

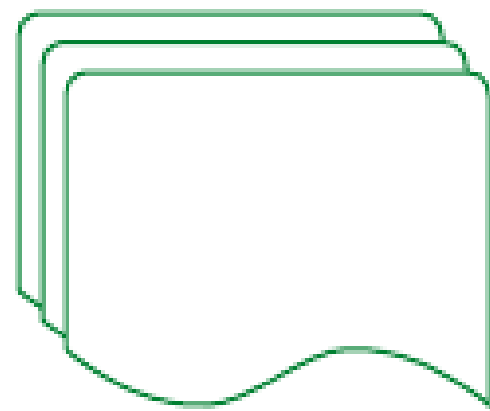
# Extracting non-tabular data

ETL AND ELT IN PYTHON

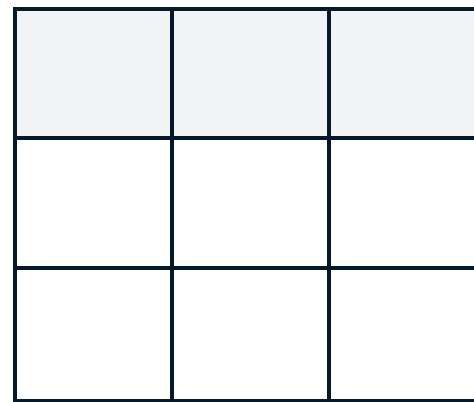


**Jake Roach**  
Data Engineer

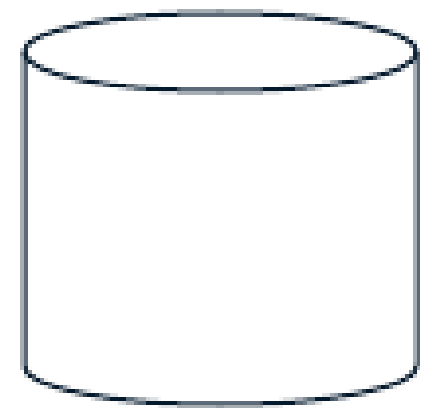
# Extracting non-tabular data



**Extract**



**Transform**

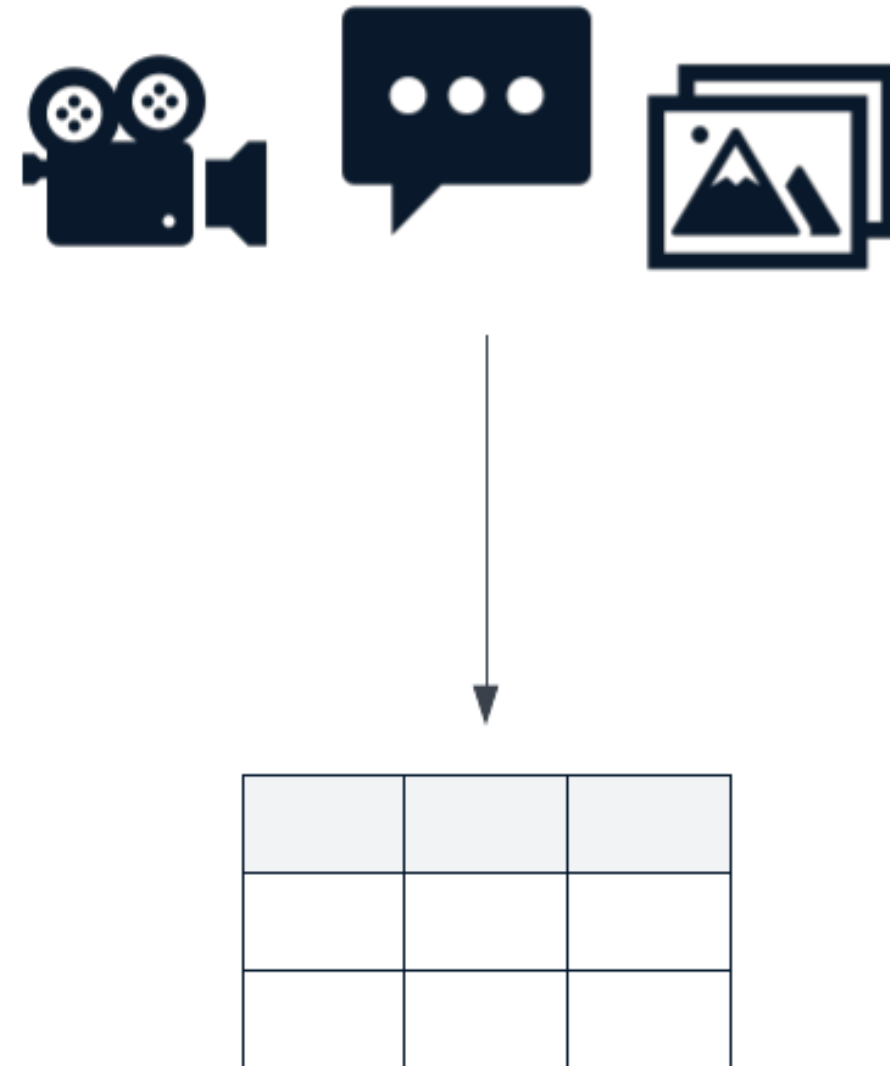


**Load**

# Types of non-tabular data

Most data produced and consumed is unstructured data

- Text
- Audio
- Image
- Video
- Spatial
- IoT



<sup>1</sup> <https://mitsloan.mit.edu/ideas-made-to-matter/tapping-power-unstructured-data>

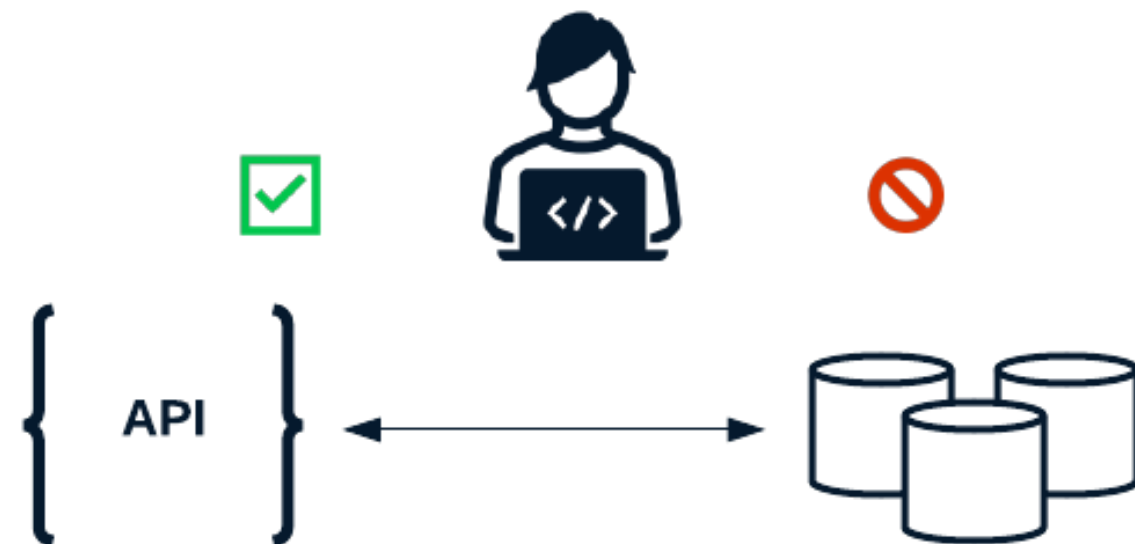
# Working with APIs and JSON data

## API (Application Programming Interface)

- Software that sits on top of data sources
- Prevents direct interaction with database

## JSON (JavaScript Object Notation)

- Key-value pairs
- No set schema
- Look and feel similar to `dict` ionaries



```
{  
  "key": "value",  
  ...  
  "open": 0.121875  
}
```

# Reading JSON files with pandas

```
{  
    "timestamps": [863703000, 863789400, ...],  
    "open": [0.121875, 0.098438, ...],  
    "close": [...],  
    "volume": [...]  
}
```

Use the `.read_json()` function

```
# Read in a JSON file in the format above  
raw_stock_data = pd.read_json("raw_stock_data.json", orient="columns")
```

<sup>1</sup> [https://pandas.pydata.org/docs/reference/api/pandas.read\\_json.html](https://pandas.pydata.org/docs/reference/api/pandas.read_json.html)

# Nested or unstructured JSON data

Data is not always DataFrame-ready

- Nested objects
- Varying "schema"

```
{
  "863703000": {
    "volume": 1443120000,
    "price": {
      "close": 0.09791,
      "open": 0.12187
    }
  },
  "863789400": {
    ...
  }, ...
}
```

# Reading JSON files with json

```
import json

with open("raw_stock_data.json", "r") as file:
    # Load the file into a dictionary
    raw_stock_data = json.load(file)

# Confirm the type of the raw_stock_data variable
print(type(raw_stock_data))
```

```
<class 'dict'>
```

# Let's practice!

ETL AND ELT IN PYTHON



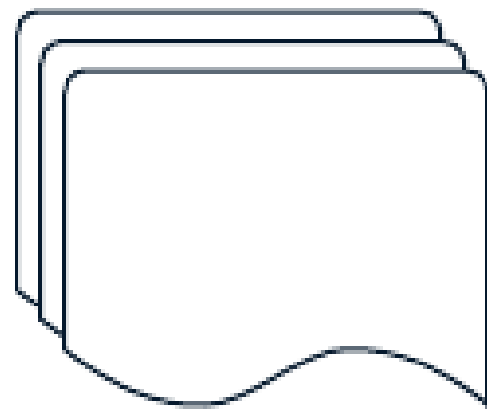
# Transforming non-tabular data

ETL AND ELT IN PYTHON

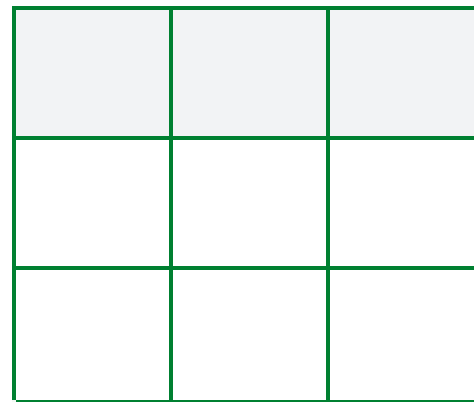


**Jake Roach**  
Data Engineer

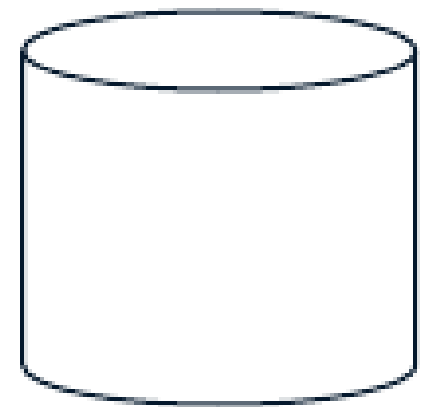
# Transforming non-tabular data



**Extract**



**Transform**



**Load**

# Storing data in dictionaries

## Nested JSON

```
{
  "863703000": {
    "price": {
      "open": 0.12187,
      "close": 0.09791
    },
    "volume": 1443120000
  },
  "863789400": {
    }, ...
}
```

## Goal:

- Convert dictionary into a DataFrame-ready format

```
[
  [863703000, 0.12187, 0.09791, 1443120000],
  [863789400, 0.09843, ...]
]
```

# Iterating over dictionary components

```
# Loop over keys
```

```
for key in raw_data.keys():  
    ...
```

```
# Loop over values
```

```
for value in raw_data.values():  
    ...
```

```
# Loop over keys and values
```

```
for key, value in raw_data.items():  
    ...
```

`.keys()`

- Creates a list of keys stored in a dictionary

`.values()`

- Creates a list of values stored in a dictionary

`.items()`

- Generates a list of tuples, made up of the key-value pairs

# Parsing data from dictionaries

```
entry = {  
    "volume": 1443120000,  
    "price": {  
        "open": 0.12187,  
        "close": 0.09791,  
    }  
}
```

```
# Parse data from dictionary using .get()  
volume = entry.get("volume")
```

```
ticker = entry.get("ticker", "DCMP")
```

```
# Call .get() twice to return the nested "open" value  
open_price = entry.get("price").get("open", 0)
```

# Creating a DataFrame from a list of lists

Pass a list of lists to `pd.DataFrame()`

```
# Pass a list of lists to pd.DataFrame
raw_data = pd.DataFrame(flattened_rows)
```

Set column headers using `.columns`

```
# Create columns
raw_data.columns = ["timestamps", "open", "close", "volume"]
```

Set an index using `.set_index()`

```
# Set the index column to be "timestamps"
raw_data.set_index("timestamps")
```

# Transforming stock data

```
parsed_stock_data = []

# Loop through each key-value pair of the raw_stock_data dictionary
for timestamp, ticker_info in raw_stock_data.items():
    parsed_stock_data.append([
        timestamp,
        ticker_info.get("price", {}).get("open", 0), # Parse the opening price
        ticker_info.get("price", {}).get("close", 0), # Parse the closing price
        ticker_info.get("volume", 0) # Parse the volume
    ])
```

```
# Create a DataFrame, assign column names, and set an index
transformed_stock_data = pd.DataFrame(parsed_stock_data)
transformed_stock_data.columns = ["timestamps", "open", "close", "volume"]
transformed_stock_data = transformed_stock_data.set_index("timestamps")
```

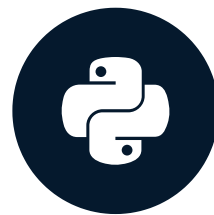
# Let's practice!

ETL AND ELT IN PYTHON



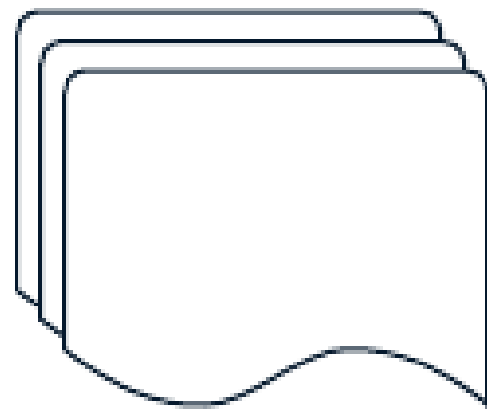
# Advanced data transformation with pandas

ETL AND ELT IN PYTHON

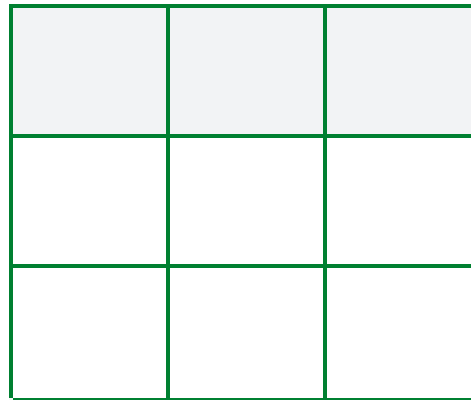


**Jake Roach**  
Data Engineer

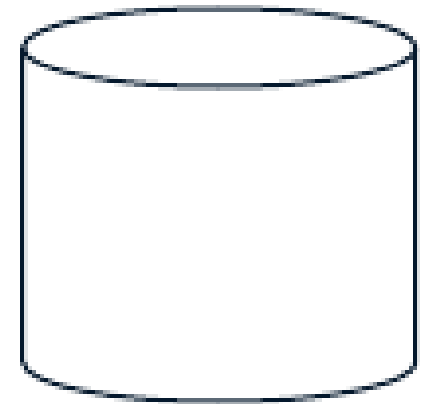
# Advanced data transformation with pandas



**Extract**



**Transform**



**Load**

# Filling missing values with pandas

timestamps	volume	open	close
1997-05-15 13:30:00	1443120000	0.121875	0.097917
1997-05-16 13:30:00	294000000	NaN	0.086458
1997-05-19 13:30:00	122136000	0.088021	NaN

```
# Fill all NaN with value 0
```

```
clean_stock_data = raw_stock_data.fillna(value=0)
```

timestamps	volume	open	close
1997-05-15 13:30:00	1443120000	0.121875	0.097917
1997-05-16 13:30:00	294000000	0.000000	0.086458
1997-05-19 13:30:00	122136000	0.088021	0.000000

# Filling missing values with pandas

timestamps	volume	open	close
1997-05-15 13:30:00	1443120000	0.121875	0.097917
1997-05-16 13:30:00	294000000	NaN	0.086458
1997-05-19 13:30:00	122136000	0.088021	NaN

```
# Fill NaN values with specific value for each column  
clean_stock_data = raw_stock_data.fillna(value={"open": 0, "close": .5}, axis=1)
```

timestamps	volume	open	close
1997-05-15 13:30:00	1443120000	0.121875	0.097917
1997-05-16 13:30:00	294000000	0.000000	0.086458
1997-05-19 13:30:00	122136000	0.088021	0.500000

# Filling missing values with pandas

timestamps	volume	open	close
1997-05-15 13:30:00	1443120000	0.121875	0.097917
1997-05-16 13:30:00	294000000	NaN	0.086458
1997-05-19 13:30:00	122136000	0.088021	NaN

```
# Fill NaN value using other columns
```

```
raw_stock_data["open"].fillna(raw_stock_data["close"], inplace=True)
```

timestamps	volume	open	close
1997-05-15 13:30:00	1443120000	0.121875	0.097917
1997-05-16 13:30:00	294000000	0.086458	0.086458
1997-05-19 13:30:00	122136000	0.088021	NaN

# Grouping data

```
SELECT
    ticker,
    AVG(volume),
    AVG(open),
    AVG(close)
FROM raw_stock_data
GROUP BY ticker;
```

The `.groupby()` method can recreate the query above, using `pandas`

# Grouping data with pandas

ticker	volume	open	close
AAPL	1443120000	0.121875	0.097917
AAPL	297000000	0.098146	0.086458
AMZN	124186000	0.247511	0.251290

```
# Use Python to group data by ticker, find the mean of the remaining columns
grouped_stock_data = raw_stock_data.groupby(by=["ticker"], axis=0).mean()
```

	volume	open	close
ticker			
AAPL	1.149287e+08	34.998377	34.986851
AMZN	1.434213e+08	30.844692	30.830233

Can use `.min()`, `.max()` and `.sum()` to aggregate data

# Applying advanced transformations to DataFrames

The `.apply()` method can handle more advanced transformations

```
def classify_change(row):  
    change = row["close"] - row["open"]  
    if change > 0:  
        return "Increase"  
    else:  
        return "Decrease"  
  
# Apply transformation to DataFrame  
raw_stock_data["change"] = raw_stock_data.apply(  
    classify_change,  
    axis=1  
)
```

Before transformation

ticker	...	open	close
AAPL		0.121875	0.097917
AAPL		0.098146	0.086458
AMZN		0.247511	0.251290

After transformation

ticker	...	open	close	change
AAPL		0.121875	0.097917	Decrease
AAPL		0.098146	0.086458	Decrease
AMZN		0.247511	0.251290	Increase



# Let's practice!

ETL AND ELT IN PYTHON

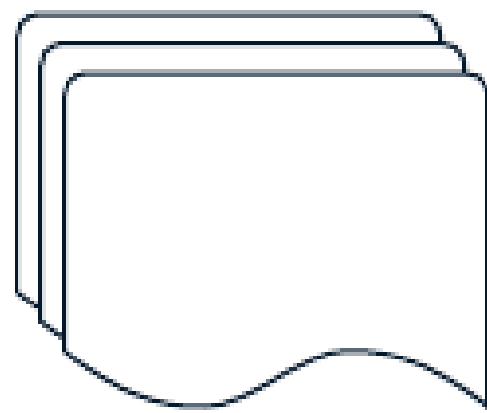
# Loading data to a SQL database with pandas

ETL AND ELT IN PYTHON

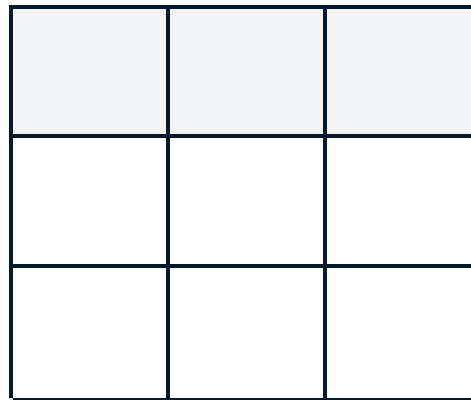


**Jake Roach**  
Data Engineer

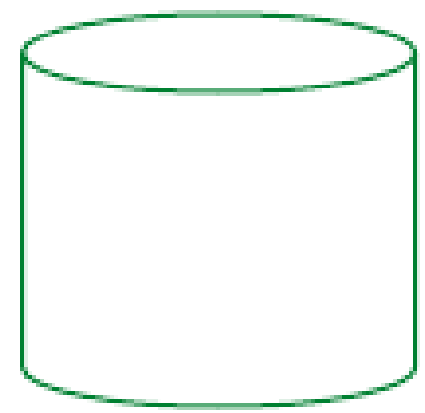
# Load data to a SQL database with pandas



**Extract**



**Transform**

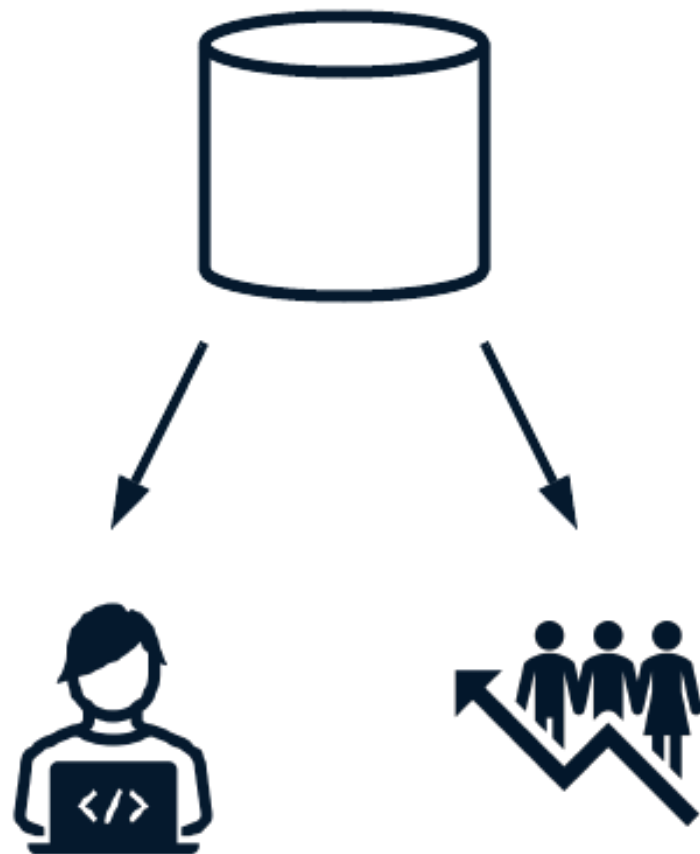


**Load**

# Loading data into a SQL database with pandas

`pandas` provides `.to_sql()` to persist data to SQL

- `name`
- `con`
- `if_exists`
- `index`
- `index_label`



# Persisting data to Postgres with pandas

```
# Create a connection object
```

```
connection_uri = "postgresql+psycopg2://repl:password@localhost:5432/market"
```

```
db_engine = sqlalchemy.create_engine(connection_uri)
```

```
# Use the .to_sql() method to persist data to SQL
```

```
clean_stock_data.to_sql(  
    name="filtered_stock_data",  
    con=db_engine,  
    if_exists="append",  
    index=True,  
    index_label="timestamps"  
)
```

# Validating data persistence with pandas

It's important to validate that data is persisted as expected.

- Ensure data can be queried
- Make sure counts match
- Validate that each row is present

```
# Pull data written to SQL table  
to_validate = pd.read_sql("SELECT * FROM cleaned_stock_data", db_engine)
```

```
# Validate counts, record equality, etc  
...
```

# Let's practice!

ETL AND ELT IN PYTHON