one showing the most common hashtags in the dataset:

```
sqlContext.sql("SELECT hashtag.text,count(*) as inst_count from twitter  LATERAL VIEW OUTER explode(entities.hashtags) hashtagsTable AS
hashtag GROUP BY hashtag.text order by inst_count desc").show(4)

+-----------+----------+
|       text|inst_count|
+-----------+----------+
|     Hadoop|       165|
|     Oracle|       151|
|        job|       128|
|    BigData|       112|
```

You can find the full Jupyter Notebook with all these nested/array JSON examples here:

https://gist.github.com/a38e853d3a7dcb48a9df99ce1e3505ff (https://gist.github.com/a38e853d3a7dcb48a9df99ce1e3505ff)

(gist link (https://gist.github.com/a38e853d3a7dcb48a9df99ce1e3505ff))

You may decide after looking at this that you'd rather just go back to Hive and SerDes, and as is frequently the case in 'data wrangling' there's multiple ways to achieve the same end. The route you take comes down to personal preference and familiarity with the toolsets. In this particular case I'd still go for SparkSQL for the initial exploration as it's quicker to 'poke around' the dataset than with defining and re-defining Hive tables -- YMMV (http://dictionary.cambridge.org/dictionary/english/ymmv). A final point to consider before we dig in is that SparkSQL importing JSON and saving back to HDFS/Hive is a static process, and if your underlying data is changing (e.g. streaming to HDFS from Flume) then you **would** probably want a Hive table over the HDFS file so that it is live when queried.

Loading an Excel workbook with many sheets

This was the use-case that led me to researching programmatic import of datasets in the first place. I was doing some work with a dataset of road traffic accident data (https://data.gov.uk/dataset/road-accidents-safety-data), which included a single XLS file with over 30 sheets, each a lookup table for a separate set of dimension attributes. Importing each sheet one by one through the BDD GUI was tedious, and being a lazy geek, I looked to automate it.

Using Pandas `read_excel` function and a smidge of Python to loop through each sheet it was easily done. You can see the full notebook here:

https://gist.github.com/rmoff/3fa5d857df8ca5895356c22e420f3b22
(https://gist.github.com/rmoff/3fa5d857df8ca5895356c22e420f3b22)

(gist link (https://gist.github.com/rmoff/3fa5d857df8ca5895356c22e420f3b22))

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Contact Us

Rittman Mead Consulting Ltd.
Platf9rm, Hove Town Hall
Tisbury Road,
Brighton, BN3 3BQ
United Kingdom

Tel: (Phone) +44 1273 053956
Email: (Email)info@rittmanmead.com (mailto:info@rittmanmead.com)