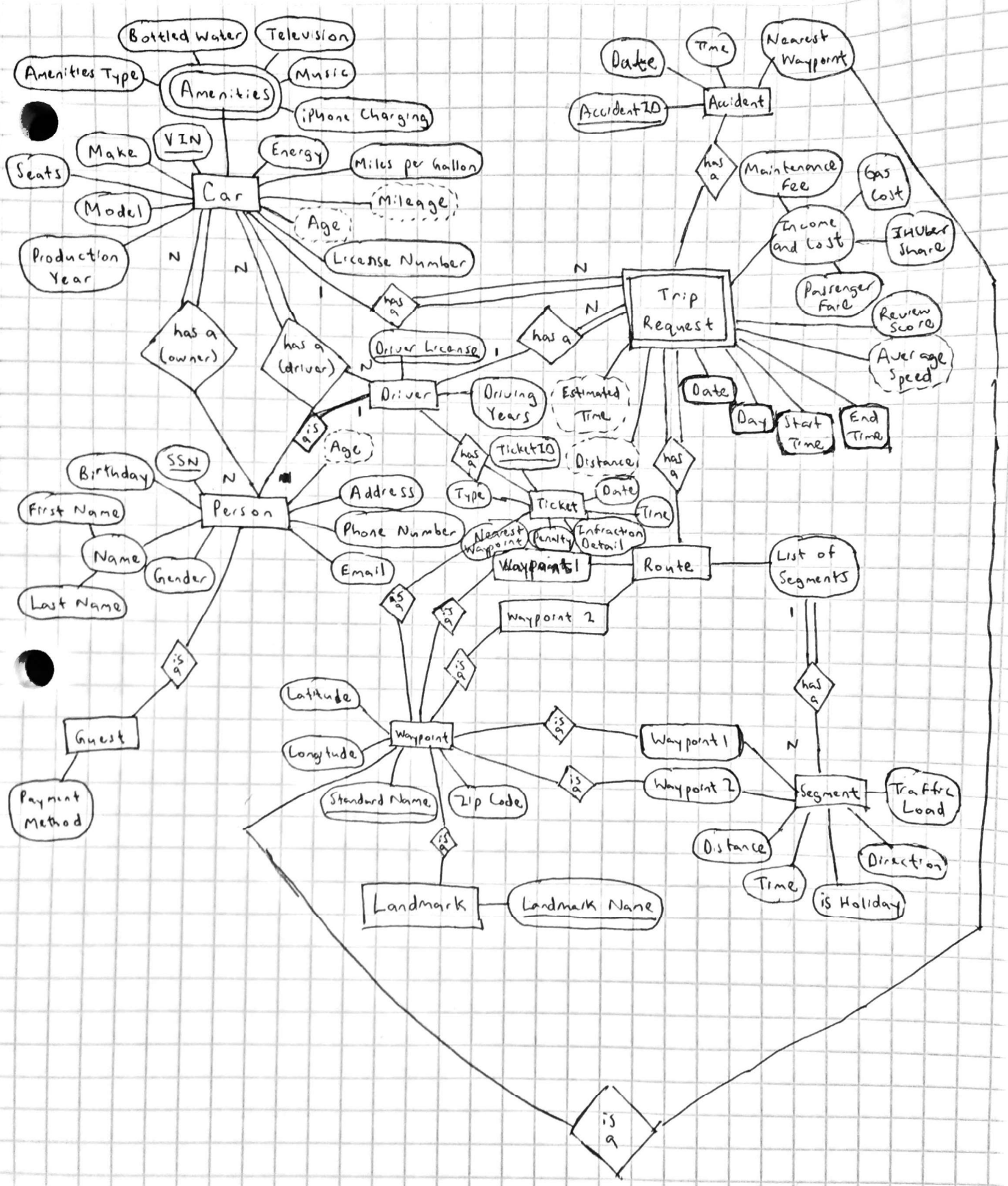

Bottled Water
Television
Amenities Type
Amenities
Music
iPhone Charging
Make
VIN
Energy
Miles per Gallon
Seats
Car
Model
Mileage
Age
Production Year
License Number
N
N
1
has a
has a (owner)
has a (driver)
Driver License
1
N
Driver
Driving Years
Estimated Time
Age
is a
Birthday
SSN
N
Person
Address
Phone Number
Email
First Name
Name
Gender
Last Name
is a
Guest
Payment Method
Date
Time
Nearest Waypoint
Accident ID
Accident
has a
Maintenance Fee
Gas Cost
Income and Cost
IHUber Share
Passenger Fare
Review Score
Average Speed
N
Trip Request
has a
Date
Day
Start Time
End Time
has a
Ticket ID
Distance
Type
Ticket
Date
Time
Nearest Waypoint
Penalty
Infraction Detail
has a
Waypoint 1
Route
List of Segments
Waypoint 2
is a
is a
is a
has a
Latitude
Longitude
Waypoint
is a
Waypoint 1
N
is a
Waypoint 2
Segment
Traffic Load
Standard Name
Zip Code
Distance
Direction
Time
is Holiday
is a
Landmark
Landmark Name
is a

2 Relation Model

Generic Car

Make	Model	Production Year	Energy	Miles per Gallon	Seats
BMW	X5	2016	Gas	20	5

JHUberCar

VIN	Make	Model	Production Year	millage	license number	age	Ammenities Type
00000000000000000	BMW	X5	2016	2123	ABC123	3	001

owner SSN	Driver SSN
123456789	123456789

Ammenities

Ammenities Type	Bottled water	Television	Music	Iphone Charging
001	Yes	NO	YES	YES

Person

SSN	Name	Gender	Birthday	Age	Address	Phone Number	Email
123456789	Mike Smith	Male	6/01/87	29	None	4101111111	m87@gmail.com

Driver

SSN	DriverName	Driver License	AccidentID	TicketID	Driving Year	Car License
123456789	Mike Smith	012345678	A001	003	8	ABC123

Guest

SSN	Name	UserName	Payment Method
123456789	Cathy Miller	Cathy@gmail.com	Credit Card

Location

Longitude	Latitude
39.3259	-76.6191

Waypoint

Latitude	Longitude	Standard Name	Zip Code
39.3259	-76.6191	E0674	21210

Landmark

Latitude	Longitude	Waypoint Standard Name	Zip Code	LandMark Name
39.3259	-76.6191	E0674	21210	Baltimore Museum of Art

Travel_Between

LandMark1	LandMark2	Standard Time	Standard Distance	Standard Cost
Baltimore Museum of Art	Inner Harbor	13 min	4.8miles	$15

Accident

AcciedntID	Driver License	Car License Number	Date	Time	NearestWaypoint
A013	012345678	ABC456	8/09/15	1:35pm	E4682

Ticket

TicketID	Driver License	Date	Time	NearestWaypoint	Type	Infraction Detail
B013	012345678	8/09/2015	1:35pm	E4682	Speeding	60 mph on Charles Street

Penalty
$50

Get

Driver License	Times
012345678	2

Been_To

Driver License	LandMark	Times
012345678	Baltimore Museum of Art	15

Drives_Near

Driver License	Waypoint	Time	Date
012345678	E3567	3:12pm	7/19/15

Segment

Waypoint1	Waypoint2	Distance	Current Time	Isholiday	Direction	Traffic Load	Estimated Time
E3566	E3567	0.6miles	7:00am	No	East	Low	2min
E3566	E3567	0.6miles	8:30am	No	East	Median	4min
E3566	E3567	0.6miles	5:45pm	No	East	High	8min

Trip

Trip ID	Waypoint1	Waypoint2	Date	Day	Estimated Time	Distance
K0782901	E3867	E3920	7/28/15	Tuesday	56min	24miles

Start Time	End Time	Average Speed	Driver	Guest UserName	Review Score
9:19am	10:12am	27.17 mph	012345678	Cathy@gmail.com	9

Start_From

Waypoints	Day	Times
E5648	Wednesday	15

End_In

Waypoints	Day	Times
E5648	Wednesday	15

Income_and_Cost

DriverSSN	Maintenance Fee	Gas Cost	JHUber Share	Passenger Fare	Total Distance
012345678	$0	$20	$20	$200	100 miles

Total Hour	Date
6	8/28/15

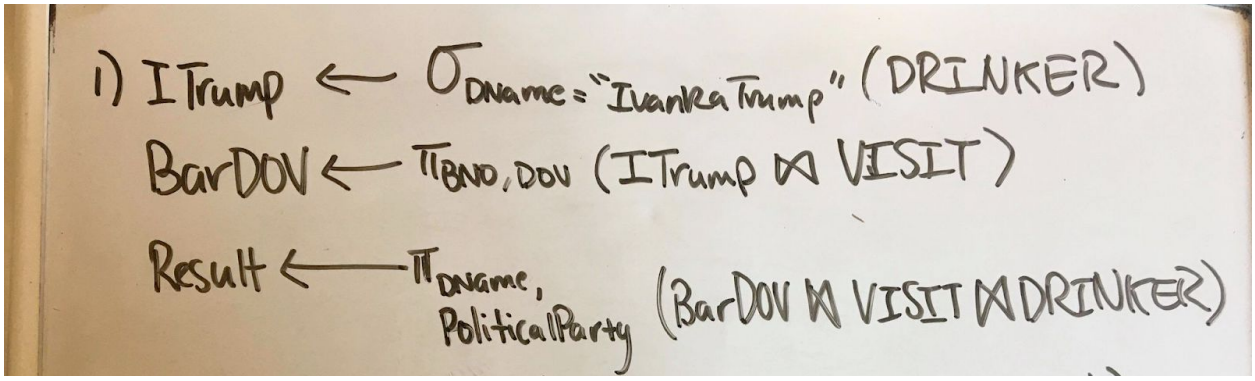
Lost

VIN	Date	Hour	Reason
00000000000000000	8/09/2014	3	Unscheduled maintenance

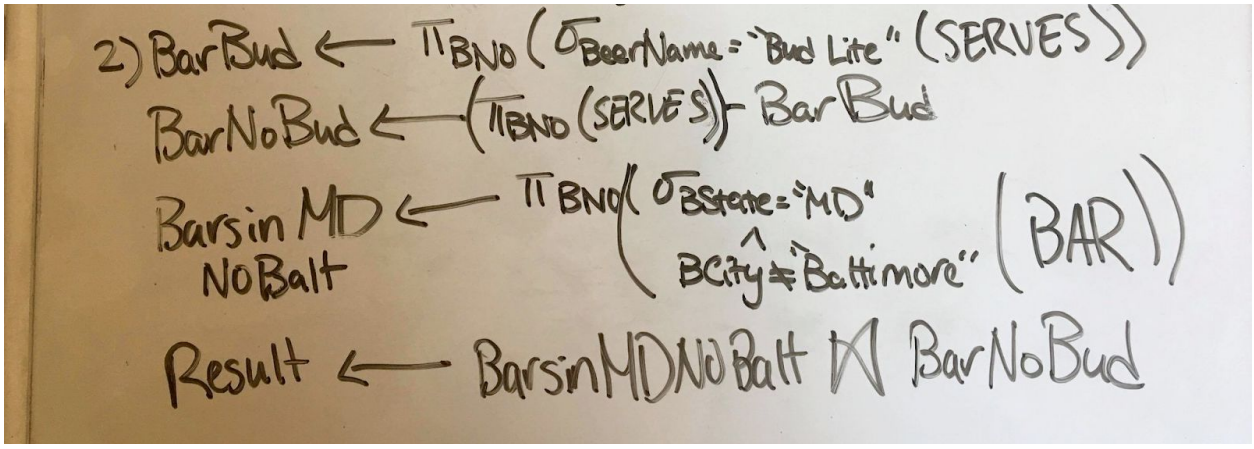
Part 2

Relational Algebra

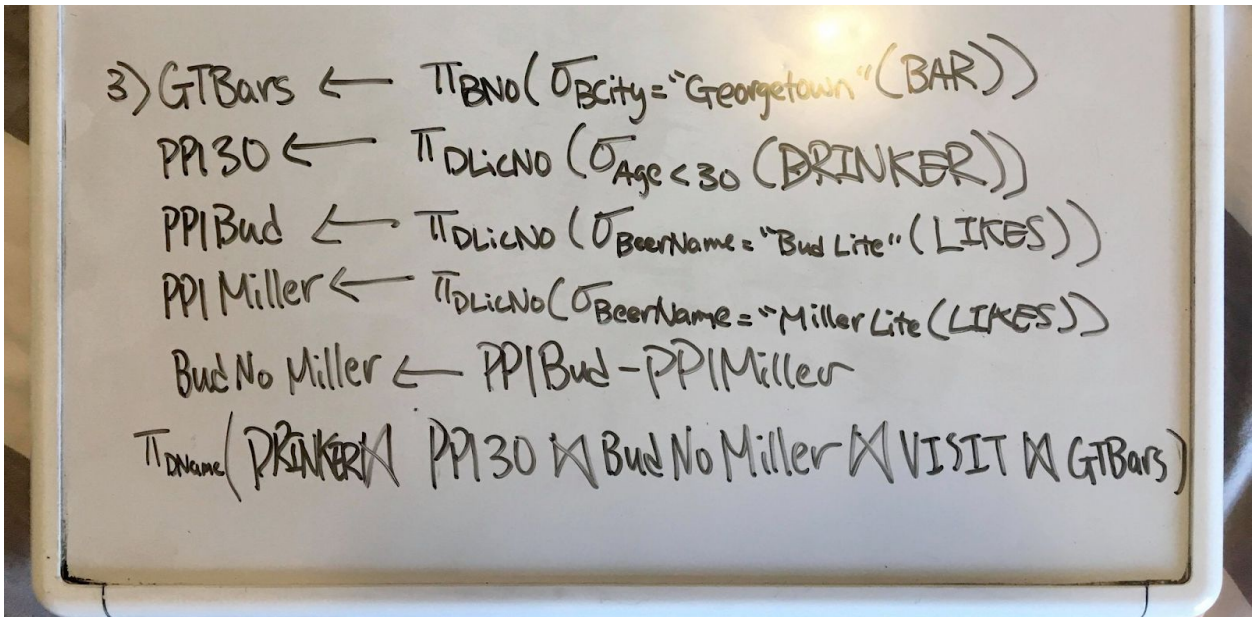
1)



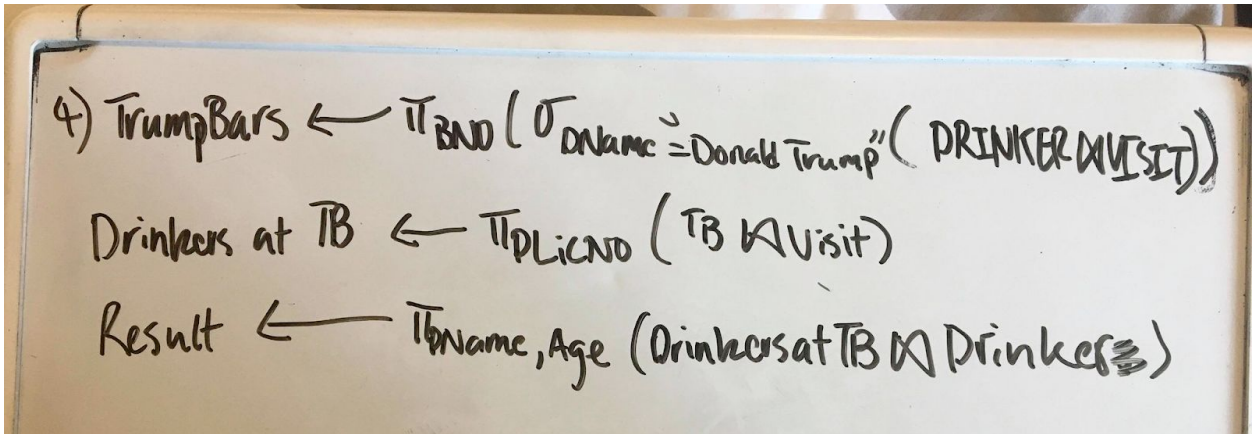
2)



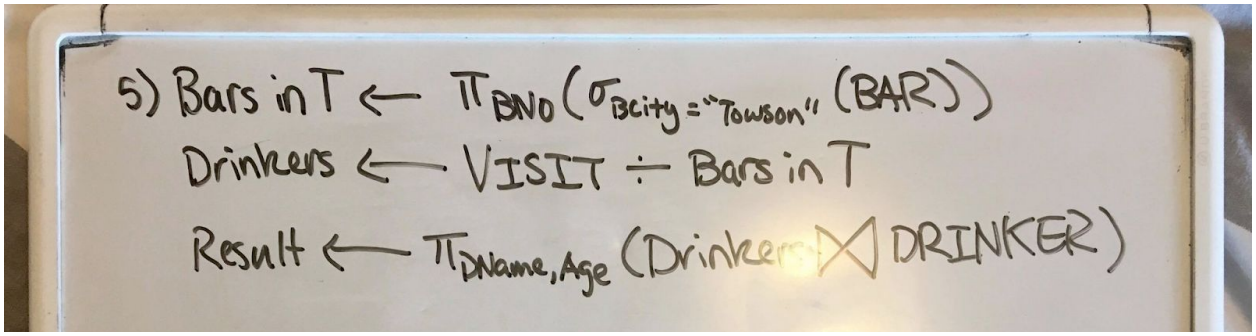
3)



4)



5)



6) $RESULT \leftarrow \Pi_{DName,\ Age}((DRINKER - COVIDDIAGNOSIS) \bowtie (DRINKER - VISIT))$

7)

$UniqueDrinkers \leftarrow \Pi_{DLicNo}((VISIT \bowtie \sigma_{DLicNo=AK117229}(VISIT)) - (VISIT \bowtie \sigma_{DLicNo=SM193312}(VISIT)))$

$RESULT \leftarrow \Pi_{DName,\ Age}(DRINKER \bowtie UniqueDrinkers)$

8)

$PeopleAtNameBar \leftarrow \Pi_{DLicNo}(\sigma_{DRINKER.DName=BAR.BarName}(DRINKER \bowtie VISIT) \bowtie BAR)$

$PeopleWithNameBeer \leftarrow \Pi_{DLicNo}(\sigma_{DRINKER.DName \neq LIKES.BeerName}(DRINKER \bowtie BEER\ PURCHASE))$

$RESULT \leftarrow \Pi_{DName}(DRINKER \bowtie PeopleAtNameBar \bowtie PeopleWithNameBeer)$

9)

$TrumpFavorites \leftarrow \Pi_{BeerName}(\sigma_{DName\ =\ Donald\ Trump}(DRINKER) \bowtie LIKES)$

$TrumpDislikes \leftarrow \Pi_{BeerName}(SERVES) - TrumpFavorites$

$RESULT \leftarrow \Pi_{BarName}(BAR \bowtie SERVES \bowtie TrumpDislikes)$

10)

$TimoniumBeers \leftarrow \Pi_{BeerName}(\sigma_{BCity=Timonium}(BAR) \bowtie SERVES)$

$$BarsThatServeTimoniumBeers \leftarrow \Pi_{BNO}(SERVES \bowtie TimoniumBeers)$$
$$RESULT \leftarrow \Pi_{BarName}(\sigma_{BCity=Towson}(BAR) - BarsThatServeTimoniumBeers)$$

11)

$$DonaldLikes \leftarrow \Pi_{BeerName}(\sigma_{DName="Donald\ Trump"}(DRINKER) \bowtie LIKES)$$
$$IvankaLikes \leftarrow \Pi_{BeerName}(\sigma_{DName="Ivanka\ Trump"}(DRINKER) \bowtie LIKES)$$
$$BothLike \leftarrow DonaldLikes \cap IvankaLikes$$
$$Result \leftarrow \Pi_{BeerName}BothLike \bowtie SERVES)$$

12)

$$BeerCount \leftarrow {}_{BNO}G_{Count\ (BeerName)}(SERVES)$$
$$MaxBeer \leftarrow {}_{BNO}\ G_{Max\ (Count-BeerName)}(BeerCount)$$
$$Result \leftarrow \Pi_{BarName,\ BCity,\ BState}(MaxBeer \bowtie Bar)$$

13)

$$LikeCount \leftarrow {}_{DLicNo}G_{Count\ (BeerName)}(LIKES)$$
$$MinLike \leftarrow \Pi_{DLicNo}(G_{Min\ (Count-BeerName)}(LikeCount))$$
$$Result \leftarrow \Pi_{DName,\ Age}(MinLike \bowtie DRINKER)$$

14)

$$DonaldMikeLike \leftarrow \Pi_{BeerName}(\sigma_{DName="Donald\ Trump"}(DRINKER) \bowtie LIKES) \cup \Pi_{BeerName}(\sigma_{DName="Mike\ Pence"}(DRINKER) \bowtie LIKES)$$
$$DislikesAll \leftarrow \Pi_{DLicNo}(DRINKER) - \Pi_{DLicNo}(DonaldMikeLike \bowtie LIKES)$$
$$Result \leftarrow \Pi_{DName,\ PoliticalParty}(DislikesAll \bowtie DRINKER)$$

15)

$$DonaldLikes \leftarrow \Pi_{BeerName}(\sigma_{DName="Donald\ Trump"}(DRINKER) \bowtie LIKES)$$
$$DrinksSame \leftarrow LIKES \div DonaldLikes$$
$$Result \leftarrow \Pi_{DName,\ PoliticalParty}(\sigma_{DName \neq "Donald\ Trump"}(DrinksSame \bowtie DRINKER))$$

16)

$$\Pi_{BeerName}(\sigma_{DateOfDiagnosis \leq DateOfPurchase\ \wedge\ EstiamtedEndDate \geq DateOfPurchase}(BEER\_\_PURCHASE \bowtie COVID\_\_DIAGNOSIS))$$

17)

$$A \leftarrow VISIT \bowtie (\sigma_{DName = Donald\ Trump}(DRINKER))$$
$$B \leftarrow A$$
$$visitedMoreThanOnce \leftarrow \sigma_{A.BNO = B.BNO \wedge A.DateOfVisit \neq B.DateOfVisit}(A \times B)$$
$$Result \leftarrow \Pi_{BarName}visitedMoreThanOnce$$

18)

$$IT\ Diagnosis \leftarrow Visit \bowtie (COVID\_Diagnosis \bowtie \sigma_{DName = "Ivanka\ Trump"}(Drinker))$$

$$IT\ COVIDDays \leftarrow \Pi_{BNO, DateOfVisit}(\sigma_{Estimated\ Start\ Date <= Date\ Of\ Visit \wedge Date\ Of\ Visit <= Estimated\ End\ Date}(IT\ Diagnosis))$$

$$Result \leftarrow \Pi_{DName, Phone}(Drinker \bowtie (Visit \bowtie IT\ COVIDDays))$$

19)

$$COVIDDays \leftarrow \Pi_{BNO, DateOfVisit}(\sigma_{Estimated\ Start\ Date <= Date\ Of\ Visit \wedge Date\ Of\ Visit <= Estimated\ End\ Date}(Visit \bowtie COVID\_Diagnosis))$$

$$Result \leftarrow \Pi_{DName, Phone}(Drinker \bowtie (Visit \bowtie COVIDDays))$$

20)

$$TEMP1 \leftarrow \sigma_{DateOfVisit \geq DateOfDiagnosis \wedge DateOfVisit \leq EstimatedEndDate}(VISIT \bowtie COVID\_DIAGNOSIS)$$

$$RESULT \leftarrow \Pi_{DName,\ BarName,\ EstimatedStartDate,\ EstimatedEndDate}(DRINKER \bowtie TEMP1 \bowtie BAR)$$

21)

$$BIDENBARTIMES \leftarrow {}_{BNO}\mathcal{G}_{Count} BNO\ (\sigma_{DName="Joe\ Biden"}(DRINKER \bowtie VISIT))$$

$$ALLBARTIMES \leftarrow {}_{DLicNo,\ BNO}\mathcal{G}_{Count} BNO\ (DRINKER \bowtie VISIT)$$

$$OUTPUT \leftarrow \Pi_{Dname,Age}(DRINKER \bowtie (ALLBARTIMES \div BIDENBARTIMES))$$

22)

$$VACTESTPOS \leftarrow \Pi_{DLicNo}(\sigma_{DateOfVaccine < DateOfDiagnosis}(COVID\_DIAGNOSIS \bowtie COVID\_VACCINE))$$

$$OUTPUT \leftarrow \Pi_{DName,Age,PoliticalParty}(VACTESTPOS \bowtie DRINKER)$$

23)

$$Bat\_Beer \leftarrow \Pi_{BNO,\ BeerName}((\sigma_{BarName="BatBar"}(BAR)) \bowtie SERVES)$$

$$All\_Purchaser \leftarrow \Pi_{DLicNo,\ BNO,\ BeerName}(BEER\_PURCHASE)$$

$$People \leftarrow All\_Purchaser \div Bat\_Beer$$

$$Result \leftarrow \Pi_{DName,\ Age}(People \bowtie DRINKER)$$

Relational Calculus (Draft)

1)

{t | ∃ d1 ∈ DRINKER (

∃ d2 ∈ DRINKER (

∃ v1 ∈ VISIT (

∃ v2 ∈ VISIT (

d1[DName] = “Ivanka Trump” ^ v1[DLicNo] = d1[VLicNo] ^

v1[DateOfVisit] = v2[DateOfVisit] ^ v2[BNO] = v1[BNO] ^

v2[DLicNo] = d2[DLicNo]))) ^

t[DName] = d2[DName] ^ t[PoliticalParty] = d2[PoliticalParty])}

2)

{t | ∃ b1 ∈ BAR (

b1[STATE] = “MD” ^ b1[BCity] ≠ “Baltimore” ^

∄ s ∈ SERVES(

s[BNO] = b1[BNO] ^ s[BeerName] = “BudLite”) ^

t[BarName] = b1[BarName])}

3)

{t| ∃ d1 ∈ DRINKER(d1[Age] < 30 ^

∃ v ∈ VISITS (

∃ b ∈ BAR (

∃ l1 ∈ LIKES(

∄ l2 ∈ LIKES(

v[BNO] = b[BNO] ^ b[BCity] = “Georgetown” ^

l1[DLicNo] = d1[DLicNo] ^ l[BeerName] = “Bud Lite”) ^

l1[DLicNo] = d1[DLicNo] ^ l2 ≠ “Miller Lite”))) ^

t[DName] = d1[DName])}

4)

{t | ∃ d1 ∈ DRINKER(t[DName] = d1[DName] ^ t[Age] = d1[Age] ^

∃ v1 ∈ VISIT(

∃ v1 ∈ VISIT(

∃ d2 ∈ DRINKER(

v1[DLicNo] = d1[DLicNo] ^ v2[DLicNo] = d2[DLicNo] ^ v1[BNo] = v2[BNo] ^

d2[Name] = “Donald Trump”

)))))}

9)

{t | ∃ b ∈ BAR(

∃ d ∈ DRINKER(d[DName] = “Donald Trump” ^

∃ s ∈ SERVES(b[BNO] = s[BNO] ^

∄ l ∈ LIKES(

l[DLicNo] = d[DLicNo] ^ l[BeerName] = s[BeerName]))) ^

t[BarName] = b[BarName])}

10)

{t | ∃ b1 ∈ BAR(b1[BCity] = “Towson” ^

∃ b2 ∈ BAR(b2[BCity] = “Timonium” ^

∃ s ∈ SERVES(s[BNO] = b1[BNO] ^

∄ s2 ∈ SERVES(

s2[BNO] = b2[BNO] ^ s1[BeerName] = s2[BeerName])) ^

t[BarName] = b1[BarName])}