

# File Ingestion and Schema Validation

Virtual Internship

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## Introduction

- A data pipeline is the series of steps that allow data from one system to move to and become useful in another system, particularly analytics, data science, or AI and machine learning systems.
- At a high level, a data pipeline works by pulling data from the source, applying rules for transformation and processing, then pushing it to its destination
- File ingestion and schema validation: In this report different ways of reading large data files (pandas, dask, chunksize, dictread, datatables, pyspark) have been explored and the most optimal way is suggested.
- The data file is then converted to YAML file and further compressed to gzip.
- Two different ways of creating yaml file has been explored using dataframes directly and second after coverting to array.

## Dataset

- The dataset for parking violation ticket issued in New York in 2017 has been used.
- Data source:

https://www.kaggle.com/datasets/new-york-city/nyc-parking-tickets?select=Parking\_Violations\_Issued\_-\_Fiscal\_Year\_2017.csv

Total number of observations	10803028
Total number of files	1
Total number of features	43
Base format of the file	.csv
Size of the data	2.09 GB

# Different ways to read data

Different methods as listed below, of reading the big data file has been tested and time to read the data is analysed to obtain the fastest method:

#### Time to read using pandas (1min 21s)

1) Pandas

```
%%time
NYC_data = pd.read_csv("Parking_Violations_Issued_-_Fiscal_Year_2017.csv")
NYC_data.head()
CPU times: user 27.8 s, sys: 15.4 s, total: 43.2 s
Wall time: lmin 21s
```

#### Time to read using pandas chunks (46s)

2) Pandas Chunksize

```
%%time
data_chunks = pd.read_csv("Parking_Violations_Issued_-_Fiscal_Year_2017.csv", chunksize=100000)
pandas_chunks = pd.concat(data_chunks)
pandas_chunks.head()

CPU times: user 29.9 s, sys: 8.71 s, total: 38.6 s
Wall time: 46.5 s
```

#### Time to read using dictreader (3.45ms)

3) DictReader

# Different ways to read data

#### Time to read using datatable (6.5s)

4) Datatable

```
%%time
data_dt = dt.fread("Parking_Violations_Issued_-_Fiscal_Year_2017.csv")
data_dt.head()

CPU times: user 16.3 s, sys: 2.71 s, total: 19 s
Wall time: 6.5 s
```

#### Time to read using pyspark (32.8s)

5) Pyspark

```
%%time
spark = SparkSession.builder.appName("EDA.com").getOrCreate()
df = spark.read.format("csv").option("header", "true").option("inferSchema", "true").load("Parking_Violations_Issued_-_Fiscal_Year_2017.cs
df.show(5)
CPU times: user 36.2 ms, sys: 78.9 ms, total: 115 ms
Wall time: 32.8 s
```

6) Dask

#### Time to read using DASK(2s)

# Most Optimal way

- Maximum time is taken by Pandas.
- Among several ways Dictreader takes the least time (3.45ms) followed by Dask (2s).
- However, Dask maintains the pandas dataframe structure hence Dask can be preferred as compared to other methods for reading large data files.

## Using YAML

- The parameterization has been done to create a general format for reading data files (Parameterization.ipynb).
- Firstly, a utility file with some important functions is created as:

```
def read config file(filepath):
    with open(filepath, 'r') as stream:
            return yaml.safe load(stream)
        except yaml.YAMLError as exc:
            logging.error(exc)
def replacer(string, char):
    pattern = char + '\{2,\}'
    string = re.sub(pattern, char, string)
    return string
def col_header_val(df,table_config):
    replace whitespaces in the column
    and standardized column names
    raw columns = list(map(lambda x: x.lower(), df.columns))
    yml columns = list(map(lambda x: x.lower(), table config['columns']))
    yml columns = [x.strip(' ') for x in yml columns]
    raw_columns = [x.strip(' ') for x in raw_columns]
    expected col=yml columns
    if len(raw columns) == len(expected col) and list(expected col) == list( raw columns):
        print("column name and column length validation passed")
        return 1
    else:
        print("column name and column length validation failed")
        mismatched columns file = list(set(raw columns).difference(expected col))
        print("Following File columns are not in the YAML file", mismatched columns file)
        missing YAML file = list(set(expected col).difference(raw columns))
        print("Following YAML columns are not in the file uploaded", missing YAML file)
        logging.info(f'df columns: {raw columns}')
        logging.info(f'expected columns: {expected col}')
        return 0
```

## Using YAML

Next, a yml file is created as:

```
%%writefile file.yaml
file type: csv
dataset name: testfile
file name: Parking Violations Issued - Fiscal Year 2017
table name: edsurv
inbound delimiter: ","
outbound delimiter: " "
skip_leading_rows: 1
columns:
- Summons Number
- Plate ID
- Registration State
- Plate Type
- Issue Date
- Violation Code
- Vehicle Body Type
- Vehicle Make
- Issuing Agency
- Street Code1
- Street Code2
- Street Code3
- Vehicle Expiration Date
- Violation Location
- Violation Precinct
- Issuer Precinct
- Issuer Code
- Issuer Command
- Issuer Squad
- Violation Time
- Time First Observed
- Violation County
- Violation In Front Of Or Opposite
- House Number
- Street Name
- Intersecting Street
- Date First Observed
- Law Section
- Sub Division
- Violation Legal Code
- Days Parking In Effect
- From Hours In Effect
- To Hours In Effect
- Vehicle Color
- Unregistered Vehicle?
- Vehicle Year
- Meter Number
```

## **GZIP**

• The data has been zipped using gzip.

```
import gzip
import shutil
with open('file.yaml', 'rb') as f_in:
    with gzip.open('file.yaml.gz', 'wb') as f_out:
        shutil.copyfileobj(f_in, f_out)
```

```
NYC_data.shape
(10803028, 43)
```

# Thank You

