## 1 MongoDB

Q1

```
> db.restaurants.find({
   borough: {
     $in: ["Bronx", "Brooklyn"]
 },{ id:0, name:1}).limit(5)
< {
   name: 'Morris Park Bake Shop'
 }
  {
   name: "Wendy'S"
 }
 {
   name: 'Riviera Caterer'
  }
  {
   name: "Wilken'S Fine Food"
  }
  {
   name: 'Regina Caterers'
```

a)

```
db.restaurants.find({
     borough: {
        $in: ["Bronx", "Brooklyn"]
  }).count()
993
b db.restaurants.find({name:/^Mad/},{_id:1, name:1, borough:1, cuisine:1}).limit(3)
< {
   _id: ObjectId("65569eab735bbc4d443faec6"),
   borough: 'Manhattan',
   cuisine: 'American ',
   name: 'Madison Square'
   _id: ObjectId("65569eab735bbc4d443faf94"),
   borough: 'Manhattan',
   cuisine: 'Indian',
   name: 'Madras Mahal'
   _id: ObjectId("65569eac735bbc4d443fb242"),
   borough: 'Manhattan',
   cuisine: 'American ',
   name: 'Madame X'
db.restaurants.find({name:/^Mad/},{_id:1, name:1, borough:1, cuisine:1}).count()
> db.restaurants.find({grades:{$elemMatch:{score:{$gte:80,$lte:90}}}},{_id:0,name:1})
< {
   name: 'B.B. Kings'
 }
```

```
name: 'West 79Th Street Boat Basin Cafe'
c)
```

b)

```
> db.restaurants.find({grades:{$elemMatch:{score:{$gte:80,$lte:90}}}}).count()
< 2</pre>
```

```
db.restaurants.find({grades:{$elemMatch:{grade:'C',date:{
         $gte: ISODate('2014-01-01'),
         $1t: ISODate('2015-01-01')
        }}}}, {_id:1, name:1}).limit(3)
< 4
   _id: ObjectId("65569eab735bbc4d443fa9c0"),
   name: 'B & M Hot Bagel & Grocery'
 }
 {
   _id: ObjectId("65569eab735bbc4d443fa9c1"),
   name: 'Texas Rotisserie'
 }
 {
   _id: ObjectId("65569eab735bbc4d443fa9ce"),
   name: 'Nyac Main Dining Room'
 }
> db.restaurants.find({grades:{$elemMatch:{grade:'C',date:{
         $gte: ISODate('2014-01-01'),
         $1t: ISODate('2015-01-01')
       }}}}, { id:1, name:1}).count()
94
```

f) Getting 8 rows

e)

```
db.restaurants.aggregate([
 $match: {cuisine:{$ne:'American'}}
 },
   {
     $unwind: "$grades"
   },
     $group: {
       id: "$restaurant id",
       average score: { $avg: "$grades.score" }
    1
   },
 $match:{average score:{$gt:30}}
 }
 1)
< {
  _id: '40393488',
   average_score: 38.6
 }
 {
   _id: '40756344',
   average_score: 36
```

```
>_MONGOSH
    average_score: 36
 }
  {
   _id: '40387237',
   average_score: 32.6
 }
  {
   _id: '40372466',
   average_score: 33.66666666666664
 }
  {
   _id: '40366157',
   average_score: 32.142857142857146
 }
  {
   _id: '40825993',
   average_score: 30.8
 }
  {
   _id: '40624470',
   average_score: 30.6
 }
  {
   _id: '40374268',
   average_score: 30.8
  }
```

g)

Q2

b) Update operations

a)

```
db.sales.updateOne({city:'Berkeley'}, {$set:{qty:750}})

{
    acknowledged: true,
    insertedId: null,
    matchedCount: 1,
    modifiedCount: 1,
    upsertedCount: 0
}
```

```
> db.sales.updateMany({state:'OR'}, {$inc:{qty:50}})
      < {
          acknowledged: true,
          insertedId: null,
          matchedCount: 3,
          modifiedCount: 3,
          upsertedCount: 0
        }
ii)
     db.sales.updateOne({_id:5}, {$set:{salespeople:['David','Martha']}})
     < {
         acknowledged: true,
         insertedId: null,
         matchedCount: 1,
         modifiedCount: 1,
         upsertedCount: 0
       }
iii)
     > db.sales.updateOne({_id:5}, {$push:{salespeople:'James'}})
     < {
         acknowledged: true,
         insertedId: null,
         matchedCount: 1,
         modifiedCount: 1,
         upsertedCount: 0
iv)
```

```
{
    _id: 5,
    city: 'Reno',
    state: 'NV',
    qty: 655,
    salespeople: [
        'David',
        'Martha',
        'James'
    ]
}
```

```
> db.sales.updateOne({_id:5,salespeople:'Martha'},{$set:{'salespeople.$':'Lisa'}})

< {
    acknowledged: true,
    insertedId: null,
    matchedCount: 1,
    modifiedCount: 1,
    upsertedCount: 0
}</pre>
```

```
{
    _id: 5,
    city: 'Reno',
    state: 'NV',
    qty: 655,
    salespeople: [
        'David',
        'Lisa',
        'James'
    ]
}
```

```
> db.sales.deleteMany({state:'CA'})

< {
    acknowledged: true,
    deletedCount: 3
}</pre>
```

vi)

```
> db.sales.find({})

< {
    _id: 2,
    city: 'Bend',
    state: 'OR',
    qty: 541
}

{
    _id: 4,
    city: 'Eugene',
    state: 'OR',
    qty: 892
}

{
    _id: 5,
    city: 'Reno',
    state: 'NV',
    qty: 655,
    salespeople: [
        'David',
        'Lisa',
        'James'
    ]
}</pre>
```

c)

```
}
{
    _id: 4,
    city: 'Eugene',
    state: 'OR',
    qty: 892
}
{
    _id: 5,
    city: 'Reno',
    state: 'NV',
    qty: 655,
    salespeople: [
        'David',
        'Lisa',
        'James'
    ]
}
{
    _id: 6,
    city: 'Portland',
    state: 'OR',
    qty: 458
}
```

```
In [1]: from pymongo import MongoClient
       client = MongoClient("localhost", 27017)
        db = client.booksdb
In [8]: category = input('Enter category')
        pipeline = [
            { "$unwind": '$categories'},
              "$match": {'categories':category}},
            {"$project":{'title':{"$ifNull":["$title","NA"]},
                          'isbn':{"$ifNull":["$isbn","NA"]},
                          ' id':0}}
        cursor = db.books.aggregate(pipeline)
        for book in cursor:
            print(f"ISBN: {book['isbn']}, title: {book['title']}")
        Enter categoryComputer Graphics
        ISBN: 1884777902, title: 3D User Interfaces with Java 3D
        ISBN: 133034054, title: Graphics File Formats
        ISBN: 1933988398, title: Gnuplot in Action
        ISBN: 1884777473, title: The Awesome Power of Direct3D/DirectX
        ISBN: 138412146, title: Power-3D
        ISBN: 1930110022, title: Graphics Programming with Perl
```

## 2 Map Reduce

Q1

Thought process: The map function extracts relevant attributes from each tuple. If that tuple doesn't have that attribute then it should return NIL. It emits the ID of that tuple along with the relevant attribute. The reduce function returns the aggregated attributes with their ID.

// Assuming that Tuple is a dictionary or JSON type data type whose attributes can be accessed // in a similar way. Also assuming that ID attribute of a tuple can be accessed as t[ID]

```
map (Tuple t, List S):
    for each attribute a in S:
        if t[a] is not NIL:
        emit(t[ID],t[a])
    else
        emit(t[ID],NIL)

reduce (Attribute ID, List attributes):
    emit(ID,attributes)
```

Thought process: The map function maps each tuple to the relation it belongs to. The reduce function returns those tuples that belong to both relations i.e. length of relations list must be 2. The reduce function kind of works like an identity function in this case i.e. it simply passes each key-value pair to the output

```
map (Tuple t, Relation X):
        emit(t,X)

reduce (Tuple t, List relations):
        if (length(relations) == 2):
        emit(t,relations)
```

Q3

Thought process: To group tuples, attribute A is used as key and attribute B is used as values. To avoid errors with the aggregation function, if any tuple doesn't have a B attribute, it is not emitted. In the reduce function the aggregation operation is applied on the B-values and are emitted along with the A attribute.

```
map (Tuple t):
    if t[B] is not NIL:
        emit(t[A],t[B])

reduce (Attribute A, List b_values):
    emit(A, θ(b_values))
```

```
from pymongo import MongoClient
In [2]:
         client = MongoClient("localhost", 27017)
         db = client.booksdb
In [3]:
         category = input('Enter category')
         pipeline = [
              { "$unwind": '$categories'},
             { "$match": {'categories':category}},
             {"$project":{'title':{"$ifNull":["$title","NA"]},
                          'isbn':{"$ifNull":["$isbn","NA"]},
                          '_id':0}}
         cursor = db.books.aggregate(pipeline)
         for book in cursor:
             print(f"ISBN: {book['isbn']}, title: {book['title']}")
        Enter categoryComputer Graphics
        ISBN: 1884777902, title: 3D User Interfaces with Java 3D
        ISBN: 133034054, title: Graphics File Formats
        ISBN: 1933988398, title: Gnuplot in Action
        ISBN: 1884777473, title: The Awesome Power of Direct3D/DirectX
        ISBN: 138412146, title: Power-3D
        ISBN: 1930110022, title: Graphics Programming with Perl
In [ ]:
In [ ]:
```

!pip install pyspark Collecting pyspark Downloading pyspark-3.5.0.tar.gz (316.9 MB) 316.9/316.9 MB 3.0 MB/s eta 0:00:00 Preparing metadata (setup.py) ... done Requirement already satisfied: py4j==0.10.9.7 in /usr/local/lib/python3.10/dist-packages (from pyspark) (0.10.9.7) Building wheels for collected packages: pyspark Building wheel for pyspark (setup.py) ... done Created wheel for pyspark: filename=pyspark-3.5.0-py2.py3-none-any.whl size=317425344 sha256=f04e5ec94893948e582d8da6d21dcc11c30f048c02e29f281af4e0ea654452e3 Stored in directory: /root/.cache/pip/wheels/41/4e/10/c2cf2467f71c678cfc8a6b9ac9241e5e44a01940da8fbb17fc Successfully built pyspark Installing collected packages: pyspark Successfully installed pyspark-3.5.0 In [2]: !pip install -U -q PyDrive !apt install openjdk-8-jdk-headless -qq The following additional packages will be installed: libxtst6 openjdk-8-jre-headless Suggested packages: openjdk-8-demo openjdk-8-source libnss-mdns fonts-dejavu-extra fonts-nanum fonts-ipafont-gothic fonts-ipafont-mincho fonts-wqy-microhei fonts-wqy-zenhei fonts-indic The following NEW packages will be installed: libxtst6 openjdk-8-jdk-headless openjdk-8-jre-headless O upgraded, 3 newly installed, O to remove and 9 not upgraded. Need to get 39.7 MB of archives. After this operation, 144 MB of additional disk space will be used. Selecting previously unselected package libxtst6:amd64. (Reading database ... 120880 files and directories currently installed.) Preparing to unpack .../libxtst6\_2%3a1.2.3-1build4\_amd64.deb ... Unpacking libxtst6:amd64 (2:1.2.3-1build4) ... Selecting previously unselected package openjdk-8-jre-headless:amd64. Preparing to unpack .../openjdk-8-jre-headless\_8u382-ga-1~22.04.1\_amd64.deb ... Unpacking openjdk-8-jre-headless:amd64 (8u382-ga-1~22.04.1) ... Selecting previously unselected package openjdk-8-jdk-headless:amd64. Preparing to unpack .../openjdk-8-jdk-headless\_8u382-ga-1~22.04.1\_amd64.deb ... Unpacking openjdk-8-jdk-headless:amd64 (8u382-ga-1~22.04.1) ... Setting up libxtst6:amd64 (2:1.2.3-1build4) ... Setting up openjdk-8-jre-headless:amd64 (8u382-ga-1~22.04.1) ... update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/jre/bin/orbd to provide /usr/bin/orbd (orbd) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/jre/bin/servertool to provide /usr/bin/servertool (servertool) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/jre/bin/tnameserv to provide /usr/bin/tnameserv (tnameserv) in auto mode Setting up openjdk-8-jdk-headless:amd64 (8u382-ga-1~22.04.1) ... update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/clhsdb to provide /usr/bin/clhsdb (clhsdb) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/extcheck to provide /usr/bin/extcheck (extcheck) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/hsdb to provide /usr/bin/hsdb (hsdb) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/idlj to provide /usr/bin/idlj (idlj) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/javah to provide /usr/bin/javah (javah) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/jhat to provide /usr/bin/jhat (jhat) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/jsadebugd to provide /usr/bin/jsadebugd (jsadebugd) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/native2ascii to provide /usr/bin/native2ascii (native2ascii) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/schemagen to provide /usr/bin/schemagen (schemagen) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/wsgen to provide /usr/bin/wsgen (wsgen) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/wsimport to provide /usr/bin/wsimport (wsimport) in auto mode update-alternatives: using /usr/lib/jvm/java-8-openjdk-amd64/bin/xjc to provide /usr/bin/xjc (xjc) in auto mode Processing triggers for libc-bin (2.35-Oubuntu3.4) ... /sbin/ldconfig.real: /usr/local/lib/libtbbbind\_2\_5.so.3 is not a symbolic link /sbin/ldconfig.real: /usr/local/lib/libtbbmalloc.so.2 is not a symbolic link /sbin/ldconfig.real: /usr/local/lib/libtbbmalloc\_proxy.so.2 is not a symbolic link /sbin/ldconfig.real: /usr/local/lib/libtbbbind\_2\_0.so.3 is not a symbolic link /sbin/ldconfig.real: /usr/local/lib/libtbb.so.12 is not a symbolic link /sbin/ldconfig.real: /usr/local/lib/libtbbbind.so.3 is not a symbolic link import os os.environ["JAVA\_HOME"] = "/usr/lib/jvm/java-8-openjdk-amd64" from pyspark import SparkContext In [6]: sc = SparkContext('local', 'My App') **SparkContext** Spark UI Version v3.5.0 Master local **AppName** Му Арр from google.colab import drive drive.mount('/content/drive') Mounted at /content/drive In [8]: import time from pyspark.sql import SparkSession spark = SparkSession.builder.appName("JSON RDD Operations").getOrCreate() In [10]: path = "/content/drive/MyDrive/IDMP Assignment 4 files/Bombing\_Operations.json" # Q1 (Restarted run time before executing each operation) # With RDD operations In [13]: json\_rdd = spark.read.json(path).rdd In [14]: start\_time\_rdd = time.time() grouped\_rdd = json\_rdd.map(lambda x: (x['ContryFlyingMission'], 1)).reduceByKey(lambda a, b: a + b) result = grouped\_rdd.collect() for item in result: print(f"Country: {item[0]}, Count: {item[1]}") end\_time\_rdd = time.time() execution\_time\_rdd = end\_time\_rdd - start\_time\_rdd print(f"RDD Operation Execution Time: {execution\_time\_rdd} seconds") Country: UNITED STATES OF AMERICA, Count: 3708997 Country: AUSTRALIA, Count: 12519 Country: LAOS, Count: 32777 Country: KOREA (SOUTH), Count: 24469 Country: VIETNAM (SOUTH), Count: 622013 RDD Operation Execution Time: 96.90672063827515 seconds # With the DataFrame API In [12]: json\_df = spark.read.json(path) In [13]: json\_df.show() |AirCraft| ContryFlyingMission|MissionDate|OperationSupported|PeriodOfDay|TakeoffLocation|TargetCountry|TimeOnTarget| WeaponType | WeaponsLoadedWeight | EC-47 | UNITED STATES OF ... | 1971-06-05 | DI TAN SON NHUTI CAMBODIA 1005.0| NULL NULL 0 | EC-47|UNITED STATES OF ...| 1972-12-26| NAKHON PHANOM|SOUTH VIETNAM| NULL D 530.0| NULL 0 | RF-4|UNITED STATES OF ...| 1973-07-28| NULL| D | UDORN AB LA0S| 730.0| NULL 0 | NAKHON PHANOM| A-1|UNITED STATES OF ...| 1970-02-02| 1415.0|BLU27 FIRE BOMB (...| NULL| Ν| LA0S| 17400| VIETNAM (SOUTH)| 1970-10-08| DANANG|SOUTH VIETNAM| NULL| D 1240.0| NULL 0 | F-4|UNITED STATES OF ...| 1970-11-25| 650.0|MK 82 GP BOMB (50...| NULL| D UBON AB LA0S| 31860| A-4|UNITED STATES OF ...| 1972-03-08| NULL| D | TONKIN GULF LA0S| 1005.0 NULL 0 | F-4|UNITED STATES OF ... | 1971-12-27| NULL| NULL UDORN AB LA0S| NULL| 0.0 0 | A-7|UNITED STATES OF ... | 1972-05-24| NULL| NULL TONKIN GULF | NORTH VIETNAM | 0.0| NULL| 0 | EC-47 | UNITED STATES OF ... | 1972-09-12 | NULL| D | TAN SON NHUT | SOUTH VIETNAM | 710.0| NULL| 0 | CH-53|UNITED STATES OF ...| 1974-06-13| NULL| NAKHON PHANOM| N | THAILAND| 1800.0| NULL| 0 | CH-53|UNITED STATES OF ... | 1974-12-19| NULL| D NAKHON PHANOM| THAILAND| 800.0 NULL| 0 | VIETNAM (SOUTH)| 1973-10-24| 0-1| NULL D NHA TRANG|SOUTH VIETNAM| 800.0| NULL 0 | CARGO (TONS)| VIETNAM (SOUTH)| 1974-03-19| NULL| D | PHU CAT | SOUTH VIETNAM | 800.0| 0 | C-7|UNITED STATES OF ...| 1970-05-08| NULL| D TAN SON NHUT | SOUTH VIETNAM | 800.0| NULL 0 | A-6|UNITED STATES OF ... | 1971-05-12| TONKIN GULF 1304.0|CBU24 AN PR/MT (B...| NULL N I LA0S| 33200| EB-66|UNITED STATES OF ...| 1971-12-03| LA0S| 1445.0| NULL| N | KORAT | NULL| 0| LAOS| 1971-12-19| SAVANAKHET | D 230.0 NULL| LA0S| NULL 0 | A-6|UNITED STATES OF ...| 1972-08-18| NULL NULL TONKIN GULF | NORTH VIETNAM | 0.0 NULL 0 | A-7|UNITED STATES OF ...| 1972-10-15| NULL| TONKIN GULF|NORTH VIETNAM| D | 110.0| NULL| 0 | only showing top 20 rows In [14]: start\_time\_df = time.time() json\_df.groupBy(json\_df['ContryFlyingMission']).count().show() end\_time\_df = time.time() execution\_time\_df = end\_time\_df - start\_time\_df print(f"DataFrame API Execution Time: {execution\_time\_df} seconds") +----+ ContryFlyingMission| count| +----+ VIETNAM (SOUTH) | 622013 | KOREA (SOUTH)| 24469| |UNITED STATES OF ...|3708997| AUSTRALIA| 12519| LAOS| 32777| DataFrame API Execution Time: 22.407304048538208 seconds In [12]: # using Spark SQL In [13]: json\_df = spark.read.json(path) json\_df.createOrReplaceTempView('operations') In [14]: query = "select ContryFlyingMission, COUNT(\*) from operations group by ContryFlyingMission" In [15]: start\_time\_sql = time.time() sql\_df = spark.sql(query) sql\_df.show() end\_time\_sql = time.time() execution\_time\_sql = end\_time\_sql - start\_time\_sql print(f"Spark SQL Execution Time: {execution\_time\_sql} seconds") | ContryFlyingMission|count(1)| +----+ VIETNAM (SOUTH) | 622013| KOREA (SOUTH)| 24469| |UNITED STATES OF ...| 3708997| AUSTRALIA| 12519| LAOS| 32777| Spark SQL Execution Time: 20.657620668411255 seconds In [17]: # Hence, Spark SQL method was the most efficient as it took least amount of time to execute (20.65s) compared to # DataFrame API (22.40s) and RDD operations (96.90s) # Q2 Plot a bar chart with the number of missions by country. In [26]: from pyspark.sql.functions import col from pyspark.sql.functions import count In [33]: import pandas as pd import matplotlib.pyplot as plt In [34]: %matplotlib inline In [22]: # Read JSON File into DataFrame json\_df = spark.read.json(path) missions\_by\_country = json\_df.groupBy(json\_df['ContryFlyingMission']).count() In [31]: missions\_by\_country.show() +----+ | ContryFlyingMission| count| VIETNAM (SOUTH)| 622013| KOREA (SOUTH)| 24469| |UNITED STATES OF ...|3708997| AUSTRALIA| 12519| LAOS| 32777| +----+ In [37]: # Convert Spark DataFrame to Pandas DataFrame missions\_pd = missions\_by\_country.toPandas() In [45]: # Plotting plt.figure(figsize=(10, 4)) plt.bar(missions\_pd['ContryFlyingMission'], missions\_pd['count']) plt.xlabel('Country') plt.ylabel('Number of Missions') plt.title('Number of Missions by Country') plt.tight\_layout() plt.show() Number of Missions by Country 1e6 3.5 3.0 Missions 2.5 2.0 Number of 1.5 1.0 0.5 0.0 **AUSTRALIA** LAOS KOREA (SOUTH) UNITED STATES OF AMERICA VIETNAM (SOUTH) Country In [46]: # Q3 Plot the number of missions per day for each of the countries involved. In [53]: missions\_per\_day = json\_df.groupBy(json\_df['ContryFlyingMission'], json\_df['MissionDate']).count() In [54]: missions\_per\_day.show() | ContryFlyingMission|MissionDate|count| +----+ |UNITED STATES OF ...| 1970-04-08| 1983| |UNITED STATES OF ...| 1973-02-01| VIETNAM (SOUTH) | 1971-09-10| |UNITED STATES OF ...| 1973-08-01| 559| |UNITED STATES OF ...| 1970-12-09| 1259| |UNITED STATES OF ...| 1970-11-11| AUSTRALIA| 1970-07-23| 26 |UNITED STATES OF ...| 1971-03-18| 1342 |UNITED STATES OF ...| 1974-05-20| VIETNAM (SOUTH) | 1973-05-02| 189| VIETNAM (SOUTH) | 1972-10-30 | 486| KOREA (SOUTH) | 1973-11-22 | 26| |UNITED STATES OF ...| 1970-01-04| 1730| VIETNAM (SOUTH) | 1971-09-24 | 345 VIETNAM (SOUTH) | 1972-03-07| 408| VIETNAM (SOUTH)| 1970-05-05| 216 VIETNAM (SOUTH)| 1972-07-15| 429| LAOS| 1971-01-09| 23| AUSTRALIA| 1971-03-17| AUSTRALIA| 1970-04-21| 24| only showing top 20 rows In [55]: missions\_pd = missions\_per\_day.toPandas() In [58]: countries = missions\_pd['ContryFlyingMission'].unique() for country in countries: country\_data = missions\_pd[missions\_pd['ContryFlyingMission'] == country] plt.figure(figsize=(10, 6)) plt.bar(country\_data['MissionDate'], country\_data['count'], label=country) plt.xlabel('Date') plt.ylabel('Number of Missions') plt.title(f'Number of Missions per Day for {country}') plt.legend() plt.show() Number of Missions per Day for UNITED STATES OF AMERICA 4000 UNITED STATES OF AMERICA 3500 3000 Number of Missions 2500 2000 1500 1000 500 1967 1970 1971 1972 1973 1966 1968 1969 1974 1975 Date Number of Missions per Day for VIETNAM (SOUTH) VIETNAM (SOUTH) 600 500 Number of Missions 200 100 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 Date Number of Missions per Day for AUSTRALIA **AUSTRALIA** 40 35 30 Number of Missions 15 10 5 1970-04 1970-07 1971-07 1971-10 1970-01 1970-10 1971-01 1971-04 Date Number of Missions per Day for KOREA (SOUTH) 60 KOREA (SOUTH) 50 Number of Missions 20 10 1973-10 1973-04 1974-04 1974-07 1974-10 1975-01 1975-04 1973-07 1974-01 Date Number of Missions per Day for LAOS LAOS 100 80 of Missions 60 Number 40 20 1973-01 1970-01 1970-07 1971-01 1971-07 1972-01 1972-07 1973-07 1974-01 Date # Q4 How many takeoffs were launched to attack North Vietnam on 29 June 1966 from each location? In [61]: json\_df = spark.read.json(path) json\_df.createOrReplaceTempView('operations') In [64]: query = """select TakeoffLocation, count(\*) from operations where MissionDate = '1966-06-29' and TargetCountry = 'NORTH VIETNAM' group by TakeoffLocation In [65]: sql\_df = spark.sql(query) sql\_df.show() +----+ | TakeoffLocation|count(1)| TAN SON NHUT| DANANG | 35| UDORN AB 44| |HANCOCK (CVA-19)| 10| CONSTELLATION| 87| TAKHLI| 56| RANGER | 35| KORAT| 55| UBON AB 44| CUBI PT 1| 2| CAM RANH BAY In [66]: # Q5 Which campaigns saw the heaviest bombings? (the names of the campaigns are stored in OperationSupported). In [84]: query = """select OperationSupported, count(\*) as freq from operations WHERE OperationSupported IS NOT NULL group by OperationSupported order by freq DESC LIMIT 1 In [85]: sql\_df = spark.sql(query) sql\_df.show() |OperationSupported| freq| IN COUNTRY | 546215 | # Q6 Which month saw the highest number of missions? from pyspark.sql.functions import month In [91]: #missions\_per\_day = json\_df.groupBy(json\_df['ContryFlyingMission'], json\_df['MissionDate']).count() json\_df.printSchema() root |-- AirCraft: string (nullable = true) |-- ContryFlyingMission: string (nullable = true) |-- MissionDate: string (nullable = true) |-- OperationSupported: string (nullable = true) |-- PeriodOfDay: string (nullable = true) |-- TakeoffLocation: string (nullable = true) |-- TargetCountry: string (nullable = true) |-- TimeOnTarget: double (nullable = true) |-- WeaponType: string (nullable = true) |-- WeaponsLoadedWeight: long (nullable = true) In [92]: json\_df = json\_df.withColumn("MissionDate", col("MissionDate").cast("date")) json\_df = json\_df.withColumn("Month", month("MissionDate")) In [103.. json\_df.groupBy(json\_df['Month']).count().orderBy("count", ascending=False).head() Row(Month=5, count=457431) Out[103.. In [104.. # Q7 What was the most used aircraft type during the war (in terms of number of missions)? In [107.. path\_aircraft = '/content/drive/MyDrive/IDMP Assignment 4 files/Aircraft\_Glossary.json' aircraft\_df = spark.read.json(path\_aircraft) aircraft\_df.createOrReplaceTempView('aircrafts') In [125.. query = """ select AirCraftType, count(MissionDate) as freq from operations o join aircrafts a on o.Aircraft = a.Aircraft group by AirCraftType order by freq desc limit 1 In [126.. sql\_df = spark.sql(query) sql\_df.show() +----+ AirCraftType| freq| +----+ |Fighter Jet Bomber|1073126| +----+