

Data Mining the US DOT Statistics on Aviation

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Introduction

The goal of this paper is to analyze the transportation dataset from the US Bureau of Transportation Statistics (BTS) that is hosted as an Amazon EBS volume snapshot and answer a set of interesting questions about it. The dataset contains data and statistics on Aviation up to 2008 in CSV format. It contains flight data such as departure and arrival delays, flight times, etc.

All code and full results can be found at <https://github.com/stephendimig/cc-capstone>.

Methods and Data

System Installation and Setup

All work for this paper was performed on Amazon Web Services using a virtual machine instance running HortonWorks Sandbox 2.1. An EBS volume was created from a pre-existing snapshot containing the BTS transportation data statistics and attached to the virtual machine. In addition to this basic setup, the Apache Cassandra NoSQL database and the R Programming Language were also installed.

Attribute	Value	Description
Inst. Type	C3.xlarge	
AMI ID	ami-36d95d5e	hortonworks 2.1 - sandbox
vCPUs	4	
Memory	7.5 GB	
Inst. Storage	128 GB	Increased the storage size
EBS Vol. ID	snap-23a9cf5e	BTS transportation data
R	3.2	R programming language
Cassandra	2-1.2.10-1	NoSQL Database

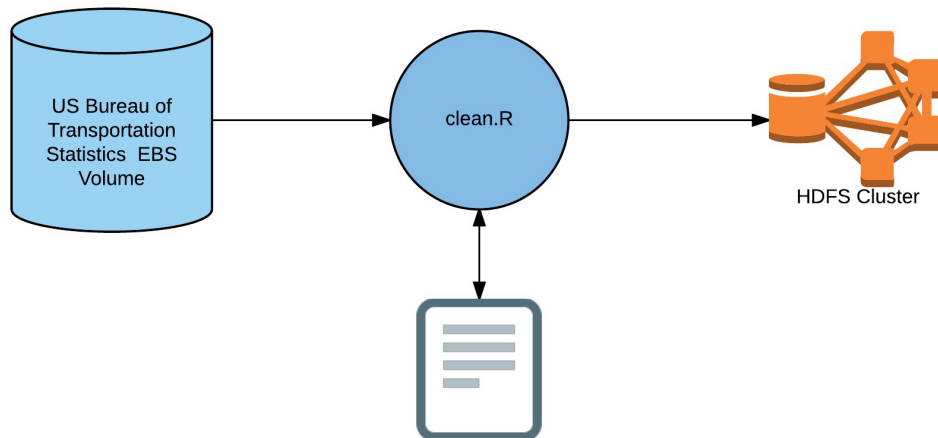
MapReduce is fantastic at parallellizing work done on large data sets, but due to it's nature it can be difficult to use for some smaller tasks. Rather than struggling to make MapReduce perform every task required here, several languages were used together to perform that task.

Language	Description
Java	Used for map reduce programs to solve problems in Group 1
Pig	A language that generates map reduce from an SQL-like syntax
R	Used for post processing data filtered by MapReduce
Python	Used to filter and process data
cql	SQL-like query language for Cassandra

R is a programming language and software environment for statistical computing. It is exceptional at dealing with tabular data like what was found in this set of problems, but does not scale and is performs poorly on large datasets. R was used to process data where the majority of the heavy lifting was already done using MapReduce (either with Java or Pig).

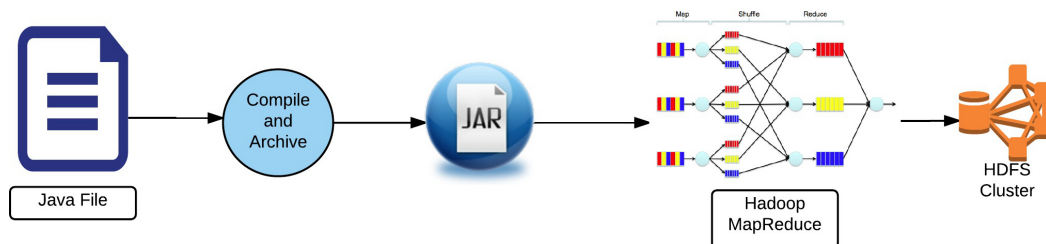
Cleaning the Data

The data was cleaned by reading it off the attached EBS data volume, processing it with R to filter out only the required fields, generating a temporary file, and then moving the file to HDFS.



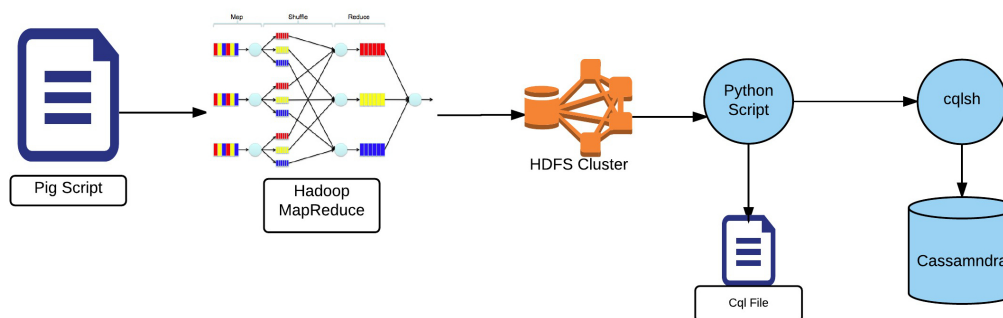
Group 1 Problems

The Group 1 Problems were solved using straight MapReduce with Java. For smaller problems this works well. A Java program is written using the Hadoop MapReduce framework and compiler. The jar file is then executed within Hadoop and the output is stored in HDFS.



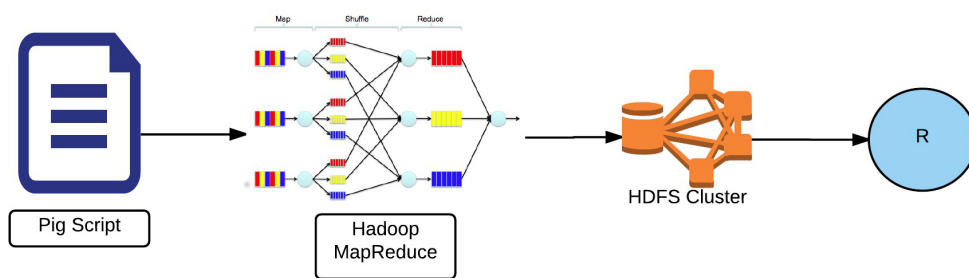
Group 2 Problems

The Group 2 Problems were the most complex as far as integration goes. I could not get the Cassandra/Pig interface to work so instead, I wrote a python language filter for each problem that took the output from the Pig script and created all of the cql commands that were required to load that data into Cassandra. The cql file was then run through cqlsh.



Group 3 Problems

The Group 3 problems required more analysis with no database interaction. This set of problems was solved with R directly reading the output of the Pig script from HDFS.



Results

Group 1 Questions

1.1 - Rank the top 10 most popular airports by numbers of flights to/from the airport.

Here are the top 3 airports by total flights. See Appendix A.1.1 for the full top 10.

Airport	Description	Flights
ORD	Chicago O'Hare International	12449354
ATL	Hartsfield Jackson Atlanta International	11540422
DFW	Dallas Fort Worth International	10799303

1.2 - Rank the top 10 airlines by on-time arrival performance.

Here are the top 3 carriers by average arrival delay. See A.1.2 for the full top 10 list.

Carrier	Description	Avg Delay
HA	Hawaiian Airlines, Inc.	3.9542668
AQ	9 Air Co Ltd	4.9505897
PS	Ukraine International Airlines	5.627902

1.3 - Rank the days of the week by on-time arrival performance.

Here are the top 3 days of the week by average arrival delay. See A.1.3 for the full top 10 list.

Day	Avg Delay
FRI	9.265108
MON	10.237862

SUN 10.864509

Group 2 Questions

Note that Cassandra does not output the queries in the same order that the INSERT operation was done. I included both the HDFS and Cassandra output for the queries to show they were in sorted order.

2.1 - For each airport X, rank the top-10 carriers in decreasing order of on-time departure performance from X. See Task 1 Queries for specific queries.

origin	unique_carrier	dep_delay_avg
CMI	US	2.8827
CMI	TW	4.1582
CMI	PI	4.5229

Top 3 carriers for the CMI airport. See Appendix A.2.1 for all queries.

2.2 - For each airport X, rank the top-10 airports in decreasing order of on-time departure performance from X. See Task 1 Queries for specific queries.

origin	dest	dep_delay_avg
CMI	ABI	0
CMI	PIT	2.1701
CMI	DAY	3.6273

Top 3 destinations from CMI. See Appendix A.2.2 for all queries.

2.3 - For each source-destination pair X-Y, rank the top-10 carriers in decreasing order of on-time arrival performance at Y from X. See Task 1 Queries for specific queries.

origin	dest	unique_carrier	arrival_delay_avg
ATL	PHX	FL	12.61
ATL	PHX	US	12.687
ATL	PHX	HP	13.367

Top 3 carriers from ATL to Phoenix. See Appendix A.2.3 for all queries.

Group 3 Questions

3.1 - Does the popularity distribution of airports follow a Zipf distribution? If not, what distribution does it follow?

Zipf distributions are used in linguistics. Zipf's law states that given some corpus of natural language utterances, the frequency of any word is inversely proportional to its rank in the frequency table. As applied to airports in our problem, this means that the highest ranked airport should have roughly double the number of flights as the second ranked. The second ranked should have double the third and so on. Our data when the number of flights looks very much like a zipf distribution. There is enough doubt about that bulge in the middle though (a typical zipf has an almost 90 degree elbow) to warrant some analysis.

Analysis with the zipfR package shows our data is not a zipf distribution. So what distribution does our data follow? In our case, the data seem to fit a Weibull distribution almost perfectly.

See Appendix A.3.1 for a full analysis.

3.2 - Tom's Unusual Flight

```
[1] "JAX -> DFW Flights"
[1] "===== "
      flightno origin dest carrier      date dep_time delay
1545      845    JAX  DFW     AA 2008-09-09      722      1
[1] ""
[1] "DFW -> CRP Flights"
[1] "===== "
      flightno origin dest carrier      date dep_time delay
1493      3627   DFW  CRP     MQ 2008-09-11     1648      0
1521      3701   DFW  CRP     MQ 2008-09-11     1310      8
1438      3419   DFW  CRP     MQ 2008-09-11     1504      9
```

Tom's flight options from JAX->DFW->CRP on 9/09/2008. See Appendix A.3.2 for all queries.

Discussion

I like the results in the data but I believe it could have been cleaned better. Flight cancellations should be removed rather than replacing the delay values with zeroes which can skew the data for carriers with a smaller number of flights. I struggled on this project due to some technical difficulties with the ami image I was using. I figured that out though and had a lot of fun. I was wanting to do something similar to this in the Data Science specialization from Johns Hopkins since R is so slow with larger data sets. This proves to me you can extract the majority of the data using Hadoop and do the final analysis in R in a powerful way.

Appendix

A.1.1 Rank the top 10 most popular airports by numbers of flights to/from the airport.

Airport	Description	Flights
ORD	Chicago O'Hare International	12449354
ATL	Hartsfield Jackson Atlanta International	11540422
DFW	Dallas Fort Worth International	10799303
LAX	Los Angeles International	7723596
PHX	Phoenix Sky Harbor International Airport	6585534
DEN	Denver International	6273787
DTW	Detroit Metropolitan Wayne County	5636622
IAH	George Bush Intercontinental Houston	5480734
MSP	Minneapolis-St Paul International	5199213
SFO	San Francisco International	5171023

A.1.2 Rank the top 10 airlines by on-time arrival performance.

Carrier	Description	Avg Delay
HA	Hawaiian Airlines, Inc.	3.9542668
AQ	9 Air Co Ltd	4.9505897
PS	Ukraine International Airlines	5.627902
ML	Air Mediterranee	8.518365
WN	Southwest Airlines Co.	9.025299
F9	Frontier Airlines, Inc.	9.871182
PA	M/S Airblue (PVT) Ltd	10.189628
US	Piedmont Airlines, Inc	10.285916
NW	Northwest Airlines, Inc.	10.332496
EA	Operador Aereo Andalus S.A	10.360811

A.1.3 Rank the days of the week by on-time arrival performance.

Day	Avg Delay
FRI	9.265108
MON	10.237862
SUN	10.864509
SAT	11.019846
TUE	11.180128
WED	12.689463

THU 13.256688

A.2.1 For each airport X, rank the top-10 carriers in decreasing order of on-time departure performance from X. See Task 1 Queries for specific queries.

HDFS:

CMI US 2.8827454718779792
CMI TW 4.158153846153846
CMI PI 4.522930315664086
CMI OH 5.364254792826221
CMI DH 9.649402390438247
CMI EV 9.692660550458715
CMI MQ 11.754489920586439

BWI F9 4.916083916083916
BWI PA (1) 5.942857142857143
BWI CO 7.1413334153013865
BWI AA 7.657054909239057
BWI YV 7.675990675990676
BWI NW 8.30940419738016
BWI US 8.514172363028138
BWI DL 8.81506807645978
BWI TW 9.084856211928034
BWI EA 9.171986970684038

MIA 9E 0.5
MIA PA (1) 4.84346374454242
MIA EV 5.669603524229075
MIA XE 6.1033769813921435
MIA TZ 6.823035392921415
MIA NW 6.9902354593253
MIA US 7.427278231684071
MIA ML (1) 7.6319514661274015
MIA UA 8.273468482892824
MIA PI 9.063902838987394

LAX PS 4.973895803502589
LAX MQ 5.069745783395635
LAX OO 6.09525787073169
LAX ML (1) 7.101275318829708
LAX NW 7.252479152149109
LAX TZ 7.456864216054013
LAX US 7.803737590192616
LAX FL 8.082327701796729
LAX F9 8.362138132928548
LAX AA 8.41992740869826

IAH PI 4.643304503429764
IAH PA (1) 5.73430303030303
IAH NW 6.1597593951768665
IAH WN 6.232248922121386
IAH US 7.055723274437524
IAH AA 7.269662304240027
IAH TW 7.453365263423242
IAH OO 7.943149703051403
IAH HP 8.040625479074047
IAH DL 8.277057959223324

CASSANDRA:

origin	unique_carrier	dep_delay_avg
CMI	DH	9.6494
CMI	EV	9.6927
CMI	MQ	11.754
CMI	OH	5.3643
CMI	PI	4.5229
CMI	TW	4.1582
CMI	US	2.8827

origin	unique_carrier	dep_delay_avg
BWI	AA	7.6571
BWI	CO	7.1413
BWI	DL	8.8151
BWI	EA	9.172
BWI	F9	4.9161
BWI	NW	8.3094
BWI	PA (1)	5.9429
BWI	TW	9.0849
BWI	US	8.5142
BWI	YV	7.676

origin	unique_carrier	dep_delay_avg
MIA	9E	0.5
MIA	EV	5.6696
MIA	ML (1)	7.632
MIA	NW	6.9902
MIA	PA (1)	4.8435
MIA	PI	9.0639
MIA	TZ	6.823
MIA	UA	8.2735

MIA	US	7.4273
MIA	XE	6.1034

origin	unique_carrier	dep_delay_avg

LAX	AA	8.4199
LAX	F9	8.3621
LAX	FL	8.0823
LAX	ML (1)	7.1013
LAX	MQ	5.0697
LAX	NW	7.2525
LAX	OO	6.0953
LAX	PS	4.9739
LAX	TZ	7.4569
LAX	US	7.8037

origin	unique_carrier	dep_delay_avg

IAH	AA	7.2697
IAH	DL	8.2771
IAH	HP	8.0406
IAH	NW	6.1598
IAH	OO	7.9431
IAH	PA (1)	5.7343
IAH	PI	4.6433
IAH	TW	7.4534
IAH	US	7.0557
IAH	WN	6.2322

A.2.2 For each airport X, rank the top-10 airports in decreasing order of on-time departure performance from X. See Task 1 Queries for specific queries.

HDFS:

CMI ABI 0.0
CMI PIT 2.170138888888889
CMI DAY 3.627294117647059
CMI STL 4.018326693227092
CMI PIA 4.632432432432433
CMI CVG 6.37942425672487
CMI DFW 9.556245151280063
CMI ATL 9.692660550458715
CMI ORD 11.943169761273209

BWI SAV 0.0

BWI MLB 2.384180790960452
BWI IAD 3.087108013937282
BWI DAB 3.8378378378378377
BWI SRQ 4.2688853671421025
BWI CHO 4.826086956521739
BWI MDT 4.901430842607313
BWI UCA 4.939938791124713
BWI OAJ 5.32
BWI GSP 5.431125131440589

MIA SHV 0.0
MIA BUF 1.0
MIA SAN 2.5136612021857925
MIA HOU 3.641137855579869
MIA SLC 4.070247933884297
MIA ISP 4.456647398843931
MIA PSE 4.946859903381642
MIA MCI 5.360544217687075
MIA TLH 5.442896639727776
MIA GNV 6.008032128514056

LAX RSW 0.0
LAX PIH 0.0
LAX LAX 0.0
LAX IDA 0.0
LAX DRO 0.0
LAX MAF 0.0
LAX SDF 0.0
LAX BZN 1.0
LAX VIS 2.4805194805194803
LAX PMD 3.0

IAH MSN 0.0
IAH MLI 0.0
IAH HOU 2.3019052956010086
IAH AGS 2.8315334773218144
IAH EFD 3.9198736358414705
IAH PIH 4.0
IAH VCT 5.3175675675675675
IAH RNO 5.507233065442021
IAH MTJ 5.635007849293563
IAH MDW 5.9158371040723985

SFO FAR 0.0
SFO PIH 0.0
SFO SDF 0.0
SFO MSO 0.5833333333333334
SFO LGA 1.2121212121212122
SFO OAK 2.548567870485679

SFO PIE 2.7283236994219653
SFO BNA 3.064916119620715
SFO SCK 4.0
SFO MEM 5.439648554124371

CASSANDRA:

origin	dest	dep_delay_avg
CMI	ABI	0
CMI	ATL	9.6927
CMI	CVG	6.3794
CMI	DAY	3.6273
CMI	DFW	9.5562
CMI	ORD	11.943
CMI	PIA	4.6324
CMI	PIT	2.1701
CMI	STL	4.0183

origin	dest	dep_delay_avg
BWI	CHO	4.8261
BWI	DAB	3.8378
BWI	GSP	5.4311
BWI	IAD	3.0871
BWI	MDT	4.9014
BWI	MLB	2.3842
BWI	OAJ	5.32
BWI	SAV	0
BWI	SRQ	4.2689
BWI	UCA	4.9399

origin	dest	dep_delay_avg
MIA	BUF	1
MIA	GNV	6.008
MIA	HOU	3.6411
MIA	ISP	4.4566
MIA	MCI	5.3605
MIA	PSE	4.9469
MIA	SAN	2.5137
MIA	SHV	0
MIA	SLC	4.0702
MIA	TLH	5.4429

origin	dest	dep_delay_avg
--------	------	---------------

LAX	BZN	1
LAX	DRO	0
LAX	IDA	0
LAX	LAX	0
LAX	MAF	0
LAX	PIH	0
LAX	PMD	3
LAX	RSW	0
LAX	SDF	0
LAX	VIS	2.4805

origin	dest	dep_delay_avg
IAH	AGS	2.8315
IAH	EFD	3.9199
IAH	HOU	2.3019
IAH	MDW	5.9158
IAH	MLI	0
IAH	MSN	0
IAH	MTJ	5.635
IAH	PIH	4
IAH	RNO	5.5072
IAH	VCT	5.3176

origin	dest	dep_delay_avg
SFO	BNA	3.0649
SFO	FAR	0
SFO	LGA	1.2121
SFO	MEM	5.4396
SFO	MSO	0.58333
SFO	OAK	2.5486
SFO	PIE	2.7283
SFO	PIH	0
SFO	SCK	4
SFO	SDF	0

A.2.3 For each source-destination pair X-Y, rank the top-10 carriers in decreasing order of on-time arrival performance at Y from X. See Task 1 Queries for specific queries.

HDFS:

CMI ORD MQ 15.739150630391507

```

IND CMH CO 4.394163964798518
IND CMH NW 7.601538461538461
IND CMH US 7.838587981676098
IND CMH HP 7.990588235294117
IND CMH AA 8.25
IND CMH DL 12.629807692307692
IND CMH EA 13.065420560747663

DFW IAH UA 8.899408284023668
DFW IAH PA (1) 9.333333333333334
DFW IAH OO 9.736549165120593
DFW IAH CO 10.00064736160672
DFW IAH DL 10.204433400386542
DFW IAH EV 10.691978609625668
DFW IAH AA 12.147884747647687
DFW IAH XE 12.8929173693086
DFW IAH MQ 12.975917431192661

LAX SFO PS 5.830402722631877
LAX SFO TZ 6.238095238095238
LAX SFO F9 6.965310206804537
LAX SFO US 10.821992785172284
LAX SFO MQ 10.933456561922366
LAX SFO AA 12.465499230261711
LAX SFO NW 12.79028697571744
LAX SFO EV 13.39871382636656
LAX SFO DL 13.483850453526124
LAX SFO CO 14.001739130434782

JFK LAX UA 11.469386288506684
JFK LAX HP 14.865141955835963
JFK LAX AA 15.044821251483475
JFK LAX DL 16.631231597116457
JFK LAX PA (1) 17.09370780448285
JFK LAX TW 18.287762061126546

ATL PHX FL 12.61
ATL PHX US 12.687394957983193
ATL PHX HP 13.367140921409215
ATL PHX DL 13.867261117830722
ATL PHX EA 14.008673469387755

```

CASSANDRA:

```

origin | dest | unique_carrier | arrival_delay_avg
-----+-----+-----+-----
CMI | ORD | MQ | 15.739

```

origin	dest	unique_carrier	arrival_delay_avg
IND	CMH	AA	8.25
IND	CMH	CO	4.3942
IND	CMH	DL	12.63
IND	CMH	EA	13.065
IND	CMH	HP	7.9906
IND	CMH	NW	7.6015
IND	CMH	US	7.8386

origin	dest	unique_carrier	arrival_delay_avg
DFW	IAH	AA	12.148
DFW	IAH	CO	10.001
DFW	IAH	DL	10.204
DFW	IAH	EV	10.692
DFW	IAH	MQ	12.976
DFW	IAH	OO	9.7365
DFW	IAH	PA (1)	9.3333
DFW	IAH	UA	8.8994
DFW	IAH	XE	12.893

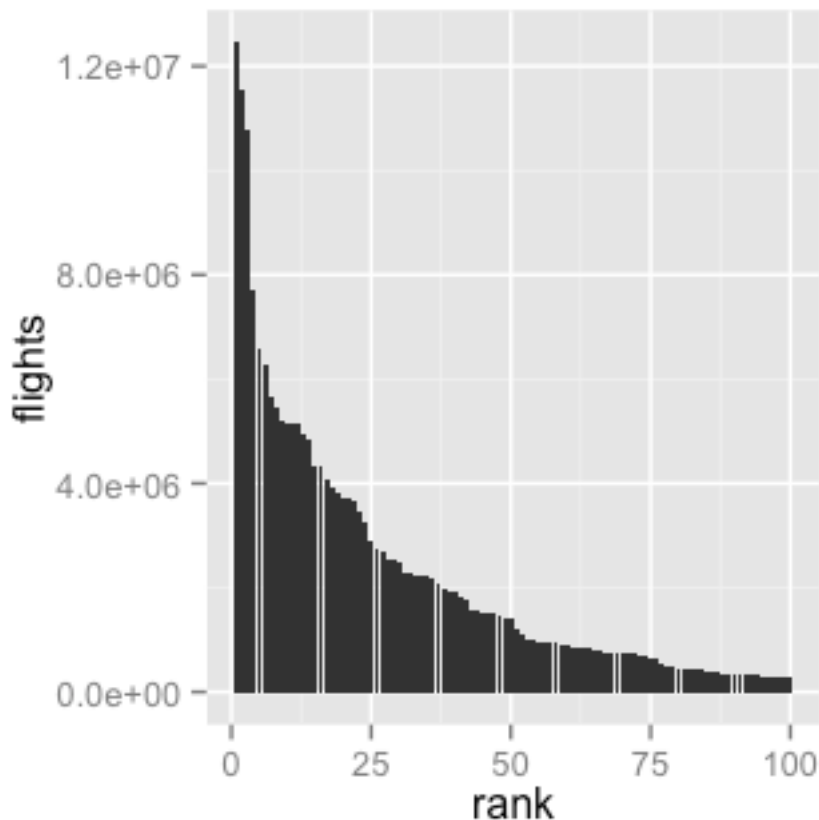
origin	dest	unique_carrier	arrival_delay_avg
LAX	SFO	AA	12.465
LAX	SFO	CO	14.002
LAX	SFO	DL	13.484
LAX	SFO	EV	13.399
LAX	SFO	F9	6.9653
LAX	SFO	MQ	10.933
LAX	SFO	NW	12.79
LAX	SFO	PS	5.8304
LAX	SFO	TZ	6.2381
LAX	SFO	US	10.822

origin	dest	unique_carrier	arrival_delay_avg
JFK	LAX	AA	15.045
JFK	LAX	DL	16.631
JFK	LAX	HP	14.865
JFK	LAX	PA (1)	17.094
JFK	LAX	TW	18.288
JFK	LAX	UA	11.469

origin	dest	unique_carrier	arrival_delay_avg
ATL	PHX	DL	13.867
ATL	PHX	EA	14.009
ATL	PHX	FL	12.61
ATL	PHX	HP	13.367
ATL	PHX	US	12.687

A.3.1 Does the popularity distribution of airports follow a Zipf distribution? If not, what distribution does it follow?

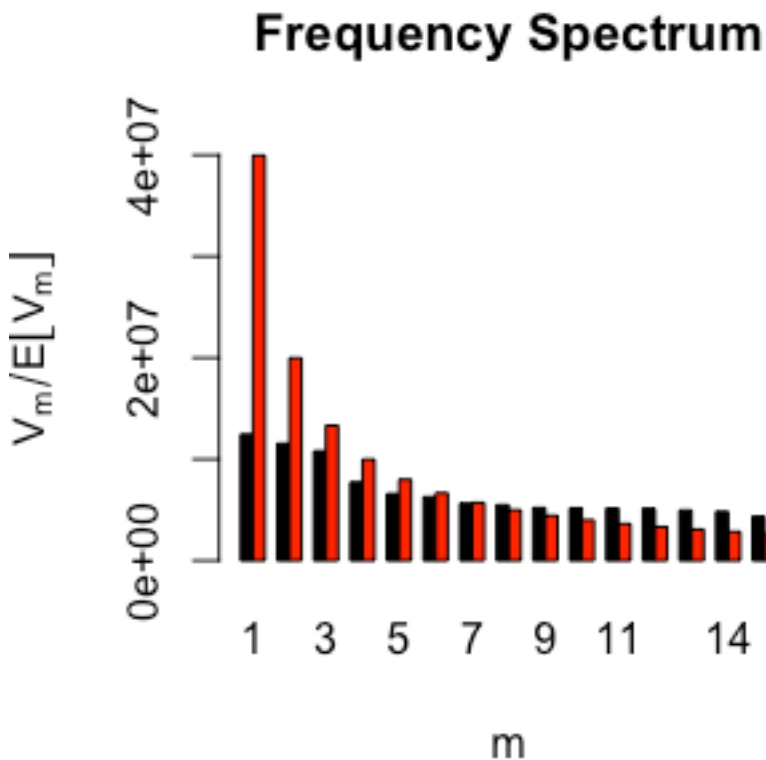
Zipf distributions are used in linguistics. Zipf's law states that given some corpus of natural language utterances, the frequency of any word is inversely proportional to its rank in the frequency table. As applied to airports in our problem, this means that the highest ranked airport should have roughly double the number of flights as the second rated. The second rated should have double the third and so on. Our data when the number of flights looks very much like a zipf distribution. There is enough doubt about that bulge in the middle though (a typical zipf has an almost 90 degree elbow) to warrant some analysis.



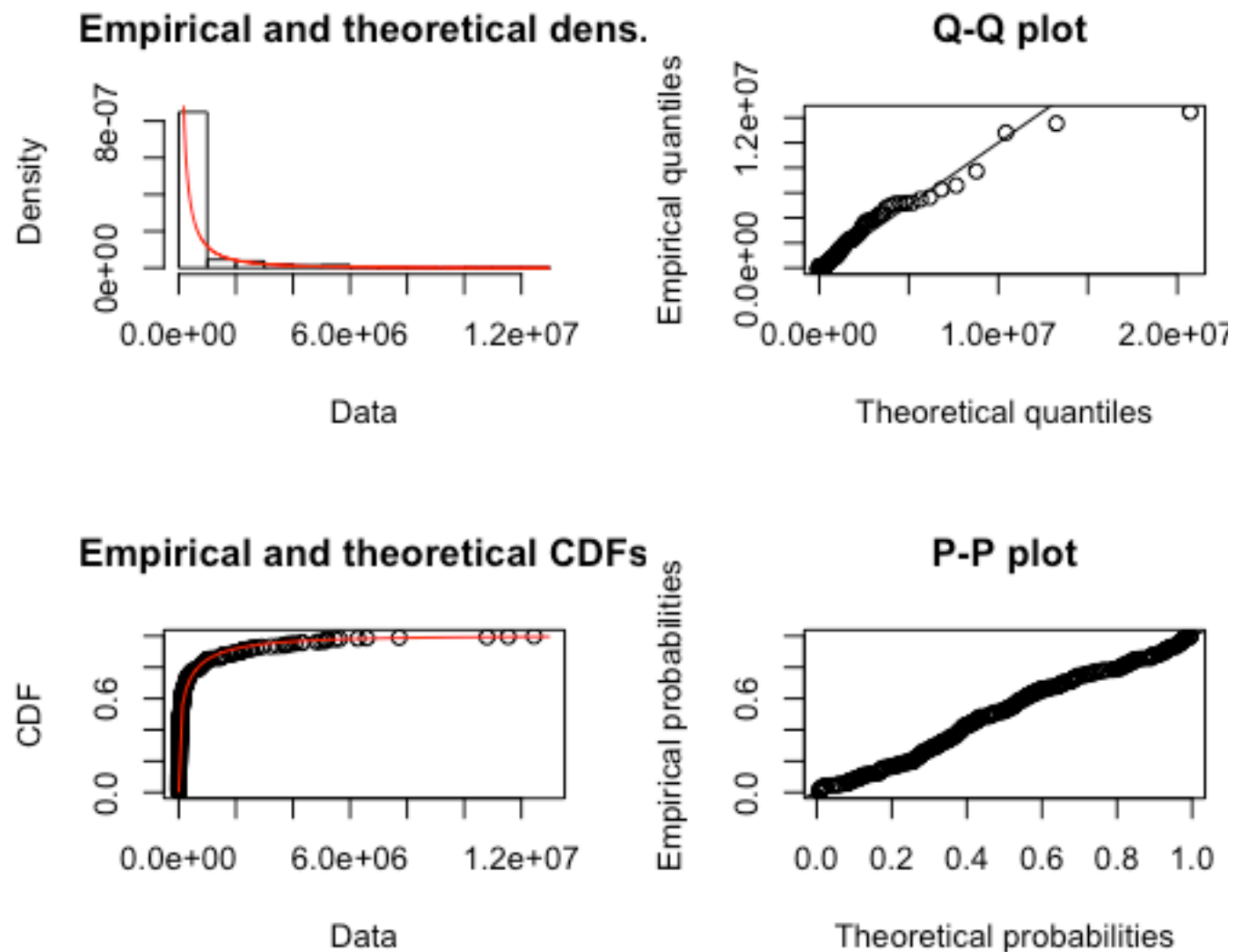
The zipfR R package allows you to compare your data against what a theoretical zipf distribution would look like if it had the same kind of bounds. When you run our

data against the theoretical zipf, you see the problem that the most popular airports are not quite popular enough for a zipf.

```
## Warning in estimate.model.lnre.zm(model, spc = spc, param.names =  
## missing.param, : estimated parameter values may be incorrect (code  
3)
```



So what distribution does our data follow? The fitdistrplus R packages allows you to run various diagnostics against your data to determine which distribution it follows. It is a kind of trial and error approach, but the tools are nice enough that you can find a distribution. In our case, the data seem to fit a Weibull distribution almost perfectly.



A.3.2 Tom's Unusual Flight

Moved: 'hdfs://sandbox.hortonworks.com:8020/user/root/output' to trash
 at: hdfs://sandbox.hortonworks.com:8020/user/root/.Trash/Current

```
[1] "CMI -> ORD Flights"
[1] "=====
      flightno origin dest carrier      date dep_time delay
3206      4278   CMI  ORD      MQ 2008-04-03      706      0
3236      4373   CMI  ORD      MQ 2008-04-03      908      0
3265      4374   CMI  ORD      MQ 2008-04-03      557      0
3290      4401   CMI  ORD      MQ 2008-04-03      808      0
[1] ""
[1] "ORD -> LAX Flights"
[1] "=====
      flightno origin dest carrier      date dep_time delay
```

3031	121	ORD	LAX	UA	2008-04-05	1219	0
3375	607	ORD	LAX	AA	2008-04-05	1948	0
3403	889	ORD	LAX	AA	2008-04-05	1815	0
3435	1345	ORD	LAX	AA	2008-04-05	1404	0
3463	1407	ORD	LAX	AA	2008-04-05	1213	0
3369	557	ORD	LAX	AA	2008-04-05	1641	6
3094	129	ORD	LAX	UA	2008-04-05	2102	12
3153	943	ORD	LAX	UA	2008-04-05	1506	12
3123	941	ORD	LAX	UA	2008-04-05	1712	19
3064	127	ORD	LAX	UA	2008-04-05	1847	20
3023	111	ORD	LAX	UA	2008-04-05	1208	38

[1] ""

Moved: 'hdfs://sandbox.hortonworks.com:8020/user/root/output' to trash
at: hdfs://sandbox.hortonworks.com:8020/user/root/.Trash/Current

[1] "JAX -> DFW Flights"

[1] "=====

	flightno	origin	dest	carrier	date	dep_time	delay
1545	845	JAX	DFW	AA	2008-09-09	722	1

[1] ""

[1] "DFW -> CRP Flights"

[1] "=====

	flightno	origin	dest	carrier	date	dep_time	delay
1493	3627	DFW	CRP	MQ	2008-09-11	1648	0
1521	3701	DFW	CRP	MQ	2008-09-11	1310	8
1438	3419	DFW	CRP	MQ	2008-09-11	1504	9

[1] ""

Moved: 'hdfs://sandbox.hortonworks.com:8020/user/root/output' to trash
at: hdfs://sandbox.hortonworks.com:8020/user/root/.Trash/Current

[1] "No flights found matching criteria X=SLC; Y=BFL; Z=LAX; DATE=2008-01-04"

Moved: 'hdfs://sandbox.hortonworks.com:8020/user/root/output' to trash
at: hdfs://sandbox.hortonworks.com:8020/user/root/.Trash/Current

[1] "No flights found matching criteria X=LAX; Y=SFO; Z=PHX; DATE=2008-12-07"

Moved: 'hdfs://sandbox.hortonworks.com:8020/user/root/output' to trash
at: hdfs://sandbox.hortonworks.com:8020/user/root/.Trash/Current

[1] "DFW -> ORD Flights"

[1] "=====

	flightno	origin	dest	carrier	date	dep_time	delay
5155	6441	DFW	ORD	OO	2008-10-06	920	0
5232	1104	DFW	ORD	UA	2008-10-06	655	0
5289	2268	DFW	ORD	AA	2008-10-06	920	0
5320	2320	DFW	ORD	AA	2008-10-06	556	0
5418	2328	DFW	ORD	AA	2008-10-06	812	0
5542	2336	DFW	ORD	AA	2008-10-06	1003	0
5604	2340	DFW	ORD	AA	2008-10-06	1047	0
5665	2344	DFW	ORD	AA	2008-10-06	1148	0
5356	2324	DFW	ORD	AA	2008-10-06	703	6

[1] ""

[1] "ORD -> DFW Flights"

```
[1] "=====
```

	flightno	origin	dest	carrier	date	dep_time	delay
5175	357	ORD	DFW	UA	2008-10-08	1658	0
5204	725	ORD	DFW	UA	2008-10-08	2016	0
5260	47	ORD	DFW	AA	2008-10-08	1919	0
5389	2325	ORD	DFW	AA	2008-10-08	1240	0
5451	2329	ORD	DFW	AA	2008-10-08	1332	0
5636	2341	ORD	DFW	AA	2008-10-08	1650	0
5692	2345	ORD	DFW	AA	2008-10-08	1754	0
5748	2357	ORD	DFW	AA	2008-10-08	1945	0
5776	2361	ORD	DFW	AA	2008-10-08	2100	0
5482	2331	ORD	DFW	AA	2008-10-08	1429	2
5138	5949	ORD	DFW	OO	2008-10-08	1529	11
5513	2333	ORD	DFW	AA	2008-10-08	1520	17
5721	2349	ORD	DFW	AA	2008-10-08	2024	94
5575	2337	ORD	DFW	AA	2008-10-08	1909	184

```
[1] ""
```

Moved: 'hdfs://sandbox.hortonworks.com:8020/user/root/output' to trash
at: hdfs://sandbox.hortonworks.com:8020/user/root/.Trash/Current

```
[1] "LAX -> ORD Flights"
```

```
[1] "=====
```

	flightno	origin	dest	carrier	date	dep_time	delay
1898	944	LAX	ORD	UA	2008-01-01	700	1
1831	110	LAX	ORD	UA	2008-01-01	1005	9
1957	88	LAX	ORD	AA	2008-01-01	853	11
1985	764	LAX	ORD	AA	2008-01-01	558	11
1802	106	LAX	ORD	UA	2008-01-01	856	12
2070	2276	LAX	ORD	AA	2008-01-01	631	12
2032	1372	LAX	ORD	AA	2008-01-01	1106	70
2055	1740	LAX	ORD	AA	2008-01-01	217	161

```
[1] ""
```

```
[1] "ORD -> JFK Flights"
```

```
[1] "=====
```

	flightno	origin	dest	carrier	date	dep_time	delay
2135	918	ORD	JFK	B6	2008-01-03	1853	0
1743	5366	ORD	JFK	OH	2008-01-03	1736	2
2133	908	ORD	JFK	B6	2008-01-03	1208	5
2134	916	ORD	JFK	B6	2008-01-03	1603	10
2103	2352	ORD	JFK	AA	2008-01-03	1708	18
1927	4138	ORD	JFK	MQ	2008-01-03	1425	28
1744	5466	ORD	JFK	OH	2008-01-03	1335	145

```
[1] ""
```