

# Lec4



explain the code line by line and if there is error in the execution of the code then remove it by updating the code snippet and state the reason for the update



Please share the code snippet you'd like to review line by line, and I will explain each part in detail. Additionally, if any errors are present, I will correct them and explain why the changes were necessary.



Big data with Dask
The following code is part of the youtube videos below,

Download building footprint dataset from Google Working with big data in panadas import pandas as pd import numpy as np import geopandas as gpd Dataset
There are two input dataset;

20 GB csv file This is the dataset downloaded from Google's open buildings.

AOI shapefile AOI shapefile is the created on geojson.io website. It is the small area near Kathmandu.

df['geometry'] = gpd.GeoSeries.from\_wkt(df['geometry'])

gdf = gpd.GeoDataFrame(df, geometry='geometry')

gdf.head()

gdf.to\_file(r"C:\Users\tek.kshetri\Downloads\687\_buildings.shp")

import dask.dataframe as dd

 $\label{lem:ddf} $$ ddf = dd.read_csv(r"C:\Users\tek.kshetri\Downloads\39f_buildings.csv\39f_buildings.csv") $$ ddf.head() $$$ 

import dask\_geopandas

# ddf['geometry'] = ddf.set\_geometry(dask\_geopandas.from\_wkt(ddf['geometry']))

# add ddf to the geopandas dataframe using dask geopandas

qddf = dask\_geopandas.from\_dask\_dataframe(ddf,

geometry=ddf['geometry']

.map\_partitions(gpd.GeoSeries

.from\_wkt, meta=gpd.GeoSeries([])))



```
gddf = gddf.reset_index()
gddf.crs = 'epsg:4326'
aoi = gpd.read_file(r"C:\Users\tek.kshetri\Downloads\download\layers\POLYGON.shp")
aoi.head()
aoi.crs = 'epsg:4326'
gddf = gddf.to_crs(aoi.crs)
## clip the buildings to the aoi
clipped = dask_geopandas.clip(gddf, aoi)
clipped.head()
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
clipped = clipped.compute()
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
```



Let's go through the code line by line, explaining its purpose and identifying any potential errors or improvements that might be needed. I'll also update the code if necessary and explain the reasons for the changes.

### **Initial Imports**

```
import pandas as pd
import numpy as np
import geopandas as gpd
```

- **Purpose:** These imports bring in three common libraries:
  - `pandas`: Used for data manipulation and analysis.
  - `numpy`: For numerical operations.
  - o `geopandas`: Extends `pandas` for geospatial data.
- No issues here.

## Reading CSV Dataset into a Pandas DataFrame

```
python

df = pd.read_csv(r"C:\Users\tek.kshetri\Downloads\30f_buildings.csv\30f_buildings.csv")
  df.head()
```

- **Purpose:** Loads a large CSV file (building footprint dataset) into a `pandas` DataFrame and displays the first few rows using `head()`.
- Potential Issues:
  - If the CSV file is too large (20GB in this case), using `pandas.read\_csv` may cause memory issues, especially with limited RAM. For large datasets, `dask.dataframe` should be used instead of `pandas`.

### **Converting Geometry Column to Geometrical Data**

```
df['geometry'] = gpd.GeoSeries.from_wkt(df['geometry'])
gdf = gpd.GeoDataFrame(df, geometry='geometry')
gdf.head()
```

- **Purpose:** Converts the `geometry` column from WKT (Well-Known Text) format to a `GeoSeries`, making it usable for geospatial operations. Then, it creates a `GeoDataFrame` from the original `DataFrame` and the newly created `GeoSeries`.
- No issues, but this can be memory-intensive for large datasets.

## Writing the Geospatial Data to a Shapefile

```
gdf.to_file(r"C:\Users\tek.kshetri\Downloads\687_buildings.shp")
```

- **Purpose:** Writes the geospatial data (`gdf`) to a Shapefile format.
- Potential Issues:
  - Writing large GeoDataFrames to disk could be slow. You might want to consider using `dask\_geopandas` for this step as well if you face performance issues.
  - Ensure the directory exists and has write permissions.

## Switching to Dask for Big Data Handling

```
import dask.dataframe as dd
ddf = dd.read_csv(r"C:\Users\tek.kshetri\Downloads\39f_buildings.csv\39f_buildings.csv")
ddf.head()
```

- **Purpose:** Imports `dask.dataframe` and reads a large CSV dataset in parallel, without loading the entire dataset into memory. `head()` shows the first few rows.
- No issues here. Dask is a better choice for large datasets like 20GB CSV files.

## **Dask-Geopandas: Handling Geospatial Data**

```
import dask_geopandas
# ddf['geometry'] = ddf.set_geometry(dask_geopandas.from_wkt(ddf['geometry']))
```

#### • Commented-out Line:

The commented-out line attempts to convert the `geometry` column in the Dask DataFrame
to a proper geometry format using `dask\_geopandas.from\_wkt`. You can uncomment this line

if the geometry conversion is needed in the Dask DataFrame.

#### Convert Dask DataFrame to Dask GeoDataFrame

- **Purpose:** Converts a Dask DataFrame into a Dask GeoDataFrame, ensuring that the `geometry` column is interpreted correctly.
- Potential Issue:
  - The `map\_partitions` step creates a geometry column from the `wkt` strings, but the `meta` argument (`gpd.GeoSeries([])`) must be correctly aligned with the schema of the dataset.
  - Update: Ensure that the correct metadata (geometry type) is passed to avoid any schema mismatch errors.

### **Resetting Index and Setting CRS**

```
gddf = gddf.reset_index()
gddf.crs = 'epsg:4326'
```

- **Purpose:** Resets the index of the Dask GeoDataFrame and sets the CRS (Coordinate Reference System) to `EPSG:4326` (WGS84), commonly used for geographical data.
- No issues here.

## Reading AOI (Area of Interest) Shapefile

```
python

aoi = gpd.read_file(r"C:\Users\tek.kshetri\Downloads\download\layers\POLYGON.shp")
aoi.head()
aoi.crs = 'epsg:4326'
```

- **Purpose:** Reads an AOI shapefile (polygon) using `geopandas` and assigns the same CRS (`EPSG:4326`) as the buildings dataset for compatibility.
- No issues here.

### **CRS Transformation and Clipping**

```
gddf = gddf.to_crs(aoi.crs)
```



- **Purpose:** Ensures the buildings dataset and the AOI shapefile share the same CRS before clipping.
- No issues here.

### Clipping the Dataset with AOI

```
clipped = dask_geopandas.clip(gddf, aoi)
clipped.head()
```

- Purpose: Clips the buildings dataset to the area defined by the AOI shapefile.
- No issues, but ensure that the `dask geopandas.clip` function is supported.

### **Writing Clipped Data to Shapefile**

```
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
clipped = clipped.compute()
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
```

- Purpose:
  - 1. Writes the clipped dataset to a shapefile.
  - 2. The `.compute()` step converts the Dask GeoDataFrame into a regular `geopandas` GeoDataFrame for further operations.
  - 3. The final step writes the computed GeoDataFrame to disk.
- Issue:
  - The line `clipped.to\_file(r"C:\Users\tek.kshetri\Downloads\test\_buildings.shp")` is repeated. The first instance of `clipped.to\_file()` will not work since Dask operates lazily and requires `compute()` first.
- **Update:** You should call `compute()` before trying to write the clipped file.

### **Updated Code:**

```
gddf = gddf.reset_index()
gddf.crs = 'epsg:4326'

# Load AOI shapefile
aoi = gpd.read_file(r"C:\Users\tek.kshetri\Downloads\download\layers\POLYGON.shp")
aoi.crs = 'epsg:4326'

# Transform buildings CRS to match AOI CRS
gddf = gddf.to_crs(aoi.crs)

# Clip the buildings dataset to AOI
clipped = dask_geopandas.clip(gddf, aoi)

# Compute the Dask GeoDataFrame into a regular GeoDataFrame
clipped = clipped.compute()

# Write the clipped dataset to a Shapefile
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
```

### **Key Updates:**

- Remove Repeated `clipped.to\_file`: The second `.to\_file()` call is redundant since
   `.compute()` has already been called.
- 2. **Memory Efficiency:** Dask is used appropriately for large datasets, and `compute()` is called before writing the output to a file.

This updated code should handle large datasets more efficiently and ensure correct execution without redundant steps.



missed some of the codes



Let's revisit the code and go through every line again, making sure that nothing is missed this time. Below is the **complete line-by-line explanation** along with necessary updates.

## **Importing Required Libraries**

```
import pandas as pd
import numpy as np
import geopandas as gpd
import dask.dataframe as dd
import dask_geopandas
```

- **Explanation:** We are importing libraries:
  - `pandas`: For handling structured data (like CSV).
  - o `numpy`: For numerical operations (though it's not directly used in this code).
  - `geopandas`: Extending pandas to handle geospatial data.
  - `dask.dataframe`: For handling large datasets using Dask.
  - o `dask geopandas`: Provides Dask support for geospatial data.



### **Loading a Large CSV File with Pandas**

```
python

df = pd.read_csv(r"C:\Users\tek.kshetri\Downloads\30f_buildings.csv\30f_buildings.csv")
 df.head()
```

- Explanation:
  - This reads the CSV file using pandas and displays the first few rows.
  - **Issue:** If the file is 20GB, using pandas will likely lead to memory issues on most machines. Therefore, we should switch to `dask.dataframe.read\_csv()` for memory efficiency.

### **Updated Code:**

```
python

ddf = dd.read_csv(r"C:\Users\tek.kshetri\Downloads\30f_buildings.csv\30f_buildings.csv")
    ddf.head()
```

• **Reason:** Dask can handle large datasets that don't fit in memory by processing them in chunks (lazy evaluation). This should prevent memory issues.

# **Converting WKT Geometry Column into a GeoSeries (with GeoPandas)**

```
df['geometry'] = gpd.GeoSeries.from_wkt(df['geometry'])
gdf = gpd.GeoDataFrame(df, geometry='geometry')
gdf.head()
```

- **Explanation:** Converts the `geometry` column from WKT format into a `GeoSeries` and then creates a GeoDataFrame with that geometry.
  - **Issue:** Again, `pandas` is used for this step, which may not be efficient with large datasets.

# **Updated Code:**

```
ddf['geometry'] = ddf['geometry'].map_partitions(gpd.GeoSeries.from_wkt, meta=gpd.GeoSerie
s([]))
gddf = dask_geopandas.from_dask_dataframe(ddf, geometry=ddf['geometry'])
gddf.head()
```

• **Reason for Update:** We switch to `dask\_geopandas` to handle large data efficiently, with `map\_partitions` applying `from\_wkt` to each partition lazily.



### Saving the GeoDataFrame to a Shapefile

```
gdf.to_file(r"C:\Users\tek.kshetri\Downloads\687_buildings.shp")
```

- **Explanation:** This line writes the GeoDataFrame to a Shapefile.
  - **Issue:** Since we are dealing with a large dataset, we need to use Dask to parallelize this operation.

## **Updated Code:**

```
python

gddf.to_file(r"C:\Users\tek.kshetri\Downloads\687_buildings.shp")
```

Reason for Update: Use `gddf` which is the Dask GeoDataFrame rather than the in-memory `gdf`.

### Using Dask to Load a Large CSV File Again

```
python

ddf = dd.read_csv(r"C:\Users\tek.kshetri\Downloads\39f_buildings.csv\39f_buildings.csv")
  ddf.head()
```

- **Explanation:** This reads another large CSV file using `dask.dataframe.read\_csv()`.
  - No issue here.

# **Working with Dask Geopandas for Geometry Conversion**

- **Explanation:** Converts a Dask DataFrame to a Dask GeoDataFrame using `dask\_geopandas`, while ensuring that the `geometry` column is interpreted correctly.
  - No issue here.

### Resetting Index and Setting CRS (Coordinate Reference System)

```
gddf = gddf.reset_index()
gddf.crs = 'epsg:4326'
```

#### • Explanation:

- This resets the index of the GeoDataFrame and sets the CRS (Coordinate Reference System) to `EPSG:4326` which is WGS 84, a commonly used geographic coordinate system.
- No issues here.

### Loading the AOI (Area of Interest) Shapefile

```
python

aoi = gpd.read_file(r"C:\Users\tek.kshetri\Downloads\download\layers\POLYGON.shp")
aoi.head()
aoi.crs = 'epsg:4326'
```

#### • Explanation:

- This reads the AOI shapefile into a GeoDataFrame and ensures the CRS is **EPSG:4326** to match the buildings data.
- No issues here.

# Reprojecting Data to Match CRS of AOI

```
gddf = gddf.to_crs(aoi.crs)
```

#### • Explanation:

- Ensures that the buildings data (`gddf`) is reprojected to the same CRS as the AOI.
- No issues here.

# **Clipping Buildings Data to the AOI**

```
python

clipped = dask_geopandas.clip(gddf, aoi)
clipped.head()
```

#### • Explanation:

• This clips the buildings data (`gddf`) to the bounds of the AOI.

No issues here, but be sure to check if `dask\_geopandas.clip()` is supported in your version of `dask geopandas`.

### Computing the Result and Saving to Shapefile

```
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
clipped = clipped.compute()
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
```

#### • Explanation:

- First line: This tries to write the clipped Dask GeoDataFrame to a file before computing it.
- **Second line:** The `.compute()` method converts the Dask GeoDataFrame to a regular `geopandas.GeoDataFrame` by computing the entire dataset into memory.
- **Third line:** Finally, it writes the computed GeoDataFrame to a shapefile.
- Issue: The first `clipped.to\_file()` call should be after the `.compute()` step, as Dask operations are lazy and need to be computed first.

### **Updated Code:**

```
python

clipped = clipped.compute()
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
```

• **Reason for Update:** `clipped.compute()` must be called before trying to write the GeoDataFrame to disk.

### **Full Updated Code:**

```
import pandas as pd
import numpy as np
import geopandas as gpd
import dask.dataframe as dd
import dask.geopandas

# Read large dataset using Dask (instead of pandas)
ddf = dd.read_csv(r"C:\Users\tek.kshetri\Downloads\30f_buildings.csv\30f_buildings.csv")
ddf.head()

# Convert WKT geometry to GeoSeries for Dask
ddf['geometry'] = ddf['geometry'].map_partitions(gpd.GeoSeries.from_wkt, meta=gpd.GeoSeries([]))

# Convert Dask DataFrame to Dask GeoDataFrame
```



```
gddf = dask_geopandas.from_dask_dataframe(ddf, geometry=ddf['geometry'])

# Reset index and set CRS (Coordinate Reference System)
gddf = gddf.reset_index()
gddf.crs = 'epsg:4326'

# Load the AOI shapefile
aoi = gpd.read_file(r"C:\Users\tek.kshetri\Downloads\download\layers\POLYGON.shp")
aoi.crs = 'epsg:4326'

# Reproject buildings dataset to the CRS of AOI
gddf = gddf.to_crs(aoi.crs)

# Clip the buildings dataset to the AOI
clipped = dask_geopandas.clip(gddf, aoi)

# Compute the result into a regular GeoDataFrame
clipped = clipped.compute()

# Write the clipped GeoDataFrame to a Shapefile
clipped.to_file(r"C:\Users\tek.kshetri\Downloads\test_buildings.shp")
```

### Summary of Key Updates:

- Memory Efficiency: Changed `pandas.read\_csv()` to `dask.dataframe.read\_csv()` to handle large datasets efficiently.
- 2. **Proper Geometry Handling:** Used `dask\_geopandas` to convert WKT geometries and clip the data.
- 3. **Order of Operations:** Corrected the order by calling `.compute()` before trying to save the final clipped data to a shapefile.

This should allow you to handle the 20GB dataset without running into memory issues. Let me know if you need further assistance!



explain the concept



## Concept Overview: Handling Big Data with Dask and GeoPandas

The goal of the code is to process a large geospatial dataset, too large to fit into memory, and perform spatial operations like clipping using a smaller Area of Interest (AOI). Traditional libraries like `pandas` and `geopandas` load all data into memory, making them unsuitable for large datasets. This is where Dask and Dask-GeoPandas come into play, enabling parallel processing and out-of-core computations.

Here's a breakdown of the key concepts:

## 1. Big Data and Memory Limitations

• **Problem:** The dataset is approximately **20GB**, which is too large for traditional libraries like `pandas` and `geopandas`. These libraries load the entire dataset into memory, which can lead to memory exhaustion and crashes.



• **Solution:** To solve this, we use **Dask**, a parallel computing library that works with large datasets by splitting them into manageable chunks (partitions) and processing them incrementally without loading everything into memory. This technique is called **out-of-core computation**.

### 2. Dask for Handling Large Datasets

Dask is a flexible library that extends **pandas** for large datasets by providing a **lazy evaluation** model, meaning it delays the computation until the result is actually needed. Instead of immediately loading and processing the entire dataset in memory, Dask breaks it into smaller **partitions** that fit in memory, allowing for parallel computation across many CPU cores.

#### **Key Concepts of Dask:**

- Lazy Evaluation: Operations are not computed immediately, but when you call `.compute()`, Dask processes the data.
- **Parallelism:** Dask operates in parallel, distributing tasks over multiple CPU cores, which improves performance.

#### **Example:**

• `dd.read\_csv()` works similarly to `pd.read\_csv()`, but it loads data in chunks, allowing you to work with large datasets in a memory-efficient way.

## 3. Geospatial Data and GeoPandas

- **Geospatial Data:** The dataset contains geographical information, typically in the form of coordinates or geometries (points, lines, polygons). This data can be processed using **GeoPandas**, which extends the capabilities of **pandas** to handle spatial data types.
- **GeoPandas** uses **WKT (Well-Known Text)** format for storing geometrical information, which needs to be converted to GeoSeries objects for geospatial operations (e.g., clipping, projection, spatial joins).
- Coordinate Reference Systems (CRS): Spatial data often needs to be reprojected to a common CRS (e.g., `EPSG:4326`, commonly used for GPS coordinates) to ensure that geometries align correctly when performing spatial operations.

# 4. Dask-GeoPandas: Parallel Geospatial Data Processing

- **Dask-GeoPandas** extends GeoPandas functionality for big geospatial data, allowing spatial operations like clipping, reprojecting, and writing to file in parallel.
- `dask\_geopandas.from\_dask\_dataframe()` converts a Dask DataFrame into a Dask GeoDataFrame, which enables geospatial operations while keeping the data in Dask's out-of-core computation model.

#### **Example:**

Converting WKT to Geometry: The geometry column in the CSV file is in WKT format, which is a
text-based representation of geometries. It needs to be converted into GeoPandas' `GeoSeries`
for spatial operations. With Dask, this conversion happens in parallel over multiple chunks using
`map\_partitions()`.

### 5. Spatial Clipping

- **Clipping:** This is a spatial operation where you limit or "clip" the dataset (buildings) to a specific area, called the **Area of Interest (AOI)**. Only the geometries within the AOI are retained, and everything outside is discarded.
- `dask\_geopandas.clip()` performs this operation efficiently using Dask by clipping large geospatial datasets in parallel.

### 6. Saving Data with Dask

- **Saving the Result:** Once the operations (e.g., clipping) are complete, Dask's lazy evaluation model requires us to **compute** the result, which triggers the actual processing. Once computed, the result can be written to a file (e.g., a Shapefile) using `to file()`.
- `.compute()`: This is crucial in Dask. It materializes the result, i.e., after performing all the operations lazily, the actual computation happens when `.compute()` is called. The result is loaded into memory at this point, making it a `geopandas.GeoDataFrame`, which can then be saved to disk.

## **Key Operations in the Code:**

### 1. Reading Large Datasets with Dask:

 Use Dask's `read\_csv()` instead of `pandas.read\_csv()` to efficiently load large CSV files in chunks.

#### 2. Converting Geometry with GeoPandas:

 The geometry column in the dataset is in WKT format and must be converted into a geospatial format (`GeoSeries`) using `from\_wkt()`.

#### 3. Clipping the Dataset:

• Clip the buildings dataset to the Area of Interest using `dask\_geopandas.clip()`. Only the geometries within the AOI will be retained.

#### 4. Computing and Saving the Final Result:

• After performing the operations lazily (through Dask), call `.compute()` to materialize the result into memory and then save it to a shapefile.

## Why Use Dask + GeoPandas?



- **Memory Management:** Dask breaks large datasets into chunks, allowing you to process only as much data as can fit into memory at any given time.
- **Parallelism:** Dask runs operations in parallel across multiple cores, speeding up the computation, especially useful when working with large geospatial datasets.
- **Lazy Evaluation:** This allows you to chain multiple operations (e.g., reading a file, converting geometries, clipping data) without immediately executing them, reducing memory usage and allowing efficient computations.

### **Concept Summary:**

- **Dask** is used to handle large datasets efficiently by splitting data into smaller partitions.
- **GeoPandas** adds geospatial functionality to **pandas** and **Dask-GeoPandas** extends this for large datasets, allowing geospatial operations like clipping and reprojecting.
- Lazy Evaluation and Parallel Processing in Dask allow you to perform complex operations on large datasets without running out of memory, and only compute the result when necessary (`.compute()`).

This combination of Dask and GeoPandas allows you to work with massive geospatial datasets, process them efficiently, and save the results in a format such as a shapefile.

Is this conversation helpful so far?

ChatGPT can make mistakes. Check important info.