e63_brzozowski_adam_final_project

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1 CSCI E-63 Big Data Analytics

1.1 Final Project Report - Spark CPU vs GPU

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2 Problem Statement

One of my interests when I started CSCI E-63 this semester was to learn if I could leverage a GPU with Spark. I had recently seen just how powerful even a modest a GPU could be when used for deep learning in terms of speeding up the computation of each epoch, and I began looking for ways to leverage a GPU for more basic data processing tasks as well. The primary purpose of this technology demonstration will be to showcase how easy it is to leverage an NVIDIA GPU with Spark. After spending time reviewing the materials NVIDIA developed for this purpose, I believe a shorter and simpler demonstration will add value on YouTube as well. I hope to show that comparatively small up front incremental configuration tasks provide time savings in excess of watching the technology demo and going through the setup. Demonstrations like this add value by improving the utilization of existing hardware resources. GPUs are probably one of the most under exploited pieces of hardware in a computer from a utilization perspective. Greater workforce awareness of how to leverage a GPU reduces unnecessary retirement of computers and e-waste.

3 Introduction

Throughout this workbook, I put Spark through its paces on a 120 million record 12 gb dataset. My primary objective is to see how well an ordinary, older consumer grade GPU can do on this dataset compared to using CPUs. To accomplish this, the workbook will be run twice - once with a CPU runtime and once with a GPU runtime. The total time to run the workbook will be compared in terms of:

(1) data preparation ;

(2) data visualization / descriptives; and

(3) a basic machine learning regression on the dependent variable in the dataset

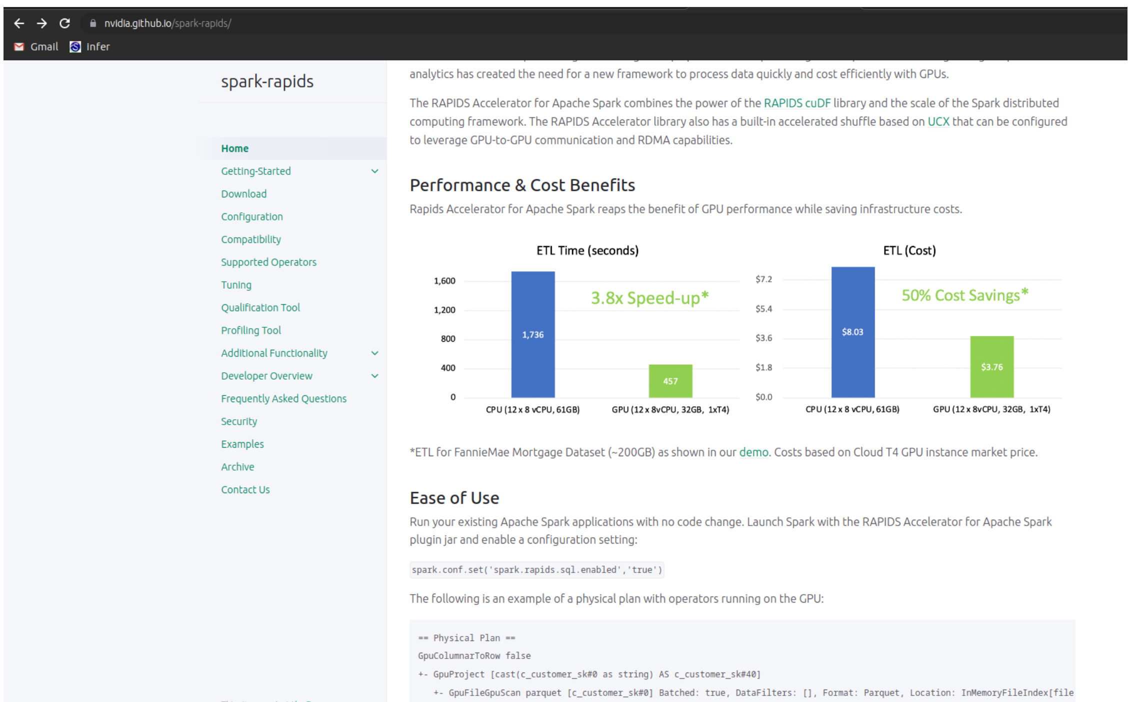
To get the most out of the data processing work being done, I decided to look at the airline on time performance dataset from Kaggle from a different perspective than most people have used this dataset for. In the news lately, there have been a number of high profile problems with America's transportation system - airline mass cancellations and widespread lateness. Purportedly, these issues are recent and due to supply shocks from Covid19. Is Covid19 really to blame for industry performance issues or are we looking at more of the same?

[1]:
```python
from IPython import display
```

NVIDIA makes some pretty remarkable product claims. Specifically, on their website for Spark RAPIDS, there is a key product claim for doing ETL work that getting Spark to work with a GPU is as simple as invoking the jar file at launch and setting a single configuration.

[2]:
```python
display.Image('nvidia_rapids_product_claims.png')
```

[2]:



4 Setting up Spark for RAPIDS

RAPIDS is NVIDIA's framework for using Spark with a GPU. To set it up is very simple. The first step is to download the spark-rapids jar file to use with Pyspark. I downloaded that from: https://repo1.maven.org/maven2/com/nvidia/rapids-4-spark_2.12/23.02.0/rapids-4-spark_2.12-23.02.0.jar

Per the instructions here: https://nvidia.github.io/spark-rapids/docs/download.html

Then start Pyspark with the applicable command to use the jar in the classpath - your filepath will be different depending on where you put those and your username:

pyspark –jars /home/data_guru/classpath/rapids-4-spark_2.12-23.02.0.jar

In the code below, after the initialization of Spark, I tell Spark to use the GPU with this command:

cp_u = False
if cp_u is False:

```
spark.conf.set('spark.rapids.sql.enabled','true')
```

For the baseline study, I simply changed: cp_u = True and started Pyspark with :

Since I only have 4 physical cores, and 4 logical cores, I reserve 1 for other processes to start the program. It's what the computer came with - just like the GPU - so I regard it as a fair comparison.

pyspark –master local[3]

5 Updated Spark ML with GPU Libraries

During the course of working on this study, after some weeks of planning, I found an additional library announcement from NVIDIA in an April 2023 release.

https://github.com/NVIDIA/spark-rapids-ml/blob/branch-23.04/python/README.md

The new Spark Rapids ML library from NVIDIA provides significant out of the box functionality that can be used for large scale GPU based computation for a number of functions. Per the NVIDIA web site:

"You can download the Spark RAPIDS ML package from the NVIDIA/spark-rapids-ml GitHub repository under the Apache v2 license. The initial release provides GPU acceleration for the following Spark ML algorithms:

PCA
K-means clustering
Linear regression with ridge and elastic net regularization
Random forest classification and regression"

As I was struggling with how to get a more detailed regression study to work, I found this library. Time permitting, I will incorporate this at the end into an expanded version of this study. For now, suffice to say that it is another option for going further in this direction - which appears to be on the cutting edge of the field.

6 Non local runtime options

The purpose of this demo was to identify the difficulty level in using NVIDIA RAPIDS to achieve any sort of low cost performance improvement on a local machine. In some cases, local runtimes are necessary for security or compliance purposes and the cloud is not always an option. However, in the event that you do have a cloud environment to work in on Paperspace and want to give this a try, there are some articles about doing this. It's one of the standard options on Paperspace as well. Here's one article I found - I have not investigated the claims in great detail: https://medium.com/rapids-ai/up-and-running-with-rapids-and-paperspace-gradient-652bdb7bcab0

Here is a toy example that I was going to use to test a working spark rapids environment. I will return to this later: https://github.com/NVIDIA/spark-rapids-ml/blob/branch-23.04/python/README.md

7 Python Environment

In addition, I found it expedient to create a brand new python environment just for this project so that I could get a more controlled test of the capabilities of this workbook without any confounding environmental variables. Here is a copy of the yaml create statement for this project.

[3]:
```
with open('/home/data_guru/Documents/hes_data_science_program/general_configs/
↪cscie63finalproject.yml','r') as file:
    for line in file:
        print(line)
```

```
name: csci_e_63_final_project

channels:

  - nvidia

  - conda-forge

  - default

dependencies:

  - python==3.10

  - numpy

  - matplotlib

  - jupyter

  - seaborn

  - pandas

  - IPython

  - pytorch

  - pip

  - nvidia::cudatoolkit

  - conda-forge::ncurses
```

```
- cupy

- psutil

- GPUtil

- tabulate

- pyspark

- nbconvert

- gcc
```

8 System resources

In order to fulfill a key objective of this demonstration, system hardware resources are presented below in order to demonstrate that this was run on very modest hardware that would be financially within reach of most people. The total cost of the machine plus upgrades over the years was approximately $700 at the time.

For this section, there was a ready code template available here that I was able to use for this purely descriptive type task: https://www.thepythoncode.com/article/get-hardware-system-information-python

[4]:
```python
import psutil
import platform
from datetime import datetime



def get_size(bytes, suffix="B"):
    """
    Scale bytes to its proper format
    e.g:
        1253656 => '1.20MB'
        1253656678 => '1.17GB'
    """
    factor = 1024
    for unit in ["", "K", "M", "G", "T", "P"]:
        if bytes < factor:
            return f"{bytes:.2f}{unit}{suffix}"
        bytes /= factor



print("="*40, "System Information", "="*40)
uname = platform.uname()
print(f"System: {uname.system}")
```

```
print(f"Node Name: {uname.node}")
print(f"Release: {uname.release}")
print(f"Version: {uname.version}")
print(f"Machine: {uname.machine}")
print(f"Processor: {uname.processor}")

# Boot Time
print("="*40, "Boot Time", "="*40)
boot_time_timestamp = psutil.boot_time()
bt = datetime.fromtimestamp(boot_time_timestamp)
print(f"Boot Time: {bt.year}/{bt.month}/{bt.day} {bt.hour}:{bt.minute}:{bt.
 ↪second}")

# let's print CPU information
print("="*40, "CPU Info", "="*40)
# number of cores
print("Physical cores:", psutil.cpu_count(logical=False))
print("Total cores:", psutil.cpu_count(logical=True))
# CPU frequencies
cpufreq = psutil.cpu_freq()
print(f"Max Frequency: {cpufreq.max:.2f}Mhz")
print(f"Min Frequency: {cpufreq.min:.2f}Mhz")
print(f"Current Frequency: {cpufreq.current:.2f}Mhz")
# CPU usage
print("CPU Usage Per Core:")
for i, percentage in enumerate(psutil.cpu_percent(percpu=True, interval=1)):
    print(f"Core {i}: {percentage}%")
print(f"Total CPU Usage: {psutil.cpu_percent()}%")
```

```
======================================== System Information
========================================
System: Linux
Node Name: deeplearningcomputer
Release: 6.2.0-20-generic
Version: #20-Ubuntu SMP PREEMPT_DYNAMIC Thu Apr  6 07:48:48 UTC 2023
Machine: x86_64
Processor: x86_64
======================================== Boot Time
========================================
Boot Time: 2023/4/22 21:23:38
======================================== CPU Info
========================================
Physical cores: 4
Total cores: 4
Max Frequency: 3100.00Mhz
Min Frequency: 1550.00Mhz
Current Frequency: 1417.81Mhz
CPU Usage Per Core:
```

```
Core 0: 5.9%
Core 1: 4.0%
Core 2: 10.1%
Core 3: 10.1%
Total CPU Usage: 14.8%
```

[5]:
```python
# Memory Information
print("="*40, "Memory Information", "="*40)
# get the memory details
svmem = psutil.virtual_memory()
print(f"Total: {get_size(svmem.total)}")
print(f"Available: {get_size(svmem.available)}")
print(f"Used: {get_size(svmem.used)}")
print(f"Percentage: {svmem.percent}%")
print("="*20, "SWAP", "="*20)
# get the swap memory details (if exists)
swap = psutil.swap_memory()
print(f"Total: {get_size(swap.total)}")
print(f"Free: {get_size(swap.free)}")
print(f"Used: {get_size(swap.used)}")
print(f"Percentage: {swap.percent}%")
```

```
======================================== Memory Information
========================================
Total: 15.54GB
Available: 13.12GB
Used: 2.06GB
Percentage: 15.5%
==================== SWAP ====================
Total: 2.00GB
Free: 2.00GB
Used: 0.00B
Percentage: 0.0%
```

[6]:
```python
# Disk Information
print("="*40, "Disk Information", "="*40)
print("Partitions and Usage:")
# get all disk partitions
partitions = psutil.disk_partitions()
for partition in partitions:
    print(f"=== Device: {partition.device} ===")
    print(f"  Mountpoint: {partition.mountpoint}")
    print(f"  File system type: {partition.fstype}")
    try:
        partition_usage = psutil.disk_usage(partition.mountpoint)
    except PermissionError:
        # this can be catched due to the disk that
        # isn't ready
```

```python
            continue
        print(f"  Total Size: {get_size(partition_usage.total)}")
        print(f"  Used: {get_size(partition_usage.used)}")
        print(f"  Free: {get_size(partition_usage.free)}")
        print(f"  Percentage: {partition_usage.percent}%")
# get IO statistics since boot
disk_io = psutil.disk_io_counters()
print(f"Total read: {get_size(disk_io.read_bytes)}")
print(f"Total write: {get_size(disk_io.write_bytes)}")
```

```
======================================== Disk Information
========================================
Partitions and Usage:
=== Device: /dev/sda3 ===
  Mountpoint: /
  File system type: ext4
  Total Size: 456.88GB
  Used: 148.59GB
  Free: 285.02GB
  Percentage: 34.3%
=== Device: /dev/loop0 ===
  Mountpoint: /snap/bare/5
  File system type: squashfs
  Total Size: 128.00KB
  Used: 128.00KB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop1 ===
  Mountpoint: /snap/bitwarden/85
  File system type: squashfs
  Total Size: 82.25MB
  Used: 82.25MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop2 ===
  Mountpoint: /snap/bitwarden/86
  File system type: squashfs
  Total Size: 82.25MB
  Used: 82.25MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop3 ===
  Mountpoint: /snap/code/124
  File system type: squashfs
  Total Size: 291.88MB
  Used: 291.88MB
  Free: 0.00B
  Percentage: 100.0%
```

```
=== Device: /dev/loop4 ===
  Mountpoint: /snap/core/14784
  File system type: squashfs
  Total Size: 116.88MB
  Used: 116.88MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop5 ===
  Mountpoint: /snap/core/14946
  File system type: squashfs
  Total Size: 116.88MB
  Used: 116.88MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop6 ===
  Mountpoint: /snap/core18/2714
  File system type: squashfs
  Total Size: 55.62MB
  Used: 55.62MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop7 ===
  Mountpoint: /snap/core18/2721
  File system type: squashfs
  Total Size: 55.62MB
  Used: 55.62MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop8 ===
  Mountpoint: /snap/core20/1828
  File system type: squashfs
  Total Size: 63.38MB
  Used: 63.38MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop9 ===
  Mountpoint: /snap/core20/1852
  File system type: squashfs
  Total Size: 63.38MB
  Used: 63.38MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop12 ===
  Mountpoint: /snap/core22/607
  File system type: squashfs
  Total Size: 73.00MB
  Used: 73.00MB
  Free: 0.00B
```

```
  Percentage: 100.0%
=== Device: /dev/loop10 ===
  Mountpoint: /snap/code/126
  File system type: squashfs
  Total Size: 291.88MB
  Used: 291.88MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop11 ===
  Mountpoint: /snap/core22/583
  File system type: squashfs
  Total Size: 73.00MB
  Used: 73.00MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop13 ===
  Mountpoint: /snap/firefox/2517
  File system type: squashfs
  Total Size: 242.25MB
  Used: 242.25MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop14 ===
  Mountpoint: /snap/firefox/2585
  File system type: squashfs
  Total Size: 242.50MB
  Used: 242.50MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop15 ===
  Mountpoint: /snap/geforcenow-electron/17
  File system type: squashfs
  Total Size: 77.00MB
  Used: 77.00MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop18 ===
  Mountpoint: /snap/gnome-3-38-2004/119
  File system type: squashfs
  Total Size: 346.38MB
  Used: 346.38MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop16 ===
  Mountpoint: /snap/gnome-3-28-1804/194
  File system type: squashfs
  Total Size: 164.88MB
  Used: 164.88MB
```

```
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop17 ===
  Mountpoint: /snap/gnome-3-28-1804/198
  File system type: squashfs
  Total Size: 164.88MB
  Used: 164.88MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop19 ===
  Mountpoint: /snap/gnome-3-38-2004/137
  File system type: squashfs
  Total Size: 349.75MB
  Used: 349.75MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop20 ===
  Mountpoint: /snap/gnome-42-2204/68
  File system type: squashfs
  Total Size: 460.50MB
  Used: 460.50MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop21 ===
  Mountpoint: /snap/gnome-42-2204/87
  File system type: squashfs
  Total Size: 460.62MB
  Used: 460.62MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop22 ===
  Mountpoint: /snap/gtk-common-themes/1535
  File system type: squashfs
  Total Size: 91.75MB
  Used: 91.75MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/sda2 ===
  Mountpoint: /boot/efi
  File system type: vfat
  Total Size: 511.96MB
  Used: 6.07MB
  Free: 505.89MB
  Percentage: 1.2%
=== Device: /dev/loop23 ===
  Mountpoint: /snap/kde-frameworks-5-96-qt-5-15-5-core20/7
  File system type: squashfs
  Total Size: 436.38MB
```

```
  Used: 436.38MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop24 ===
  Mountpoint: /snap/qt515-core20/27
  File system type: squashfs
  Total Size: 389.88MB
  Used: 389.88MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop25 ===
  Mountpoint: /snap/snap-store/599
  File system type: squashfs
  Total Size: 46.00MB
  Used: 46.00MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop28 ===
  Mountpoint: /snap/snapd/18933
  File system type: squashfs
  Total Size: 53.25MB
  Used: 53.25MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop26 ===
  Mountpoint: /snap/snapd/18596
  File system type: squashfs
  Total Size: 49.88MB
  Used: 49.88MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop27 ===
  Mountpoint: /snap/snap-store/638
  File system type: squashfs
  Total Size: 46.00MB
  Used: 46.00MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop29 ===
  Mountpoint: /snap/snapd-desktop-integration/57
  File system type: squashfs
  Total Size: 512.00KB
  Used: 512.00KB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop30 ===
  Mountpoint: /snap/snapd-desktop-integration/83
  File system type: squashfs
```

```
  Total Size: 512.00KB
  Used: 512.00KB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/sda3 ===
  Mountpoint: /var/snap/firefox/common/host-hunspell
  File system type: ext4
  Total Size: 456.88GB
  Used: 148.59GB
  Free: 285.02GB
  Percentage: 34.3%
=== Device: /dev/loop31 ===
  Mountpoint: /snap/whatsie/140
  File system type: squashfs
  Total Size: 17.38MB
  Used: 17.38MB
  Free: 0.00B
  Percentage: 100.0%
=== Device: /dev/loop32 ===
  Mountpoint: /snap/whatsie/142
  File system type: squashfs
  Total Size: 17.38MB
  Used: 17.38MB
  Free: 0.00B
  Percentage: 100.0%
Total read: 2.11GB
Total write: 160.00MB
```

[7]:

```
# GPU information
import GPUtil
from tabulate import tabulate
print("="*40, "GPU Details", "="*40)
gpus = GPUtil.getGPUs()
list_gpus = []
for gpu in gpus:
    # get the GPU id
    gpu_id = gpu.id
    # name of GPU
    gpu_name = gpu.name
    # get % percentage of GPU usage of that GPU
    gpu_load = f"{gpu.load*100}%"
    # get free memory in MB format
    gpu_free_memory = f"{gpu.memoryFree}MB"
    # get used memory
    gpu_used_memory = f"{gpu.memoryUsed}MB"
    # get total memory
    gpu_total_memory = f"{gpu.memoryTotal}MB"
```

```python
    # get GPU temperature in Celsius
    gpu_temperature = f"{gpu.temperature} °C"
    gpu_uuid = gpu.uuid
    list_gpus.append((
        gpu_id, gpu_name, gpu_load, gpu_free_memory, gpu_used_memory,
        gpu_total_memory, gpu_temperature, gpu_uuid
    ))

print(tabulate(list_gpus, headers=("id", "name", "load", "free memory", "used␣
 ↪memory", "total memory",
                                   "temperature", "uuid")))
```

```
======================================== GPU Details
========================================
  id  name                        load                free memory    used memory
total memory    temperature    uuid
----  --------------------------  ------------------  -------------
-------------  --------------  -------------
----------------------------------------
   0  NVIDIA GeForce GTX 1050 Ti  7.000000000000001%  3656.0MB       379.0MB
4096.0MB        26.0 °C        GPU-9ed7d513-be94-def1-ffdb-838e613f1e13
```

9 Demonstration baseline

In order to set a performance baseline using a CPU, we need to first run a study on a sufficiently impressive / large dataset to create some meaningful computing burdens that Spark is designed to handle. For this purpose, I chose to work with the Airline on-time Performance Data set from Kaggle. It's a 12 gb dataset with 120 million records in total and pertains to all commercial flights within the United States between October 1987 and April 2008. It consists of flight arrival and departure data points, and contains the following 29 fields:

1 Year 1987-2008
2 Month 1-12
3 DayofMonth 1-31
4 DayOfWeek 1 (Monday) - 7 (Sunday)
5 DepTime actual departure time (local, hhmm)
6 CRSDepTime scheduled departure time (local, hhmm)
7 ArrTime actual arrival time (local, hhmm)
8 CRSArrTime scheduled arrival time (local, hhmm)
9 UniqueCarrier unique carrier code
10 FlightNum flight number
11 TailNum plane tail number
12 ActualElapsedTime in minutes
13 CRSElapsedTime in minutes
14 AirTime in minutes
15 ArrDelay arrival delay, in minutes
16 DepDelay departure delay, in minutes
17 Origin origin IATA airport code

18 Dest destination IATA airport code
19 Distance in miles
20 TaxiIn taxi in time, in minutes
21 TaxiOut taxi out time in minutes
22 Cancelled was the flight cancelled?
23 CancellationCode reason for cancellation (A = carrier, B = weather, C = NAS, D = security)
24 Diverted 1 = yes, 0 = no
25 CarrierDelay in minutes
26 WeatherDelay in minutes
27 NASDelay in minutes
28 SecurityDelay in minutes
29 LateAircraftDelay in minutes

https://www.kaggle.com/datasets/bulter22/airline-data?resource=download&select=airline.csv.shuffle

There are a number of different potential outcomes in the study, depending on what industry the reader is from. However, arrival delay is actually the most important outcome - did the passenger arrive at the intended destination on time. We are given the number of minutes for this - which means we can eventually utilize regression to predict this as a continuous random variable. Intuitively, the other predictor variables could be used to predict the arrival delay. I would expect there to be some relationship, but not a strong one, since jet aircraft ultimately do have the option in many cases of being able to simply accelerate to make up for delays. Perhaps the late minutes we are able to predict will be on the extreme end of the distribution.

[8]:
```
from IPython import display
from pyspark import SparkContext, SparkConf
from pyspark.sql import Row, SparkSession, SQLContext
from pyspark.sql.types import *
from pyspark.sql.functions import *

conf = SparkConf().setMaster("local").setAppName("Hw01App")
sc.setLogLevel("ERROR")
spark = SparkSession.builder.getOrCreate()
df = spark.sql("select 'spark' as hello ")
df.show()
```

```
+-----+
|hello|
+-----+
|spark|
+-----+
```

[9]:
```
spark
```

[9]:
```
<pyspark.sql.session.SparkSession at 0x7fe6a415ee60>
```

Since I plan on testing this workbook first with CPUs and then with a GPU, I set up a switch to conditionally utilize the GPU setting:

[10]:
```
cp_u = True
if cp_u is False:
    spark.conf.set('spark.rapids.sql.enabled','true')
```

First, the data will be imported and pre-processed into Spark as with any typical modeling process. There are two csv files in the file download. The first is the airline data itself. It's a plain text document called "airline.csv.shuffle." It contains all of the airline flight on time performance data except for some reference data about the airlines. The second is a set of reference data about the airlines called "carriers.csv".

The datetime library was used throughout this workbook to track the computation time differences for each task. I got a good refresher on this from: https://www.geeksforgeeks.org/calculate-time-difference-in-python/

[11]:
```
import time
from datetime import datetime

# take an initial timing read - this will be diffed for the CPU and GPU runs of␣
↪this workbook
start_notebook_preprocessing = datetime.now()
```

[12]:
```
path = '/home/data_guru/Documents/archive/airline.csv.shuffle'
```

Below, I use the inferSchema option to do most of the work around data preprocessing. I then make incremental tweaks to that using column schema changes.

[13]:
```
# Good refresher on how to compute time differences in Python
#https://www.geeksforgeeks.org/calculate-time-difference-in-python/

start_time_seconds_load_df = datetime.now()

df = spark.read.options(inferSchema=True, delimiter=',', header=True).csv(path)
#df = spark.read.options(schema=on_time_schema, delimiter=',', header=True).
↪csv(path)

end_time_seconds_load_df = datetime.now()
```

[14]:
```
delta =  end_time_seconds_load_df - start_time_seconds_load_df

seconds_load_cpu = delta.total_seconds()
print('difference in seconds is:', seconds_load_cpu)
```

```
difference in seconds is: 141.727981
```

[15]:
```
df.printSchema()
```

```
root
 |-- ActualElapsedTime: string (nullable = true)
```

```
 |-- AirTime: string (nullable = true)
 |-- ArrDelay: string (nullable = true)
 |-- ArrTime: string (nullable = true)
 |-- CRSArrTime: integer (nullable = true)
 |-- CRSDepTime: integer (nullable = true)
 |-- CRSElapsedTime: string (nullable = true)
 |-- CancellationCode: string (nullable = true)
 |-- Cancelled: integer (nullable = true)
 |-- CarrierDelay: string (nullable = true)
 |-- DayOfWeek: integer (nullable = true)
 |-- DayofMonth: integer (nullable = true)
 |-- DepDelay: string (nullable = true)
 |-- DepTime: string (nullable = true)
 |-- Dest: string (nullable = true)
 |-- Distance: string (nullable = true)
 |-- Diverted: integer (nullable = true)
 |-- FlightNum: integer (nullable = true)
 |-- LateAircraftDelay: string (nullable = true)
 |-- Month: integer (nullable = true)
 |-- NASDelay: string (nullable = true)
 |-- Origin: string (nullable = true)
 |-- SecurityDelay: string (nullable = true)
 |-- TailNum: string (nullable = true)
 |-- TaxiIn: string (nullable = true)
 |-- TaxiOut: string (nullable = true)
 |-- UniqueCarrier: string (nullable = true)
 |-- WeatherDelay: string (nullable = true)
 |-- Year: integer (nullable = true)
```

Below, I make some very initial corrections for column data type errors based on the select statements above and some of the statements below this section as well.

[16]:
```
df = df.withColumn("ActualElapsedTime",df.ActualElapsedTime.cast(IntegerType()))
df = df.withColumn("AirTime",df.AirTime.cast(IntegerType()))
df = df.withColumn("ArrDelay",df.ArrDelay.cast(IntegerType()))
df = df.withColumn("ArrTime",df.ArrTime.cast(IntegerType()))
df = df.withColumn("CRSElapsedTime",df.CRSElapsedTime.cast(IntegerType()))
df = df.withColumn("DepDelay",df.DepDelay.cast(StringType()))
df = df.withColumn("DepTime",df.DepTime.cast(IntegerType()))
df = df.withColumn("Distance",df.Distance.cast(IntegerType()))
df = df.withColumn("FlightNum",df.FlightNum.cast(StringType()))
```

[17]:
```
df.printSchema()
```

```
root
 |-- ActualElapsedTime: integer (nullable = true)
 |-- AirTime: integer (nullable = true)
 |-- ArrDelay: integer (nullable = true)
```

```
|-- ArrTime: integer (nullable = true)
|-- CRSArrTime: integer (nullable = true)
|-- CRSDepTime: integer (nullable = true)
|-- CRSElapsedTime: integer (nullable = true)
|-- CancellationCode: string (nullable = true)
|-- Cancelled: integer (nullable = true)
|-- CarrierDelay: string (nullable = true)
|-- DayOfWeek: integer (nullable = true)
|-- DayofMonth: integer (nullable = true)
|-- DepDelay: string (nullable = true)
|-- DepTime: integer (nullable = true)
|-- Dest: string (nullable = true)
|-- Distance: integer (nullable = true)
|-- Diverted: integer (nullable = true)
|-- FlightNum: string (nullable = true)
|-- LateAircraftDelay: string (nullable = true)
|-- Month: integer (nullable = true)
|-- NASDelay: string (nullable = true)
|-- Origin: string (nullable = true)
|-- SecurityDelay: string (nullable = true)
|-- TailNum: string (nullable = true)
|-- TaxiIn: string (nullable = true)
|-- TaxiOut: string (nullable = true)
|-- UniqueCarrier: string (nullable = true)
|-- WeatherDelay: string (nullable = true)
|-- Year: integer (nullable = true)
```

We have >120 million rows:

[18]:
```
df.count()
```

[18]:
```
123534969
```

The file is over 12 gigabytes:

[19]:
```
# https://www.geeksforgeeks.org/how-to-get-file-size-in-python/
import os

file_size = os.path.getsize(path)
print("File Size is :", file_size, "bytes")
```

```
File Size is : 12029207752 bytes
```

Next, I'll start looking at some of the data to see what I've got:

[20]:
```
df.select("ActualElapsedTime","AirTime","ArrDelay",␣
↪"ArrTime","CRSArrTime","CRSDepTime", "CRSElapsedTime",
```

```
        "CancellationCode", "Cancelled").show(5)
```

```
+-----------------+-------+--------+-------+----------+----------+--------------
+----------------+---------+
|ActualElapsedTime|AirTime|ArrDelay|ArrTime|CRSArrTime|CRSDepTime|CRSElapsedTime
|CancellationCode|Cancelled|
+-----------------+-------+--------+-------+----------+----------+--------------
+----------------+---------+
|               53|     32|      -8|   1642|      1650|      1545|
65|              NA|        0|
|              164|    155|     -11|   1754|      1805|      1610|
175|              NA|        0|
|               60|   null|      15|   2005|      1950|      1850|
60|              NA|        0|
|               51|   null|      -5|   1818|      1823|      1728|
55|              NA|        0|
|               45|     29|       2|   1120|      1118|      1030|
48|            null|        0|
+-----------------+-------+--------+-------+----------+----------+--------------
+----------------+---------+
only showing top 5 rows
```

[21]:

```
df.select("CarrierDelay","DayOfWeek", "DayofMonth", "DepDelay","DepTime",␣
↪"Dest", "Distance",
        "Diverted", "Diverted", "FlightNum", "LateAircraftDelay").show(5)
```

```
+------------+---------+----------+--------+-------+----+--------+--------+-----
---+---------+-----------------+
|CarrierDelay|DayOfWeek|DayofMonth|DepDelay|DepTime|Dest|Distance|Diverted|Diver
ted|FlightNum|LateAircraftDelay|
+------------+---------+----------+--------+-------+----+--------+--------+-----
---+---------+-----------------+
|          NA|        4|        10|       4|   1549| PIT|     205|       0|
0|      209|               NA|
|          NA|        4|         2|       0|   1610| MCI|    1072|       0|
0|      109|               NA|
|          NA|        5|        10|      15|   1905| CLT|     227|       0|
0|     1276|               NA|
|          NA|        4|        28|      -1|   1727| BNA|     200|       0|
0|      961|               NA|
|           0|        1|        19|       5|   1035| CMH|     116|       0|
0|     5873|                0|
+------------+---------+----------+--------+-------+----+--------+--------+-----
---+---------+-----------------+
only showing top 5 rows
```

[22]:
```
df.select("Month","NASDelay", "Origin", "SecurityDelay", "TailNum","TaxiIn",␣
↪"TaxiOut","UniqueCarrier",
         "WeatherDelay", "Year").show(5)
```

```
+-----+--------+------+-------------+-------+------+-------+-------------+------
------+----+
|Month|NASDelay|Origin|SecurityDelay|TailNum|TaxiIn|TaxiOut|UniqueCarrier|Weathe
rDelay|Year|
+-----+--------+------+-------------+-------+------+-------+-------------+------
------+----+
|   10|      NA|   DCA|           NA| N443US|     7|     14|           US|
NA|2002|
|   12|      NA|   MCO|           NA|   N755|     2|      7|           WN|
NA|1999|
|   12|      NA|   ATL|           NA|     NA|    NA|     NA|           DL|
NA|1993|
|    9|      NA|   MEM|           NA|     NA|    NA|     NA|           AA|
NA|1989|
|    6|       0|   CVG|            0| N785CA|     3|     13|           OH|
0|2006|
+-----+--------+------+-------------+-------+------+-------+-------------+------
------+----+
only showing top 5 rows
```

In this section, my goal is just to look at the data to get a more direct sense of the data types. I undertake this step the way I usually do - some group by statements to see if what I'm looking at are actually strings, numbers that are misclassified, or strings that are misclassified. Needless to say, this will eat up quite a bit of resources - which should provide a very good performance test in a real world context. Of course, by the end of this pre-processing step, I'll have some good preliminary EDA done as well.

[23]:
```
df.select("DepDelay").groupby("DepDelay").count().show()
```

```
[Stage 9:=======================================================>(89 + 1) / 90]

+--------+-------+
|DepDelay|  count|
+--------+-------+
|      -4|5542037|
|     296|   1008|
|    1436|     59|
|     467|     84|
|     675|     40|
|     125|  30803|
|     451|    116|
|     944|     14|
|     -30|   1548|
|       7|1744675|
```

```
|      51| 131248|
|     124|  22564|
|     447|    145|
|     307|    921|
|     475|    139|
|     613|     23|
|     205|   6752|
|     169|   9105|
|     334|    602|
|     747|     24|
+--------+-------+
only showing top 20 rows
```

[24]:
```
df.select("LateAircraftDelay").groupby("LateAircraftDelay").count().show()
```

```
[Stage 12:=======================================================>(89 + 1) / 90]

+-----------------+------+
|LateAircraftDelay| count|
+-----------------+------+
|              296|   166|
|              125|  4674|
|                7| 60462|
|               51| 23565|
|              124|  4151|
|              447|     8|
|              307|   127|
|              613|     3|
|              169|  1679|
|              205|   965|
|              334|    87|
|              272|   254|
|               15|111270|
|               54| 21469|
|              282|   203|
|              232|   495|
|              234|   533|
|              383|    48|
|              155|  2566|
|              154|  2252|
+-----------------+------+
only showing top 20 rows
```

[25]:
```
df.select("CarrierDelay").groupby("CarrierDelay").count().show()
```

```
[Stage 15:========================================================> (88 + 2) / 90]

+------------+------+
|CarrierDelay| count|
+------------+------+
|         296|   155|
|         467|    34|
|         125|  3022|
|           7|118127|
|          51| 15642|
|         124|  2533|
|         447|    38|
|         475|    38|
|         307|   156|
|         169|  1077|
|         334|    96|
|         205|   680|
|         442|    47|
|         272|   194|
|         470|    34|
|         462|    29|
|          15|134370|
|          54| 14261|
|         232|   390|
|         234|   344|
+------------+------+
only showing top 20 rows
```

[26]:
```
df.select("Dest").groupby("Dest").count().show()
```

```
[Stage 18:========================================================> (88 + 2) / 90]

+----+-------+
|Dest|  count|
+----+-------+
| BGM|  26330|
| DLG|   4940|
| PSE|   2929|
| INL|    290|
| MSY| 951585|
| GEG| 262264|
| BUR| 579731|
| SNA| 820658|
| GRB|  86390|
| GTF|  60822|
```

```
| IDA|  35521|
| GRR| 240478|
| LWB|   1697|
| EUG|  72786|
| PSG|  14992|
| PVD| 440405|
| GSO| 386589|
| MYR|  82534|
| ISO|   5906|
| OAK|1160059|
+----+-------+
only showing top 20 rows
```

[27]:
```
df.select("SecurityDelay").groupby("SecurityDelay").count().show()
```

```
[Stage 21:======================================================> (88 + 2) / 90]

+-------------+--------+
|SecurityDelay|   count|
+-------------+--------+
|            7|    2135|
|           51|      98|
|           15|    2211|
|           54|      74|
|           11|    1452|
|           69|      50|
|           29|     334|
|           73|      34|
|            3|    1475|
|           30|     427|
|           34|     268|
|           59|      61|
|            8|    1970|
|           22|     782|
|           28|     436|
|          184|       5|
|          199|       5|
|           16|    1528|
|           35|     301|
|           NA|89329433|
+-------------+--------+
only showing top 20 rows
```

[28]:
```
df.select("TaxiIn").groupby("TaxiIn").count().show()
```

```
[Stage 24:=========================================================>(89 + 1) / 90]

+------+-------+
|TaxiIn|  count|
+------+-------+
|  1394|     10|
|     7|7310604|
|    51|   4018|
|   124|    102|
|   447|      9|
|  1445|   2857|
|   470|     12|
|    15| 623793|
|    54|   3049|
|   234|      9|
|   700|     17|
|   155|     42|
|   862|      7|
|   940|      4|
|   886|      6|
|   132|     78|
|   317|      6|
|   521|     10|
|    11|1864915|
|   101|    174|
+------+-------+
only showing top 20 rows
```

[29]:
```
df.select("TaxiOut").groupby("TaxiOut").count().show()
```

```
[Stage 27:=========================================================>(89 + 1) / 90]

+-------+-------+
|TaxiOut|  count|
+-------+-------+
|    125|   2036|
|      7|3693681|
|     51|  56869|
|    124|   2020|
|    169|    578|
|    205|    232|
|     15|4776327|
|     54|  45045|
|   1435|     12|
|    155|    834|
```

```
|     132|   1646|
|     154|    897|
|     317|      8|
|     625|      1|
|     200|    226|
|      11|6085204|
|     101|   4403|
|     279|     41|
|     138|   1354|
|      29| 589856|
+--------+-------+
only showing top 20 rows
```

[30]:
```python
df.select("TailNum").groupby("TailNum").count().show()
```

```
[Stage 30:=======================================================> (88 + 2) / 90]

+-------+-----+
|TailNum|count|
+-------+-----+
| 89709E| 3712|
| N513UA|15114|
| N902DE|24888|
| N33637|16331|
| N485A1| 1537|
| N411US|11557|
| N745AS|21349|
| N102UW|11167|
| N607NW|17747|
| N516UA|15019|
| N912TW| 9329|
| N952 1| 1771|
| N407AA|16737|
| N466SW|10506|
| N88770| 1482|
| N330 1| 1625|
| N9616G| 4567|
| -N726A|  625|
| N672SW|11176|
| N919UA|24574|
+-------+-----+
only showing top 20 rows
```

[31]:
```
df.select("UniqueCarrier").groupby("UniqueCarrier").count().show()
```

```
[Stage 33:=======================================================>(89 + 1) / 90]

+-------------+--------+
|UniqueCarrier|   count|
+-------------+--------+
|           UA|13299817|
|           EA|  919785|
|           PI|  873957|
|           PS|   83617|
|           AA|14984647|
|           NW|10292627|
|           EV| 1697172|
|           B6|  811341|
|           HP| 3636682|
|           TW| 3757747|
|           DL|16547870|
|           OO| 3090853|
|           F9|  336958|
|           YV|  854056|
|           TZ|  208420|
|           US|14075530|
|           AQ|  154381|
|           MQ| 3954895|
|           OH| 1464176|
|           HA|  274265|
+-------------+--------+
only showing top 20 rows
```

[32]:
```
df.select("WeatherDelay").groupby("WeatherDelay").count().show()
```

```
[Stage 36:======================================================> (88 + 2) / 90]

+------------+-----+
|WeatherDelay|count|
+------------+-----+
|         125|  910|
|           7|14860|
|          51| 3269|
|         124|  646|
|         591|    6|
|         334|   23|
|         205|  223|
|         169|  301|
|          15|17644|
|          54| 3144|
```

```
|         234|   98|
|         232|   93|
|         155|  517|
|         154|  399|
|         132|  541|
|         200|  245|
|          11|11990|
|         101| 1040|
|         433|    8|
|         138|  536|
+------------+-----+
only showing top 20 rows
```

[33]:

```
df.select("Year").groupby("Year").count().show()
```

```
[Stage 39:=======================================================> (88 + 2) / 90]

+----+-------+
|Year|  count|
+----+-------+
|1990|5270893|
|2003|6488540|
|2007|7453215|
|2006|7141922|
|1997|5411843|
|1988|5202096|
|1994|5180048|
|2004|7129270|
|1991|5076925|
|1989|5041200|
|1996|5351983|
|1998|5384721|
|1987|1311826|
|1995|5327435|
|2001|5967780|
|1992|5092157|
|2005|7140596|
|2000|5683047|
|2008|7009728|
|1999|5527884|
+----+-------+
only showing top 20 rows
```

[34]:
```
df.printSchema()
```

```
root
 |-- ActualElapsedTime: integer (nullable = true)
 |-- AirTime: integer (nullable = true)
 |-- ArrDelay: integer (nullable = true)
 |-- ArrTime: integer (nullable = true)
 |-- CRSArrTime: integer (nullable = true)
 |-- CRSDepTime: integer (nullable = true)
 |-- CRSElapsedTime: integer (nullable = true)
 |-- CancellationCode: string (nullable = true)
 |-- Cancelled: integer (nullable = true)
 |-- CarrierDelay: string (nullable = true)
 |-- DayOfWeek: integer (nullable = true)
 |-- DayofMonth: integer (nullable = true)
 |-- DepDelay: string (nullable = true)
 |-- DepTime: integer (nullable = true)
 |-- Dest: string (nullable = true)
 |-- Distance: integer (nullable = true)
 |-- Diverted: integer (nullable = true)
 |-- FlightNum: string (nullable = true)
 |-- LateAircraftDelay: string (nullable = true)
 |-- Month: integer (nullable = true)
 |-- NASDelay: string (nullable = true)
 |-- Origin: string (nullable = true)
 |-- SecurityDelay: string (nullable = true)
 |-- TailNum: string (nullable = true)
 |-- TaxiIn: string (nullable = true)
 |-- TaxiOut: string (nullable = true)
 |-- UniqueCarrier: string (nullable = true)
 |-- WeatherDelay: string (nullable = true)
 |-- Year: integer (nullable = true)
```

[35]:
```
end_data_preprocessing = datetime.now()

delta =  end_data_preprocessing - start_notebook_preprocessing

preprocessing_total_time = delta.total_seconds()
print('difference in seconds is:', preprocessing_total_time)
```

```
difference in seconds is: 1004.216919
```

Now that we've got all of the data preprocessed, it's time to do some visualizations to help us understand the history of flight lateness and cancellations over the decades. Using the historical big data asset we have is a really good quantitative (not qualitative) way of doing that. Here is a contemporary / relevant analysis plan for the descriptive statistics for this dataset - which many have looked at previously:

(1) Have there been large numbers of cancels in any particular year ;

(2) Has flight timeliness changed over time? ;

(3) Have On Time Performance or cancellation levels changed with the consolidation of the airline industry ;

(4) Are there particular routes that are more prone to lateness or cancellations? ;

(5) Are there particular airplanes that were poorly managed and prone to lateness or cancellations ;

There are a number of other types of things that could have been done but these will suffice for demonstrating the capabilities of a GPU enabled Spark Session.

[36]:
```
start_data_visualizations = datetime.now()
```

First, we will visualize the late flight and cancellation rate by year and plot these. To do that, I will utilize Spark to compute an aggregate dataframe in which a late flight is defined as occuring when ArrDelay is greater than 0. I will not consider any grace period for the sake of simplicity in the analysis. Cancellations will be defined as cancel code is not null. I will not consider reason for the sake of simplicity in the analysis. With cancels, there is already a convenient field for doing this called "Cancelled" that is a 1 for cancel and 0 for not cancel. With late arrival, I created a new field called "LateArrival."

[37]:
```
df.select("Cancelled").groupby("Cancelled").count().show()
```

```
[Stage 42:=========================================================>(89 + 1) / 90]

+---------+---------+
|Cancelled|    count|
+---------+---------+
|        1|  2303324|
|        0|121231645|
+---------+---------+
```

[38]:
```
# adding a column: https://sparkbyexamples.com/spark/
 ↪spark-add-new-column-to-dataframe/
df = df.withColumn("LateArrival",col("ArrDelay") > 0)
df.show()
```

```
+-----------------+-------+--------+-------+----------+----------+--------------
+----------------+---------+------------+---------+----------+--------+-------+-
---+--------+--------+---------+-----------------+-----+--------+------+--------
-----+-------+------+-------+-------------+------------+----+-----------+
|ActualElapsedTime|AirTime|ArrDelay|ArrTime|CRSArrTime|CRSDepTime|CRSElapsedTime
|CancellationCode|Cancelled|CarrierDelay|DayOfWeek|DayofMonth|DepDelay|DepTime|D
```

```
est|Distance|Diverted|FlightNum|LateAircraftDelay|Month|NASDelay|Origin|Security
Delay|TailNum|TaxiIn|TaxiOut|UniqueCarrier|WeatherDelay|Year|LateArrival|
+----------------+-------+-------+-------+---------+---------+-------------
+---------------+--------+-----------+--------+---------+--------+-------+-
---+--------+-------+--------+--------------+-----+-------+------+--------
-----+-------+------+-------+-----------+----------+----+----------+
|              53|     32|      -8|   1642|      1650|       1545|
65|              NA|        0|          NA|        4|         10|       4|
1549| PIT|     205|       0|      209|              NA|   10|       NA|   DCA|
NA| N443US|     7|     14|           US|          NA|2002|      false|
|             164|    155|     -11|   1754|      1805|       1610|
175|              NA|        0|          NA|        4|          2|       0|
1610| MCI|    1072|       0|      109|              NA|   12|       NA|   MCO|
NA|   N755|     2|      7|           WN|          NA|1999|      false|
|              60|   null|      15|   2005|      1950|       1850|
60|              NA|        0|          NA|        5|         10|      15|
1905| CLT|     227|       0|     1276|              NA|   12|       NA|   ATL|
NA|     NA|    NA|     NA|           DL|          NA|1993|       true|
|              51|   null|      -5|   1818|      1823|       1728|
55|              NA|        0|          NA|        4|         28|      -1|
1727| BNA|     200|       0|      961|              NA|    9|       NA|   MEM|
NA|     NA|    NA|     NA|           AA|          NA|1989|      false|
|              45|     29|       2|   1120|      1118|       1030|
48|            null|        0|           0|        1|         19|       5|
1035| CMH|     116|       0|     5873|               0|    6|        0|   CVG|
0| N785CA|     3|     13|           OH|           0|2006|       true|
|              49|     37|       2|   1137|      1135|       1048|
47|              NA|        0|          NA|        4|          2|       0|
1048| CLT|     156|       0|      353|              NA|    1|       NA|   MYR|
NA| N934VJ|     6|      6|           US|          NA|1997|       true|
|              61|     40|      -3|   1537|      1540|       1440|
60|            null|        0|          NA|        7|         20|      -4|
1436| LAW|     140|       0|     3281|              NA|    7|       NA|   DFW|
NA| N286AE|     7|     14|           MQ|          NA|2008|      false|
|             150|    126|     -19|   2015|      2034|       1745|
169|              NA|        0|          NA|        4|         15|       0|
1745| ATL|     903|       0|     1521|              NA|   10|       NA|   PVD|
NA| N919DE|    14|     10|           DL|          NA|1998|      false|
|             115|    103|      -5|    735|       740|        640|
120|              NA|        0|          NA|        2|         16|       0|
640| SEA|     689|       0|     1678|              NA|    6|       NA|   SLC|
NA|   N346|     2|     10|           WN|          NA|1998|      false|
|            null|   null|    null|   null|       730|        605|
85|               B|        1|           0|        7|         10|      NA|
null| SLC|     391|       0|     4117|               0|    4|        0|   DEN|
0| N705EV|     0|      0|           EV|           0|2005|       null|
|             102|   null|      -4|   1603|      1607|       1320|
107|              NA|        0|          NA|        2|          3|       1|
```

```
1321| DFW|    641|       0|      280|              NA|   12|      NA|   DEN|
NA|     NA|    NA|     NA|           CO|          NA|1991|      false|
|             87|   null|      -8|   1547|      1555|       1322|
93|             NA|       0|           NA|       3|         13|      -2|
1320| CLE|    487|       0|      142|              NA|   11|      NA|   STL|
NA|     NA|    NA|     NA|           TW|          NA|1991|      false|
|            170|    135|      10|   1051|      1041|        800|
161|              NA|       0|           NA|       4|         22|       1|
801| MCO|     950|       0|     1123|             NA|   10|      NA|   LGA|
NA| N558AA|     3|     32|           AA|          NA|1998|       true|
|            100|     81|      -2|   1220|      1222|       1045|
97|            null|       0|            0|       1|          6|      -5|
1040| ATL|    300|       0|     4120|              0|   11|       0|   GNV|
0| N632AS|    10|      9|           EV|          0|2006|      false|
|             60|   null|      -5|   2040|      2045|       1940|
65|             NA|       0|           NA|       6|         27|       0|
1940| DFW|    247|       0|      559|              NA|   10|      NA|   SAT|
NA|     NA|    NA|     NA|           AA|          NA|1990|      false|
|             79|     70|     -16|   1444|      1500|       1220|
100|              NA|       0|           NA|       7|         19|       5|
1225| PIT|    553|       0|      754|              NA|   11|      NA|   STL|
NA| N970VJ|     5|      4|           US|          NA|1995|      false|
|            174|   null|      43|   1213|      1130|       1031|
179|              NA|       0|           NA|       5|          8|      48|
1119| DEN|   1199|       0|      545|              NA|   10|      NA|   ATL|
NA|     NA|    NA|     NA|           DL|          NA|1993|       true|
|            133|    117|      40|   1429|      1349|       1044|
125|              NA|       0|           NA|       4|         30|      32|
1116| BOS|    867|       0|     1270|              NA|    1|      NA|   ORD|
NA| N7280U|     5|     11|           UA|          NA|1997|       true|
|             33|     22|      -3|   1916|      1919|       1845|
34|            null|       0|            0|       2|          6|      -2|
1843| HNL|    100|       0|      549|               0|   11|       0|   OGG|
0| N477HA|     5|      6|           HA|          0|2007|      false|
|             57|     31|      -9|   1659|      1708|       1612|
56|            null|       0|            0|       5|          4|     -10|
1602| ATL|    152|       0|     4632|               0|    2|       0|   TYS|
0| N846AS|     9|     17|           EV|          0|2005|      false|
+-----------------+-------+--------+-------+----------+----------+-------------
+----------------+---------+------------+---------+----------+--------+-------+-
---+--------+--------+---------+----------------+-----+--------+------+--------
-----+-------+------+-------+------------+-----------+----+-----------+
only showing top 20 rows
```

For expediency, I create a spark SQL view to perform these queries from since I find this faster than the dataframe API.

[39]:
```python
df.createOrReplaceTempView("df")
```

[40]:
```python
import pyspark.sql.functions as f

late_cancel_flights_by_year = spark.sql("""

Select

d.Year, sum(d.Cancelled) / count(*) as cancel_rate,
sum(case when d.LateArrival is True then 1 else 0 end) / count(d.LateArrival)␣
↪as on_time_performance

from df as d

Group by 1
order by 1 asc

""")

late_cancel_flights_by_year.show()
```

```
[Stage 46:=========================================================>(89 + 1) / 90]

+----+--------------------+-------------------+
|Year|         cancel_rate|on_time_performance|
+----+--------------------+-------------------+
|1987|0.015005801074227831| 0.6273202590027679|
|1988|0.009642843961357115| 0.5429083462238518|
|1989|0.014711774974212489| 0.5720157279719946|
|1990|0.009952393266188481| 0.5268774648095783|
|1991|0.008569163420771431| 0.4881460952212132|
|1992|0.010375956593639985|  0.499331236648351|
|1993|0.011802581243944139|0.49398828835657216|
|1994|0.012884050495284986|0.49595115033672454|
|1995| 0.01725126632234837| 0.5090623264366689|
|1996|0.024016518737073715| 0.5424027983658538|
|1997|0.018064640825685447| 0.5117707491080251|
|1998| 0.02683685932845917| 0.4805935507420915|
|1999|0.027915021371649622|0.48323438466064855|
|2000| 0.03299110494775074| 0.5068256580597715|
|2001| 0.03874103938147854|0.42624080725785696|
|2002|0.012357913775176383| 0.3913741424355408|
|2003| 0.01563818671072383|0.38291406622876367|
|2004| 0.01792006755249836| 0.4319632315448982|
|2005| 0.01872812857638214| 0.4380513319484879|
|2006| 0.01707299519653113| 0.4565186166028109|
+----+--------------------+-------------------+
only showing top 20 rows
```

[41]:

```
late_flights_by_year_pd = late_cancel_flights_by_year.toPandas()
late_flights_by_year_pd
```

[41]:

	Year	cancel_rate	on_time_performance
0	1987	0.015006	0.627320
1	1988	0.009643	0.542908
2	1989	0.014712	0.572016
3	1990	0.009952	0.526877
4	1991	0.008569	0.488146
5	1992	0.010376	0.499331
6	1993	0.011803	0.493988
7	1994	0.012884	0.495951
8	1995	0.017251	0.509062
9	1996	0.024017	0.542403
10	1997	0.018065	0.511771
11	1998	0.026837	0.480594
12	1999	0.027915	0.483234
13	2000	0.032991	0.506826
14	2001	0.038741	0.426241
15	2002	0.012358	0.391374
16	2003	0.015638	0.382914
17	2004	0.017920	0.431963
18	2005	0.018728	0.438051
19	2006	0.017073	0.456519
20	2007	0.021568	0.474683
21	2008	0.019606	0.434645

We will start with some basic summary level statistics and visualizations to understand our data. For our purposes, the focus will be on creating creating a lot of processing loads to create a meaningful test based on a real world workflow while a descriptive analysis of industry trends is developed.

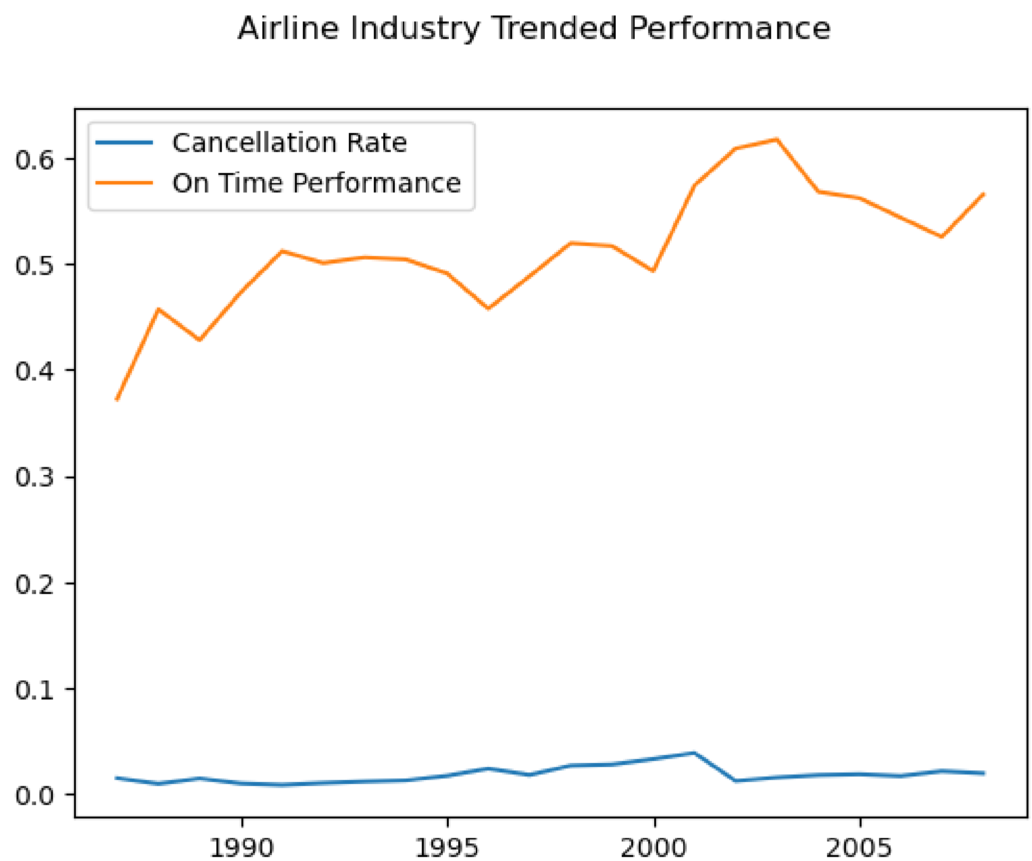
[42]:

```
import matplotlib.pyplot as plt

#https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.subplots.html

fig, ax = plt.subplots()
ax.plot(late_flights_by_year_pd["Year"],␣
 ↪late_flights_by_year_pd["cancel_rate"], label = "Cancellation Rate")
ax.plot(late_flights_by_year_pd["Year"],␣
 ↪1-late_flights_by_year_pd["on_time_performance"], label = "On Time␣
 ↪Performance")
ax.legend()
```

```
fig.suptitle('Airline Industry Trended Performance')
plt.show()
```



On time performance is consistently poor but trended upwards over time. Cancel rates have remained relatively constant with some deterioration in the late 90s and early 2000s.

Next, a crude notion of industry concentration will be developed by looking at the total number of flights by airline over time.

[43]:
```
import pyspark.sql.functions as f

carriers = spark.sql("""

Select

d.Year,
count(distinct d.UniqueCarrier) as unique_carriers

from df as d

```

```
Group by 1
order by 1 asc

""")

carriers.show()
```

```
[Stage 57:=======================================================>(89 + 1) / 90]

+----+---------------+
|Year|unique_carriers|
+----+---------------+
|1987|             14|
|1988|             14|
|1989|             13|
|1990|             12|
|1991|             12|
|1992|             10|
|1993|             10|
|1994|             10|
|1995|             10|
|1996|             10|
|1997|             10|
|1998|             10|
|1999|             10|
|2000|             11|
|2001|             12|
|2002|             10|
|2003|             18|
|2004|             19|
|2005|             20|
|2006|             20|
+----+---------------+
only showing top 20 rows
```

[44]:
```
carriers = carriers.toPandas()
carriers
```

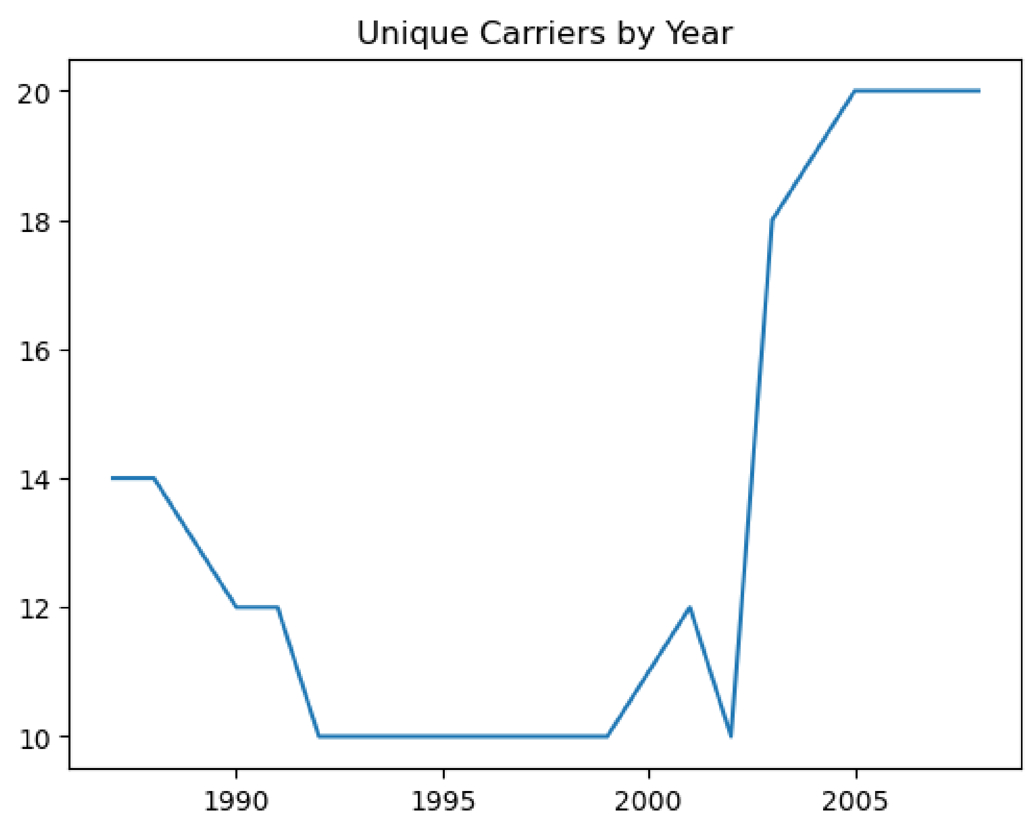
[44]:

	Year	unique_carriers
0	1987	14
1	1988	14
2	1989	13
3	1990	12
4	1991	12

```
5    1992                  10
6    1993                  10
7    1994                  10
8    1995                  10
9    1996                  10
10   1997                  10
11   1998                  10
12   1999                  10
13   2000                  11
14   2001                  12
15   2002                  10
16   2003                  18
17   2004                  19
18   2005                  20
19   2006                  20
20   2007                  20
21   2008                  20
```

[45]:
```
plt.plot(carriers['Year'], carriers["unique_carriers"])
plt.title("Unique Carriers by Year")
```

[45]:
```
Text(0.5, 1.0, 'Unique Carriers by Year')
```



Intriguingly enough, there was a brief period of apparent industry consolidation in the airline industry. The trough was 10 carriers, down from 14 in 1987. By the end of the series there are 20 carriers - more than there were at the start of it. Industry level competition seems like an unlikely explanation for any sort of performance trend - which as demonstrated above is overall upward.

Next, let's look at whether there are any troublesome routes. To do this, origin and destination ordered pairs will be created and on time performance computed on those ordered pairs. A histogram plot will then be created to examine the central tendency of the distribution visually.

[46]:
```
import pyspark.sql.functions as f

tough_routes = spark.sql("""

Select

d.Origin,
d.Dest,
sum(d.Cancelled) / count(*) as cancel_rate,
sum(case when d.LateArrival is True then 1 else 0 end) / count(d.LateArrival)␣
 ↪as on_time_performance,
count(*) as sample

from df as d

Group by 1,2
Order by on_time_performance asc

""")

tough_routes.show()
```

```
[Stage 76:=======================================================>(89 + 1) / 90]

+------+----+------------------+-------------------+------+
|Origin|Dest|       cancel_rate|on_time_performance|sample|
+------+----+------------------+-------------------+------+
|   ISP| AGS|               0.0|               null|     1|
|   HLN| PIH|               0.0|               null|     4|
|   AUS| GJT|               0.0|               null|     2|
|   BIL| CPR|               0.0|               null|     1|
|   MSP| BHM|               0.0|               null|     1|
|   BFL| PIH|               0.0|               null|     1|
|   LNK| CYS|               0.0|               null|     1|
|   ABQ| GJT|               0.0|               null|     7|
|   MFR| MRY|               0.0|               null|     2|
|   EUG| SMF|               0.0|               null|     3|
|   SMF| TWF|               0.0|               null|     5|
```

```
|   COD| PIH|               0.0|              null|     2|
|   SBP| SMX|0.6666666666666666|              null|     3|
|   ORD| GJT|               0.0|              null|    20|
|   COS| GJT|               0.0|              null|     8|
|   BOS| GGG|               0.0|              null|     2|
|   CPR| PIH|               0.0|              null|    10|
|   RAP| COS|               0.0|              null|     5|
|   AUS| PIH|               0.0|              null|     1|
|   BZN| COS|               0.0|              null|     3|
+------+----+------------------+------------------+------+
only showing top 20 rows
```

[47]:
```
tough_routes = tough_routes.toPandas()
tough_routes.head()
```

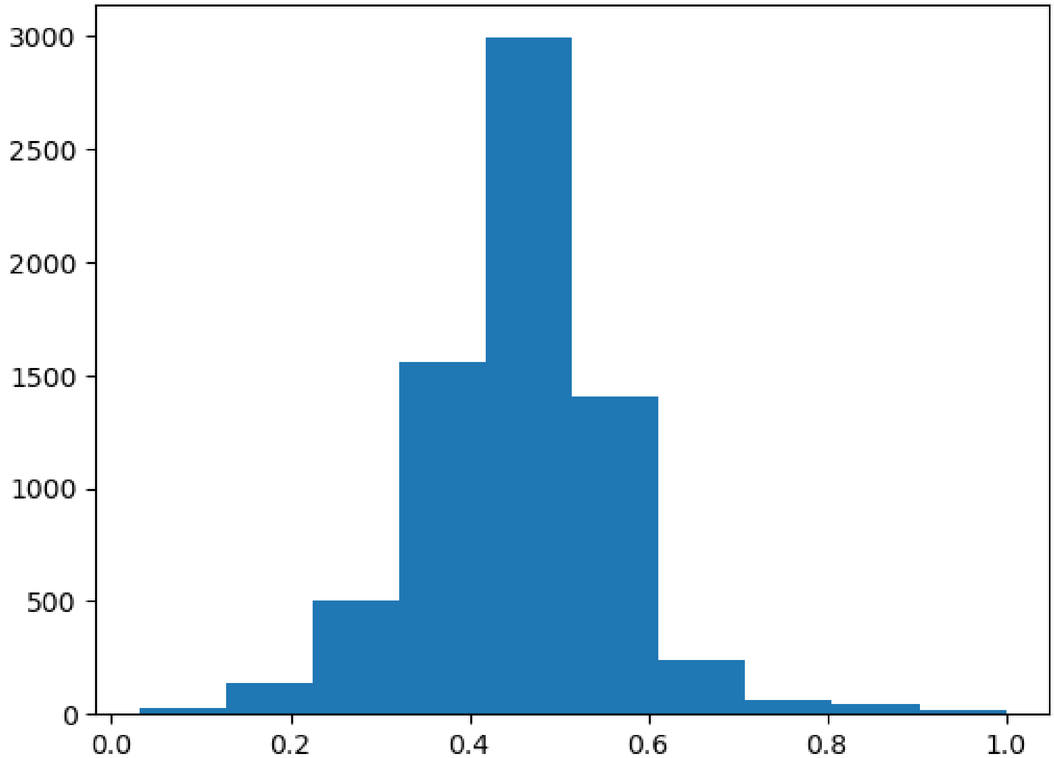
[47]:
```
  Origin Dest  cancel_rate  on_time_performance  sample
0    CLD  ONT          0.0                  NaN       2
1    COD  PIH          0.0                  NaN       2
2    EUG  TWF          0.0                  NaN       5
3    FSD  SBN          0.0                  NaN       1
4    MSN  MLI          0.0                  NaN       1
```

[48]:
```
tough_routes = tough_routes.dropna()
tough_routes = tough_routes[tough_routes['sample'] > 30]
```

Evidently, there were indeed some routes that were chronically late. However, lateness seems to have strong central tendency - suggesting that this is really an industry level problem.

[49]:
```
import numpy as np
#https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.hist.html
# https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.dropna.html
counts, bins = np.histogram(tough_routes['on_time_performance'])
plt.hist(bins[:-1], bins, weights=counts)
```

[49]:
```
(array([  28.,  138.,  506., 1559., 2990., 1402.,  237.,   65.,   44.,
          16.]),
 array([0.03067485, 0.12760736, 0.22453988, 0.32147239, 0.41840491,
        0.51533742, 0.61226994, 0.70920245, 0.80613497, 0.90306748,
        1.        ]),
 <BarContainer object of 10 artists>)
```



Last, a similar histogram will be done to look at airplane management by tail number.

[50]:
```
import pyspark.sql.functions as f

bad_planes = spark.sql("""

Select

d.TailNum,
sum(d.Cancelled) / count(*) as cancel_rate,
sum(case when d.LateArrival is True then 1 else 0 end) / count(d.LateArrival)␣
↪as on_time_performance,
count(*) as sample

from df as d

Group by 1
Order by on_time_performance asc

""")
```

[51]:
```
bad_planes = bad_planes.toPandas()
bad_planes
```

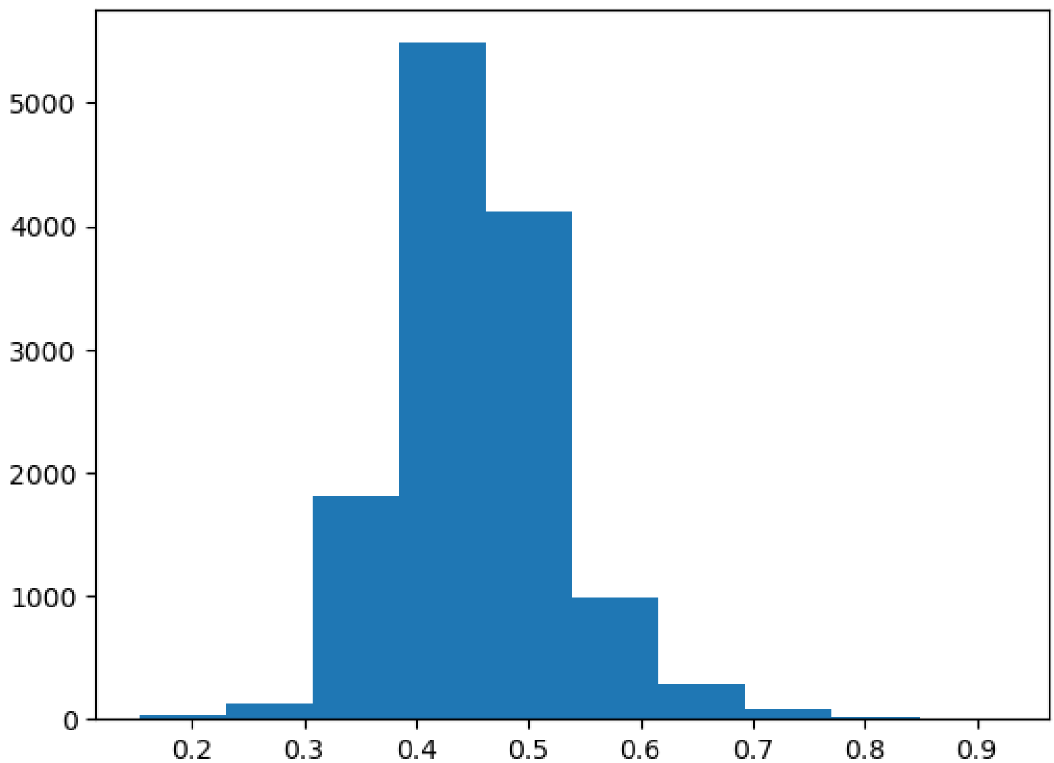
[51]:
```
      TailNum  cancel_rate  on_time_performance  sample
0      000000          1.0                  NaN   55349
1      N703AW          1.0                  NaN      14
2       9169E          1.0                  NaN      78
3      N853BR          1.0                  NaN       1
4      N850BR          1.0                  NaN       3
…        …            …                     …     …
13145  N432AW          0.5                  1.0       4
13146  N668           0.0                  1.0       1
13147  N601QX          0.0                  1.0       2
13148    NCHD          0.0                  1.0       2
13149  N611QX          0.0                  1.0       2

[13150 rows x 4 columns]
```

[52]:
```
bad_planes = bad_planes.dropna()
bad_planes = bad_planes[bad_planes['sample'] > 30]
```

[53]:
```
import numpy as np
#https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.hist.html
# https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.dropna.html
counts, bins = np.histogram(bad_planes['on_time_performance'])
plt.hist(bins[:-1], bins, weights=counts)
```

[53]:
```
(array([  34.,  131., 1814., 5485., 4120.,  984.,  291.,   80.,   15.,
           6.]),
 array([0.15279938, 0.23011203, 0.30742469, 0.38473734, 0.46205   ,
        0.53936265, 0.61667531, 0.69398796, 0.77130062, 0.84861327,
        0.92592593]),
 <BarContainer object of 10 artists>)
```



[54]:
```
end_data_visualizations = datetime.now()
```

From the above, we can see that there are indeed some planes that are chronically late. To the extent to which they are merely on some of the late routes is a good follow up question. However, this also shows predictably strong central tendency as well - which it would have to in aggregate given the size of the problem and the prior results.

[55]:
```
delta =  end_data_visualizations - start_data_visualizations
visualization_total_time = delta.total_seconds()
print('difference in seconds is:', visualization_total_time)
```

```
difference in seconds is: 673.104079
```

10 Analysis

Now that I've had the chance to see the basic descriptive statistics, a few conclusions jump out:

(1) The airline industry has consistently struggled with on time performance issues - with almost half of flights being late;

(2) Cancellations increased during the 1990s and then dropped back to longer term trends in the early 2000s;

(3) There are some troublesome routes and planes but these appear to be industry level problems ;

(4) A lack of competition was not an obvious driver of quality issues ;

There aren't any obvious structural explanations for airline lateness. How well do the other measurement parameters explain on time performance? With this step of the problem, I will utilize the late minutes themselves as the dependent variable instead of the boolean.

11 Machine Learning on Late Minutes

For the purposes of this demonstration, I'll work with just the quantitative variables for the non cancelled flights to fit a regression. The variables chosen for this demonstration are as follows:

1 ArrDelay 2 AirTime in minutes
3 ArrDelay arrival delay, in minutes
4 Distance in miles
5 TaxiIn taxi in time, in minutes
6 TaxiOut taxi out time in minutes
7 CarrierDelay in minutes
8 WeatherDelay in minutes
9 NASDelay in minutes
10 SecurityDelay in minutes
11 LateAircraftDelay in minutes

[56]:
```
ml_model_start = datetime.now()
```

[57]:
```
import pyspark.sql.functions as f

model_df = spark.sql("""

Select
ArrDelay,
AirTime,
Distance,
TaxiIn,
TaxiOut,

case when CarrierDelay <> 'NA' then CarrierDelay else 0 end as CarrierDelay,
case when WeatherDelay <> 'NA' then WeatherDelay else 0 end as WeatherDelay,
case when NASDelay <> 'NA' then NASDelay else 0 end as NASDelay,
case when SecurityDelay <> 'NA' then SecurityDelay else 0 end as SecurityDelay,
case when LateAircraftDelay <> 'NA' then LateAircraftDelay else 0 end as␣
 ↪LateAircraftDelay

from df as d
where d.Cancelled = 0
and d.AirTime is not null

```

```
""")
```

[58]:
```
model_df.show(15)
```

```
+--------+-------+--------+------+-------+------------+------------+--------+---
----------+-----------------+
|ArrDelay|AirTime|Distance|TaxiIn|TaxiOut|CarrierDelay|WeatherDelay|NASDelay|Sec
urityDelay|LateAircraftDelay|
+--------+-------+--------+------+-------+------------+------------+--------+---
----------+-----------------+
|      -8|     32|     205|     7|     14|           0|           0|       0|
0|                0|
|     -11|    155|    1072|     2|      7|           0|           0|       0|
0|                0|
|       2|     29|     116|     3|     13|           0|           0|       0|
0|                0|
|       2|     37|     156|     6|      6|           0|           0|       0|
0|                0|
|      -3|     40|     140|     7|     14|           0|           0|       0|
0|                0|
|     -19|    126|     903|    14|     10|           0|           0|       0|
0|                0|
|      -5|    103|     689|     2|     10|           0|           0|       0|
0|                0|
|      10|    135|     950|     3|     32|           0|           0|       0|
0|                0|
|      -2|     81|     300|    10|      9|           0|           0|       0|
0|                0|
|     -16|     70|     553|     5|      4|           0|           0|       0|
0|                0|
|      40|    117|     867|     5|     11|           0|           0|       0|
0|                0|
|      -3|     22|     100|     5|      6|           0|           0|       0|
0|                0|
|      -9|     31|     152|     9|     17|           0|           0|       0|
0|                0|
|      13|     65|     480|     3|     11|           0|           0|       0|
0|                0|
|     136|     74|     563|     3|     18|         136|           0|       0|
0|                0|
+--------+-------+--------+------+-------+------------+------------+--------+---
----------+-----------------+
only showing top 15 rows
```

Doing that step of the pipeline created some unintended consequences. All numbers will be treated as floats for the purposes of the machine learning study:

[59]:
```
model_df.printSchema()
```

```
root
 |-- ArrDelay: integer (nullable = true)
 |-- AirTime: integer (nullable = true)
 |-- Distance: integer (nullable = true)
 |-- TaxiIn: string (nullable = true)
 |-- TaxiOut: string (nullable = true)
 |-- CarrierDelay: string (nullable = true)
 |-- WeatherDelay: string (nullable = true)
 |-- NASDelay: string (nullable = true)
 |-- SecurityDelay: string (nullable = true)
 |-- LateAircraftDelay: string (nullable = true)
```

[60]:
```
model_df = model_df.withColumn("ArrDelay",model_df.ArrDelay.cast(FloatType()))
model_df = model_df.withColumn("AirTime",model_df.AirTime.cast(FloatType()))
model_df = model_df.withColumn("Distance",model_df.Distance.cast(FloatType()))
model_df = model_df.withColumn("TaxiIn",model_df.TaxiIn.cast(FloatType()))
model_df = model_df.withColumn("TaxiOut",model_df.TaxiOut.cast(FloatType()))
model_df = model_df.withColumn("CarrierDelay",model_df.CarrierDelay.
 ↪cast(FloatType()))
model_df = model_df.withColumn("WeatherDelay",model_df.WeatherDelay.
 ↪cast(FloatType()))
model_df = model_df.withColumn("NASDelay",model_df.NASDelay.cast(FloatType()))
model_df = model_df.withColumn("SecurityDelay",model_df.SecurityDelay.
 ↪cast(FloatType()))
model_df = model_df.withColumn("LateAircraftDelay",model_df.LateAircraftDelay.
 ↪cast(FloatType()))
```

[61]:
```
#https://spark.apache.org/docs/3.1.2/api/python/reference/api/pyspark.sql.
 ↪DataFrame.dropna.html
model_df = model_df.na.drop()
```

For our purposes, a basic multiple linear regression should be a reasonable goodness of fit test for whether the data being collected over many decades explains the dependent variable of late minutes well. Other more elaborate algorithms were explored as part of this exercise, but there was not sufficient time to work out the issues with Spark RAPIDS.

[62]:
```
from pyspark.ml.feature import VectorAssembler
label_name = "ArrDelay"
feature_names = [x.name for x in model_df.schema if x.name != label_name]
vectorAssembler = VectorAssembler(inputCols = feature_names, outputCol =␣
 ↪'features')
model_df = vectorAssembler.transform(model_df)
```

[63]:
```
splits = model_df.randomSplit([0.3, 0.05])
train_df = splits[0]
```

```
test_df = splits[1]
```

[ ]:
```
from pyspark.ml.regression import LinearRegression

lr = LinearRegression(featuresCol = 'features', labelCol='ArrDelay',␣
↪maxIter=20, regParam=0.3, elasticNetParam=0.8)
lr_model = lr.fit(train_df)
print("Coefficients: " + str(lr_model.coefficients))
print("Intercept: " + str(lr_model.intercept))
```

```
[Stage 98:==========================================>             (66 + 3) / 90]
```

[ ]:
```
trainingSummary = lr_model.summary
print("RMSE: %f" % trainingSummary.rootMeanSquaredError)
print("r2: %f" % trainingSummary.r2)
```

12 Regression analysis results

While I would say that the regression performance is hardly conclusive, based on the lack of the usual diagnostic plots as well as other modeling attempts, it does seem like the variables chosen should have been able to easily explain on time performance. At a minimum, the idea that the wrong data points have been tracked for an extended period seems like a strong possibility.

[ ]:
```

```

13 XGBoost rapids - failed test

I could not get this to work due to issues with Java. However, I will come back to this at a later date.

XGBoost now includes some documentation around GPUs in its section on Spark on its web site: https://xgboost.readthedocs.io/en/stable/tutorials/spark_estimator.html

There is a very convenient template available for this type of problem. However, I would note that it does not work with a GPU unless specifically told to do so via the use_GPU=True command. It's not clear if this is common type of requirement for Spark applications. In any case, the coding burden is relatively minimal.

I would also note that running this project also requires taking the availability of a GPU into consideration at the environment level. In the docs, it talks about which commands to use to install the xgboost package to use the GPU vs the CPU: https://xgboost.readthedocs.io/en/stable/install.html#conda

I utilized the py-xgboost package from conda-forge:

conda install -c conda-forge py-xgboost

https://xgboost.readthedocs.io/en/stable/tutorials/spark_estimator.html from xgboost.spark import SparkXGBRegressor spark = SparkSession.builder.getOrCreate()

label_name = "ArrDelay"

create a xgboost pyspark regressor estimator and set use_gpu=True regressor = SparkXGBRegressor(features_col="features", label_col=label_name, num_workers=4, use_gpu=False, handleInvalid = "skip")

train and return the model model = regressor.fit(train_df)

predict on test data predict_df = model.transform(test_df) predict_df.show()

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14 Conclusion of real world performance test

[ ]:
```
ml_model_end = datetime.now()

delta =  ml_model_end - ml_model_start
ml_model_total_time = delta.total_seconds()
print('difference in seconds is:', ml_model_total_time)
```

[ ]:
```
end_notebook_preprocessing = datetime.now()

delta =  end_notebook_preprocessing - start_notebook_preprocessing

notebook_total_processing_time = delta.total_seconds()
print('difference in seconds is:', notebook_total_processing_time)
```

Next, I gather up all of the time performance into a single dataframe for export for later comparison:

[ ]:
```
# switch to report CPU vs GPU runtimes
if cp_u is True:
    processing_env = 'CPU'
else:
    processing_env = 'GPU'
```

[ ]:
```
export_string = processing_env+"runtime.csv"
export_string
```

[ ]:
```python
import pandas as pd
performance = [notebook_total_processing_time, preprocessing_total_time,␣
↪visualization_total_time ,ml_model_total_time ]
performance_labels = ['Notebook Total Processing Time', 'Preprocessing Time',␣
↪'Visualization Time', 'Machine Learning Time']
runtime_env_name = [processing_env, processing_env, processing_env,␣
↪processing_env, processing_env]
export_df = pd.DataFrame(list(zip(runtime_env_name,performance_labels,␣
↪performance )), columns=['Runtime','Stage','Seconds'])
```

[ ]:
```python
export_df
```

[ ]:
```python
export_df.to_csv(export_string)
```

[ ]:
```python
!jupyter nbconvert e63_brzozowski_adam_final_project.ipynb --to pdf
```

[ ]:
```python

```