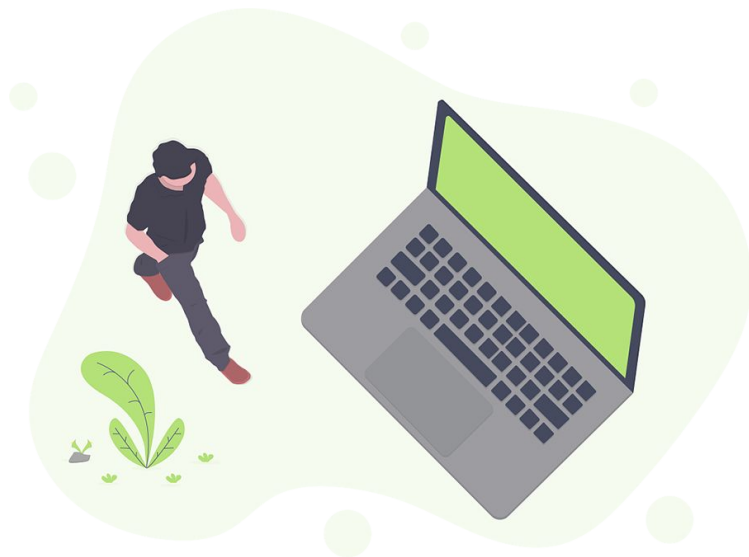


# Pandas and PostgreSQL

A comparison of dataframes and data stores

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# Data store

repository for persistently storing and managing collections of data

# Data store: Postgres

repository for persistently storing and managing collections of data

- Customizable open-source RDBMS that extends the SQL language
- Only accepts writes on a single node → CP system
- Row-based storage

# Data store: SQLite

repository for persistently storing and managing collections of data

- Small, embeddable RDBMS
- Stores all data in a single transferable file → CA system
- Memory-sqlite: in-memory system, like Pandas

# Dataframe

2-dimensional container for labeled data

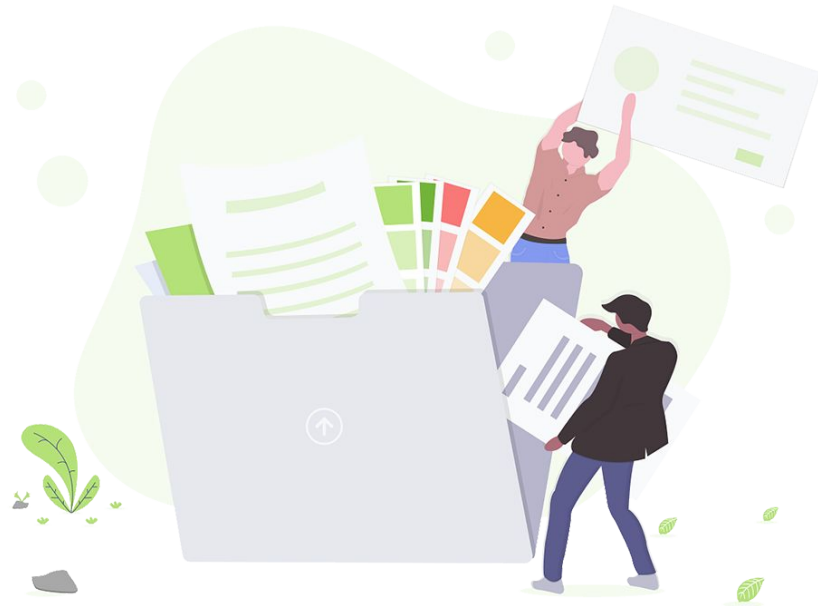
# Dataframe: Pandas

2-dimensional container for labeled data

- Easy-to-use, fast data wrangling library in Python
- Initialized and stored in memory → CA System
- Columnar store

# Comparison 1: Storage

How is data stored?



# PostgreSQL: Partitioned Storage

- All tables stored as separate files in a PGDATA directory, indices stored as B-trees
- When a table exceeds 1 GB, it is divided into 1GB segments, to avoid file size limitations
- Rows are stored in pages in heap files



# Pandas: Block Storage

	UID	Product	Quantity	Member	Promo	Points	Paid
Timestamp							
2015-07-01 02:50:00	xgy7b	A	3	True	SEA15	30	21.50
2015-07-01 03:30:00	sot5y	C	1	False	NaN	10	15.00
2015-07-02 03:52:00	g8z8l	B	2	False	NaN	30	10.25
2015-07-03 04:01:00	lxzuo	A	2	False	SEA15	15	16.25
2015-07-03 05:30:00	3peyj	C	4	True	BOB10	10	28.50

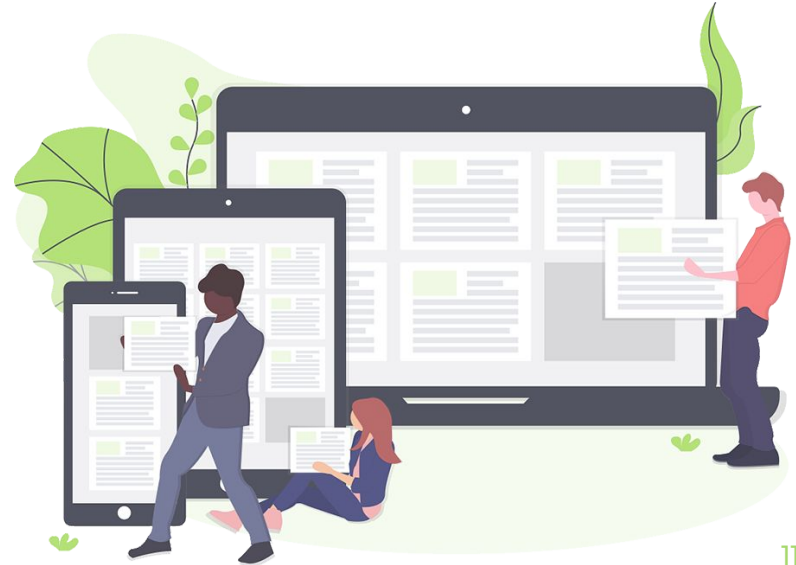


# Efficient at what?

- Operations within dtypes are quite fast
- Appending to the dataframe means copying every block

# Comparison 2: Query Syntax

How do we access and  
manipulate the data?



# Query Overview

## SQL: Declarative

- Pseudo-English
- Compose the query with what you want (but not how to get it)

## Python: Imperative

- Apply operations to the dataset
- Manually chain operations in the logical order they need to appear

# Basic Select

## SQL

```
SELECT id  
FROM airports  
WHERE ident="KLAX"
```

## Pandas

```
airports[  
    airports.ident=="KLAX"  
].id
```

# Select with 2 Conditions

## SQL

```
SELECT *  
FROM airports  
WHERE iso_region = 'USA-CA'  
and type = 'seaplane_base'
```

## Pandas

```
airports[  
    (airports.iso_region ==  
     'USA-CA') &  
    (airports.type ==  
     'seaplane_base')  
]
```

# GroupBy

## SQL

```
SELECT iso_country, type,  
       count(*)  
FROM airports  
GROUPBY iso_country, type  
ORDERBY iso_country, type
```

## Pandas

```
airports.groupby([  
    'iso_country', 'type'  
]).size()
```

# Inner Join

## SQL

```
SELECT airport_ident, type,  
description  
FROM airport_freq join  
airports on  
airport_freq.airport_ref=airp  
orts.id  
WHERE airports.ident='KLAX'
```

## Pandas

```
airport_freq.merge(  
    airports[airports.ident==  
    'KLAX'] [['id']],  
    left_on='airport_ref',  
    right_on='id',  
    how='inner'  
) [['airport_ident', 'ident',  
    'description']]
```



# Comparison 3: Benchmarking

What is each framework  
optimized for?



# Test 1: Operations

	PostgreS			Pandas		
Operation	Slowest	Fastest	Median	Slowest	Fastest	Median
join	21.2	19.8	20.0	27.9	26.4	27.0
groupby	8.9	8.6	8.6	38.6	35.7	37.8
filter	10.2	9.5	9.7	27.5	25.0	25.3
sort	30.9	28.2	28.7	30.1	28.0	28.9

# Test 2: Complex Queries

```
def do_it_in_sql():
    sql1 = """
    with recent_views as (
        select user_id, model_name
        from car_config_table
        where created_at > current_date - interval '2 months'
    ),
    popular_models as (
        select model_name as slug,
               count(distinct user_id) configs
        from recent_configurations
        group by 1
        having count(distinct user_id) > 3
    ),
    popular_configurations as (
        select C.model_name, C.user_id, M.configs
        from recent_configurations C
        join popular_models M on M.slug = C.model_name
    )

    SELECT
    C1.model_name model_name,
    C1.configs model_configs,
    C2.model_name recommended_model_name,
    C2.configs recommended_model_configs,
    count(distinct C1.user_id) combo_configs
    from popular_configurations C1
    join popular_configurations C2 on C1.user_id = C2.user_id
    where
    C1.model_name <> C2.model_name
    group by 1,2,3,4
    order by model_name
    """
    df = execute_to_postgres(sql1)
    return df
```

```
def do_it_in_pandas():
    sql= """
    select user_id, model_name
    from car_config_table
    where created_at > current_date - interval '2 months'
    """
    df = query_postgres(sql)
    df['configs'] = df.groupby(['model_name'])
    ['user_id'].transform('nunique')
    df = df[df['configs'] > 3]
    crossdf = df.merge(df, on='user_id', how='outer')
    crossdf = crossdf[crossdf.model_name_y != crossdf.model_name_x]
    crossdf['combo_configs'] = crossdf.groupby(['model_name_x',
    'model_name_y'])['user_id'].transform('nunique')
    crossdf = crossdf[['model_name_x', 'users_x', 'model_name_y',
    'users_y', 'combo_configs']].drop_duplicates().sort_values('model_name_x')
    return crossdf
```

```
sql2 = """
with recent_configurations as (
    select user_id,
           model_name,
           COUNT(user_id) OVER (PARTITION BY model_name) as configs
    from car_config_table
    where created_at > current_date - interval '2 months'
    group by 1,2
)

SELECT C1.model_name model_name,
       C1.configs model_configs,
       C2.model_name recommended_model_name,
       C2.configs recommended_model_configs,
       count(distinct C1.user_id) combo_configs
from recent_configurations C1
join recent_configurations C2 on C1.user_id = C2.user_id
where C1.model_name <> C2.model_name
group by 1,2,3,4
having count(distinct C1.user_id) > 3
"""
```

```
sql3 = """
drop table IF EXISTS analytics.mv;
create table analytics.mv as (
    select user_id,
           model_name,
           COUNT(user_id) OVER (PARTITION BY model_name) as configs
    from car_config_table
    where created_at > current_date - interval '2 months'
    group by 1,2);

SELECT C1.model_name model_name,
       C1.configs model_configs,
       C2.model_name recommended_model_name,
       C2.configs recommended_model_configs,
       count(distinct C1.user_id) combo_configs
from analytics.mv C1
join analytics.mv C2 on C1.user_id = C2.user_id
where C1.model_name <> C2.model_name
group by 1,2,3,4
having count(distinct C1.user_id) > 3
"""
```

# Test 2: Complex Queries

	PostgreS			Pandas		
	Slowest	Fastest	Median	Slowest	Fastest	Median
Default	7.5	6.9	7.0	6.7	5.8	6.0
Optimized (V2)	6.6	6.1	6.2	-	-	-
Optimized (V3)	7.4	6.4	6.6	-	-	-

# So....why?

- Postgres is doing a lot more for us behind the scenes.
- SQL isn't made for complex mathematical operations, even with User Defined Functions.
- Benefits of keeping more tasks on SQL can go far beyond execution time.

# Conclusions

What's next?



# Further Directions:

- Custom benchmarking of queries with SQLite
- Comparisons between Pandas and In-memory SQLite?
- Limitations of the `df.to_sql()` function in Pandas, and more on Pandas-SQL interfaces