Extract

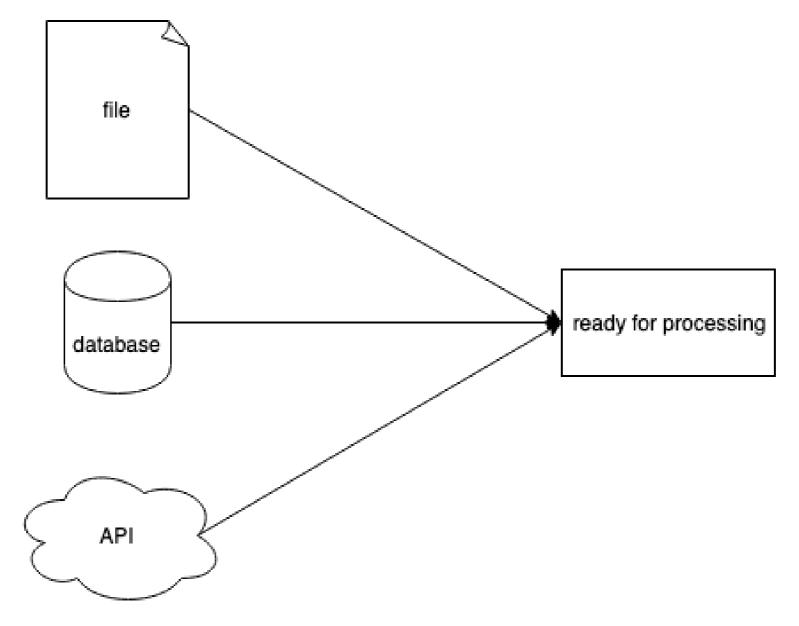
INTRODUCTION TO DATA ENGINEERING



Vincent Vankrunkelsven
Data Engineer @ DataCamp



Extracting data: what does it mean?



Extract from text files

Unstructured

- Plain text
- E.g. chapter from a book

Call me Ishmael. Some years ago—never mind how long precisely—having little or no money in my purse, and nothing particular to interest me on shore, I thought

Flat files

- Row = record
- Column = attribute
- E.g. .tsv or .csv

Year, Make, Model, Price 1997, Ford, E350, 3000.00 1999, Chevy, "Venture Extended Edition", 4900.00 1999, Chevy, "Venture Extended Edition", 5000.00 1996, Jeep, Grand Cherokee, 4799.00

JSON

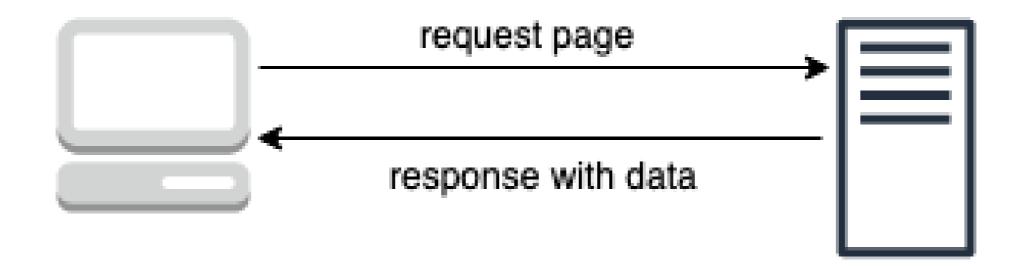
- JavaScript Object Notation
- Semi-structured
- Atomic
 - o number
 - o string
 - boolean
 - null
- Composite
 - o array
 - object

```
{
   "an_object": {
      "nested": [
          "one",
          "two",
          "three",
          {
                "key": "four"
          }
     ]
}
```

```
value_1
```

Data on the Web

Requests



Example

- 1. Browse to Google
- 2. Request to Google Server
- 3. Google responds with web page

Data on the Web through APIs

- Send data in JSON format
- API: application programming interface
- Examples
 - Twitter API

```
{ "statuses": [{ "created_at": "Mon May 06 20:01:29 +0000 2019", "text": "this is a tweet"}] }
```

Hackernews API

```
import requests
response = requests.get("https://hacker-news.firebaseio.com/v0/item/16222426.json")
print(response.json())
```

```
{'by': 'neis', 'descendants': 0, 'id': 16222426, 'score': 17, 'time': 1516800333, 'title': .... }
```



Data in databases

Applications databases

- Transactions
- Inserts or changes
- OLTP
- Row-oriented

Analytical databases

- OLAP
- Column-oriented

Extraction from databases

Connection string/URI

```
postgresql://[user[:password]@][host][:port]
```

Use in Python

```
import sqlalchemy
connection_uri = "postgresql://repl:password@localhost:5432/pagila"
db_engine = sqlalchemy.create_engine(connection_uri)

import pandas as pd
pd.read_sql("SELECT * FROM customer", db_engine)
```

Let's practice!

INTRODUCTION TO DATA ENGINEERING



Transform

INTRODUCTION TO DATA ENGINEERING



Vincent Vankrunkelsven
Data Engineer @ DataCamp



Kind of transformations

customer_id	email	state	created_at
1	jane.doe@theweb.com	New York	2019-01-01 07:00:00

- Selection of attribute (e.g. 'email')
- Translation of code values (e.g. 'New York' -> 'NY')
- Data validation (e.g. date input in 'created_at')
- Splitting columns into multiple columns
- Joining from multiple sources

An example: split (Pandas)

customer_id	email	username	domain
1	jane.doe@theweb.com	jane.doe	theweb.com

```
customer_df # Pandas DataFrame with customer data

# Split email column into 2 columns on the '@' symbol
split_email = customer_df.email.str.split("@", expand=True)
# At this point, split_email will have 2 columns, a first
# one with everything before @, and a second one with
# everything after @

# Create 2 new columns using the resulting DataFrame.
customer_df = customer_df.assign(
    username=split_email[0],
    domain=split_email[1],
)
```



Transforming in PySpark

Extract data into PySpark

An example: join

A new ratings table

customer_id	film_id	rating
1	2	1
2	1	5
2	2	3
•••	•••	•••

The customer table

customer_id	first_name	last_name	•••
1	Jane	Doe	•••
2	Joe	Doe	•••
•••	•••	•••	•••

customer_id overlaps with ratings table

An example: join (PySpark)

```
customer_df # PySpark DataFrame with customer data
ratings_df # PySpark DataFrame with ratings data

# Groupby ratings
ratings_per_customer = ratings_df.groupBy("customer_id").mean("rating")

# Join on customer ID
customer_df.join(
    ratings_per_customer,
    customer_df.customer_id==ratings_per_customer.customer_id
)
```

Let's practice!

INTRODUCTION TO DATA ENGINEERING



Loading INTRODUCTION TO DATA ENGINEERING



Vincent Vankrunkelsven
Data Engineer @ DataCamp



Analytics or applications databases

Analytics



- Aggregate queries
- Online analytical processing (OLAP)

Applications



- Lots of transactions
- Online transaction processing (OLTP)

Column- and row-oriented

Analytics

Column-oriented

name	diameter (cm)			weight (g)		
apple		10			100	
grape		2			10	

- Queries about subset of columns
- Parallelization

Applications

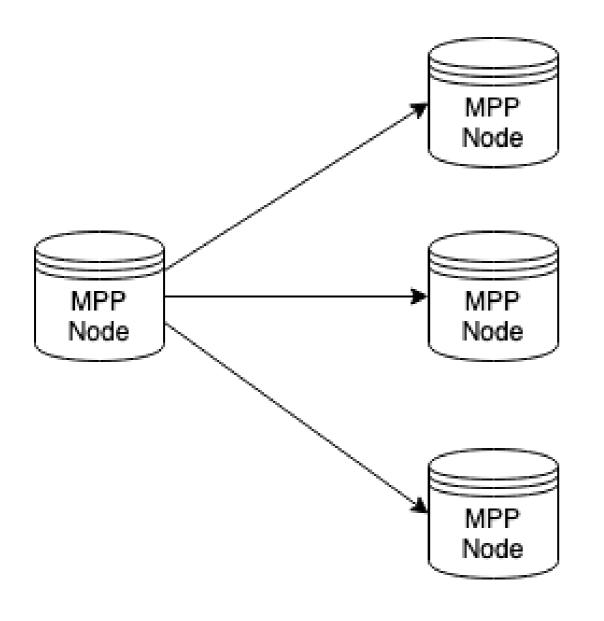
Row-oriented

name	diameter (cm)	weight (g)
apple	10	100
grape	2	10

- Stored per record
- Added per transaction
- E.g. adding customer is fast

MPP Databases

Massively Parallel Processing Databases



- Amazon Redshift
- Azure SQL Data Warehouse
- Google BigQuery

An example: Redshift

Load from file to columnar storage format

```
# Pandas .to_parquet() method
df.to_parquet("./s3://path/to/bucket/customer.parquet")
# PySpark .write.parquet() method
df.write.parquet("./s3://path/to/bucket/customer.parquet")
```

```
COPY customer
FROM 's3://path/to/bucket/customer.parquet'
FORMAT as parquet
...
```

Load to PostgreSQL

pandas.to_sql()

Let's practice!

INTRODUCTION TO DATA ENGINEERING



Putting it all together

INTRODUCTION TO DATA ENGINEERING



Vincent Vankrunkelsven
Data Engineer @ DataCamp



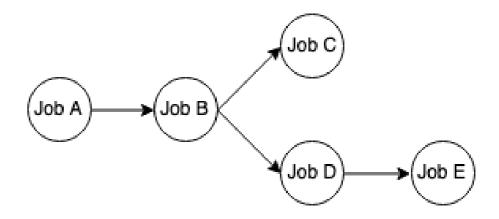
The ETL function

```
def extract_table_to_df(tablename, db_engine):
 return pd.read_sql("SELECT * FROM {}".format(tablename), db_engine)
def split_columns_transform(df, column, pat, suffixes):
 # Converts column into str and splits it on pat...
def load_df_into_dwh(film_df, tablename, schema, db_engine):
  return pd.to_sql(tablename, db_engine, schema=schema, if_exists="replace")
db_engines = { ... } # Needs to be configured
def etl():
 # Extract
 film_df = extract_table_to_df("film", db_engines["store"])
 # Transform
 film_df = split_columns_transform(film_df, "rental_rate", ".", ["_dollar", "_cents"])
 # Load
 load_df_into_dwh(film_df, "film", "store", db_engines["dwh"])
```

Airflow refresher



- Workflow scheduler
- Python
- DAGs



Tasks defined in operators (e.g.

BashOperator)

Scheduling with DAGs in Airflow

cf. https://crontab.guru



The DAG definition file

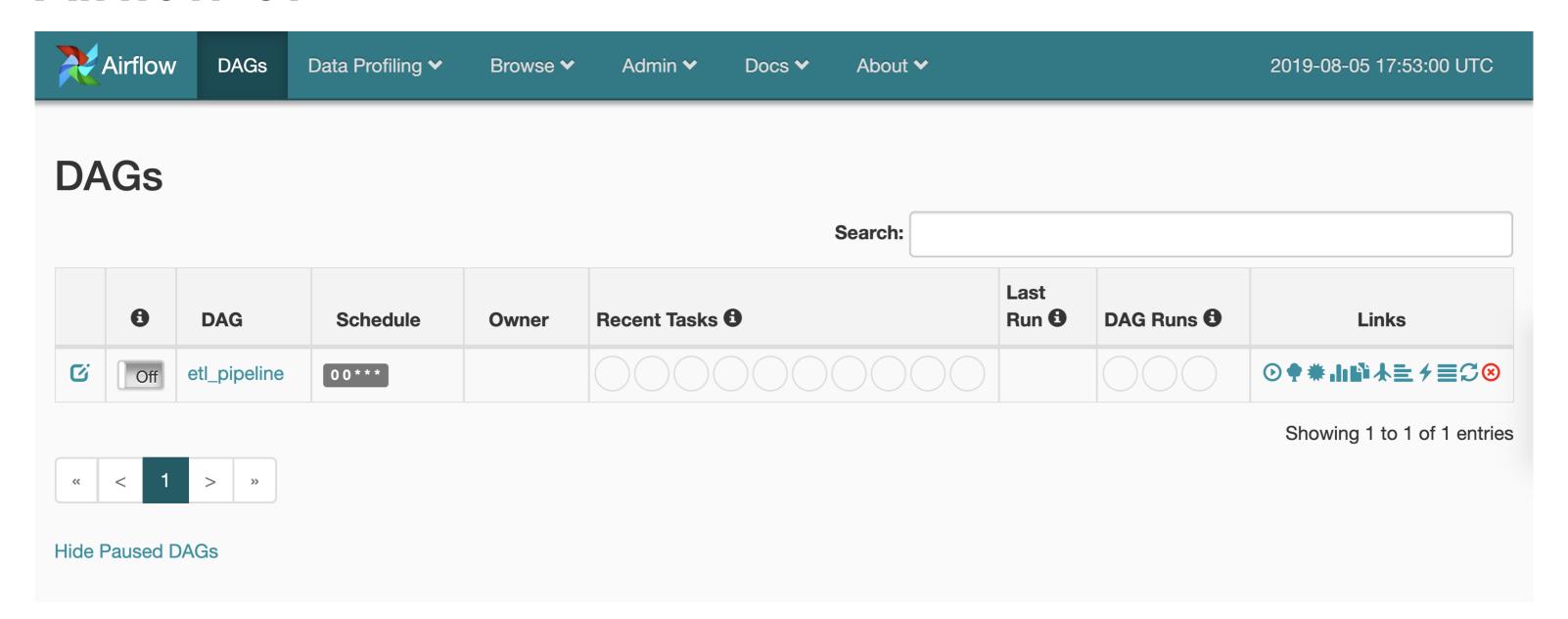
```
from airflow.models import DAG
from airflow.operators.python_operator import PythonOperator
dag = DAG(dag_id="etl_pipeline",
          schedule_interval="0 0 * * *")
etl_task = PythonOperator(task_id="etl_task",
                          python_callable=etl,
                          dag=dag)
etl_task.set_upstream(wait_for_this_task)
```

The DAG definition file

```
from airflow.models import DAG
from airflow.operators.python_operator import PythonOperator
...
etl_task.set_upstream(wait_for_this_task)
```

Saved as etl_dag.py in ~/airflow/dags/

Airflow UI



Let's practice!

INTRODUCTION TO DATA ENGINEERING

