Udacity Data Engineering Capstone Project - Obira Daniel

Course 5 of 5: Udacity Data Engineering Nano Degree

Project Summary

In a NutShell Parquet is a Hero

Processing All US Visitors in March 2016, about 3,157,072 People from Raw SAS data to some few insights.

The project follows the follow steps:

- Step 1: Scope the Project and Gather Data
- Step 2: Explore and Assess the Data
- Step 3: Define the Data Model
- Step 4: Run ETL to Model the Data
- Step 5: Complete Project Write Up

In [1]:

```
# Do all imports and installs here
import pandas as pd
import geopandas
#import pyspark.pandas as ps
import matplotlib.pyplot as plt
from matplotlib.ticker import FormatStrFormatter, StrMethodFormatter
import seaborn as sns
import sys
import os
#import contextily as cx
water = 'dodgerblue'
earth = 'tan'
from datetime import datetime, timedelta

import boto3
import configparser

config = configparser.ConfigParser()
#config.read('dwh.cfg')
#os.environ["AWS_ACCESS_KEY_ID"] = config.get("CREDENTIALS", "AWS_ACCESS_KEY_ID")
#os.environ["AWS_SECRET_ACCESS_KEY"] = config.get("CREDENTIALS", "AWS_SECRET_ACCESS_KEY"

from pyspark.sql import SparkSession
from pyspark.sql import functions as F
from pyspark.sql.functions import col, lit
from pyspark.sql.functions import udf

from pyspark.sql.types import (
    StructType,
    StructField,
    DoubleType,
    StringType,
    IntegerType,
    DateType)
```

Pandas Display Settings

In [2]:

```
pd.set_option('display.max_colwidth', 200)
```

```
pd.set_option('display.precision', 2)
pd.set_option('display.max_rows', 200)
pd.set_option('display.float_format',  '{:,.2f}'.format)
```

Step 1: Scope the Project and Gather Data

Scope

Explain what you plan to do in the project in more detail. What data do you use? What is your end solution look like? What tools did you use? etc>

1. I94 migration SAS Data from the Udacity Workspace is read using pyspark, it is first converted from SAS to parquet, then columns names are improved, Data types cast appropriately, it is joined to other key data then it is exported to Parquet achieving a compression of over 800% for each month. This will be the pre-processed raw data.

For all 40,790,529 Records, ~499 MB Parquet file instead of the ~5.92 GB SAS files (12 of them ranging from 374 MB to 684 MB), effective compression 1,215%, the same data is 12.15 times smaller and faster to read.

The Parquet data is then pushed to an S3 Bucket using Boto3 under the raw data folder ready for cleaning, analysis and mapping.

2. The other data, US City Demographic Data and Airport Codes are cleaned and will be mapped to the I94 data or joined, they are then uploaded to S3, this is a one off task, that data will be used each time as is.

3. Spatial Data (World Countries, US States and World Cities will be joined to the summarized I94 data to make simple maps using GeoPandas to quickly visually communicate quick insights), they are then uploaded to S3, this is a one off task, that data will be used each time as is.

4. The parquet data is loaded to EMR using PySpark from S3 in the same region if possible same zone, where it is mapped, cleaned, analysed and any new calcuations are added to complete the full ETL.

I used the Udacity WorkSpace mainly and my local PC for the GIS Maps because of the GeoPandas library.

At this point any additonal joins/mappings/integration can be done.

The cleaned, mapped and joined parquet data is then exported to the same S3 bucket under the final data folder because it can now be used for analysis and can be loaded straight to an OLAP or NO SQL database. The Data Model is then documented at this Stage.

5. I used March 2016 Data for the Analysis in this notebook, with 3,157,072 Visitors to US

6. The summary insights of the 3,157,072 Records are joined to the spatial data to make the following maps using GeoPandas:

```
1. US Map showing summary of total vistors to US by destination State for the
year 2016
2. World Map showing passenger traffic to US for the year 2016 by Airport
3. World Map showing passenger traffic to US for the year 2016 by Country
4. If possible in the data model,  World Map showing passenger traffic to US
for the year 2016 by City
```

7. Potential pipelines for Airflow

```
1. For Udacity Workspace: DAG1 - scheduled monthly, performs Step 1 of the
workflow: Reading SAS data by month, renaming columns, casting data types to
enforce a schema then writes to parquet in the workspace by month and for all
months it has run as one parquet file, then uploads the base folder with all
parquet data to S3.
2. For AWS EMR and Redshift after DAG1: DAG2 - scheduled monthly, performs
Steps 4, 5 and 6: An EMR Cluster reads the raw parquet data, cleans, analyses,
integrates and maps columns to appropriate values then exports to S3 Parquet as
final data, then also loads the data straight to redshift.
```

8. Documentation

Describe and Gather Data

Describe the data sets you're using. Where did it come from? What type of information is included? Data to be Used:

1. I94 Immigration Data This data comes from the US National Tourism and Trade Office

2. Airports Simple table of airport codes and corresponding cities

1. US Demograchics(us-cities-demographics.csv) This data comes from OpenSoft showing the population and age group statics for several US Cities

2. CountryCodes(Country_Codes.csv) Mapped from the I94 Immigration Data Metadata Description include Codes

1. PortCodes(Port_Codes.csv) Mapped from the I94 Immigration Data Metadata Description include Codes

2. TransportCodes(TransportMeansCode.csv) Mapped from the I94 Immigration Data Metadata Description include Codes

3. US_State_Codes(US_States.csv) Mapped from the I94 Immigration Data Metadata Description include Codes

4. VisaReasonsCodes(VisaReasons.csv) Mapped from the I94 Immigration Data Metadata Description include Codes

GIS Data Shapefiles (GIS_Data Folder, All are in GCS_WGS_1984 Projection (EPSG:4326))

1. All US States - All 50 US States with key attributes - From ESRI (ArcGIS hub)

2. Cities - World Cities with key attributes - From ESRI (ArcGIS hub)

3. Countries - World Countries with key attributes - From ESRI (ArcGIS hub)

4. US states without Hawaii and Alaska to optimize map display extent, I processed this from all states

Step 2: Explore and Assess the Data

Explore the Data

Identify data quality issues, like missing values, duplicate data, etc.

Cleaning Steps

Document steps necessary to clean the data

2.1 I94 migration data

In [3]:
```
spark = SparkSession.builder.appName("Udacity Data Eng Capstone OD")\
    .config("spark.jars.repositories", "https://repos.spark-packages.org/")\
    .config("spark.jars.packages", "saurfang:spark-sas7bdat:2.0.0-s_2.11,org.apache.hado
    .config("spark.hadoop.fs.s3a.impl", "org.apache.hadoop.fs.s3a.S3AFileSystem") \
    .enableHiveSupport().getOrCreate()

#df_spark = spark.read.format('com.github.saurfang.sas.spark').load('../../data/18-83510
```

In [4]:
```
Fullmonths = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
          'August', 'September', 'October', 'November', 'December']

months_list= ['jan', 'feb', 'mar', 'apr', 'may', 'jun', 'jul', 'aug', 'sep', 'oct', 'nov

#months_list = ['jan']

months_data = {'jan':'01', 'feb':'02', 'mar':'03', 'apr':'04',
               'may':'05', 'jun':'06', 'jul':'07', 'aug':'08',
               'sep':'09', 'oct':'10', 'nov':'11', 'dec':'12'}
```

Step 1 *Converting all SAS Data to Parquet (reduce size from ~5.92Gb to ~ 700MB)*

In [ ]:
```
#df_spark = spark.read.format('com.github.saurfang.sas.spark').load('../../data/18-83510
startTime = datetime.now()
totalRecords = 0
for month in months_list:
    startMonth = datetime.now()
    print(month)
    df_spark = spark.read.format('com.github.saurfang.sas.spark').load('../../data/18-83
    Records = df_spark.count()
    totalRecords += Records
    df_spark.write.parquet("sas_data_raw/2016/{}".format(months_data[month]))

    print((datetime.now() - startMonth), "time for SAS to Parquet", month, "with ", "{:,

print((datetime.now() - startTime), "time running for 2016 SAS to Parquet with ", "{:,}"
```

In [101…
```
#write to parquet
#df_spark.write.parquet("sas_data")
#df_spark=spark.read.parquet('s3a://obirad1/sas_data_all_old/2016/03')
#df_spark=spark.read.parquet('sas_data/2016/03')
```

Step 2 *Pushing all Raw Parquet Data to S3*

In [ ]:
```
def upload_files_to_s3(path, bucket_name, region):
    bytes_MB = 2**20
    start = datetime.now()
    session = boto3.Session(
        aws_access_key_id=os.environ["AWS_ACCESS_KEY_ID"],
        aws_secret_access_key=os.environ["AWS_SECRET_ACCESS_KEY"],
        region_name=region#e.g'us-east-1'
    )
    s3 = session.resource('s3')
    bucket = s3.Bucket(bucket_name)
    totalsize, count = 0, 0
    for subdir, dirs, files in os.walk(path):
```

```
        for file in files:
            count+=1
            full_path = os.path.join(subdir, file)
            totalsize += os.path.getsize(full_path)
            with open(full_path, 'rb') as data:
                bucket.put_object(Key=subdir.replace("\\", '/')+'/'+file, Body=data)
            if (count%20) == 0:
                print(file, "Uploaded, {:,} files so far uploaded, {:,.2f} MB total, {}

    overall = str(datetime.now() - startTime) + " Time running Uploaded, {:,} files uplo
    print(overall)
    print("COMPLETED")

upload_files_to_s3("sas_data_raw", 'obirad1', 'us-east-1')
```

Step 3 *Renaming all Columns, Schema Enforcement and Joins/Integration*

Joining the preprocessed raw parquet to Countries, Countres, Port, TransportCodes, US_State_Codes, VisaReasons

This is done for all months and the updated dataframe exported to parquet, this will now be ready for EMR

In [5]:

```
i94_schema = StructType([StructField('i94_id', IntegerType(), True),
                         StructField('Year', IntegerType(), True),
                         StructField('Month', IntegerType(), True),
                         StructField('CountryCode', IntegerType(), True),
                         StructField('CountryResidenceCode', IntegerType(), True),
                         StructField('AirportCode', StringType(), True),
                         StructField('DateOfArrival', DateType(), True),
                         StructField('ModeOfTransport', IntegerType(), True),
                         StructField('StateCodeUS', StringType(), True),
                         StructField('DateOfDeparture', DateType(), True),
                         StructField('AgeYears', DoubleType(), True),
                         StructField('VisaReason', IntegerType(), True),
                         StructField('CountVar', IntegerType(), True),
                         StructField('ValidAdress', StringType(), True),
                         StructField('DeleteDays', StringType(), True),
                         StructField('DeleteMexl', StringType(), True),
                         StructField('DeleteDup', StringType(), True),
                         StructField('DeleteVisa', StringType(), True),
                         StructField('DeleteRecd', StringType(), True),
                         StructField('DateAdded_I94', StringType(), True),
                         StructField('VisaIssueDepartment', StringType(), True),
                         StructField('OccupationUS', StringType(), True),
                         StructField('ArrivalSituation', StringType(), True),
                         StructField('DepartureStatus', StringType(), True),
                         StructField('CurrentStatus', StringType(), True),
                         StructField('MatchArrivalDeparture', StringType(), True),
                         StructField('YearofBirth', IntegerType(), True),
                         StructField('DateAdmittedUS', StringType(), True),
                         StructField('Gender', StringType(), True),
                         StructField('InsNum', StringType(), True),
                         StructField('Airline', StringType(), True),
                         StructField('AdminNum', IntegerType(), True),
                         StructField('FlightNum', StringType(), True),
                         StructField('VisaType', StringType(), True)])
```

In [6]:

```
i94s_label_map = {'cicid':'i94_id',
                  'i94yr':'Year',
                  'i94mon':'Month',
                  'i94cit':'CountryCode',
                  'i94res':'CountryResidenceCode',
                  'i94port':'AirportCode',
```

```
                   'arrdate':'DateOfArrival',
                   'i94mode':'ModeOfTransport',
                   'i94addr':'StateCodeUS',
                   'depdate':'DateOfDeparture',
                   'i94bir':'AgeYears',
                   'i94visa':'VisaReason',
                   'count':'CountVar',
                   'validres':'ValidAdress',
                   'delete_days':'DeleteDays',
                   'delete_mexl':'DeleteMexl',
                   'delete_dup':'DeleteDup',
                   'delete_visa':'DeleteVisa',
                   'delete_recdup':'DeleteRecd',
                   'dtadfile':'DateAdded_I94',
                   'visapost':'VisaIssueDepartment',
                   'occup':'OccupationUS',
                   'entdepa':'ArrivalSituation',
                   'entdepd':'DepartureStatus',
                   'entdepu':'CurrentStatus',
                   'matflag':'MatchArrivalDeparture',
                   'biryear':'YearofBirth',
                   'dtaddto':'DateAdmittedUS',
                   'gender':'Gender',
                   'insnum':'InsNum',
                   'airline':'Airline',
                   'admnum':'AdminNum',
                   'fltno':'FlightNum',
                   'visatype':'VisaType'}

i94_fields_map = ['CountryCode', 'CountryResidenceCode', 'AirportCode', 'ModeOfTransport

date_fields = ['DateOfArrival', 'DateAdmittedUS']
```

In [7]:

```
CountryCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/Country_Code
PortCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/Port_Codes.csv'
TransportCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/TransportM
US_State_Codes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/US_States.
VisaReasonsCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/VisaReas
```

In [8]:

```
@udf(returnType=DateType())
def convert_to_date(days_timestamp):
    try:
        if days_timestamp > 0:
            return pd.to_datetime(days_timestamp, unit='D', origin=pd.Timestamp('1960-01
        else:
            return None
    except:
        return None

@udf(returnType=StringType())
def convert_to_date2(date_string):
    try:
        if date_string == 'D/S':
            return 'D/S'
        else:
            return str(pd.to_datetime(date_string, format ="%m%d%Y").date())
    except:
        return None
```

In [ ]:

```
startTime = datetime.now()
totalRecords = 0
for month in months_list:
    startMonth = datetime.now()
    print(month)
```

```
    df_spark=spark.read.parquet("sas_data_raw/2016/{}".format(months_data[month]))
    u=list(i94s_label_map[key] for key in df_spark.columns)
    Records = df_spark.count()
    totalRecords += Records
    df_spark = df_spark.toDF(*u)
    df_spark = df_spark.withColumn("DateOfArrival", convert_to_date("DateOfArrival"))
    df_spark = df_spark.withColumn("DateOfDeparture", convert_to_date("DateOfDeparture")
    df_spark = df_spark.withColumn("DateAdmittedUS", convert_to_date2("DateAdmittedUS"))

    #Casting DataTypes
    df_spark  = df_spark.withColumn('i94_id', col('i94_id').cast('Integer'))\
                    .withColumn('Year', col('Year').cast('Integer'))\
                    .withColumn('Month', col('Month').cast('Integer'))\
                    .withColumn('CountryCode', col('CountryCode').cast('Integer'))\
                    .withColumn('CountryResidenceCode', col('CountryResidenceCode').
                    .withColumn('ModeOfTransport', col('ModeOfTransport').cast('Inte
                    .withColumn('VisaReason', col('VisaReason').cast('Integer'))\
                    .withColumn('CountVar', col('CountVar').cast('Integer'))\
                    .withColumn('YearofBirth', col('YearofBirth').cast('Integer'))\
                    .withColumn('AdminNum', col('AdminNum').cast('Integer'))

    #Joining to the other datasets and dropping the join id Columns after
    #Another option would be to use pyspark SQL views, this is much simpler for simple j
    df_spark = df_spark.join(US_State_Codes, df_spark.StateCodeUS == US_State_Codes.Code
    df_spark = df_spark.drop(df_spark.Code)
    df_spark = df_spark.join(CountryCodes, df_spark.CountryCode == CountryCodes.Code, "l
    df_spark = df_spark.drop(df_spark.Code)
    df_spark = df_spark.join(TransportCodes, df_spark.ModeOfTransport == TransportCodes.
    df_spark = df_spark.drop(df_spark.Code)
    df_spark = df_spark.join(VisaReasonsCodes, df_spark.VisaReason == VisaReasonsCodes.C
    df_spark = df_spark.drop(df_spark.Code)
    df_spark = df_spark.join(PortCodes, df_spark.CountryCode == PortCodes.Code, "left")
    df_spark = df_spark.drop(df_spark.Code)

    #Writing the Parquet Files to local Storage, they will be pushed to S3
    #df_spark.write.parquet("s3a://obirad1/Udacity/data-eng-capstone/2016/{}".format(mon
    df_spark.write.parquet("sas_data_final/2016/{}".format(months_data[month]))
    #df_spark.write.mode('append').parquet("sas_data/2016/all/2016_all_data.parquet")

    #df_spark.write.mode('append').parquet("s3a://obirad1/Udacity/data-eng-capstone/2016

    print((datetime.now() - startMonth), "time running for renaming and integration", mo

print((datetime.now() - startTime), "time running for 2016 with ", "{:,}".format(totalRe
```

```
jan
```

In [ ]:

```
df_spark.limit(5).toPandas()
```

Step 4 ***Pushing all Processed and Integrated Parquet Data to S3***

In [ ]:

```
upload_files_to_s3("sas_data", 'obirad1', 'us-east-1')
```

In [194…

```
df_spark.limit(5).toPandas()
```

Out[194]:

	i94_id	Year	Month	CountryCode	CountryResidenceCode	AirportCode	DateOfArrival	ModeOfTransport	Sta
0	963221	2016	3	209	209	WAS	2016-03-06	1	
1	963222	2016	3	209	209	WAS	2016-03-06	1	
2	963223	2016	3	209	209	WAS	2016-03-06	1	

3	963224	2016	3	209	209	WAS	2016-03-06	1
4	963225	2016	3	209	209	WAS	2016-03-06	1

5 rows × 34 columns

In [ ]:
```
#final_raw = spark.createDataFrame(df_spark_final_raw.rdd, i94_schema)
```

In [195…
```
df_spark.printSchema()
```

```
root
 |-- i94_id: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Month: integer (nullable = true)
 |-- CountryCode: integer (nullable = true)
 |-- CountryResidenceCode: integer (nullable = true)
 |-- AirportCode: string (nullable = true)
 |-- DateOfArrival: date (nullable = true)
 |-- ModeOfTransport: integer (nullable = true)
 |-- StateCodeUS: string (nullable = true)
 |-- DateOfDeparture: date (nullable = true)
 |-- AgeYears: integer (nullable = true)
 |-- VisaReason: integer (nullable = true)
 |-- CountVar: integer (nullable = true)
 |-- DateAdded_I94: string (nullable = true)
 |-- VisaIssueDepartment: string (nullable = true)
 |-- OccupationUS: string (nullable = true)
 |-- ArrivalSituation: string (nullable = true)
 |-- DepartureStatus: string (nullable = true)
 |-- CurrentStatus: string (nullable = true)
 |-- MatchArrivalDeparture: string (nullable = true)
 |-- YearofBirth: integer (nullable = true)
 |-- DateAdmittedUS: string (nullable = true)
 |-- Gender: string (nullable = true)
 |-- InsNum: string (nullable = true)
 |-- Airline: string (nullable = true)
 |-- AdminNum: integer (nullable = true)
 |-- FlightNum: string (nullable = true)
 |-- VisaType: string (nullable = true)
 |-- US_State: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- TransportMeans: string (nullable = true)
 |-- ReasonForVisa: string (nullable = true)
 |-- PortOfEntry: string (nullable = true)
 |-- Us_State_Country: string (nullable = true)
```

In [196…
```
'{:,} Records in Spark DataFrame'.format(df_spark.count())
```

Out[196]:
```
'3,157,072 Records in Spark DataFrame'
```

2.2 US City Demographic Data

In [142…
```
us_demographics = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/us-cities
```

In [143…
```
us_demographics.limit(5).toPandas()
```

Out[143]:

	City	State	Median Age	Male Population	Female Population	Total Population	Number of Veterans	Foreign-born	Average Household Size	State Code

0	Silver Spring	Maryland	33.8	40601	41862	82463	1562	30908	2.6	MD
1	Quincy	Massachusetts	41.0	44129	49500	93629	4147	32935	2.39	MA
2	Hoover	Alabama	38.5	38040	46799	84839	4819	8229	2.58	AL
3	Rancho Cucamonga	California	34.5	88127	87105	175232	5821	33878	3.18	CA
4	Newark	New Jersey	34.6	138040	143873	281913	5829	86253	2.73	NJ

In [145…

```
us_demographics.describe().toPandas()
```

Out[145]:

	summary	City	State	Median Age	Male Population	Female Population	Total Population
0	count	2891	2891	2891	2888	2888	2891
1	mean	None	None	35.49488066413016	97328.42624653739	101769.63088642659	198966.77931511588
2	stddev	None	None	4.401616730099886	216299.93692873296	231564.57257148277	447555.9296335903
3	min	Abilene	Alabama	22.9	100135	100260	100247
4	max	Yuma	Wisconsin	70.5	99967	99430	99897

2.3 Airport Codes Data

In [6]:

```
Airports = pd.read_csv(r'Mapping\Airports_Processed.csv',header=0)
```

In [7]:

```
Airports.head()
```

Out[7]:

	Unnamed: 0	ident	name	continent	iso_country	municipality	iata_code	local_code	lat	long
0	0	00A	Total Rf Heliport	NaN	US	Bensalem	NaN	00A	-74.93	40.07
1	1	00AA	Aero B Ranch Airport	NaN	US	Leoti	NaN	00AA	-101.47	38.70
2	2	00AK	Lowell Field	NaN	US	Anchor Point	NaN	00AK	-151.70	59.95
3	3	00AL	Epps Airpark	NaN	US	Harvest	NaN	00AL	-86.77	34.86
4	4	00AR	Newport Hospital & Clinic Heliport	NaN	US	Newport	NaN	NaN	-91.25	35.61

In [10]:

```
Airports.describe(include="all")
```

Out[10]:

	Unnamed: 0	ident	name	continent	iso_country	municipality	iata_code	local_code	lat	
count	55,075.00	55075	55075	27356	54828	49399	9189	28686	55,075.00	55,0
unique	NaN	55075	52144	6	243	27133	9042	27436	NaN	
top	NaN	00A	Centre	EU	US	Seoul	0	AMA	NaN	

			Hospitalier Heliport							
freq	NaN	1	85	7840	22757	404	80	5	NaN	
mean	27,537.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-35.08	
std	15,898.93	NaN	NaN	NaN	NaN	NaN	NaN	NaN	79.74	
min	0.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-179.88	
25%	13,768.50	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-92.01	
50%	27,537.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-72.13	
75%	41,305.50	NaN	NaN	NaN	NaN	NaN	NaN	NaN	14.82	
max	55,074.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	179.98	

2.4.1 World Countries (Spatial Data), 252 Countries

In [83]:
```
worldpath = r'GIS_Data\Countries\WorldCountries.shp'
world = geopandas.read_file(worldpath)
```

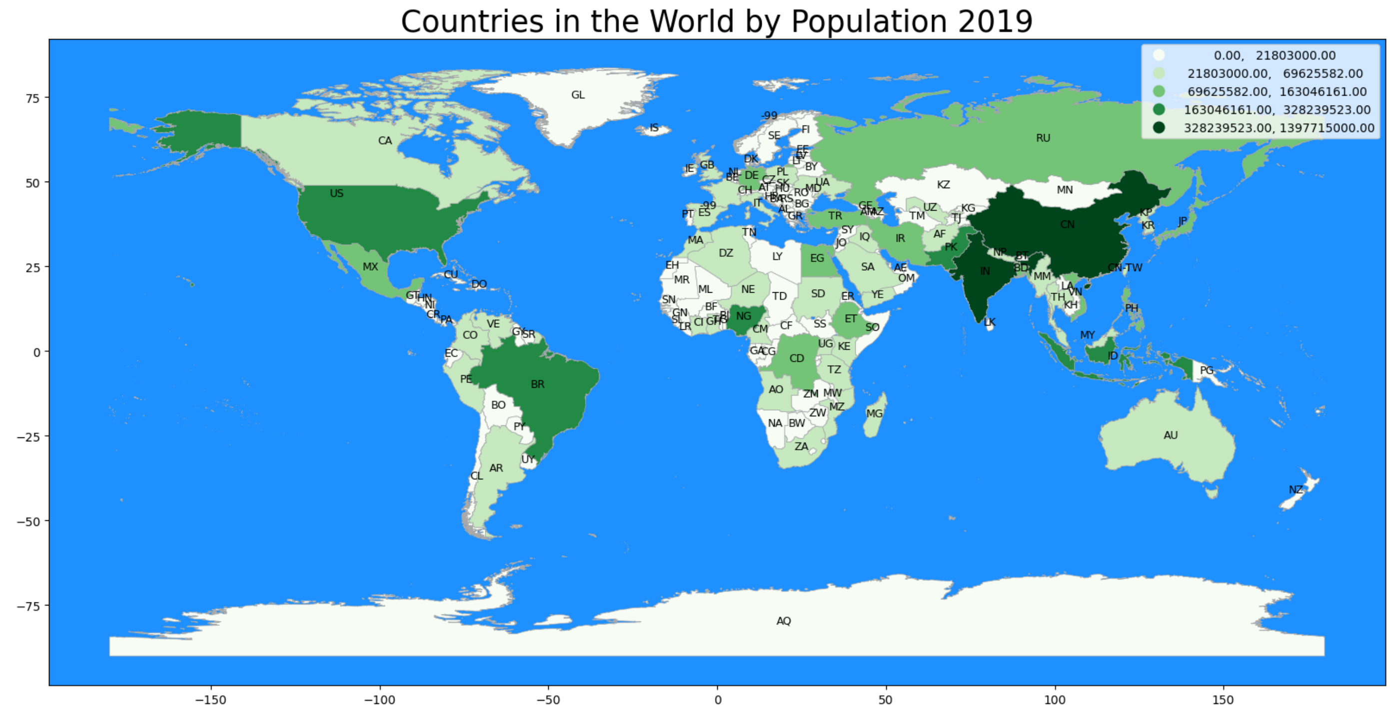
In [13]:
```
world[['LABELRANK', 'NAME', 'NAME_LONG', 'ABBREV',
       'POP_EST', 'POP_RANK', 'POP_YEAR', 'GDP_MD', 'GDP_YEAR', 'ECONOMY',
       'INCOME_GRP', 'ISO_A2', 'ISO_A3', 'CONTINENT', 'REGION_UN', 'SUBREGION', 'REGION_
```

Out[13]:

	LABELRANK	NAME	NAME_LONG	ABBREV	POP_EST	POP_RANK	POP_YEAR	GDP_MD	GDP_YEAR	E
0	2	Indonesia	Indonesia	Indo.	270,625,568.00	17	2019	1119190	2019	
1	3	Malaysia	Malaysia	Malay.	31,949,777.00	15	2019	364681	2019	D
2	2	Chile	Chile	Chile	18,952,038.00	14	2019	282318	2019	
3	3	Bolivia	Bolivia	Bolivia	11,513,100.00	14	2019	40895	2019	
4	2	Peru	Peru	Peru	32,510,453.00	15	2019	226848	2019	

In [ ]:
```
#world[world['NAME']=='Uganda']['geometry'].area
```

In [14]:
```
fig, ax = plt.subplots(figsize=(20, 15))
#world.plot('NAME', legend=False, ax=ax)
world.plot('POP_EST', legend=True, scheme='NaturalBreaks', ax=ax, cmap="Greens", edgecol
#world.boundary.plot('Greys_r', ax=ax, linewidth=0.5)
world.apply(lambda x: ax.annotate(text=x['ISO_A2'] if x['geometry'].area >3 else '', xy=
ax.set_title('Countries in the World by Population 2019', fontdict={'fontsize':25, 'font
ax.set_facecolor(water)
```



2.4.2 US States (Spatial Data), 48 States (Alaska and Hawaii Dropped) + DC

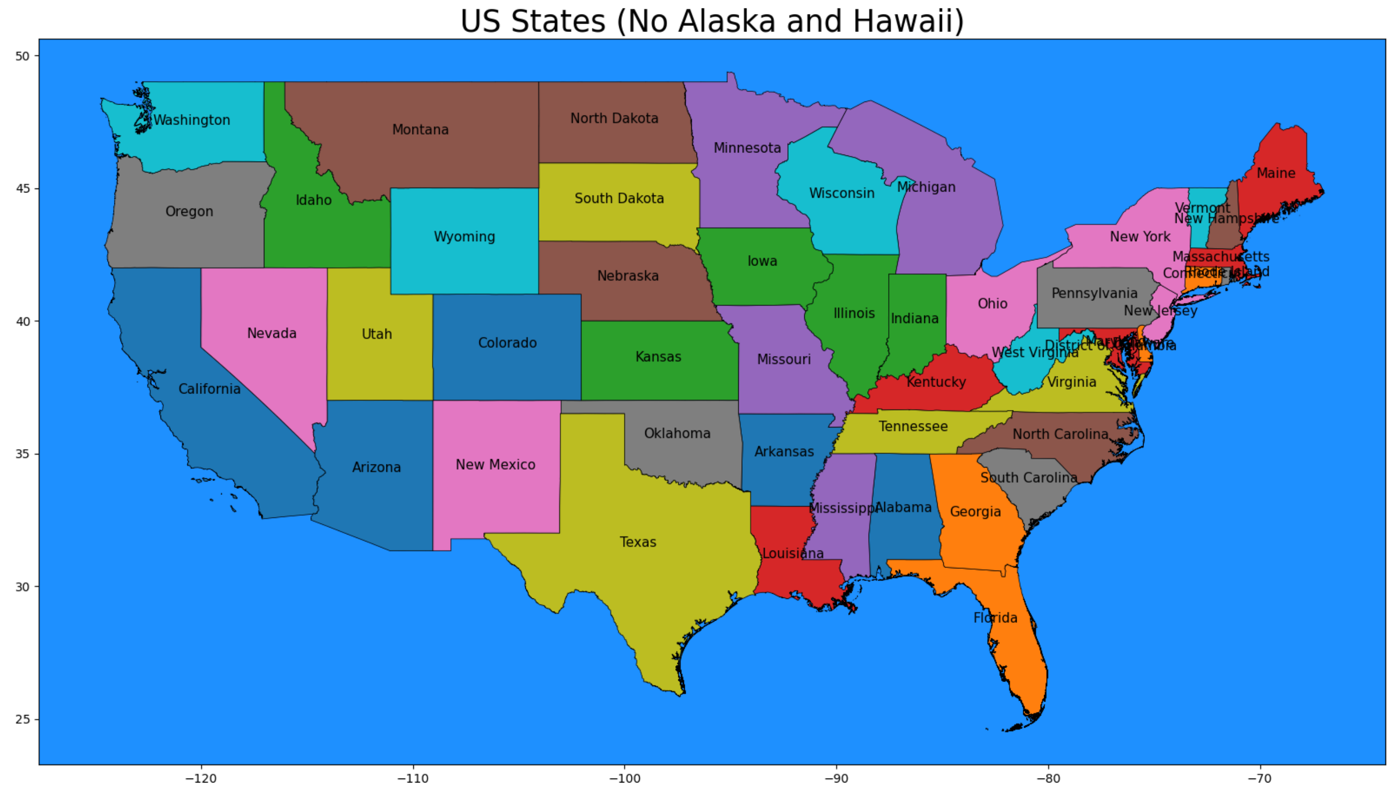
In [15]:
```
uspath = r'GIS_Data\US\US_States.shp'
usa = geopandas.read_file(uspath)
```

In [17]:
```
usa[['GID_1','NAME_1','TYPE_1', 'HASC_1', 'ISO_1', 'StateUS']].head()
```

Out[17]:

	GID_1	NAME_1	TYPE_1	HASC_1	ISO_1	StateUS
0	USA.1_1	Alabama	State	US.AL	US-AL	AL
1	USA.3_1	Arizona	State	US.AZ	US-AZ	AZ
2	USA.4_1	Arkansas	State	US.AR	US-AR	AR
3	USA.5_1	California	State	US.CA	US-CA	CA
4	USA.6_1	Colorado	State	US.CO	US-CO	CO

In [18]:
```
fig, ax = plt.subplots(figsize=(20, 15))
usa.plot('StateUS', legend=False, ax=ax, edgecolor="black", linewidth=.5)
usa.apply(lambda x: ax.annotate(text=x['NAME_1'], xy=x.geometry.centroid.coords[0], ha='
ax.set_title('US States (No Alaska and Hawaii)', fontdict={'fontsize':25, 'fontweight':3
ax.set_facecolor(water)
```



2.4.3 World Cities Data 2,540 Cities from 231 Countries

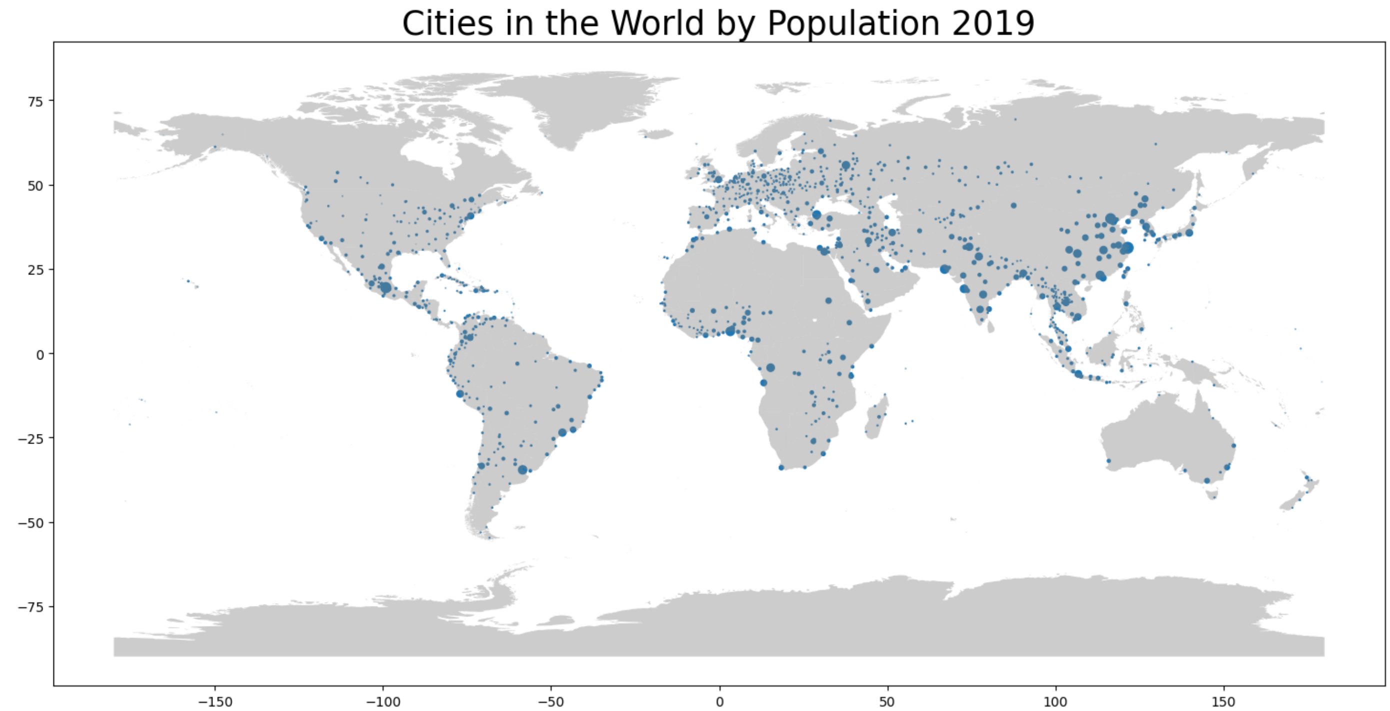
In [81]:
```
worldcities = r'GIS_Data\Cities\WorldCities.shp'
cities = geopandas.read_file(worldcities)
```

In [21]:
```
cities.head()
```

Out[21]:

	FID_1	OBJECTID	CITY_NAME	GMI_ADMIN	ADMIN_NAME	FIPS_CNTRY	CNTRY_NAME	STATUS	POP	P
0	1	1	Cuiaba	BRA-MGR	Mato Grosso	BR	Brazil	Provincial capital	540814	
1	2	2	Brasilia	BRA-DFD	Distrito Federal	BR	Brazil	National and provincial capital	2481272	
2	3	3	Goiania	BRA-GOI	Goias	BR	Brazil	Provincial capital	1297154	
3	4	4	Campo Grande	BRA-MGD	Mato Grosso do Sul	BR	Brazil	Provincial capital	776242	
4	5	5	Pedro Juan Caballero	PRY-AMM	Amambay	PA	Paraguay	Provincial capital	0	

In [84]:
```
fig, ax = plt.subplots(figsize=(18, 12))
cities.plot(markersize=cities['POP']/400000, legend=False, ax=ax)
world.plot(ax=ax, alpha=0.4, color="grey")
#world.apply(lambda x: ax.annotate(text=x['name'], xy=x.geometry.centroid.coords[0], ha=
ax.set_title('Cities in the World by Population 2019', fontdict={'fontsize':25, 'fontwei
```



Will use March for analysis (This can be replicated on Each Month or the whole dataset on EMR)

In [103…

```
df_spark=spark.read.parquet("sas_data_final/2016/03")
```

In [ ]:

```
"""
i94_fields_map = ['CountryCode', 'CountryResidenceCode', 'AirportCode', 'ModeOfTransport

TransportModeMap = {1:'Air', 2:'Sea', 3:'Land', 9:'Not Reported'}

VisaReasonMap = {1:'Business', 2:'Pleasure', 3:'Student'}

us_states_file = r"Mapping\US_States.txt"
port_codes_file = r"Mapping\Port_Codes.txt"
countries_file = r"Mapping\Country_Codes.txt"

def mapfile(file, KeyType):
    map_dic = {}

    with open(file) as data:
        for line in data:
            try:
                code, value = line.split('=')
                if "'" in code:
                    code = code.replace("'","")

                code = code.strip()
                if "'" in value:
                    value = value.replace("'","")
                value = value.strip()

                if KeyType == 'String':
                    map_dic[code] = value
                elif KeyType == 'Integer':
                    map_dic[int(code)] = value

            except Exception as e:
                print(line, e )
                continue

    return map_dic
```

```
StateCodes_dic = mapfile(us_states_file, 'String')
CountryCodes_dic = mapfile(countries_file, 'Integer')
PortCodes_dic = mapfile(port_codes_file, 'String')
"""
```

In [ ]:

```
#TransportModeMap_bc = spark.sparkContext.broadcast(TransportModeMap)
#VisaReasonMap_bc = spark.sparkContext.broadcast(VisaReasonMap)
#StateCodes_bc = spark.sparkContext.broadcast(StateCodes_dic)
#CountryCodes_bc = spark.sparkContext.broadcast(CountryCodes_dic)
#PortCodes_bc = spark.sparkContext.broadcast(PortCodes_dic)
```

In [149…

```
#check for duplicates
distinct_count = df_spark.distinct().count()
count = df_spark.count()
if  distinct_count == count:
    print("No Duplicates")
else:
    print("Duplicates are there, ", abs(distinct_count - count), "Records.")
```

```
No Duplicates
```

In [120…

```
df_spark.limit(5).toPandas()
```

Out[120]:

	i94_id	Year	Month	CountryCode	CountryResidenceCode	AirportCode	DateOfArrival	ModeOfTransport	Sta
0	963221	2016	3	209	209	WAS	2016-03-06	1	
1	963222	2016	3	209	209	WAS	2016-03-06	1	
2	963223	2016	3	209	209	WAS	2016-03-06	1	
3	963224	2016	3	209	209	WAS	2016-03-06	1	
4	963225	2016	3	209	209	WAS	2016-03-06	1	

5 rows × 34 columns

In [150…

```
df_spark.printSchema()
```

```
root
 |-- i94_id: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Month: integer (nullable = true)
 |-- CountryCode: integer (nullable = true)
 |-- CountryResidenceCode: integer (nullable = true)
 |-- AirportCode: string (nullable = true)
 |-- DateOfArrival: date (nullable = true)
 |-- ModeOfTransport: integer (nullable = true)
 |-- StateCodeUS: string (nullable = true)
 |-- DateOfDeparture: date (nullable = true)
 |-- AgeYears: integer (nullable = true)
 |-- VisaReason: integer (nullable = true)
 |-- CountVar: integer (nullable = true)
 |-- DateAdded_I94: string (nullable = true)
 |-- VisaIssueDepartment: string (nullable = true)
 |-- OccupationUS: string (nullable = true)
 |-- ArrivalSituation: string (nullable = true)
 |-- DepartureStatus: string (nullable = true)
 |-- CurrentStatus: string (nullable = true)
```

```
 |-- MatchArrivalDeparture: string (nullable = true)
 |-- YearofBirth: integer (nullable = true)
 |-- DateAdmittedUS: string (nullable = true)
 |-- Gender: string (nullable = true)
 |-- InsNum: string (nullable = true)
 |-- Airline: string (nullable = true)
 |-- AdminNum: integer (nullable = true)
 |-- FlightNum: string (nullable = true)
 |-- VisaType: string (nullable = true)
 |-- US_State: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- TransportMeans: string (nullable = true)
 |-- ReasonForVisa: string (nullable = true)
 |-- PortOfEntry: string (nullable = true)
 |-- Us_State_Country: string (nullable = true)
```

2.3 I94 migration data Exploration, Cleaning, Mapping and Integration Options

2.1.1 Cleaning I94 data, (Missing Data and Wrong Values)

In [121…

```
categorical = [
 'AirportCode',
 'VisaIssueDepartment',
 'OccupationUS',
 'ArrivalSituation',
 'DepartureStatus',
 'CurrentStatus',
 'MatchArrivalDeparture',
 'Gender',
 'Airline',
 'VisaType',
 'US_State',
 'Country',
 'TransportMeans',
 'ReasonForVisa',
 'PortOfEntry',
 'Us_State_Country',
 'DateOfArrival']
```

In [7]:

```
numbers = ['AgeYears','YearofBirth']
```

In [8]:

```
df_spark.limit(5).toPandas()
```

Out[8]:

	i94_id	Year	Month	CountryCode	CountryResidenceCode	AirportCode	DateOfArrival	ModeOfTransport	Sta
0	963221	2016	3	209	209	WAS	2016-03-06	1	
1	963222	2016	3	209	209	WAS	2016-03-06	1	
2	963223	2016	3	209	209	WAS	2016-03-06	1	
3	963224	2016	3	209	209	WAS	2016-03-06	1	
4	963225	2016	3	209	209	WAS	2016-03-06	1	

5 rows × 34 columns

In [105…

```
df_spark[numbers].describe().toPandas()
```

Out[105]:

	summary	AgeYears	YearofBirth
0	count	3156188	3156188
1	mean	39.29775761139704	1976.702242388603
2	stddev	17.66352066223753	17.66352066223585
3	min	-2.0	204
4	max	1812.0	2018

In [28]:

```
df_spark.createOrReplaceTempView("Analysis")
```

In [31]:

```
spark.sql("SELECT AgeYears from Analysis ORDER BY AgeYears DESC LIMIT 5 ").toPandas()
```

Out[31]:

	AgeYears
0	1,812.00
1	1,812.00
2	116.00
3	115.00
4	114.00

In [34]:

```
spark.sql("SELECT AgeYears from Analysis  WHERE AgeYears IS NOT NULL ORDER BY AgeYears A
```

Out[34]:

	AgeYears
0	-2.00
1	0.00
2	0.00
3	0.00
4	0.00

In [55]:

```
spark.sql("SELECT YearofBirth from Analysis ORDER BY YearofBirth DESC LIMIT 5 ").toPanda
```

Out[55]:

	YearofBirth
0	2018
1	2016
2	2016
3	2016
4	2016

In [57]:

```
spark.sql("SELECT YearofBirth from Analysis WHERE YearofBirth IS NOT NULL ORDER BY Yearo
```

Out[57]:

	YearofBirth
0	204
1	204

2	1900
3	1901
4	1902

AgeYears of -2 and 1,812 will be replace with None, similarly YearofBirth of 204 and 2018

In [60]:
```
df_spark[numbers].describe().toPandas()
```

Out[60]:

	summary	AgeYears	YearofBirth
0	count	3156188	3156188
1	mean	39.29775761139704	1976.702242388603
2	stddev	17.66352066223753	17.66352066223585
3	min	-2.0	204
4	max	1812.0	2018

In [106…
```
@udf(returnType=IntegerType())
def ageupdate(age):
    try:
        age=int(age)
        if (120 > age) and (age >=0):
            return age
        else:
            return None
    except:
        return None

@udf(returnType=IntegerType())
def yearupdate(year):
    try:
        #year=int(year)
        if (2017 > year) and (year >=1896):
            return year
        else:
            return None
    except:
        return None
```

In [108…
```
df_spark = df_spark.withColumn("AgeYears", ageupdate("AgeYears"))
```

In [109…
```
df_spark = df_spark.withColumn("YearofBirth", yearupdate("YearofBirth"))
```

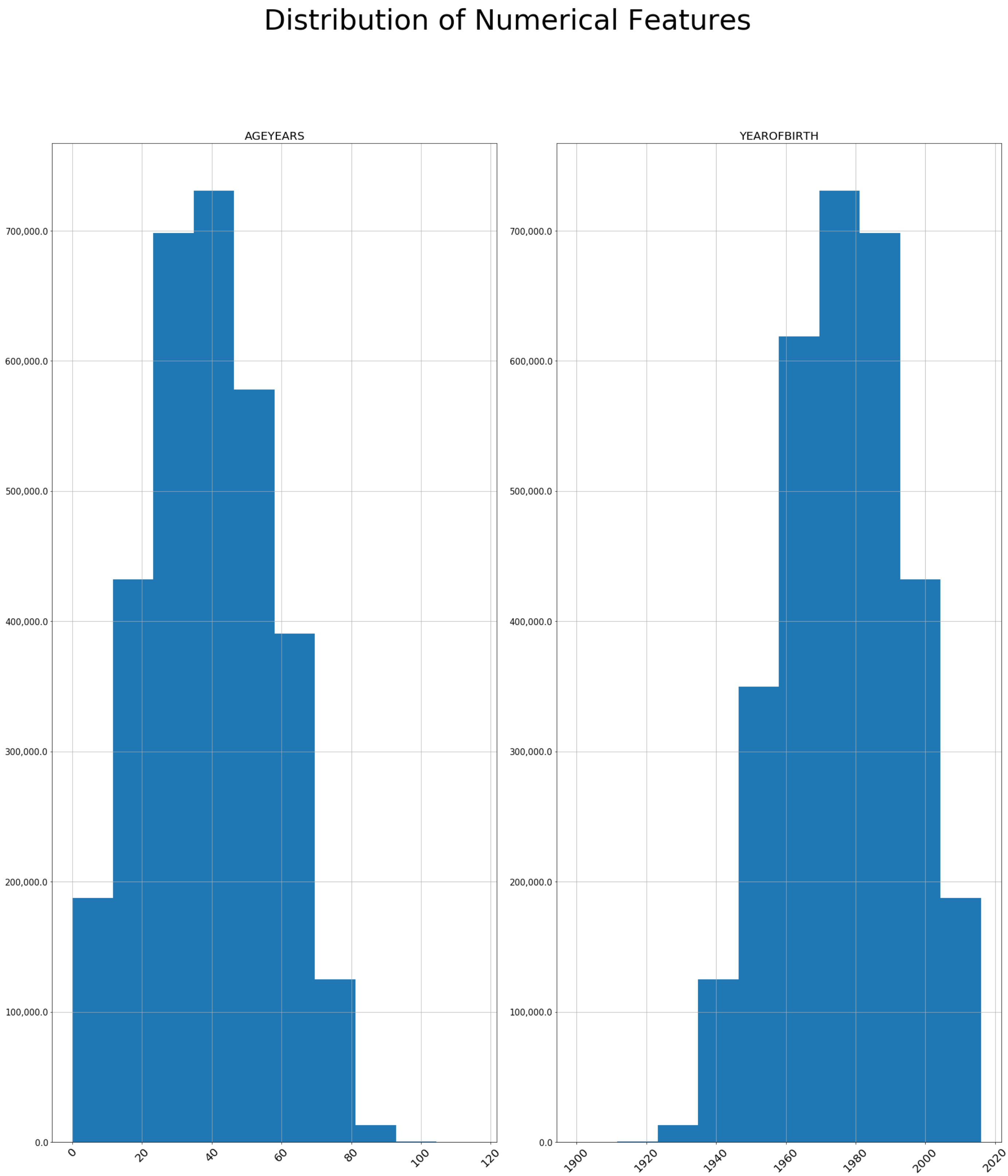
In [18]:
```
#import pyspark.sql.functions as f
#my_list = df.select(f.collect_list('name')).first()[0]
#df_spark.select(F.collect_list('Gender')).first()[0]
```

In [111…
```
#Distribution of Numerical Data
fig = plt.figure(figsize=(25, 30))
st = fig.suptitle("Distribution of Numerical Features", fontsize=50, verticalalignment="
for col, num in zip(numbers, range(1,len(numbers)+1)):
    print("Plotting", col, ": Variable {}.".format(num))
    ax = fig.add_subplot(1,2, num)
    ax.hist(df_spark.select(F.collect_list(col)).first()[0])
    ax.yaxis.set_major_formatter(StrMethodFormatter('{x:,}'))
    plt.grid(True)
    plt.xticks(rotation=45, fontsize=20)
    plt.yticks(fontsize=15)
```

```
    plt.title(col.upper(), fontsize=20)

plt.tight_layout()
st.set_y(0.95)
fig.subplots_adjust(top=0.85, hspace=0.4)
plt.show()
```

```
Plotting AgeYears : Variable 1.
Plotting YearofBirth : Variable 2.
```



In [11]:
```
df_spark[categorical].describe().toPandas()
```

Out[11]:

	summary	AirportCode	VisaIssueDepartment	OccupationUS	ArrivalSituation	DepartureStatus	CurrentSta
0	count	3157072	1246740	13991	3156918	3020248	

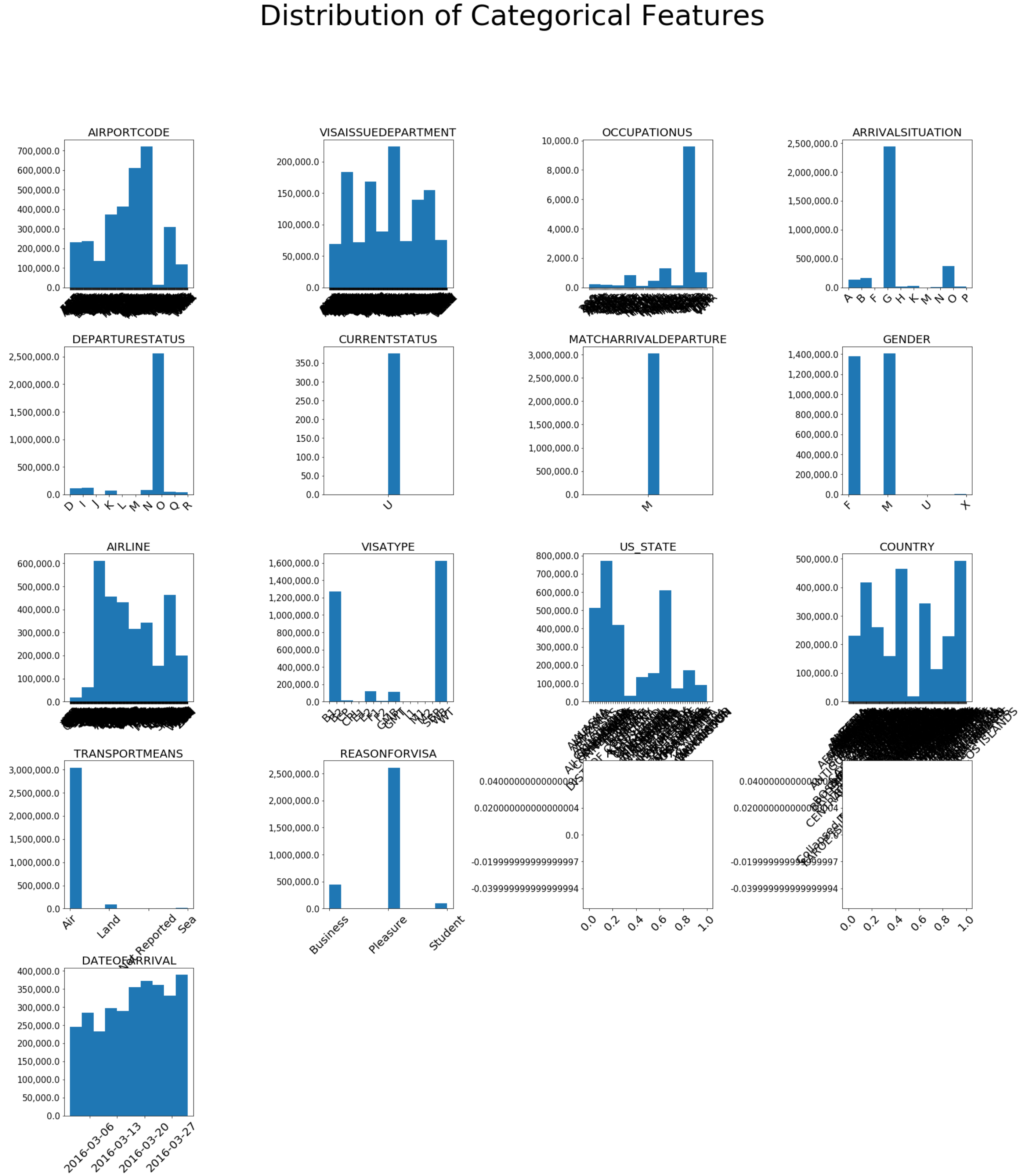
1	mean	None	999.0	941.8	None	None	N
2	stddev	None	0.0	177.56619567404672	None	None	N
3	min	5KE	999	200	A	D	
4	max	YSL	ZZZ	WTR	Z	W	

In [124…

```
#Distribution of Categorical Data
#Idea picked from shared from Data Science for Everyone YouTube Channel
#https://github.com/markumreed/data_science_for_everyone/blob/main/pyspark_examples/pima
fig = plt.figure(figsize=(30, 30))
st = fig.suptitle("Distribution of Categorical Features", fontsize=50, verticalalignment
for col, num in zip(categorical, range(1,len(categorical)+1)):
    print("Plotting", col, ": Variable {}.".format(num))
    ax = fig.add_subplot(5,4, num)
    ax.hist(df_spark.select(F.collect_list(col)).first()[0])
    ax.yaxis.set_major_formatter(StrMethodFormatter('{x:,}'))
    plt.grid(False)
    plt.xticks(rotation=45, fontsize=20)
    plt.yticks(fontsize=15)
    plt.title(col.upper(), fontsize=20)

plt.tight_layout()
st.set_y(0.95)
fig.subplots_adjust(top=0.85, hspace=0.4)
plt.show()
```

```
Plotting AirportCode : Variable 1.
Plotting VisaIssueDepartment : Variable 2.
Plotting OccupationUS : Variable 3.
Plotting ArrivalSituation : Variable 4.
Plotting DepartureStatus : Variable 5.
Plotting CurrentStatus : Variable 6.
Plotting MatchArrivalDeparture : Variable 7.
Plotting Gender : Variable 8.
Plotting Airline : Variable 9.
Plotting VisaType : Variable 10.
Plotting US_State : Variable 11.
Plotting Country : Variable 12.
Plotting TransportMeans : Variable 13.
Plotting ReasonForVisa : Variable 14.
Plotting PortOfEntry : Variable 15.
Plotting Us_State_Country : Variable 16.
Plotting DateOfArrival : Variable 17.
```



QUICK FACTS

TOP 10 Countries

In [117…

```
spark.sql("""SELECT Country, COUNT(*) AS Records
                FROM Analysis
                GROUP BY Country
                ORDER BY Records
                DESC LIMIT 10 """).toPandas()
```

Out[117]:

	Country	Records
0	None	426629

1	UNITED KINGDOM	400118
2	JAPAN	266022
3	MEXICO	227555
4	CHINA	186941
5	BRAZIL	110778
6	FRANCE	108154
7	AUSTRALIA	87559
8	ITALY	85068
9	SPAIN	81631

TOP 10 US STATE DESTINATIONS

In [118…

```
spark.sql("""SELECT US_State, COUNT(*) AS Records
             FROM Analysis
             GROUP BY US_State
             ORDER BY Records
             DESC LIMIT 10 """).toPandas()
```

Out[118]:

	US_State	Records
0	FLORIDA	694386
1	NEW YORK	524046
2	CALIFORNIA	477069
3	None	190048
4	HAWAII	176540
5	TEXAS	145347
6	GUAM	119435
7	NEVADA	101078
8	MASSACHUSETTS	74434
9	ILLINOIS	70130

TOP 10 AIRLINES

In [119…

```
spark.sql("""SELECT Airline, COUNT(*) AS Records
             FROM Analysis
             GROUP BY Airline
             ORDER BY Records
             DESC LIMIT 10 """).toPandas()
```

Out[119]:

	Airline	Records
0	AA	335381
1	UA	291634
2	DL	267864
3	BA	199806
4	LH	120745
5	VS	116462

6	None	101573
7	JL	78065
8	KE	71204
9	AM	70471

Query and store Data to be used for mapping

TRAVELLERS TO EACH US STATE 2016 March

In [127...
```
US_Visitors_State= spark.sql("""SELECT StateCodeUS, COUNT(*) AS Records
                                 FROM Analysis
                                 GROUP BY StateCodeUS
                                 ORDER BY Records""").toPandas()
```

In [131...
```
US_Visitors_State.to_csv("US_State_Visitors.csv")
```

TOTAL TRAVELLERS TO BY EACH AIRPORT

In [132...
```
Airport_Visitors = spark.sql("""SELECT AirportCode, COUNT(*) AS Records
                                 FROM Analysis
                                 GROUP BY AirportCode
                                 ORDER BY Records""").toPandas()
```

In [133...
```
Airport_Visitors.to_csv("Airport_Visitors.csv")
```

TOTAL TRAVELLERS TO BY EACH COUNTRY

In [135...
```
Country_Visitors = spark.sql("""SELECT Country, COUNT(*) AS Records
                                 FROM Analysis
                                 GROUP BY Country
                                 ORDER BY Records""").toPandas()
```

In [137...
```
Country_Visitors["CountryMatch"] = Country_Visitors["Country"].str.title()
```

In [139...
```
Country_Visitors.to_csv("Country_Visitors.csv")
```

Step 3: Define the Data Model

3.1 Conceptual Data Model

Map out the conceptual data model and explain why you chose that model

1. Then main data is the I94 Immmigration data then the others are supplementary.
2. Being able to export insights for other systems to use like in this case the GIS mapping

3.2 Mapping Out Data Pipelines

1. SAS data to RAW Parquet Data
2. Uploading Parquet Data to S3 for EMR to access and storage accessible from anywhere
3. Reading the Raw Parquet Data doing the following (Either on the Udacity workspace, locally or EMR from S3)
   A. Changing Column Names to meaningful human friendly names
   B. Schema Enforcement through type casting

    C. Joining some required tables e.g Country Codes e.t.c
    D. Exporting this to a new parquet ready for further upstream data analytics and futher processing
4. Data Quality Checks
5. Data Analysis (Exploraty Data Analysis (EDA), Futher Error Checking, Modelling e.t.c
6. Exporting Key Insights to for GIS Map Making

Additional Potential Pipelines

1. EMR to RedShift (there is more processing required)
2. RedShift from Parquet export from stage 3
3. If Data gets more massive and more people require access then EMR to No SQL, Cassandra or DyanamoDB or from Parquet e.t.c

Step 4: Run Pipelines to Model the Data

4.1 Create the data model

Build the data pipelines to create the data model.

In [141…

```
# these are functions that process data pretty much or push it somewhere or both
# the print statements will chane to logging for an AirFlow dag operator definition base
#1 Convert SAS to Parquet
def sas_to_parquet(required_months:list):
    """
    Only works on the Udacity WorkSpace, it reads the attached drive with SAS files
    and converts them to a prescribed path that you can vary.
    Assumption is spark is already intiallized
    input e.g ['jan', 'feb'], similiar to months_list defined earlier
    """

    startTime = datetime.now()
    totalRecords = 0
    for month in required_months:
        startMonth = datetime.now()
        print(month)
        df_spark = spark.read.format('com.github.saurfang.sas.spark').load('../../data/1
        Records = df_spark.count()
        totalRecords += Records
        df_spark.write.parquet("sas_data_raw/2016/{}".format(months_data[month]))

        print((datetime.now() - startMonth), "time for SAS to Parquet", month, "with ",

    print((datetime.now() - startTime), "time running for 2016 SAS to Parquet with ", "{

#2 Push a whole folder with Parquet files from workspace to S3
def upload_files_to_s3(path, bucket_name, region):
    """
    Pushes a whole folder (path) with the same structure to an S3 bucket.
    Also shows progress for every 20 files and the total size in MD
    transferred so far or in Total
    """
    bytes_MB = 2**20
    start = datetime.now()
    session = boto3.Session(
        aws_access_key_id=os.environ["AWS_ACCESS_KEY_ID"],
        aws_secret_access_key=os.environ["AWS_SECRET_ACCESS_KEY"],
        region_name=region#e.g'us-east-1'
    )
    s3 = session.resource('s3')
    bucket = s3.Bucket(bucket_name)
```

```
    totalsize, count = 0, 0
    for subdir, dirs, files in os.walk(path):
        for file in files:
            count+=1
            full_path = os.path.join(subdir, file)
            totalsize += os.path.getsize(full_path)
            with open(full_path, 'rb') as data:
                bucket.put_object(Key=subdir.replace("\\", '/')+'/'+file, Body=data)
            if (count%20) == 0:
                print(file, "Uploaded, {:,} files so far uploaded, {:,.2f} MB total, {}

    overall = str(datetime.now() - startTime) + " Time running Uploaded, {:,} files uplo
    print(overall)
    print("COMPLETED")

#3 Process, Clean, Intergrate and Refine Parquet for Analysis
def parse_parquet_for_analysis(required_months:list):
    """
    This process the raw parquet dump from SAS by:
        1. Renaming Columns to having meaningful names
        2. Casting Columns to their required DataTypes
        3. Joining the data to the following datasets based on custom mappings:
            1. Country Codes Mapped to Country Names
            2. Port Codes mapped to Port Names
            3. Transport Codes mapped to Transport Classifications
            4. US State Codes mapped to US State Name
            5. Visa Reasons Codes mapped to Reasons for Visas
        4. Exporting this to a new parquet file ready for EDA and another futher analysi
    """
    startTime = datetime.now()
    totalRecords = 0
    for month in required_months:
        startMonth = datetime.now()
        print(month)
        df_spark=spark.read.parquet("sas_data_raw/2016/{}".format(months_data[month]))
        u=list(i94s_label_map[key] for key in df_spark.columns)
        Records = df_spark.count()
        totalRecords += Records
        df_spark = df_spark.toDF(*u)
        df_spark = df_spark.withColumn("DateOfArrival", convert_to_date("DateOfArrival")
        df_spark = df_spark.withColumn("DateOfDeparture", convert_to_date("DateOfDepartu
        df_spark = df_spark.withColumn("DateAdmittedUS", convert_to_date2("DateAdmittedU

        #Casting DataTypes
        df_spark  = df_spark.withColumn('i94_id', col('i94_id').cast('Integer'))\
                    .withColumn('Year', col('Year').cast('Integer'))\
                    .withColumn('Month', col('Month').cast('Integer'))\
                    .withColumn('CountryCode', col('CountryCode').cast('Integer'
                    .withColumn('CountryResidenceCode', col('CountryResidenceCod
                    .withColumn('ModeOfTransport', col('ModeOfTransport').cast('
                    .withColumn('VisaReason', col('VisaReason').cast('Integer'))
                    .withColumn('CountVar', col('CountVar').cast('Integer'))\
                    .withColumn('YearofBirth', col('YearofBirth').cast('Integer'
                    .withColumn('AdminNum', col('AdminNum').cast('Integer'))

        #Reading Data to be joined to the DataFrame
        CountryCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/Coun
        PortCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/Port_Co
        TransportCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/Tr
        US_State_Codes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/US
        VisaReasonsCodes = spark.read.csv('s3a://obirad1/Udacity/data-eng-capstone/data/

        #Joining to the other datasets and dropping the join id Columns after
        #Another option would be to use pyspark SQL views, this is much simpler for simp
        df_spark = df_spark.join(US_State_Codes, df_spark.StateCodeUS == US_State_Codes.
        df_spark = df_spark.drop(df_spark.Code)
```

```
        df_spark = df_spark.join(CountryCodes, df_spark.CountryCode == CountryCodes.Code
        df_spark = df_spark.drop(df_spark.Code)
        df_spark = df_spark.join(TransportCodes, df_spark.ModeOfTransport == TransportCo
        df_spark = df_spark.drop(df_spark.Code)
        df_spark = df_spark.join(VisaReasonsCodes, df_spark.VisaReason == VisaReasonsCod
        df_spark = df_spark.drop(df_spark.Code)
        df_spark = df_spark.join(PortCodes, df_spark.CountryCode == PortCodes.Code, "lef
        df_spark = df_spark.drop(df_spark.Code)

        #Writing the Parquet Files to local Storage, they will be pushed to S3
        #df_spark.write.parquet("s3a://obirad1/Udacity/data-eng-capstone/2016/{}".format
        df_spark.write.parquet("sas_data/2016/{}".format(months_data[month]))
        #df_spark.write.mode('append').parquet("sas_data/2016/all/2016_all_data.parquet"

        #df_spark.write.mode('append').parquet("s3a://obirad1/Udacity/data-eng-capstone/

        print((datetime.now() - startMonth), "time running for renaming and integration"
    print((datetime.now() - startTime), "time running for 2016 with ", "{:,}".format(tot

#4 Further automation can be done after the EDA, the issue is this only March Data, the
# these will be figured out during the data analysis

#These can be built into DAGS using Airflow if need be
```

4.2 Data Quality Checks

Explain the data quality checks you'll perform to ensure the pipeline ran as expected. These could include:

- Integrity constraints on the relational database (e.g., unique key, data type, etc.)
- Unit tests for the scripts to ensure they are doing the right thing
- Source/Count checks to ensure completeness

Run Quality Checks

In [185…

```
# Perform quality checks here

#Check Counts
def check_count(dataframe):
    """
    The Dataframe should have at least one Record
    """
    count = dataframe.count()
    if count > 0:
        print("Passed Count Check with {:,} Records".format(count))
    else:
        print("Failed No Data")

#Check Number of Columns
def check_columns(dataframe):
    """
    The Dataframe should have at least one 2 Columns
    """
    cols = len(dataframe.columns)
    if cols >= 2:
        print("Passed Column Check with {:,} Columns".format(cols))
    else:
        print("Failed Insuffecent Columns")


def check_expectd_columns(dataframe, expectedcolumns):
    """
    The Dataframe should have at least one 2 Columns
    """
```

```python
    cols = len(dataframe.columns)
    if cols == expectedcolumns:
        print("Passed Expected Column Check with {:,} Columns Expected ".format(cols))
    else:
        print("Failed Insuffcient Columns, difference is {}, columns.".format(cols-expec

#Datatypes

#Values limit for some numeric fields
def checkValues(dataframe, column, valuelimits:list):
    """
    The Dataframe column values should be in the range (valuelimits[0] and valuelimits[1
    """
    maxLimit = max(valuelimits)
    minLimit = min(valuelimits)

    cols_Min = dataframe.agg(F.min(column)).collect()[0][0]
    cols_Max = dataframe.agg(F.max(column)).collect()[0][0]

    if cols_Max <= maxLimit:
        if cols_Min >= minLimit:
            print("PASSED: Columns Values are with in range: MaxValue is {:,} and MinVal
        else:
            print(" PARTIAL PASS: MinValue {:,} smaller than the limit Minimun {:,}.".fo
    else:
        if cols_Min >= minLimit:
            print(" PARTIAL PASS: MaxValue  {:,} bigger than expected Maximun  {:,}.".fo
        else:
            print("FAILED: Columns Values are with not in the range:  {:,} to {:,}.".for

#Check Schema - Can check with a schema map

#Human Eye
#Max Length of a Character Variable if Enforcement is required
#Other checks can look at text values

#More checks can be added

check_count(df_spark)
check_columns(df_spark)
check_expectd_columns(df_spark, 34)
checkValues(df_spark, 'AgeYears', [0,120])
df_spark.printSchema()
```

```
Passed Count Check with 3,157,072 Records
Passed Column Check with 34 Columns
Passed Expected Column Check with 34 Columns Expected
PASSED: Columns Values are with in range: MaxValue is 116 and MinValue is 0.
root
 |-- i94_id: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Month: integer (nullable = true)
 |-- CountryCode: integer (nullable = true)
 |-- CountryResidenceCode: integer (nullable = true)
 |-- AirportCode: string (nullable = true)
 |-- DateOfArrival: date (nullable = true)
 |-- ModeOfTransport: integer (nullable = true)
 |-- StateCodeUS: string (nullable = true)
 |-- DateOfDeparture: date (nullable = true)
 |-- AgeYears: integer (nullable = true)
 |-- VisaReason: integer (nullable = true)
 |-- CountVar: integer (nullable = true)
 |-- DateAdded_I94: string (nullable = true)
 |-- VisaIssueDepartment: string (nullable = true)
 |-- OccupationUS: string (nullable = true)
 |-- ArrivalSituation: string (nullable = true)
```

```
 |-- DepartureStatus: string (nullable = true)
 |-- CurrentStatus: string (nullable = true)
 |-- MatchArrivalDeparture: string (nullable = true)
 |-- YearofBirth: integer (nullable = true)
 |-- DateAdmittedUS: string (nullable = true)
 |-- Gender: string (nullable = true)
 |-- InsNum: string (nullable = true)
 |-- Airline: string (nullable = true)
 |-- AdminNum: integer (nullable = true)
 |-- FlightNum: string (nullable = true)
 |-- VisaType: string (nullable = true)
 |-- US_State: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- TransportMeans: string (nullable = true)
 |-- ReasonForVisa: string (nullable = true)
 |-- PortOfEntry: string (nullable = true)
 |-- Us_State_Country: string (nullable = true)
```

Mapping Results

Visitors by US State, March 2016

In [15]:
```
uspath = r'GIS_Data\US\US_States.shp'
usa = geopandas.read_file(uspath)
```

In [16]:
```
usa.columns
```

Out[16]:
```
Index(['GID_1', 'GID_0', 'COUNTRY', 'NAME_1', 'VARNAME_1', 'TYPE_1', 'HASC_1',
       'ISO_1', 'StateUS', 'geometry'],
      dtype='object')
```

In [17]:
```
usa[['GID_1','NAME_1','TYPE_1', 'HASC_1', 'ISO_1', 'StateUS']].head()
```

Out[17]:

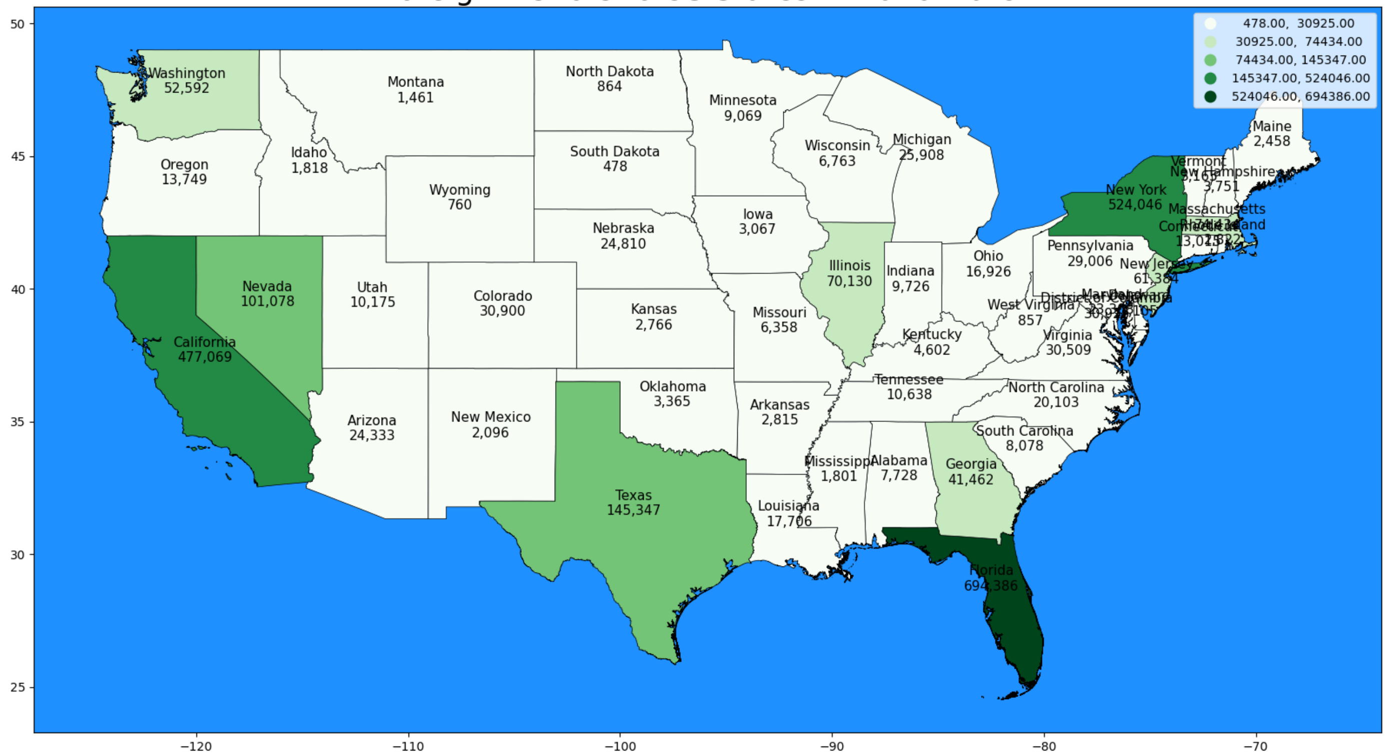
	GID_1	NAME_1	TYPE_1	HASC_1	ISO_1	StateUS
0	USA.1_1	Alabama	State	US.AL	US-AL	AL
1	USA.3_1	Arizona	State	US.AZ	US-AZ	AZ
2	USA.4_1	Arkansas	State	US.AR	US-AR	AR
3	USA.5_1	California	State	US.CA	US-CA	CA
4	USA.6_1	Colorado	State	US.CO	US-CO	CO

In [24]:
```
us_state_visitors = pd.read_csv(r"Analysis_Output\US_State_Visitors.csv")
```

In [35]:
```
usa=usa.merge(us_state_visitors, left_on='StateUS', right_on='StateCodeUS')
```

In [39]:
```
fig, ax = plt.subplots(figsize=(20, 15))
usa.plot('Records', legend=True, scheme='NaturalBreaks', ax=ax, cmap="Greens", edgecolor
usa.apply(lambda x: ax.annotate(text=x['NAME_1'] +"\n"+'{:,}'.format(x['Records']), xy=x
ax.set_title('Foreign Visitors to US States in 2016 March', fontdict={'fontsize':25, 'fo
ax.set_facecolor(water)
```

Foreign Visitors to US States in 2016 March



Visitors by Country, March 2016

In [12]:
```
world.columns
```

Out[12]:
```
Index(['LABELRANK', 'SOVEREIGNT', 'TYPE', 'ADMIN', 'ADM0_A3', 'GEOUNIT',
       'SUBUNIT', 'NAME', 'NAME_LONG', 'ABBREV', 'FORMAL_EN', 'FORMAL_FR',
       'POP_EST', 'POP_RANK', 'POP_YEAR', 'GDP_MD', 'GDP_YEAR', 'ECONOMY',
       'INCOME_GRP', 'ISO_A2', 'ISO_A2_EH', 'ISO_A3', 'ISO_A3_EH', 'ISO_N3',
       'ISO_N3_EH', 'UN_A3', 'WB_A2', 'WB_A3', 'WOE_ID', 'ADM0_ISO',
       'ADM0_DIFF', 'CONTINENT', 'REGION_UN', 'SUBREGION', 'REGION_WB',
       'geometry'],
      dtype='object')
```

In [40]:
```
world_visitors = pd.read_csv(r'Analysis_Output\Country_Visitors.csv')
```

In [43]:
```
world = world.merge(world_visitors, left_on='NAME', right_on='CountryMatch')
```

In [13]:
```
world[['LABELRANK', 'NAME', 'NAME_LONG', 'ABBREV',
       'POP_EST', 'POP_RANK', 'POP_YEAR', 'GDP_MD', 'GDP_YEAR', 'ECONOMY',
       'INCOME_GRP', 'ISO_A2', 'ISO_A3', 'CONTINENT', 'REGION_UN', 'SUBREGION', 'REGION_
```

Out[13]:

	LABELRANK	NAME	NAME_LONG	ABBREV	POP_EST	POP_RANK	POP_YEAR	GDP_MD	GDP_YEAR	E
0	2	Indonesia	Indonesia	Indo.	270,625,568.00	17	2019	1119190	2019	
1	3	Malaysia	Malaysia	Malay.	31,949,777.00	15	2019	364681	2019	D
2	2	Chile	Chile	Chile	18,952,038.00	14	2019	282318	2019	
3	3	Bolivia	Bolivia	Bolivia	11,513,100.00	14	2019	40895	2019	

4	2	Peru	Peru	Peru	32,510,453.00	15	2019	226848	2019

In [ ]:
```
#world[world['NAME']=='Uganda']['geometry'].area
```

In [45]:
```
fig, ax = plt.subplots(figsize=(20, 15))
#world.plot('NAME', legend=False, ax=ax)
world.plot('Records', legend=True, scheme='NaturalBreaks', ax=ax, cmap="Greens", edgecol
#world.boundary.plot('Greys_r', ax=ax, linewidth=0.5)
world.apply(lambda x: ax.annotate(text=x['ISO_A2'] if x['geometry'].area >3 else '', xy=
ax.set_title('Visitors to US from the World 2016, March', fontdict={'fontsize':25, 'font
ax.set_facecolor(water)
```

Visitors by Airport, March 2016

In [46]:
```
Airport_visitors = pd.read_csv(r'Analysis_Output\Airport_Visitors.csv')
```

In [51]:
```
US_Airports = Airports[Airports['iso_country']=='US']
```

In [54]:
```
Airports_with_Visitors = US_Airports.merge(Airport_visitors, left_on='iata_code', right_
```

In [62]:
```
airport_gdf = geopandas.GeoDataFrame(Airports_with_Visitors,
                                      geometry=geopandas.points_from_xy(Airports_with_Vis
                                                                        Airports_with_Vis
```

In [100…
```
airport_gdf['Label'] = airport_gdf['name'].str.replace('Airport', '')
```

In [91]:
```
airport_gdf[['Records']].describe(include='all')
```

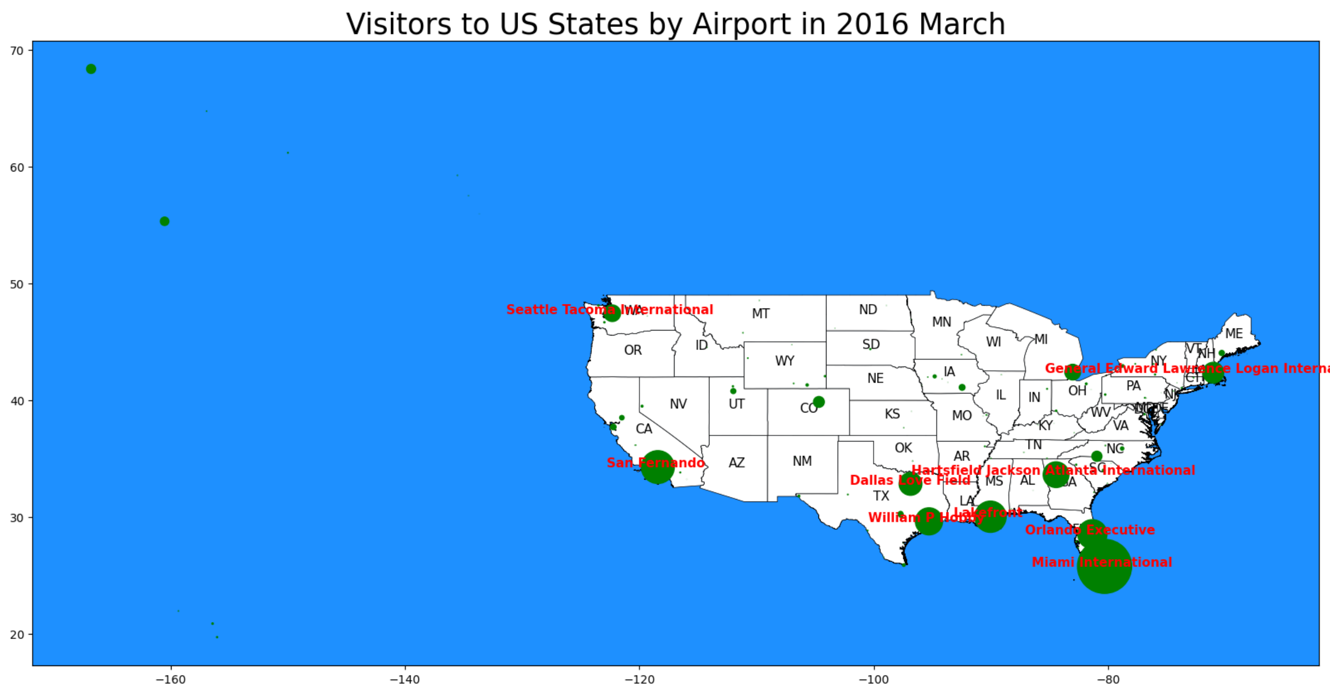
Out[91]:

	Records
count	135.00
mean	10,654.76
std	45,847.78
min	1.00

25%	8.50
50%	47.00
75%	543.50
max	441,151.00

In [110…

```
fig, ax = plt.subplots(figsize=(20, 15))
mapus = usa.boundary.plot(ax=ax, facecolor = "white", edgecolor="black", linewidth=.5, z
usa.apply(lambda x: mapus.annotate(text=x['StateUS'], xy=x.geometry.centroid.coords[0],
airport_gdf.plot(ax=ax, markersize=airport_gdf['Records']/200, color='green', zorder=3)
airport_gdf.apply(lambda x: ax.annotate(text=x['Label'] if x['Records'] >40_000 else '',
ax.set_title('Visitors to US States by Airport in 2016 March', fontdict={'fontsize':25,
ax.set_facecolor(water)
plt.show()
```



4.3 Data dictionary

Create a data dictionary for your data model. For each field, provide a brief description of what the data is and where it came from. You can include the data dictionary in the notebook or in a separate file.

Data Dictionary (Variables are meaningful, the name matches the meaning) 1.i94 Processed(Processed Parquet Data in /sas_data_final/ folder by month or /sas_data_final/ S3 bucket) |-- i94_id: integer - Primary Key |-- Year: integer - Year of Travel |-- Month: integer - Month of Travel |-- CountryCode: integer - Custom Numeric Country Code |-- CountryResidenceCode: integer - Custom Numeric Country Code |-- AirportCode: string - Airport Code to be joined to IATA Airports data |-- DateOfArrival: date - Arrival in US |-- ModeOfTransport: integer - Code for Means of Tansport |-- StateCodeUS: string - US State Code |-- DateOfDeparture: date - Date of Departure from US |-- AgeYears: integer - Age of Passenger in years |-- VisaReason: integer - Numeric Code for Visa Reason |-- CountVar: integer -Count Variable, Constant of 1 |-- DateAdded_I94: string -Date Added to I94 database |-- VisaIssueDepartment: string -Department that issude Visa |-- OccupationUS: string - Professional Ocupation |-- ArrivalSituation: string -Situation on Arrival to US e.g in Custody |-- DepartureStatus: string -Status of Departure e.g Deported |-- CurrentStatus: string -Status Currently |-- MatchArrivalDeparture: string -Arrival and Departure Dataes match expectations |-- YearofBirth: integer -Birth year |-- DateAdmittedUS: string -Date Addmited to US |-- Gender: string |-- InsNum: string |-- Airline: string |-- AdminNum: integer |-- FlightNum: string |-- VisaType: string |-- US_State: string |-- Country: string |-- TransportMeans: string |-- ReasonForVisa: string |-- PortOfEntry: string |-- Us_State_Country: string 2.Airports(Airports_Processed.csv) |-- _c0: string |-- ident: string |-- name: string |-- continent: string |-- iso_country: string |-- municipality: string |-- iata_code: string |-- local_code: string |-- lat: string |-- long: string 3.US Demograchics(us-cities-demographics.csv) |-- City: string |-- State: string |-- Median Age: string |-- Male Population: string |-- Female Population: string |-- Total Population: string |-- Number of Veterans: string |-- Foreign-born: string |-- Average Household Size: string |-- State

Code: string |-- Race: string |-- Count: string 4.CountryCodes(Country_Codes.csv) |-- Code: string |-- Country: string 5.PortCodes(Port_Codes.csv) |-- Code: string |-- PortOfEntry: string |-- Us_State_Country: string 6.TransportCodes(TransportMeansCode.csv) |-- Code: string |-- TransportMeans: string 7.US_State_Codes(US_States.csv) |-- Code: string |-- US_State: string 8.VisaReasonsCodes(VisaReasons.csv) |-- Code: string |-- ReasonForVisa: string Data Exported from Analysis: (Analysis_Output Folder) for March 2016 9.All Visitors by Airport Code - joined to Airports to Make Airport map |-- AiportCode: string |-- Records: string 10.Visitors by Country of Origin - joined to World Countries Shapefile to Make World US Visitor map |-- Country: string |-- Records: string |-- CountryMatch: string 11.Visitors by US State Visited - joined to US States to Make US State Map by Number of Visitors |-- StateCodeUS: string |-- Records: string GIS Data Shapefiles (GIS_Data Folder, All are in GCS_WGS_1984 Projection (EPSG:4326)) 12. All US States - All 50 US States with key attributes 13. Cities - World Cities with key attributes 14. Countries - World Countries with key attributes 15. US states without Hawaii and Alaska to optimize map display extent

Step 5: Complete Project Write Up

- Clearly state the rationale for the choice of tools and technologies for the project.

1. I picked Parquet as the primary data format because of the massive compression abillity, it is faster to load, easy to move between systems and is also supported by several languages and big data tools.

2. S3 for Storage for universal access, EMR access and ease to share.

3. I used Geopandas to do making because it the primary mapping package other than ArcGIS and I wanted to summarize the results on some maps.

4. EMR is good for large scale ingestion, it would have ingested all the 40 million records easily and then custom analysis can be done.

- Propose how often the data should be updated and why. Data should be updated once a month because the data is posted to the trade.gov Site monthly, we don't have access to any other data apart from that, thus there will be no change.

The main reason is the frequecy of data updates that is monthly. 3-6 retries can be set in the DAG with retry intervals on 12 hours to a day depening on the experience of how longs the delays to post the data to trade.gov take.

- Write a description of how you would approach the problem differently under the following scenarios:

  - The data was increased by 100x.
  - The data populates a dashboard that must be updated on a daily basis by 7am every day.
  - The database needed to be accessed by 100+ people.

  1. Parquet would still be the primary data format.

  2. Pipelines would be scheduled every month binning SAS data to parquet on S3, then spark jobs and Juptyer notebooks, the results can be taken to other systems for dashboarding or further analysis. Currently Each Month has around ~3,400,000 Records, ~500MB of SAS DATa that is converted to ~60.25 MB of Parquet Data.

At 100X, this becomes for each Month, ~340,000,000 Records, 50GB of SAS data that could be converted to ~5.9GB of Parquet Data. The actual size of data may be larger or smaller but with in that range.

```
 1. An Airflow Cluster with a least 4-12 workers would be setup on AWS and
connections configured for AWS Credentials, a PostGRES DB would be connected to
it as the primary DB to enable paralled execution

 2. All SAS Data, raw and processed parquet data would be stored on an S3
```

```
bucket for Parqurt data with a folder scheme by RAW, FINAL and then the year,
then lastly the month similiar to the shared image on S3 bucket.
 S3_BUCKET
 _RAW
 ___YEAR
 _____MONTH (RAW Parquet Data Export from SAS Data)
 _FINAL
 ___YEAR
 _____MONTH (Cleaned Parquet Data Ready for Upstream Analyis)

 3. EMR Spark Jobs
 (with much larger Clusters (4-12) of the Compute Optimized type, at least
c5d.4xlarge with 32 RAM and 16 vcpus)
 would be set up to ingest the SAS data, convert it to Parquet then clean and
rename columns.

 4. The Parquet analysis will be a Jupyter Job using Papermill, these would
need to have more months tested to be fine tunded well, In this project I only
used March, this would also run on EMR.

 5. The insights from the Jupyter Notebo0k can be used for mapping or
Dashboarding on something like ArcGIS online.

 6. Since the Data is just one table, it can be loaded to Cassandra or
DyanamoDB, designed optimized by the required key queries for Cassandra with
partition and cluster keys and a way to convert the data to a key value for
DynamoDB.
```

1. A NO SQL database either Cassandra or DynamoDB will host all the data and will be updated Monthly. This can store Billions of Records, especially since it is just one Table and is readily available to 100+ people easily for analysis.

2. Large EMR to ingest data every Month, clean it and process it called upon need.