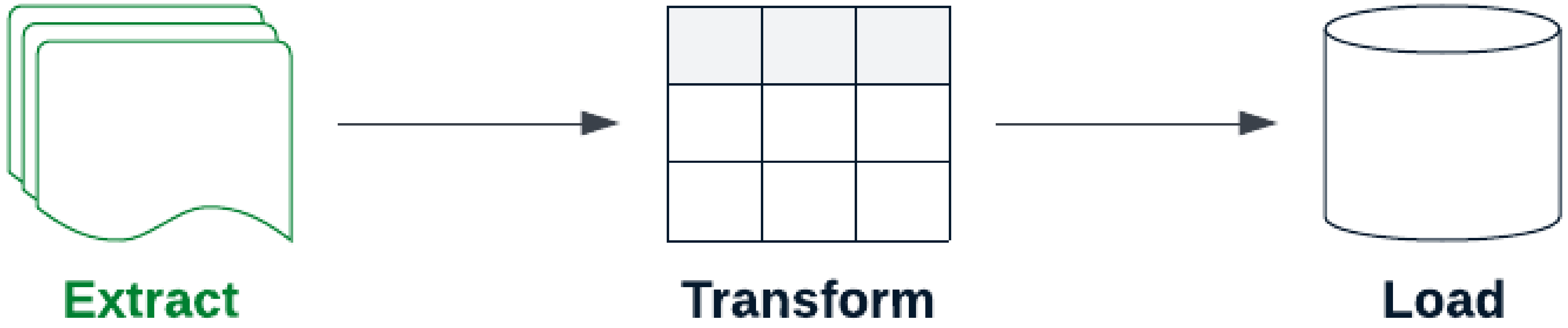
Extracting non-tabular data

INTRODUCTION TO DATA PIPELINES

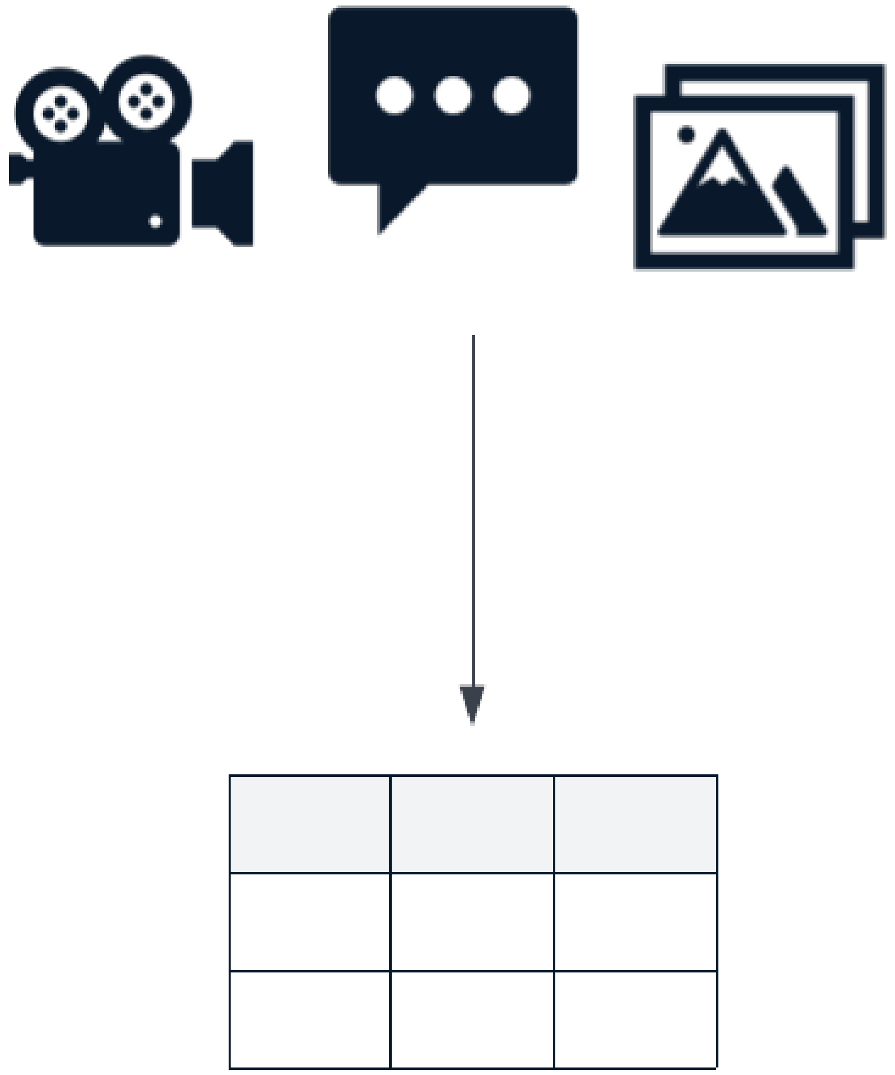
Extracting non-tabular data



Types of non-tabular data

Most data produced and consumed is unstructured data

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

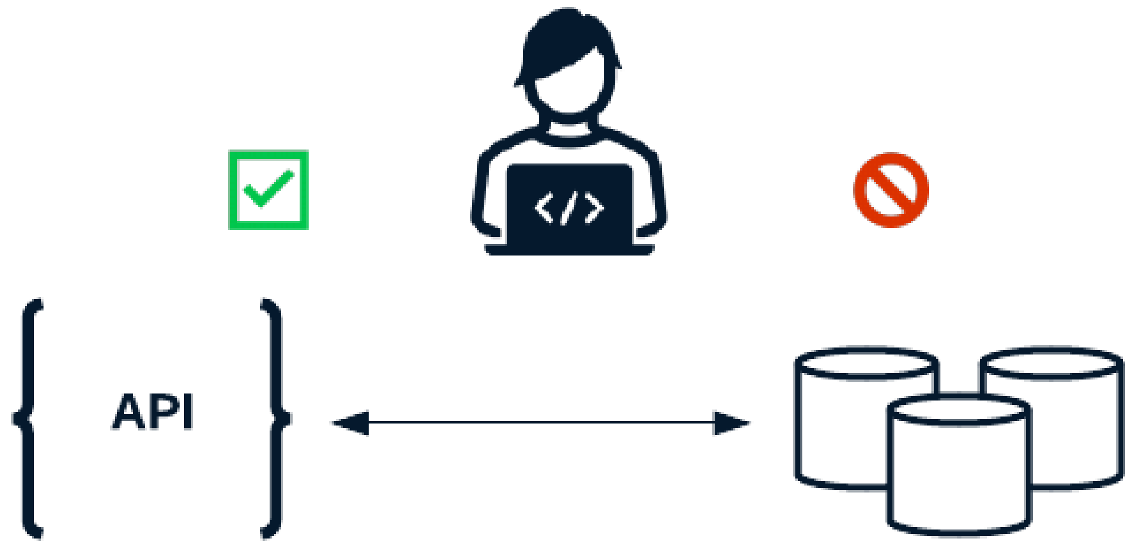


1 https://mitsloan.mit.edu/ideas-made-to-matter/tapping-power-unstructured-data

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")
```

1 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

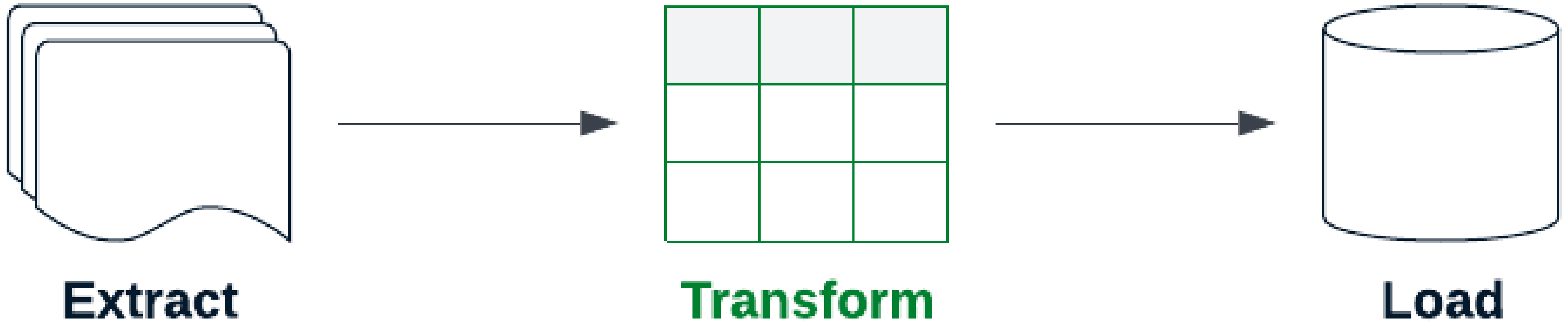
```python
import json

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'>
```

Transforming non-tabular data

INTRODUCTION TO DATA PIPELINES

Transforming non-tabular data



Storing data in dictionaries

Nested JSON

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

Goal:

- Convert JSON data to 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")
```

```
# Grab the nested values with default values
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

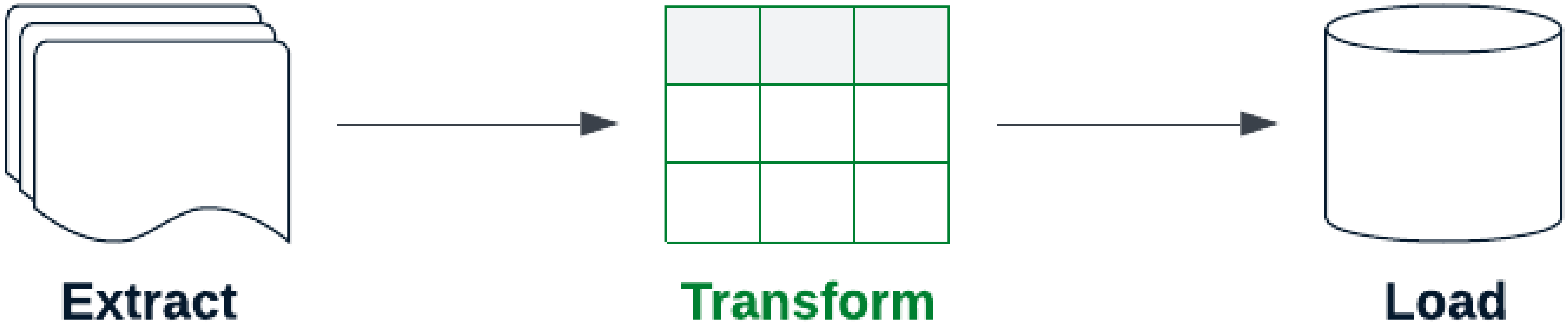
```python
parsed_stock_data = []


# 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
    ])
```

```python
# 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")
```

Advanced data transformation with pandas

INTRODUCTION TO DATA PIPELINES

Advanced data transformation with pandas



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
```

```python
# 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

```sql
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
```

```python
# Use Python to group data by ticker, find the mean of the reamining 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

```python
def classify_change(row):
    change = row["close"] - row["open"]
    if change > 0:
        return "Increase"
    else:
        return "Decrease"
```

```python
# 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
```

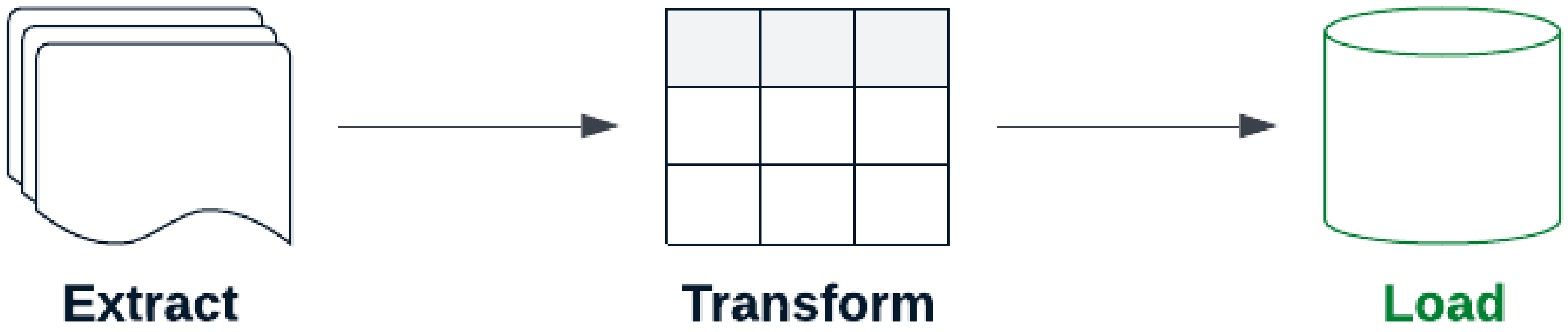
After transformation

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

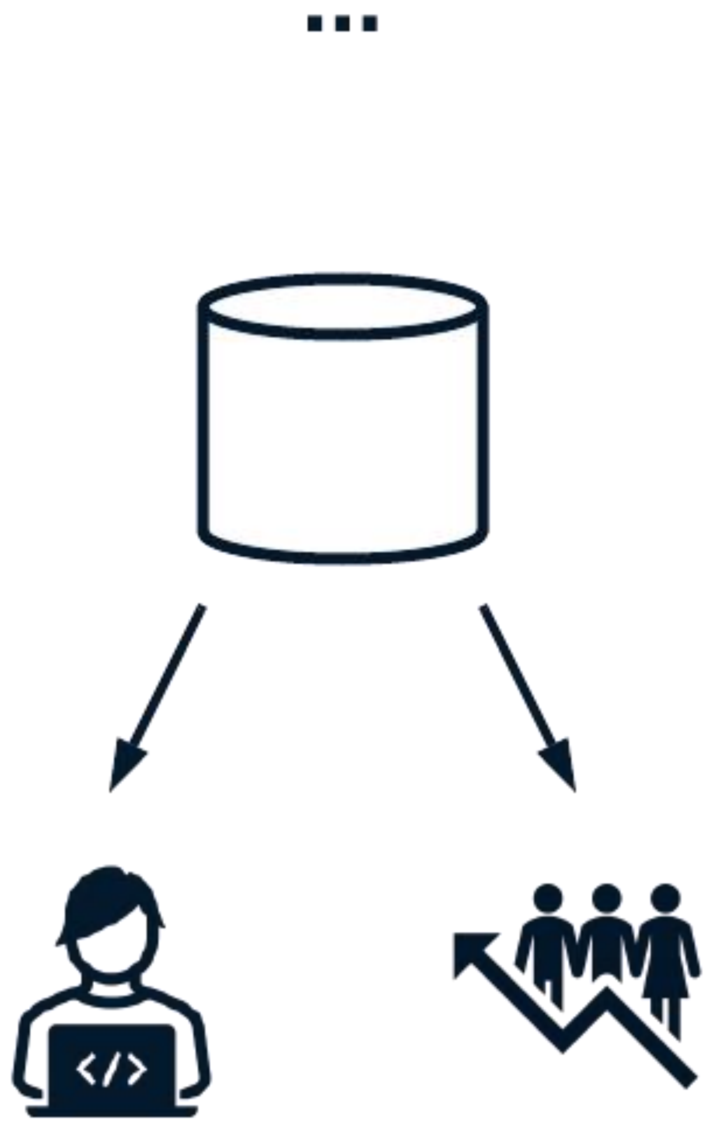
Loading data to a SQL database with pandas

INTRODUCTION TO DATA PIPELINES

Load data to a SQL database with pandas



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
...
```