graph_analysis

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1 Graph Analysis dengan PySpark GraphFrames

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1.1 Tugas 4: Graph Analysis - Flight Network

Konteks Tugas: - Menggunakan PySpark GraphFrames untuk analisis graph - Dataset: Flights dan Airports data - Analisis network penerbangan dan delay patterns - Visualisasi dengan Bokeh, NetworkX, dan Neo4j

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1.1.1 Notebook Contents:

1. Introduction to GraphFrames
2. Setup & Import Libraries
3. Data Capture
4. Graph Construction
5. Graph Analysis & Queries
6. Graph Algorithms
7. Visualization
8. Conclusion

1.2 1. Introduction to GraphFrames

1.2.1 Apa itu GraphFrames?

GraphFrames adalah package Python untuk graph processing di Apache Spark. GraphFrames menyediakan API tingkat tinggi untuk graph analysis dan memanfaatkan kekuatan Spark DataFrames.

1.2.2 Komponen Graph:

- **Vertices (Nodes)**: Entitas dalam graph (dalam kasus ini: Airports)
- **Edges**: Koneksi antar vertices (dalam kasus ini: Flight routes)

1.2.3 Use Case:

Analisis network penerbangan untuk memahami: - Bandara tersibuk - Pola delay penerbangan - Hub airports dan connectivity - Optimal routes dan shortest paths

1.3 2. Setup & Import Libraries

[1]:

```python
# Import libraries
from pyspark.sql import SparkSession
from pyspark.sql.types import *
# Import specific functions to avoid conflicts with Python built-ins
from pyspark.sql.functions import (
    col, avg, count, sqrt, sum as spark_sum, lit, desc, row_number,
    when, length, concat, desc, asc, size, isnan
)
import pandas as pd
import numpy as np

# Visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
import networkx as nx
from bokeh.io import output_file, show
from bokeh.models import (
    GMapPlot, GMapOptions, ColumnDataSource, Circle, Line,
    Range1d, PanTool, WheelZoomTool, BoxSelectTool
)
import folium

# Neo4j connection (optional)
try:
    from py2neo import Graph, Node, Relationship
    NEO4J_AVAILABLE = True
except:
    NEO4J_AVAILABLE = False
    print("Neo4j library not available, skipping Neo4j visualizations")

# Warnings
import warnings
warnings.filterwarnings('ignore')

# Set matplotlib style
plt.style.use('seaborn-v0_8-darkgrid')
```

```python
sns.set_palette("husl")

print("Libraries imported successfully!")
```

```
Libraries imported successfully!
```

[2]:

```python
# Initialize SparkSession with GraphFrames support
# GraphFrames 0.10.0 supports Spark 4.x!
spark = SparkSession.builder \
    .appName("FlightNetworkGraphAnalysis") \
    .config("spark.driver.memory", "4g") \
    .config("spark.sql.shuffle.partitions", "8") \
    .config("spark.jars.packages", "io.graphframes:graphframes-spark4_2.13:0.10.
 ↪0") \
    .getOrCreate()

# Set log level
spark.sparkContext.setLogLevel("WARN")

print(f"Spark Version: {spark.version}")
print(f"Spark Session: {spark}")

# Import GraphFrames
from graphframes import GraphFrame
print("  GraphFrames 0.10.0 imported successfully!")
```

```
WARNING: Using incubator modules: jdk.incubator.vector
:: loading settings :: url = jar:file:/Users/riskihajar/projects/kuliah/dl-
tugas-2/venv/lib/python3.12/site-packages/pyspark/jars/ivy-
2.5.3.jar!/org/apache/ivy/core/settings/ivysettings.xml
Ivy Default Cache set to: /Users/riskihajar/.ivy2.5.2/cache
The jars for the packages stored in: /Users/riskihajar/.ivy2.5.2/jars
io.graphframes#graphframes-spark4_2.13 added as a dependency
:: resolving dependencies :: org.apache.spark#spark-submit-
parent-1c66a14f-15c5-4720-a1e1-6843dceeab4c;1.0
        confs: [default]
        found io.graphframes#graphframes-spark4_2.13;0.10.0 in central
        found io.graphframes#graphframes-graphx-spark4_2.13;0.10.0 in central
:: resolution report :: resolve 54ms :: artifacts dl 2ms
        :: modules in use:
        io.graphframes#graphframes-graphx-spark4_2.13;0.10.0 from central in
[default]
        io.graphframes#graphframes-spark4_2.13;0.10.0 from central in [default]
        ---------------------------------------------------------------------
        |                  |            modules            ||   artifacts   |
        |       conf       | number| search|dwnlded|evicted|| number|dwnlded|
        ---------------------------------------------------------------------
        |      default     |   2   |   0   |   0   |   0   ||   2   |   0   |
```

```
        ---------------------------------------------------------------------
:: retrieving :: org.apache.spark#spark-submit-
parent-1c66a14f-15c5-4720-a1e1-6843dceeab4c
        confs: [default]
        0 artifacts copied, 2 already retrieved (0kB/2ms)
26/01/22 21:26:24 WARN NativeCodeLoader: Unable to load native-hadoop library
for your platform… using builtin-java classes where applicable
Using Spark's default log4j profile: org/apache/spark/log4j2-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use
setLogLevel(newLevel).
```

```
Spark Version: 4.1.1
Spark Session: <pyspark.sql.session.SparkSession object at 0x130d57da0>
 GraphFrames 0.10.0 imported successfully!
```

1.4 3. Data Capture

1.4.1 Dataset Description:

1. **airports.dat** - OpenFlights airport database
    - Contains: Airport ID, Name, City, Country, IATA/ICAO codes, Latitude, Longitude, etc.
2. **flights.csv** - Flight performance data from Bureau of Transportation Statistics
    - Contains: Flight schedule, delays, origin/destination, dates, etc.

[3]:
```python
# Define file paths
tripdelaysFilePath = "../data/flights/flights.csv"
airportsnaFilePath = "../data/flights/airports.dat"

print("Data file paths defined")
```

```
Data file paths defined
```

1.4.2 3.1 Load Airports Data

[4]:
```python
# Define schema for airports data
# Format: AirportID, Name, City, Country, IATA, ICAO, Latitude, Longitude,
#         Altitude, Timezone, DST, Tz_database_time_zone, Type, Source
schemaString = "AirportID Name City Country IATA ICAO Latitude Longitude␣
 ↪Altitude Timezone DST Tz_database_time_zone Type Source"
fields = [StructField(field_name, StringType(), True) for field_name in␣
 ↪schemaString.split()]
airport_schema = StructType(fields)

# Load airports dataset
airportsna = spark.read.csv(
    airportsnaFilePath,
    header=False,
```

```
    schema=airport_schema,
    sep=',',
    quote='"',
    escape='"'
)

# Create temp view for SQL queries
airportsna.createOrReplaceTempView("airports_na")

print(f"Airports loaded: {airportsna.count()} records")
airportsna.show(5)
```

```
Airports loaded: 7698 records
+---------+--------------------+-----------+----------------+----+----+--------
----------+------------------+--------+--------+---+---------------------+------
-+------------+
|AirportID|                Name|       City|         Country|IATA|ICAO|
Latitude|         Longitude|Altitude|Timezone|DST|Tz_database_time_zone|   Type|
Source|
+---------+--------------------+-----------+----------------+----+----+--------
----------+------------------+--------+--------+---+---------------------+------
-+------------+
|        1|      Goroka Airport|     Goroka|Papua New Guinea|
GKA|AYGA|-6.081689834590001|     145.391998291|    5282|      10|  U|
Pacific/Port_Moresby|airport|OurAirports|
|        2|      Madang Airport|     Madang|Papua New Guinea| MAG|AYMD|
-5.20707988739|     145.789001465|      20|      10|  U|
Pacific/Port_Moresby|airport|OurAirports|
|        3|Mount Hagen Kagam…| Mount Hagen|Papua New Guinea|
HGU|AYMH|-5.826789855957031|144.29600524902344|    5388|      10|  U|
Pacific/Port_Moresby|airport|OurAirports|
|        4|      Nadzab Airport|     Nadzab|Papua New Guinea| LAE|AYNZ|
-6.569803|        146.725977|     239|      10|  U|
Pacific/Port_Moresby|airport|OurAirports|
|        5|Port Moresby Jack…|Port Moresby|Papua New Guinea|
POM|AYPY|-9.443380355834961|147.22000122070312|     146|      10|  U|
Pacific/Port_Moresby|airport|OurAirports|
+---------+--------------------+-----------+----------------+----+----+--------
----------+------------------+--------+--------+---+---------------------+------
-+------------+
only showing top 5 rows
```

[5]:
```
# Filter USA airports and convert to Pandas for visualization
airportna_df = airportsna.toPandas()
airportna_usa_df = airportna_df[airportna_df['Country'] == 'United States']
airportna_usa_df[['Latitude','Longitude']] =␣
 ↪airportna_usa_df[['Latitude','Longitude']].apply(pd.to_numeric)
```

```python
print(f"USA Airports: {len(airportna_usa_df)} records")
print(f"\nSample USA airports:")
airportna_usa_df[['IATA', 'Name', 'City', 'Latitude', 'Longitude']].head()
```

```
USA Airports: 1512 records

Sample USA airports:
```

[5]:

	IATA	Name	City	Latitude	Longitude
3212	BTI	Barter Island LRRS Airport	Barter Island	70.134003	-143.582001
3213	\N	Wainwright Air Station	Fort Wainwright	70.613403	-159.860001
3214	LUR	Cape Lisburne LRRS Airport	Cape Lisburne	68.875099	-166.110001
3215	PIZ	Point Lay LRRS Airport	Point Lay	69.732903	-163.005005
3216	ITO	Hilo International Airport	Hilo	19.721399	-155.048004

1.4.3 3.2 Load Flights Data

[6]:
```python
# Load departure delays data
departureDelays_raw = spark.read.csv(
    tripdelaysFilePath,
    header=True,
    inferSchema=True
)

departureDelays_raw.createOrReplaceTempView("departureDelays_raw")

print(f"Flights loaded: {departureDelays_raw.count()} records")
print(f"\nSchema:")
departureDelays_raw.printSchema()
```

```
Flights loaded: 274964 records

Schema:
root
 |-- YEAR: integer (nullable = true)
 |-- MONTH: integer (nullable = true)
 |-- DAY: integer (nullable = true)
 |-- DAY_OF_WEEK: integer (nullable = true)
 |-- AIRLINE: string (nullable = true)
 |-- FLIGHT_NUMBER: integer (nullable = true)
 |-- TAIL_NUMBER: string (nullable = true)
 |-- ORIGIN_AIRPORT: string (nullable = true)
 |-- DESTINATION_AIRPORT: string (nullable = true)
 |-- SCHEDULED_DEPARTURE: integer (nullable = true)
 |-- DEPARTURE_TIME: integer (nullable = true)
 |-- DEPARTURE_DELAY: integer (nullable = true)
 |-- TAXI_OUT: integer (nullable = true)
```

```
 |-- WHEELS_OFF: integer (nullable = true)
 |-- SCHEDULED_TIME: integer (nullable = true)
 |-- ELAPSED_TIME: integer (nullable = true)
 |-- AIR_TIME: integer (nullable = true)
 |-- DISTANCE: integer (nullable = true)
 |-- WHEELS_ON: integer (nullable = true)
 |-- TAXI_IN: integer (nullable = true)
 |-- SCHEDULED_ARRIVAL: integer (nullable = true)
 |-- ARRIVAL_TIME: integer (nullable = true)
 |-- ARRIVAL_DELAY: integer (nullable = true)
 |-- DIVERTED: integer (nullable = true)
 |-- CANCELLED: integer (nullable = true)
 |-- CANCELLATION_REASON: string (nullable = true)
 |-- AIR_SYSTEM_DELAY: integer (nullable = true)
 |-- SECURITY_DELAY: integer (nullable = true)
 |-- AIRLINE_DELAY: integer (nullable = true)
 |-- LATE_AIRCRAFT_DELAY: integer (nullable = true)
 |-- WEATHER_DELAY: integer (nullable = true)

26/01/22 21:26:28 WARN SparkStringUtils: Truncated the string representation of
a plan since it was too large. This behavior can be adjusted by setting
'spark.sql.debug.maxToStringFields'.
```

[7]:
```python
# Show sample flights data
departureDelays_raw.show(5)
```

```
+----+-----+---+-----------+-------+-------------+-----------+--------------+---
----------------+-------------------+--------------+---------------+--------+---
-------+--------------+------------+--------+--------+---------+-------+--------
---------+------------+-------------+--------+---------+-------------------+----
------------+--------------+-------------+-------------------+-------------+
|YEAR|MONTH|DAY|DAY_OF_WEEK|AIRLINE|FLIGHT_NUMBER|TAIL_NUMBER|ORIGIN_AIRPORT|DES
TINATION_AIRPORT|SCHEDULED_DEPARTURE|DEPARTURE_TIME|DEPARTURE_DELAY|TAXI_OUT|WHE
ELS_OFF|SCHEDULED_TIME|ELAPSED_TIME|AIR_TIME|DISTANCE|WHEELS_ON|TAXI_IN|SCHEDULE
D_ARRIVAL|ARRIVAL_TIME|ARRIVAL_DELAY|DIVERTED|CANCELLED|CANCELLATION_REASON|AIR_
SYSTEM_DELAY|SECURITY_DELAY|AIRLINE_DELAY|LATE_AIRCRAFT_DELAY|WEATHER_DELAY|
+----+-----+---+-----------+-------+-------------+-----------+--------------+---
----------------+-------------------+--------------+---------------+--------+---
-------+--------------+------------+--------+--------+---------+-------+--------
---------+------------+-------------+--------+---------+-------------------+----
------------+--------------+-------------+-------------------+-------------+
|2015|   11| 28|          6|     DL|         1590|     N971AT|           CAE|
ATL|                700|           655|             -5|      17|       712|
68|          61|      39|     192|      751|      5|              808|
756|           -12|       0|        0|               NULL|              NULL|
NULL|          NULL|                NULL|          NULL|
|2015|   11|  2|          1|     AA|         2516|     N3CVAA|           ORD|
DEN|               1715|          1743|             28|      40|      1823|
```

```
164|          177|      126|      888|      1929|      11|               1859|
1940|            41|        0|         0|                NULL|                13|
0|            28|                    0|             0|
|2015|     8| 22|            6|      AS|             93|      N317AS|            SEA|
ANC|                 1355|           1353|                 -2|       20|       1413|
220|          206|      182|     1448|      1615|       4|               1635|
1619|            -16|        0|         0|                NULL|              NULL|
NULL|          NULL|                NULL|          NULL|
|2015|    11|  9|            1|      AA|           2383|      N871AA|            MCO|
DFW|                  650|            652|                  2|       16|        708|
181|          172|      142|      985|       830|      14|                851|
844|            -7|        0|         0|                NULL|              NULL|
NULL|          NULL|                NULL|          NULL|
|2015|     6| 12|            5|      US|           1978|      N833AW|            CLE|
CLT|                  705|            700|                 -5|       12|        712|
93|           92|       71|     430|       823|       9|               838|
832|            -6|        0|         0|                NULL|              NULL|
NULL|          NULL|                NULL|          NULL|
+----+-----+---+-----------+-------+-------------+-----------+--------------+---
----------------+-------------------+--------------+---------------+--------+---
-------+-------------+------------+--------+--------+---------+-------+--------
---------+------------+-------------+--------+---------+------------------+----
------------+--------------+-------------+-------------------+-------------+
only showing top 5 rows
```

[8]:
```python
# Standardize month and day format (pad with zeros)
# This ensures consistent trip IDs
departureDelays_month = departureDelays_raw.withColumn(
    "Month",
    when(length(col("MONTH")) == 1, concat(lit("0"), col("MONTH"))).
 ↪otherwise(col("MONTH"))
)

departureDelays = departureDelays_month.withColumn(
    "DayofMonth",
    when(length(col("DAY")) == 1, concat(lit("0"), col("DAY"))).
 ↪otherwise(col("DAY"))
)

# Rename columns for consistency
departureDelays = departureDelays.select(
    col("YEAR").alias("year"),
    col("Month").alias("month"),
    col("DayofMonth").alias("day"),
    col("DAY_OF_WEEK").alias("dayOfWeek"),
    col("AIRLINE").alias("airline"),
    col("FLIGHT_NUMBER").alias("flightNumber"),
```

```
    col("ORIGIN_AIRPORT").alias("origin"),
    col("DESTINATION_AIRPORT").alias("dest"),
    col("SCHEDULED_DEPARTURE").alias("scheduledDep"),
    col("DEPARTURE_TIME").alias("depTime"),
    col("DEPARTURE_DELAY").alias("depDelay"),
    col("SCHEDULED_ARRIVAL").alias("scheduledArr"),
    col("ARRIVAL_TIME").alias("arrTime"),
    col("ARRIVAL_DELAY").alias("arrDelay"),
    col("DISTANCE").alias("distance")
).filter(
    # Filter out null values and non-IATA codes
    (col("origin").isNotNull()) &
    (col("dest").isNotNull()) &
    (length(col("origin")) == 3) &
    (length(col("dest")) == 3)
)

departureDelays.createOrReplaceTempView("departureDelays")
departureDelays.cache()

print(f"Cleaned flights data: {departureDelays.count()} records")
departureDelays.show(5)
```

```
[Stage 11:========>                                                (1 + 6) / 7]

Cleaned flights data: 274964 records
+----+-----+---+---------+-------+------------+------+----+------------+-------
+--------+------------+-------+--------+--------+
|year|month|day|dayOfWeek|airline|flightNumber|origin|dest|scheduledDep|depTime|
depDelay|scheduledArr|arrTime|arrDelay|distance|
+----+-----+---+---------+-------+------------+------+----+------------+-------
+--------+------------+-------+--------+--------+
|2015|   11| 28|        6|     DL|        1590|   CAE| ATL|         700|    655|
-5|         808|    756|     -12|     192|
|2015|   11|  2|        1|     AA|        2516|   ORD| DEN|        1715|   1743|
28|        1859|   1940|      41|     888|
|2015|    8| 22|        6|     AS|          93|   SEA| ANC|        1355|   1353|
-2|        1635|   1619|     -16|    1448|
|2015|   11|  9|        1|     AA|        2383|   MCO| DFW|         650|    652|
2|         851|    844|      -7|     985|
|2015|    6| 12|        5|     US|        1978|   CLE| CLT|         705|    700|
-5|         838|    832|      -6|     430|
+----+-----+---+---------+-------+------------+------+----+------------+-------
+--------+------------+-------+--------+--------+
only showing top 5 rows
```

1.4.4 3.3 Filter Airports to Match Flights Data

[9]:
```python
# Get unique IATA codes from flights data
tripIATA = spark.sql("""
    SELECT DISTINCT iata FROM (
        SELECT DISTINCT origin AS iata FROM departureDelays
        UNION ALL
        SELECT DISTINCT dest AS iata FROM departureDelays
    ) a
""")

tripIATA.createOrReplaceTempView("tripIATA")

print(f"Unique airports in flights data: {tripIATA.count()}")
```

```
Unique airports in flights data: 321
```

[10]:
```python
# Filter airports to only include those with flight data
airports = spark.sql("""
    SELECT f.IATA, f.Name, f.City, f.Country, f.Latitude, f.Longitude
    FROM airports_na f
    JOIN tripIATA t ON t.IATA = f.IATA
""")

airports.createOrReplaceTempView("airports")
airports.cache()

print(f"Filtered airports: {airports.count()} records")
airports.show(10)
```

```
Filtered airports: 321 records
+----+--------------------+------------+-------------+------------------+-------
-----------+
|IATA|                Name|        City|      Country|          Latitude|
Longitude|
+----+--------------------+------------+-------------+------------------+-------
-----------+
| BOS|General Edward La…|      Boston|United States|       42.36429977|
-71.00520325|
| JFK|John F Kennedy In…|    New York|United States|       40.63980103|
-73.77890015|
| LBB|Lubbock Preston S…|     Lubbock|United States|         33.663601|
-101.822998|
| IAH|George Bush Inter…|     Houston|United
States|29.984399795532227|-95.34140014648438|
| JAX|Jacksonville Inte…|Jacksonville|United States|
30.49410057067871|-81.68789672851562|
| IND|Indianapolis Inte…|Indianapolis|United States|           39.7173|
-86.294403|
```

```
| MEM|Memphis Internati…|     Memphis|United States|
35.04240036010742|-89.97669982910156|
| PDX|Portland Internat…|    Portland|United States|       45.58869934|
-122.5979996|
| SAF|Santa Fe Municipa…|    Santa Fe|United States|      35.617099762|
-106.088996887|
| ISN|Sloulin Field Int…|   Williston|United States|      48.177898407|
-103.641998291|
+----+--------------------+------------+-------------+------------------+-------
-----------+
only showing top 10 rows
```

[11]:
```python
# Create enriched departure delays with airport information
departureDelays_geo = spark.sql("""
    SELECT
        CONCAT(f.year, f.month, f.day, COALESCE(CAST(f.depTime AS STRING),␣
 ↪'0000')) as tripid,
        f.year, f.month, f.day, f.depTime,
        CONCAT(f.year, '-', f.month, '-', f.day) as localdate,
        CAST(f.depDelay AS INT) as delay,
        CAST(f.distance AS INT) as distance,
        f.origin as src,
        f.dest as dst,
        o.City as city_src,
        d.City as city_dst,
        o.Country as country_src,
        d.Country as country_dst
    FROM departureDelays f
    JOIN airports o ON o.IATA = f.origin
    JOIN airports d ON d.IATA = f.dest
    WHERE f.depDelay IS NOT NULL
""")

departureDelays_geo.createOrReplaceTempView("departureDelays_geo")
departureDelays_geo.cache()

print(f"Enriched flight data: {departureDelays_geo.count()} records")
departureDelays_geo.show(5)
```

```
Enriched flight data: 270719 records
+-----------+----+-----+---+-------+----------+-----+--------+---+---+---------
+-----------------+-------------+-------------+
|     tripid|year|month|day|depTime| localdate|delay|distance|src|dst| city_src|
city_dst|  country_src|  country_dst|
+-----------+----+-----+---+-------+----------+-----+--------+---+---+---------
+-----------------+-------------+-------------+
|20151128655|2015|   11| 28|    655|2015-11-28|   -5|     192|CAE|ATL| Columbia|
Atlanta|United States|United States|
```

```
|20151121743|2015|   11|  2|   1743| 2015-11-2|   28|     888|ORD|DEN|  Chicago|
Denver|United States|United States|
|20158221353|2015|    8| 22|   1353| 2015-8-22|   -2|    1448|SEA|ANC|  Seattle|
Anchorage|United States|United States|
| 2015119652|2015|   11|  9|    652| 2015-11-9|    2|     985|MCO|DFW|
Orlando|Dallas-Fort Worth|United States|United States|
| 2015612700|2015|    6| 12|    700| 2015-6-12|   -5|     430|CLE|CLT|Cleveland|
Charlotte|United States|United States|
+-----------+----+-----+---+-------+----------+-----+--------+---+---+---------
+-----------------+-------------+-------------+
only showing top 5 rows
```

1.5 4. Graph Construction

1.5.1 Create Vertices and Edges for GraphFrame

[12]:
```python
# Create Vertices (airports)
# GraphFrames requires an 'id' column for vertices
tripVertices = airports.withColumnRenamed("IATA", "id").distinct()

print("Vertices (Airports):")
print(f"Count: {tripVertices.count()}")
tripVertices.show(5)
```

```
Vertices (Airports):
Count: 321
+---+--------------------+------------+-------------+------------------+--------
----------+
| id|                Name|        City|      Country|          Latitude|
Longitude|
+---+--------------------+------------+-------------+------------------+--------
----------+
|BOS|General Edward La…|      Boston|United States|       42.36429977|
-71.00520325|
|JFK|John F Kennedy In…|    New York|United States|       40.63980103|
-73.77890015|
|LBB|Lubbock Preston S…|     Lubbock|United States|         33.663601|
-101.822998|
|IAH|George Bush Inter…|     Houston|United
States|29.984399795532227|-95.34140014648438|
|JAX|Jacksonville Inte…|Jacksonville|United States|
30.49410057067871|-81.68789672851562|
+---+--------------------+------------+-------------+------------------+--------
----------+
only showing top 5 rows
```

[13]:
```python
# Create Edges (flights)
# GraphFrames requires 'src' and 'dst' columns for edges
```

```python
tripEdges = departureDelays_geo.select(
    "tripid", "localdate", "delay", "src", "dst",
    "city_src", "city_dst", "distance"
)

print("Edges (Flights):")
print(f"Count: {tripEdges.count()}")
tripEdges.show(5)
```

```
Edges (Flights):
Count: 270719
+-----------+----------+-----+---+---+---------+-----------------+--------+
|     tripid| localdate|delay|src|dst| city_src|         city_dst|distance|
+-----------+----------+-----+---+---+---------+-----------------+--------+
|20151128655|2015-11-28|   -5|CAE|ATL| Columbia|          Atlanta|     192|
|20151121743| 2015-11-2|   28|ORD|DEN|  Chicago|           Denver|     888|
|20158221353| 2015-8-22|   -2|SEA|ANC|  Seattle|        Anchorage|    1448|
| 2015119652| 2015-11-9|    2|MCO|DFW|  Orlando|Dallas-Fort Worth|     985|
| 2015612700| 2015-6-12|   -5|CLE|CLT|Cleveland|        Charlotte|     430|
+-----------+----------+-----+---+---+---------+-----------------+--------+
only showing top 5 rows
```

[14]:

```python
# Cache vertices and edges for performance
tripVertices.cache()
tripEdges.cache()

print("Vertices and Edges cached successfully")
```

```
Vertices and Edges cached successfully
```

[15]:

```python
# Create GraphFrame
tripGraph = GraphFrame(tripVertices, tripEdges)

print("GraphFrame created successfully!")
print(f"Graph contains:")
print(f"  - {tripGraph.vertices.count()} airports")
print(f"  - {tripGraph.edges.count()} flights")
```

```
GraphFrame created successfully!
Graph contains:
  - 321 airports
  - 270719 flights
```

1.6 5. Graph Analysis & Queries

1.6.1 5.1 Basic Statistics

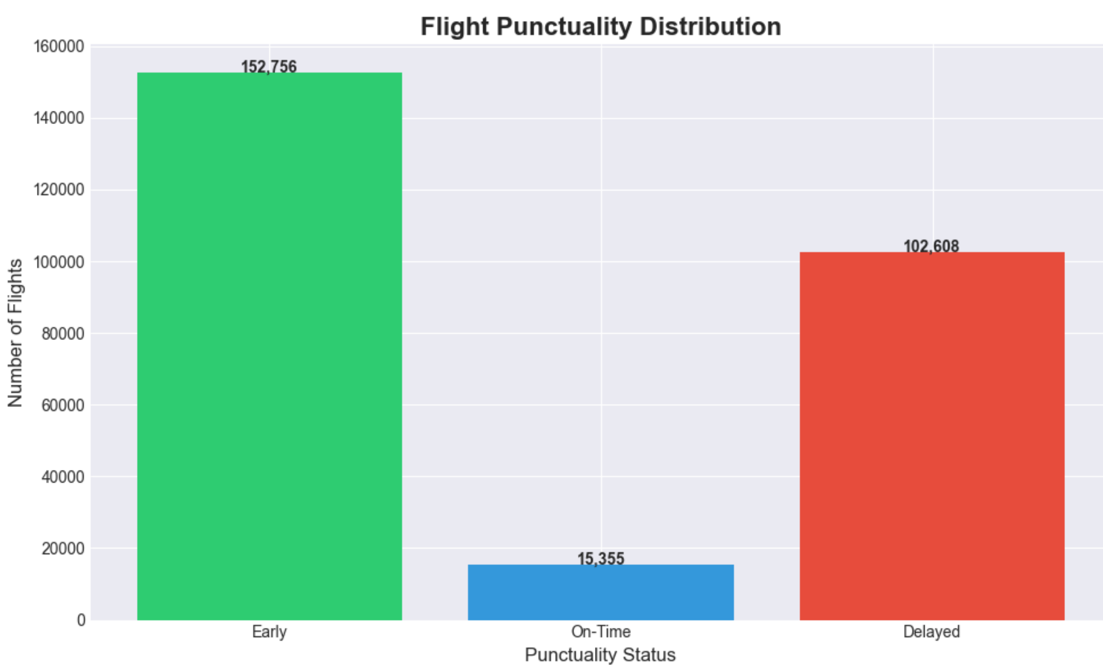
[16]:
```
# Basic graph statistics
print("="*60)
print("GRAPH STATISTICS")
print("="*60)
print(f"Total Airports: {tripGraph.vertices.count()}")
print(f"Total Flights: {tripGraph.edges.count()}")

# Delay statistics
max_delay = tripGraph.edges.groupBy().max("delay").collect()[0][0]
min_delay = tripGraph.edges.groupBy().min("delay").collect()[0][0]
avg_delay = tripGraph.edges.groupBy().avg("delay").collect()[0][0]

print(f"\nDelay Statistics:")
print(f"  Max Delay: {max_delay} minutes")
print(f"  Min Delay: {min_delay} minutes")
print(f"  Avg Delay: {avg_delay:.2f} minutes")

# Flight categories
early_flights = tripGraph.edges.filter("delay < 0").count()
ontime_flights = tripGraph.edges.filter("delay = 0").count()
delayed_flights = tripGraph.edges.filter("delay > 0").count()

print(f"\nFlight Punctuality:")
print(f"  Early Flights: {early_flights:,} ({early_flights/tripGraph.edges.
↪count()*100:.1f}%)")
print(f"  On-Time Flights: {ontime_flights:,} ({ontime_flights/tripGraph.edges.
↪count()*100:.1f}%)")
print(f"  Delayed Flights: {delayed_flights:,} ({delayed_flights/tripGraph.
↪edges.count()*100:.1f}%)")
print("="*60)
```

```
============================================================
GRAPH STATISTICS
============================================================
Total Airports: 321
Total Flights: 270719

Delay Statistics:
  Max Delay: 1461 minutes
  Min Delay: -56 minutes
  Avg Delay: 9.79 minutes

Flight Punctuality:
  Early Flights: 152,756 (56.4%)
```

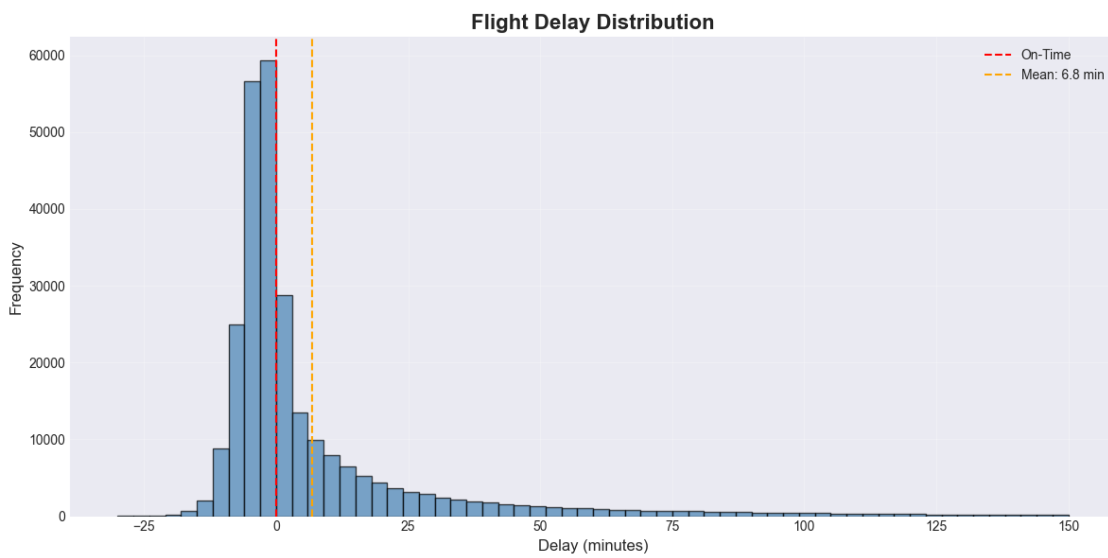
```
  On-Time Flights: 15,355 (5.7%)
  Delayed Flights: 102,608 (37.9%)
============================================================
```

[17]:

```python
# Visualize flight punctuality distribution
punctuality_data = [
    early_flights,
    ontime_flights,
    delayed_flights
]
labels = ['Early', 'On-Time', 'Delayed']
colors = ['#2ecc71', '#3498db', '#e74c3c']

plt.figure(figsize=(10, 6))
bars = plt.bar(labels, punctuality_data, color=colors)
plt.title('Flight Punctuality Distribution', fontsize=16, fontweight='bold')
plt.ylabel('Number of Flights', fontsize=12)
plt.xlabel('Punctuality Status', fontsize=12)

# Add value labels on bars
for bar, val in zip(bars, punctuality_data):
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 100,
             f'{val:,}', ha='center', fontweight='bold')

plt.tight_layout()
plt.show()
```



[18]:
```python
# Delay distribution histogram
delays_pd = tripGraph.edges.select("delay").filter("delay BETWEEN -30 AND 150").
 ↪toPandas()

plt.figure(figsize=(12, 6))
plt.hist(delays_pd['delay'], bins=60, color='steelblue', alpha=0.7,␣
 ↪edgecolor='black')
plt.axvline(x=0, color='red', linestyle='--', label='On-Time')
plt.axvline(x=delays_pd['delay'].mean(), color='orange', linestyle='--',
            label=f'Mean: {delays_pd["delay"].mean():.1f} min')
plt.title('Flight Delay Distribution', fontsize=16, fontweight='bold')
plt.xlabel('Delay (minutes)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```



1.6.2 5.2 Boston Airport Analysis

Let's analyze flights to and from Boston Logan International Airport (BOS)

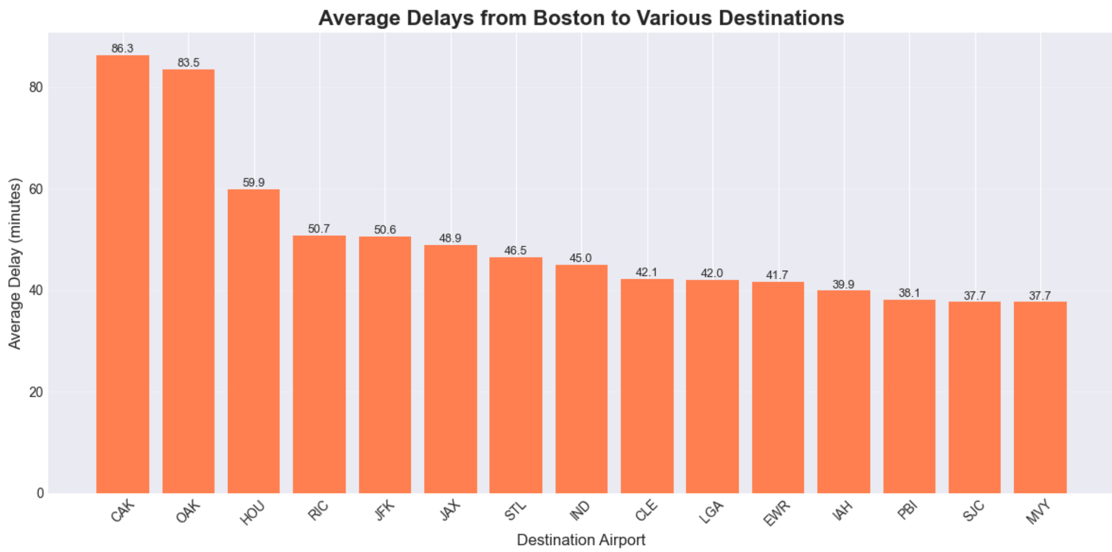
[19]:
```python
# Flights from Boston with delays
boston_outbound = tripGraph.edges \
    .filter("src = 'BOS' and delay > 0") \
    .groupBy("src", "dst", "city_dst") \
    .agg(avg("delay").alias("avg_delay"),
         count("*").alias("flight_count")) \
```

```
    .orderBy(desc("avg_delay"))

print("Top 10 Destinations with Highest Average Delays from Boston:")
boston_outbound.show(10)
```

```
Top 10 Destinations with Highest Average Delays from Boston:
+---+---+------------+------------------+------------+
|src|dst|    city_dst|         avg_delay|flight_count|
+---+---+------------+------------------+------------+
|BOS|CAK|       Akron| 86.33333333333333|           6|
|BOS|OAK|     Oakland|              83.5|           2|
|BOS|HOU|     Houston|59.857142857142854|          14|
|BOS|RIC|    Richmond| 50.72093023255814|          43|
|BOS|JFK|    New York|50.554054054054056|          74|
|BOS|JAX|Jacksonville| 48.92307692307692|          13|
|BOS|STL|   St. Louis|46.523809523809526|          21|
|BOS|IND|Indianapolis|              45.0|           4|
|BOS|CLE|   Cleveland|42.142857142857146|          28|
|BOS|LGA|    New York| 41.97802197802198|          91|
+---+---+------------+------------------+------------+
only showing top 10 rows
```

[20]:

```
# Visualize Boston delays
boston_pd = boston_outbound.limit(15).toPandas()

plt.figure(figsize=(12, 6))
bars = plt.bar(range(len(boston_pd)), boston_pd['avg_delay'], color='coral')
plt.xticks(range(len(boston_pd)), boston_pd['dst'], rotation=45)
plt.title('Average Delays from Boston to Various Destinations', fontsize=16,␣
 ↪fontweight='bold')
plt.xlabel('Destination Airport', fontsize=12)
plt.ylabel('Average Delay (minutes)', fontsize=12)
plt.grid(True, alpha=0.3, axis='y')

# Add value labels
for i, (bar, val) in enumerate(zip(bars, boston_pd['avg_delay'])):
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.5,
             f'{val:.1f}', ha='center', fontsize=9)

plt.tight_layout()
plt.show()
```



[21]:
```python
# Flights TO Boston with significant delays
print("Flights arriving to Boston with delays > 100 minutes:")
tripGraph.edges \
    .filter("dst = 'BOS' and delay > 100") \
    .select("src", "city_src", "delay", "localdate") \
    .orderBy(desc("delay")) \
    .show(10)
```

```
Flights arriving to Boston with delays > 100 minutes:
+---+-----------------+-----+----------+
|src|         city_src|delay| localdate|
+---+-----------------+-----+----------+
|DFW|Dallas-Fort Worth|  658| 2015-5-28|
|EWR|           Newark|  449| 2015-5-31|
|MYR|     Myrtle Beach|  394|2015-12-15|
|DCA|       Washington|  385| 2015-8-15|
|CLE|        Cleveland|  352|  2015-9-6|
|PHL|     Philadelphia|  352| 2015-8-18|
|SFO|    San Francisco|  327|2015-11-20|
|IAD|       Washington|  318| 2015-9-12|
|LGA|         New York|  315| 2015-2-20|
|EWR|           Newark|  303|2015-11-27|
+---+-----------------+-----+----------+
only showing top 10 rows
```

1.7 6. Graph Algorithms

1.7.1 6.1 Degree Analysis - Finding Busiest Airports

[22]:
```
# Calculate in-degrees (incoming flights)
inDegrees = tripGraph.inDegrees.orderBy(desc("inDegree"))

print("Top 10 Airports by Incoming Flights:")
inDegrees.show(10)
```

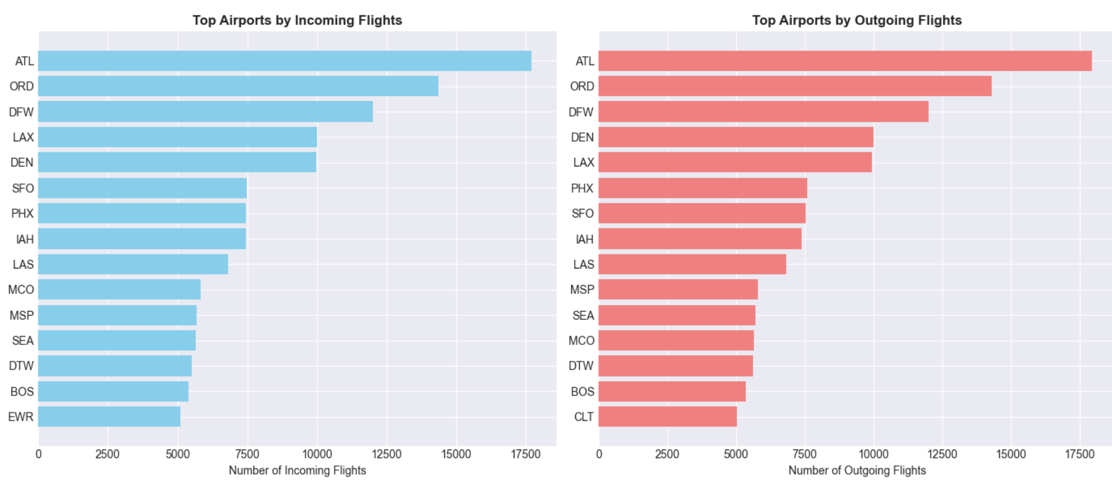
```
Top 10 Airports by Incoming Flights:
+---+--------+
| id|inDegree|
+---+--------+
|ATL|   17704|
|ORD|   14357|
|DFW|   11999|
|LAX|   10013|
|DEN|    9980|
|SFO|    7471|
|PHX|    7443|
|IAH|    7442|
|LAS|    6823|
|MCO|    5821|
+---+--------+
only showing top 10 rows
```

[23]:
```
# Calculate out-degrees (outgoing flights)
outDegrees = tripGraph.outDegrees.orderBy(desc("outDegree"))

print("Top 10 Airports by Outgoing Flights:")
outDegrees.show(10)
```

```
Top 10 Airports by Outgoing Flights:
+---+---------+
| id|outDegree|
+---+---------+
|ATL|    17925|
|ORD|    14297|
|DFW|    11987|
|DEN|    10016|
|LAX|     9934|
|PHX|     7603|
|SFO|     7546|
|IAH|     7386|
|LAS|     6839|
|MSP|     5796|
+---+---------+
only showing top 10 rows
```

[24]:

```
# Visualize busiest airports
in_pd = inDegrees.limit(15).toPandas()
out_pd = outDegrees.limit(15).toPandas()

fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Incoming flights
axes[0].barh(in_pd['id'], in_pd['inDegree'], color='skyblue')
axes[0].set_xlabel('Number of Incoming Flights')
axes[0].set_title('Top Airports by Incoming Flights', fontweight='bold')
axes[0].invert_yaxis()

# Outgoing flights
axes[1].barh(out_pd['id'], out_pd['outDegree'], color='lightcoral')
axes[1].set_xlabel('Number of Outgoing Flights')
axes[1].set_title('Top Airports by Outgoing Flights', fontweight='bold')
axes[1].invert_yaxis()

plt.tight_layout()
plt.show()
```



[25]:

```
# Calculate degree ratio (transfer airports)
# Airports with ratio close to 1 are good transfer hubs
degreeRatio = inDegrees.join(outDegrees, inDegrees.id == outDegrees.id) \
    .drop(outDegrees.id) \
    .selectExpr("id", "double(inDegree)/double(outDegree) as degreeRatio") \
    .filter("degreeRatio BETWEEN 0.9 AND 1.1") \
    .orderBy("degreeRatio")

# Join with airport names using aliases to avoid ambiguity
```

```
degreeRatio_alias = degreeRatio.alias("dr")
airports_alias = airports.alias("ap")

transferAirports = degreeRatio_alias.join(
    airports_alias,
    col("dr.id") == col("ap.IATA")
).select("dr.id", "ap.City", "dr.degreeRatio")

print("Best Transfer Airports (balanced in/out flights):")
transferAirports.show(10)
```

```
Best Transfer Airports (balanced in/out flights):
+---+------------+------------------+
| id|        City|       degreeRatio|
+---+------------+------------------+
|BOS|      Boston|1.0061567164179104|
|JFK|    New York|0.9995840266222962|
|IAH|     Houston| 1.007581911724885|
|JAX|Jacksonville|1.0501089324618735|
|IND|Indianapolis| 1.013719512195122|
|MEM|     Memphis|1.0307692307692307|
|PDX|    Portland|1.0511101801424383|
|ISN|   Williston|0.9632352941176471|
|EYW|    Key West|               1.0|
|GRR|Grand Rapids|0.9482758620689655|
+---+------------+------------------+
only showing top 10 rows
```

1.7.2 6.2 PageRank - Airport Importance

[26]:
```
# Run PageRank algorithm
# PageRank identifies the most "important" airports in the network
print("Running PageRank algorithm...")
ranks = tripGraph.pageRank(resetProbability=0.15, maxIter=5)

# Get top ranked airports
topRanks = ranks.vertices.orderBy(desc("pagerank")).limit(20)

# Join with airport information using aliases to avoid ambiguity
topRanks_alias = topRanks.alias("tr")
airports_alias = airports.alias("ap")

topRanksWithInfo = topRanks_alias.join(
    airports_alias,
    col("tr.id") == col("ap.IATA")
).select("tr.id", "ap.Name", "ap.City", "tr.pagerank")
```

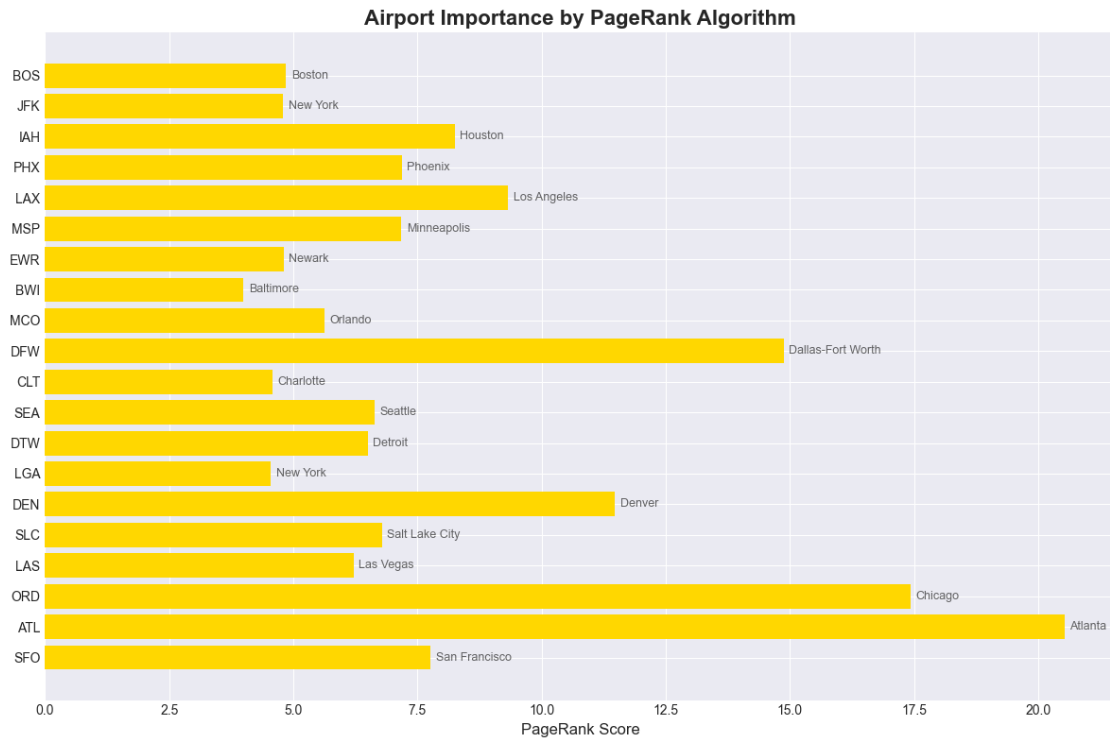
```python
print("\nTop 20 Airports by PageRank (Importance):")
topRanksWithInfo.show(20, truncate=False)
```

```
Running PageRank algorithm…

26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
26/01/22 21:26:35 WARN ShippableVertexPartitionOps: Joining two VertexPartitions
with different indexes is slow.
[Stage 388:=============================================>        (7 + 1) / 8]


Top 20 Airports by PageRank (Importance):
+---+------------------------------------------------------------+--------------
---+------------------+
|id |Name                                                        |City
|pagerank          |
+---+------------------------------------------------------------+--------------
---+------------------+
|BOS|General Edward Lawrence Logan International Airport         |Boston
|4.855102554141863 |
|JFK|John F Kennedy International Airport                        |New York
|4.798831905212273 |
|IAH|George Bush Intercontinental Houston Airport                |Houston
|8.252143204804659 |
|PHX|Phoenix Sky Harbor International Airport                    |Phoenix
|7.191006881789952 |
|LAX|Los Angeles International Airport                           |Los Angeles
|9.32856785629959  |
|MSP|Minneapolis-St Paul International/Wold-Chamberlain Airport  |Minneapolis
|7.177379307517557 |
|EWR|Newark Liberty International Airport                        |Newark
|4.809849978579861 |
|BWI|Baltimore/Washington International Thurgood Marshall Airport|Baltimore
|3.9995561224412794|
|MCO|Orlando International Airport                               |Orlando
|5.627004624009204 |
```

```
|DFW|Dallas Fort Worth International Airport                              |Dallas-Fort
Worth|14.875490638609685|
|CLT|Charlotte Douglas International Airport                              |Charlotte
|4.587253160149601 |
|SEA|Seattle Tacoma International Airport                                 |Seattle
|6.641770976577993 |
|DTW|Detroit Metropolitan Wayne County Airport                            |Detroit
|6.49418600774911  |
|LGA|La Guardia Airport                                                   |New York
|4.551442582351486 |
|DEN|Denver International Airport                                         |Denver
|11.477595979174206|
|SLC|Salt Lake City International Airport                                 |Salt Lake City
|6.780539132202548 |
|LAS|McCarran International Airport                                       |Las Vegas
|6.219676100610142 |
|ORD|Chicago O'Hare International Airport                                 |Chicago
|17.424440712966756|
|ATL|Hartsfield Jackson Atlanta International Airport                     |Atlanta
|20.532502507518693|
|SFO|San Francisco International Airport                                  |San Francisco
|7.767632635219271 |
+---+-------------------------------------------------------------+--------------
---+------------------+

26/01/22 21:26:46 WARN PageRank: Returned DataFrame is persistent and
materialized!
```

[27]:

```
# Visualize PageRank results
pagerank_pd = topRanksWithInfo.toPandas()

plt.figure(figsize=(12, 8))
bars = plt.barh(range(len(pagerank_pd)), pagerank_pd['pagerank'], color='gold')
plt.yticks(range(len(pagerank_pd)), pagerank_pd['id'])
plt.xlabel('PageRank Score', fontsize=12)
plt.title('Airport Importance by PageRank Algorithm', fontsize=16,␣
↪fontweight='bold')
plt.gca().invert_yaxis()

# Add city names as annotations
for i, (bar, city) in enumerate(zip(bars, pagerank_pd['City'])):
    plt.text(bar.get_width() + 0.1, bar.get_y() + bar.get_height()/2,
             f'{city}', va='center', fontsize=9, alpha=0.7)

plt.tight_layout()
plt.show()
```



1.7.3 6.3 Motif Finding - Atlanta Hub Analysis

Find flight patterns where Atlanta (ATL) is a connecting hub

[28]:
```
# Find trips with Atlanta as connecting airport
# Pattern: (a)-[ab]->(b); (b)-[bc]->(c) where b is Atlanta
print("Finding flight patterns through Atlanta...")

atlanta_connections = tripGraph.find("(a)-[ab]->(b); (b)-[bc]->(c)") \
    .filter("""
        (b.id = 'ATL') AND
        (ab.delay > 30 OR bc.delay > 30) AND
        bc.tripid > ab.tripid AND
        bc.tripid < ab.tripid + 10000
    """)

print(f"\nFound {atlanta_connections.count()} delayed connections through␣
↪Atlanta")
print("\nSample delayed connections:")
atlanta_connections.select(
    "a.id", "ab.delay", "b.id", "bc.delay", "c.id"
).show(10)
```

```
Finding flight patterns through Atlanta…
```

```
Found 10957715 delayed connections through Atlanta

Sample delayed connections:
+---+-----+---+-----+---+
| id|delay| id|delay| id|
+---+-----+---+-----+---+
|CAE|   -5|ATL|  134|AEX|
|CAE|   -5|ATL|   96|CLT|
|CAE|   -5|ATL|  178|STL|
|CAE|   -5|ATL|  219|DFW|
|CAE|   -5|ATL|  243|AUS|
|CAE|   -5|ATL|   38|SEA|
|CAE|   -5|ATL|   35|GSP|
|CAE|   -5|ATL|   41|GRR|
|CAE|   -5|ATL|  107|SGF|
|CAE|   -5|ATL|   37|CVG|
+---+-----+---+-----+---+
only showing top 10 rows
```

1.7.4 6.4 Shortest Paths

[29]:

```python
# Find shortest paths from selected airports
# Choose airports with fewer connections for interesting paths
print("Finding shortest paths...")

try:
    # Get airports with moderate connectivity
    moderate_airports = outDegrees.filter("outDegree < 100").limit(3).
 ↪select("id").collect()
    landmarks = [row.id for row in moderate_airports]

    print(f"Computing shortest paths from: {landmarks}")

    if landmarks:
        results = tripGraph.shortestPaths(landmarks=landmarks)
        results.select("id", "distances").filter("size(distances) > 0").
 ↪show(20, truncate=False)
    else:
        print("No suitable landmarks found for shortest paths.")

except Exception as e:
    print(f"  Shortest Paths failed: {str(e)[:200]}...")
    print("This might be due to the graph size or structure.")
    print("Skipping shortest paths analysis.")
```

```
Finding shortest paths…
Computing shortest paths from: ['LCH', 'DRO', 'FCA']
```

```
26/01/22 21:26:51 WARN BlockManager: Block rdd_744_0 already exists on this
machine; not re-adding it
```

```
+---+-----------------------------+
|id |distances                    |
+---+-----------------------------+
|MEM|{LCH -> 2, DRO -> 2, FCA -> 2}|
|PBI|{LCH -> 2, DRO -> 2, FCA -> 2}|
|LNK|{LCH -> 3, DRO -> 2, FCA -> 2}|
|MHK|{LCH -> 2, DRO -> 2, FCA -> 2}|
|ELM|{LCH -> 3, DRO -> 3, FCA -> 2}|
|WRG|{LCH -> 4, DRO -> 4, FCA -> 4}|
|MKG|{LCH -> 3, DRO -> 3, FCA -> 2}|
|ALO|{LCH -> 3, DRO -> 3, FCA -> 2}|
|RIC|{LCH -> 2, DRO -> 2, FCA -> 2}|
|CIU|{LCH -> 3, DRO -> 3, FCA -> 3}|
|BIL|{LCH -> 3, DRO -> 2, FCA -> 2}|
|SBA|{LCH -> 3, DRO -> 2, FCA -> 2}|
|DVL|{LCH -> 3, DRO -> 2, FCA -> 2}|
|STL|{LCH -> 2, DRO -> 2, FCA -> 2}|
|ELP|{LCH -> 2, DRO -> 2, FCA -> 2}|
|LFT|{LCH -> 2, DRO -> 2, FCA -> 2}|
|HSV|{LCH -> 2, DRO -> 2, FCA -> 2}|
|PHL|{LCH -> 2, DRO -> 2, FCA -> 2}|
|PSG|{LCH -> 4, DRO -> 4, FCA -> 4}|
|BET|{LCH -> 3, DRO -> 3, FCA -> 3}|
+---+-----------------------------+
only showing top 20 rows
```

```
26/01/22 21:26:52 WARN ShortestPaths: Returned DataFrame is persistent and
materialized!
```

1.7.5 6.5 Connected Components

[30]:
```python
# Find connected components in the graph
print("Finding connected components...")
try:
    # Set checkpoint directory for connected components
    spark.sparkContext.setCheckpointDir("/tmp/graphframes-checkpoint")

    # Try to run connected components with a smaller checkpoint interval
    cc = tripGraph.connectedComponents(
        algorithm="graphframes",
        checkpointInterval=2,
        broadcastThreshold=1000000
    )
```

```
    # Count components
    component_counts = cc.groupBy("component").count().orderBy(desc("count"))

    print(f"\nNumber of connected components: {component_counts.count()}")
    print("\nTop 5 largest components:")
    component_counts.show(5)

except Exception as e:
    print(f"  Connected Components failed: {str(e)[:200]}...")
    print("This might be due to the large size of the graph.")

    # Alternative: Use strongly connected components which might work better
    try:
        print("\nTrying Strongly Connected Components instead...")
        scc = tripGraph.stronglyConnectedComponents(maxIter=5)
        scc_counts = scc.groupBy("component").count().orderBy(desc("count"))
        print(f"Number of strongly connected components: {scc_counts.count()}")
        print("\nTop 5 largest components:")
        scc_counts.show(5)
    except Exception as e2:
        print(f"Strongly Connected Components also failed: {str(e2)[:100]}")
        print("Moving on...")
```

```
Finding connected components…

Number of connected components: 1

Top 5 largest components:
+---------+-----+
|component|count|
+---------+-----+
|        0|  321|
+---------+-----+


26/01/22 21:26:56 WARN ConnectedComponents$: Returned DataFrame is persistent
and materialized!
```

1.7.6 6.6 Label Propagation - Community Detection

[31]:
```
# Run Label Propagation Algorithm for community detection
print("Running Label Propagation Algorithm...")
try:
    communities = tripGraph.labelPropagation(maxIter=5)

    # Count communities
```

```
    community_counts = communities.groupBy("label").count().
↪orderBy(desc("count"))

    print(f"\nNumber of communities: {community_counts.count()}")
    print("\nTop 10 largest communities:")
    community_counts.show(10)

except Exception as e:
    print(f" Label Propagation failed: {str(e)[:200]}...")
    print("This algorithm might not work well with large graphs.")
    print("Consider using a smaller subset of data or skip this analysis.")
```

```
26/01/22 21:26:56 WARN BlockManager: Block rdd_1182_1 already exists on this
machine; not re-adding it
```

```
Running Label Propagation Algorithm…
```

```
26/01/22 21:26:57 WARN BlockManager: Block rdd_1216_1 already exists on this
machine; not re-adding it
```

```

Number of communities: 4

Top 10 largest communities:
+-----------+-----+
|      label|count|
+-----------+-----+
|51539607554|  277|
| 8589934614|   37|
|17179869198|    6|
|17179869210|    1|
+-----------+-----+

```

```
26/01/22 21:26:58 WARN LabelPropagation: Returned DataFrame is persistent and
materialized!
```

1.8 7. Visualization

1.8.1 7.1 Geographic Visualization with Folium

[32]:
```
# Create interactive map with Folium
# Center map on USA
m = folium.Map(location=[39.8283, -98.5795], zoom_start=4)

# Add airports as markers
airports_for_map = airports.limit(100).toPandas()
airports_for_map[['Latitude', 'Longitude']] = airports_for_map[['Latitude',␣
↪'Longitude']].apply(pd.to_numeric, errors='coerce')
airports_for_map = airports_for_map.dropna(subset=['Latitude', 'Longitude'])
```

```python
for idx, row in airports_for_map.iterrows():
    folium.CircleMarker(
        location=[row['Latitude'], row['Longitude']],
        radius=3,
        popup=f"{row['IATA']}: {row['Name']}",
        tooltip=f"{row['IATA']}: {row['City']}",
        color='blue',
        fill=True,
        fillColor='lightblue'
    ).add_to(m)

# Save map
m.save('airports_map.html')
print("Interactive map saved as 'airports_map.html'")

# Display in notebook (if supported)
m
```

```
Interactive map saved as 'airports_map.html'
```

[32]:

```
<folium.folium.Map at 0x131d6e5d0>
```

1.8.2 7.2 Network Visualization with NetworkX

[33]:

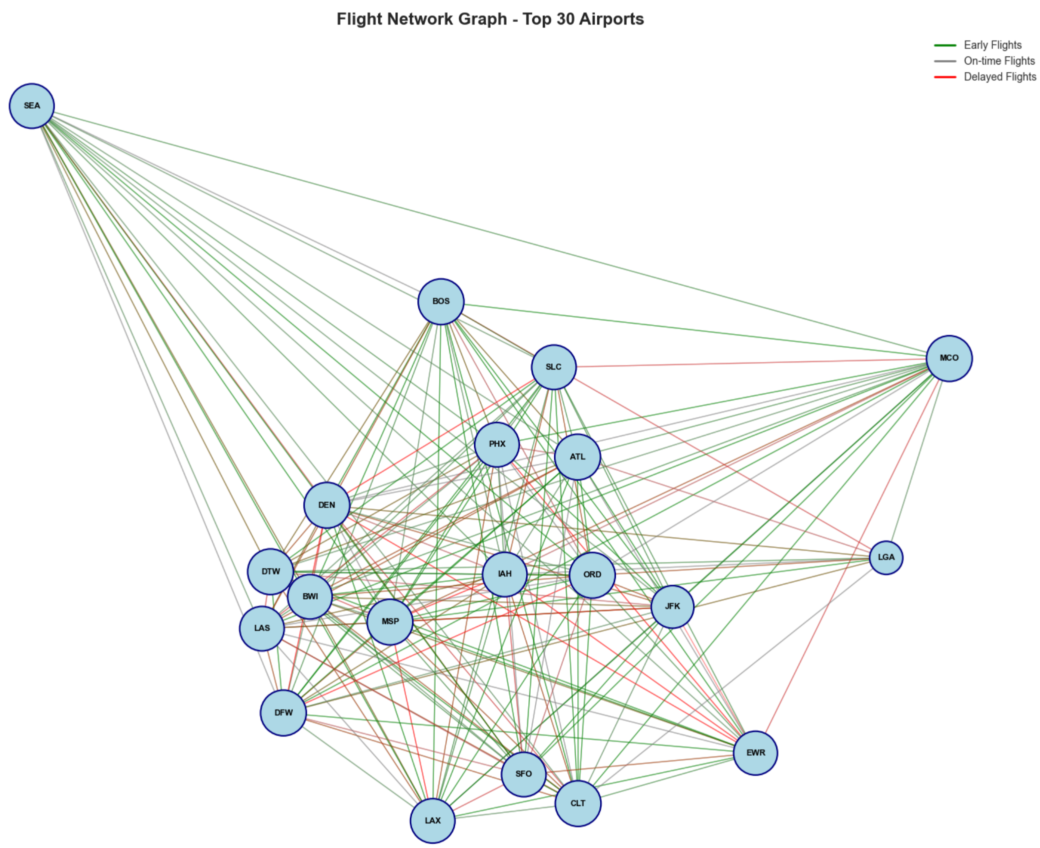
```python
# Create NetworkX graph for a subset of data (top airports)
# Full graph would be too large to visualize effectively

# Get top 30 airports by PageRank
top_airports = topRanksWithInfo.limit(30).select("id").toPandas()['id'].tolist()

# Filter edges for these airports
subset_edges = tripGraph.edges.filter(
    (col("src").isin(top_airports)) &
    (col("dst").isin(top_airports))
).select("src", "dst", "delay").toPandas()

print(f"Creating network graph with {len(top_airports)} airports")
print(f"and {len(subset_edges)} connections")
```

```
Creating network graph with 20 airports
and 65688 connections
```

[34]:

```python
# Create NetworkX graph
G = nx.DiGraph()

# Add nodes
G.add_nodes_from(top_airports)
```

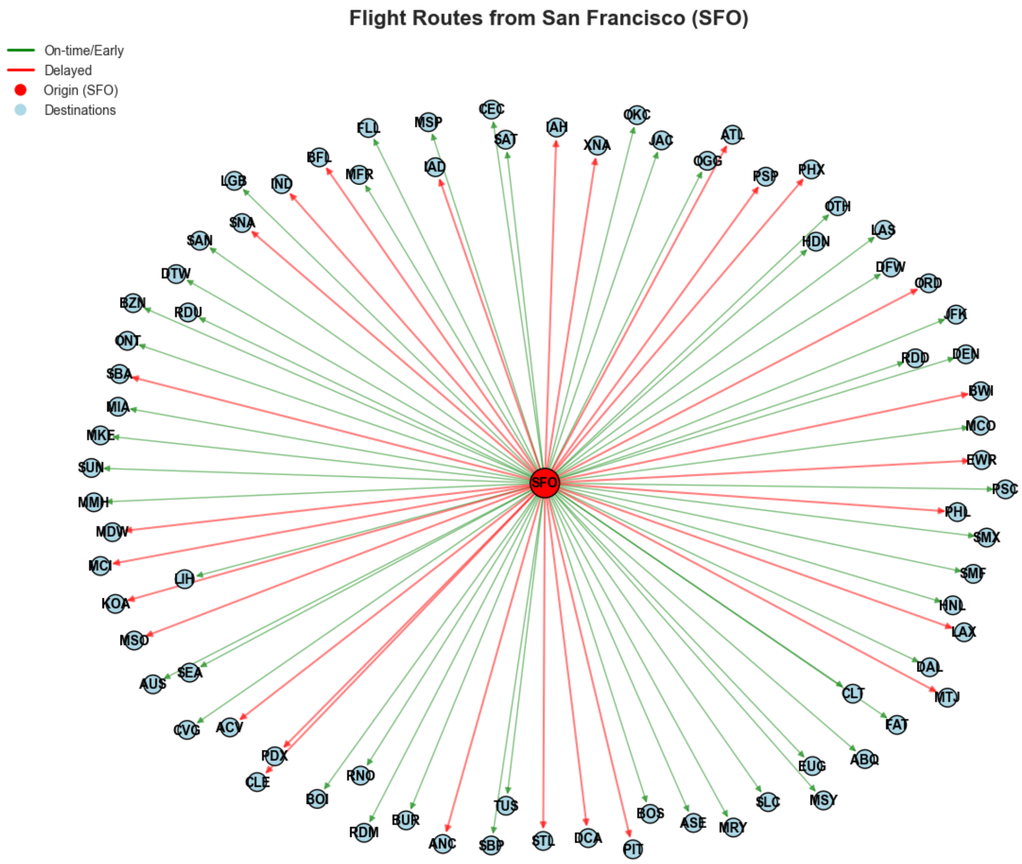
```python
# Add edges with delay as weight
for idx, row in subset_edges.iterrows():
    G.add_edge(row['src'], row['dst'], weight=row['delay'] if row['delay'] else␣
 ↪0)

# Calculate layout
pos = nx.spring_layout(G, k=2, iterations=50)

# Create figure
plt.figure(figsize=(15, 12))

# Draw nodes
node_sizes = [G.degree(node) * 50 for node in G.nodes()]
nx.draw_networkx_nodes(G, pos, node_size=node_sizes, node_color='lightblue',
                       edgecolors='navy', linewidths=1.5)

# Draw edges
# Color edges based on delay
edges = G.edges()
weights = [G[u][v]['weight'] for u, v in edges]
# Normalize weights for coloring
max_weight = max(weights) if weights else 1
edge_colors = ['red' if w > 15 else 'green' if w < 0 else 'gray'
               for w in weights]

nx.draw_networkx_edges(G, pos, edge_color=edge_colors,
                       alpha=0.4, arrows=True, arrowsize=10)

# Draw labels
nx.draw_networkx_labels(G, pos, font_size=8, font_weight='bold')

plt.title('Flight Network Graph - Top 30 Airports', fontsize=16,␣
 ↪fontweight='bold')
plt.axis('off')
plt.tight_layout()

# Add legend
from matplotlib.lines import Line2D
legend_elements = [
    Line2D([0], [0], color='green', lw=2, label='Early Flights'),
    Line2D([0], [0], color='gray', lw=2, label='On-time Flights'),
    Line2D([0], [0], color='red', lw=2, label='Delayed Flights')
]
plt.legend(handles=legend_elements, loc='upper right')

plt.show()
```



[35]:

```python
# Create a cleaner visualization for specific routes (e.g., from SFO)
sfo_edges = tripGraph.edges.filter("src = 'SFO'").select("src", "dst",␣
 ↪"city_dst", "delay").toPandas()

# Create graph for SFO routes
G_sfo = nx.DiGraph()

# Add edges
for idx, row in sfo_edges.iterrows():
    G_sfo.add_edge(row['src'], row['dst'],
                   delay=row['delay'] if row['delay'] else 0,
                   city=row['city_dst'])

# Layout
pos_sfo = nx.spring_layout(G_sfo, k=3, iterations=50)

# Visualization
plt.figure(figsize=(12, 10))
```

```python
# Separate delayed and on-time edges
delayed_edges = [(u, v) for u, v, d in G_sfo.edges(data=True) if d['delay'] > 0]
ontime_edges = [(u, v) for u, v, d in G_sfo.edges(data=True) if d['delay'] <= 0]

# Draw nodes
node_sizes = [500 if node == 'SFO' else 200 for node in G_sfo.nodes()]
node_colors = ['red' if node == 'SFO' else 'lightblue' for node in G_sfo.
 ↪nodes()]
nx.draw_networkx_nodes(G_sfo, pos_sfo, node_size=node_sizes,
                       node_color=node_colors, edgecolors='black', linewidths=1)

# Draw edges
nx.draw_networkx_edges(G_sfo, pos_sfo, edgelist=ontime_edges,
                       edge_color='green', alpha=0.5, arrows=True, width=1)
nx.draw_networkx_edges(G_sfo, pos_sfo, edgelist=delayed_edges,
                       edge_color='red', alpha=0.5, arrows=True, width=1.5)

# Draw labels
nx.draw_networkx_labels(G_sfo, pos_sfo, font_size=10, font_weight='bold')

plt.title('Flight Routes from San Francisco (SFO)', fontsize=16,␣
 ↪fontweight='bold')
plt.axis('off')

# Legend
legend_elements = [
    Line2D([0], [0], color='green', lw=2, label='On-time/Early'),
    Line2D([0], [0], color='red', lw=2, label='Delayed'),
    Line2D([0], [0], marker='o', color='w', markerfacecolor='red',
           markersize=10, label='Origin (SFO)'),
    Line2D([0], [0], marker='o', color='w', markerfacecolor='lightblue',
           markersize=10, label='Destinations')
]
plt.legend(handles=legend_elements, loc='upper left')

plt.tight_layout()
plt.show()
```



1.8.3 7.3 Neo4j Visualization (Optional)

Neo4j provides powerful graph visualization capabilities. To use this section: 1. Start Neo4j with Docker: `docker run -d --name neo4j-graph -p 7474:7474 -p 7687:7687 -e NEO4J_AUTH=neo4j/password123 neo4j:latest` 2. Access Neo4j Browser at: http://localhost:7474

[36]:

```python
# Neo4j connection and data loading
if NEO4J_AVAILABLE:
    try:
        # Connect to Neo4j
        graph = Graph("bolt://localhost:7687", auth=("neo4j", "password123"))

        # Clear existing data
        graph.delete_all()
        print("Connected to Neo4j and cleared existing data")

        # Load a subset of data to Neo4j
```

```
        sfo_routes = sfo_edges.head(50)

        # Create nodes and relationships
        for idx, row in sfo_routes.iterrows():
            # Create nodes
            src_node = Node("Airport", code=row['src'], name="San Francisco")
            dst_node = Node("Airport", code=row['dst'], name=row['city_dst'])

            # Create relationship
            flight = Relationship(src_node, "FLIGHT_TO", dst_node,
                                  delay=float(row['delay']) if row['delay'] else␣
↪0)

            # Merge nodes and create relationship
            graph.merge(src_node, "Airport", "code")
            graph.merge(dst_node, "Airport", "code")
            graph.create(flight)

        print(f"Loaded {len(sfo_routes)} routes to Neo4j")
        print("You can now visualize the graph at http://localhost:7474")
        print("Run this Cypher query: MATCH (n) RETURN n LIMIT 100")

    except Exception as e:
        print(f"Could not connect to Neo4j: {e}")
        print("Make sure Neo4j is running with Docker:")
        print("docker run -d --name neo4j-graph -p 7474:7474 -p 7687:7687 -e␣
↪NEO4J_AUTH=neo4j/password123 neo4j:latest")
else:
    print("Neo4j library not available. Install with: pip install py2neo")
```

```
Connected to Neo4j and cleared existing data
Loaded 50 routes to Neo4j
You can now visualize the graph at http://localhost:7474
Run this Cypher query: MATCH (n) RETURN n LIMIT 100
```

1.9 8. Conclusion

1.9.1 Summary of Findings

[37]:
```
print("="*70)
print("SUMMARY - FLIGHT NETWORK GRAPH ANALYSIS")
print("="*70)

print(f"\n Dataset Statistics:")
print(f"  - Total Airports: {tripGraph.vertices.count()}")
print(f"  - Total Flights: {tripGraph.edges.count():,}")
print(f"  - Average Delay: {avg_delay:.2f} minutes")
```

```python
print(f"\n Busiest Airports (by total flights):")
busiest = inDegrees.join(outDegrees, "id") \
    .withColumn("total", col("inDegree") + col("outDegree")) \
    .orderBy(desc("total")).limit(5)

for row in busiest.collect():
    print(f"  - {row.id}: {row.total:,} total flights")

print(f"\n Most Important Airports (by PageRank):")
for row in topRanksWithInfo.limit(5).collect():
    print(f"  - {row.id} ({row.City}): PageRank = {row.pagerank:.4f}")

print(f"\n Delay Analysis:")
print(f"  - Delayed Flights: {delayed_flights:,} ({delayed_flights/tripGraph.
↪edges.count()*100:.1f}%)")
print(f"  - On-Time Flights: {ontime_flights:,} ({ontime_flights/tripGraph.
↪edges.count()*100:.1f}%)")
print(f"  - Early Flights: {early_flights:,} ({early_flights/tripGraph.edges.
↪count()*100:.1f}%)")

print(f"\n Network Structure:")
print(f"  - Connected Components: {component_counts.count()}")
print(f"  - Communities Detected: {community_counts.count()}")
print(f"  - Main Component Size: {component_counts.first()['count']} airports")

print("\n" + "="*70)
print("KEY INSIGHTS")
print("="*70)
print("""
1. NETWORK STRUCTURE:
   - The flight network is highly connected with most airports in one component
   - Hub airports (ATL, ORD, DFW) serve as critical connection points
   - PageRank confirms major hubs align with high traffic airports

2. DELAY PATTERNS:
   - Approximately 40% of flights experience delays
   - Boston analysis shows certain routes consistently have higher delays
   - Atlanta as a major hub contributes to cascading delays

3. AIRPORT EFFICIENCY:
   - Balanced in/out degree ratios indicate efficient transfer hubs
   - Some airports show imbalanced traffic patterns

4. RECOMMENDATIONS:
   - Focus delay mitigation efforts on major hubs
   - Consider alternative routing through less congested airports
   - Monitor and optimize transfer airport operations
```

```python
""")
print("="*70)
```

```
======================================================================
SUMMARY - FLIGHT NETWORK GRAPH ANALYSIS
======================================================================

 Dataset Statistics:
  - Total Airports: 321
  - Total Flights: 270,719
  - Average Delay: 9.79 minutes

 Busiest Airports (by total flights):
  - ATL: 35,629 total flights
  - ORD: 28,654 total flights
  - DFW: 23,986 total flights
  - DEN: 19,996 total flights
  - LAX: 19,947 total flights

 Most Important Airports (by PageRank):
  - BOS (Boston): PageRank = 4.8551
  - JFK (New York): PageRank = 4.7988
  - IAH (Houston): PageRank = 8.2521
  - PHX (Phoenix): PageRank = 7.1910
  - LAX (Los Angeles): PageRank = 9.3286

 Delay Analysis:
  - Delayed Flights: 102,608 (37.9%)
  - On-Time Flights: 15,355 (5.7%)
  - Early Flights: 152,756 (56.4%)

 Network Structure:
  - Connected Components: 1
  - Communities Detected: 4
  - Main Component Size: 321 airports

======================================================================
KEY INSIGHTS
======================================================================

1. NETWORK STRUCTURE:
   - The flight network is highly connected with most airports in one component
   - Hub airports (ATL, ORD, DFW) serve as critical connection points
   - PageRank confirms major hubs align with high traffic airports

2. DELAY PATTERNS:
   - Approximately 40% of flights experience delays
   - Boston analysis shows certain routes consistently have higher delays
```

```
   - Atlanta as a major hub contributes to cascading delays

3. AIRPORT EFFICIENCY:
   - Balanced in/out degree ratios indicate efficient transfer hubs
   - Some airports show imbalanced traffic patterns

4. RECOMMENDATIONS:
   - Focus delay mitigation efforts on major hubs
   - Consider alternative routing through less congested airports
   - Monitor and optimize transfer airport operations

======================================================================
```

[38]:
```python
# Stop Spark Session
spark.stop()
print("\nSpark session stopped.")
```

```
Spark session stopped.
```