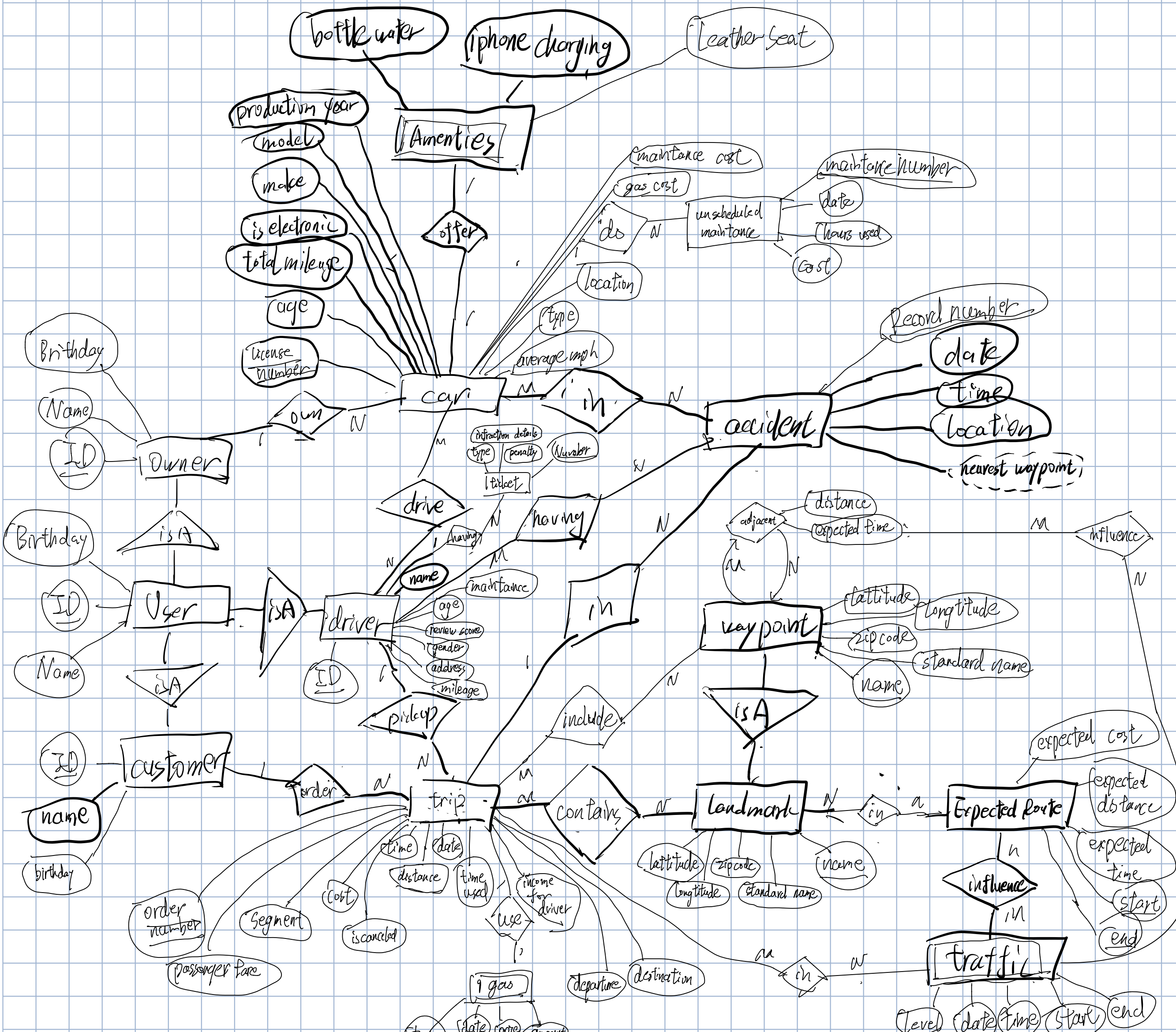
Homework 1
600.415/615 Databases
Fall 2020

October 2, 2020

Mou Zhang

1. **Part 1**
   (a) 1.1



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price
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departure
destination
name
birthday

(b) 1.2

USER	ID	NAME	BIRTHDAY
	1234-567-890	MOU ZHANG	04/29/1997

OWNER	ID	NAME	BIRTHDAY
	1234-567-890	MOU ZHANG	04/29/1997

CUSTOMER	ID	NAME	BIRTHDAY
	1234-567-890	MOU ZHANG	04/29/1997

DRIVER	ID	NAME	AGE	REVIEW SCORE	GENDER	ADDRESS	MILEDRIVED
	1234-567-899	MOU ZHANG	23	100	MALE	MARS	1000

TRIP	ORDERNUM	COST	ISCANCALLED	TIME	DISTANCE	DATE	TIME COST	GASAMOUNT	GASTYPE	GASPRICE	INCOME	DEPARTURE	DESTINATION	CUSTOMER	DRIVER
	123		123 NO	5pm	100 miles	2020/2/2	11	51	51	51	100	JHU	ICON	1234-567-890	674-75953

CAR	OWNER	CARLICNUM	AGE	TOTALMILE	ISELECTRIC	MAKE	MODEL	PRODUCTION YEAR	MPH	TYPE	LOCAITON	MAINTANCE COST	GAS COST
	MOU ZHANG	563H3C	5	5	YES	GA384A	3	2015	210	ELECTRIC	JHU	100	100

ACCIDENT	NUM	TRIP	DATE	TIME	LOCATION	NEAREST WAYPOINT
	12	123	2020/2/2	5PM	JHU	JHU

WAYPOINT	LATTITUDE	LONGTITUDE	NAME	ZIPCODE	STANDARD NAME
	12	34	JHU	21218	JHU

LANDMARK	LATTITUDE	LONGTITUDE	NAME	ZIPCDOE	STANDARD NAME
	12	34	JHU	21218	JHU

EXPECTED ROUTE	START	END	EXPECTED TIME	EXPTECTED COST	EXPECTED DISTANCE
	JHU	ICON	5	5	5

TRAFFIC	START	END	LEVEL	DATE	TIME
	JHU	ICON	LOW	2020/2/2	5PM

AMEITIES	CARLICNUM	BOTTLE WATER	IPHONE CHARGING	LEATURE SEAT	
	GARE8B	1	1	1	

TRIP2LANDMARK	TRIPNUM	LANDMARKPASS
	12	JHU

DRIVER2CAR	DRIVERID	CARLICNUM
	123-445-67	GE8EG

DRIVER2ACCIDENT	DRIVERID	ACCIDENTNUM
	123-5435	2352

TICKET	NUMBER	TYPE	PENALTY	INFRACTION DETAILS	DRIVER
	12345	CRASH	200	BALABALA	123-54-766

9	CAR2ACCIDENT	CARLICNUM	ACCIDENTNUM
0		4FAG43	3413

UNSCHEDULED MAINTAINCE	CARLICNUM	MAINTAINNUM	DATE	HOURS USED	COST
	FGRA32	2432412	2020/2/2	5	5

TRIP2LANDMARK	TRIPNUM	LANDMARK
	2313	JHU

TRIP2WAYPOINT	TRIPNUM	WAYPOINT
	13543	JHU

EXPECTEDROUTE2LANDMARK	START	END	LANDMARK
	JHU	ICON	JHU

EXPECTEDROUTE2TRAFFIC	START	END	DATE	TIME	LEVEL
	JHU	ICON	2020/2/2	5PM	HIGH

ADJACENTWAYPOINT	WAYPOINT	WAYPOINT	DISTANCE	EXPTECTEDTIME
	JHU	ICON	5	5

(c) 1.3

i. (c)$\leftarrow \Pi_{Name} DRIVER \bowtie_{ID=ID \wedge Name=Name} CUSTOMER$
$UserDriveECar \leftarrow \Pi_{Name} \sigma_{IsElectronic="YES"} DRIVER \bowtie_{CARLiCNo=CARLicNo} CAR$
$Result = BothDriverAndCustomers - UserDriveECar$

ii. (f)$CarOwner \leftarrow \sigma_{ACCIDENTNUM,Owner}(Accident \bowtie_{NUM=ACCIDENTNUM} CAR2ACCIDNE \bowtie_{CAR}$
$CAR)$
$Result \leftarrow \Pi_{date,time,nearestwaypoint,owner,driver}(Accident \bowtie_{TRIP=ORDERNUM} TRIP \bowtie_{NUM=ACCIDEN}$
$)$

iii. (h) $NotSameOneCar \leftarrow sigma_{owner \neq driver}(CAR \bowtie_{CARLICNUM=CARLICNUM} Driver2Car)$
$Result \leftarrow_{make,model,year,mileage,driver,owner} NotSameOneCar$

iv. (y)$temp1 \leftarrow \sigma_{date=09/12/20 \cap distance>expecteddistance}(Trip \bowtie_{source=start \cap destination=end}$
$ExpectRoutr)$
$Result \leftarrow \Pi_{source,destination,name}(temp1 \bowtie_{DRIVER=ID} Driver)$

v. (ss) $DriverVisit \leftarrow (\Pi_{Driver,departure(site)} Trip \cup \Pi_{Driver,departure(site)} Trip)$
$AllSites \leftarrow \Pi_{Name} LANDMARK$
$Result \leftarrow (Driver \bowtie_{id=Driver} (DriverVisit \div AllSites))$

vi. (ccc) $Reult \leftarrow_{make,model,productionyear} (\sigma_{MAX(totalmile \div gascost)}(Car))$

2. **Part 2**

(a) Relation Algebra

(.1) $VisitAllPeople \leftarrow DRINKER \bowtie_{DLicNo=DLicNo} VISIT$
$VisitOfIvanka \leftarrow \sigma_{DNAME="IvankaTrump"}(VisitAllPeople)$
$Result \leftarrow \Pi_{DName,PoliticalParty}(\Pi_{BNO,DateOfVisit}(VisitOfIvanka)$
$\bowtie_{BNO=BNO \wedge DateOfVisit=DataOfVisit} VisitAllPeople$

(.2) $BarInMD \leftarrow \Pi_{BNO} \sigma_{BState="MD"} BAR$
$BarServeBudLite \leftarrow \Pi_{BNO} \sigma_{BeerName="BudLite"} SERVES$
$BarAtBalt \leftarrow \Pi_{BNO} \sigma_{BCity="Baltimore"} BAR$
$Result =\leftarrow \Pi_{BarName}((BarInMD - BarServeBudLite - BarAtBalt) \bowtie_{BNO=BNO}$
$BAR)$

(.3) $PeopleUnderThirty \leftarrow \Pi_{DLicNo} \sigma_{Age<30} DRINKER$
$PeopleVisitAtLeastOneBar \leftarrow \Pi_{DLicNo} \sigma_{BCity="Georgetown"}(DRINKER \bowtie_{DLicNo=DLicNo}$
$VISIT \bowtie_{BNO=BNO} BAR)$
$PeopleLikeBudLite \leftarrow \Pi_{DLicNo} \sigma_{BeerName="BudLite"}(DRINKER \bowtie_{DLicNo=DLicNo}$
$LIKES)$
$PeopleLikeMillerLite \leftarrow \Pi_{DLicNo} \sigma_{BeerName="MillerLite"}(DRINKER \bowtie_{DLicNo=DLicNo}$
$LIKES)$
$PeopleNotLikeMillerLite \leftarrow (\Pi_{DLicNo} DRINKER) - PeopleLikeMillerLite$
$Result \leftarrow PeopleUnderThirty \cap PeopleVisitAtLeastOneBar \cap PeopleLikeBudLite \cap$
$PeopleNotLikeMillerLite$

(.4) $VisitByPerson \leftarrow DRINKER \bowtie_{DLicNo=DLicNo} VISIT$
$VisitOfDonald \leftarrow \sigma_{DNAME="DonaldTrump"}(VisitByPerson)$
$Result \leftarrow \Pi_{DName,Age}(\sigma_{BNO} VisitOfDonald) \bowtie_{BNO=BNO} VisitByPerson$

(.5) $VisitByPerson \leftarrow DRINKER \bowtie_{DLicNo=DLicNo} VISIT$
$BarInTowson \leftarrow \Pi_{BNO} \sigma_{BCity="Towson"} BAR$
$Result \leftarrow \Pi_{DName,Age} VisitByPerson \div BarInTowson$

(.6) $VisitByPerson \leftarrow DRINKER \bowtie_{DLicNo=DLicNo} VISIT$
$Result \leftarrow \Pi_{DName,Age}((\Pi_{DLicNo} DRINKER -$
$\Pi_{DLicNo} VisitByPerson - \Pi_{DLicNo} COVID\_DIAGNOSIS) \bowtie_{DLicNo=DLicNo} DRINKER)$

(.7) $VisitByPerson \leftarrow DRINKER \bowtie_{DLicNo=DLicNo} VISIT$
$VisitOfDonald \leftarrow \sigma_{DNAME="DonaldTrump"}(VisitByPerson)$
$VisitOfJoe \leftarrow \sigma_{DNAME="JoeBiden"}(VisitByPerson)$
$PersonVisitAllDonald \leftarrow \Pi_{DLicNo}(VisitByPerson \div \Pi_{BNO} VisitOfDonald)$

$PersonVisitAtLeastOneJoe \leftarrow \Pi_{DLicNo}(VisitByPerson \bowtie_{BNO=BNO} \Pi_{BNO}VisitByJoe)$
$Result = \Pi_{DName,Age}(PersonVisitAllDonald - PersonVisitAtLeastOneJoe) \bowtie_{DLicNo=DLicNo} DRINKER$

(.8) $PeopleDrunkSameNameBeer \leftarrow \Pi_{DLicNo}\sigma_{DName=BeerName}(DRINKER \bowtie_{DLicNo=DLicNo} BEER\_PURCHASE)$
$PeopleVisitSameNameBar \leftarrow \Pi_{DLicNo}\sigma_{DName=BarName}(DRINKER \bowtie_{DLicNO=DLicNo} VISIT \bowtie_{BNO=BNO} BAR)$
$Result \leftarrow \Pi_{DName}((PeopleVisitSameNameBar - PeopleDrunkSameNameBeer) \bowtie_{DLicNo=DLicNo} DRINKER)$

(.9) $DonaldLikeBeer \leftarrow \Pi_{BeerName}\sigma_{DName="DonaldTrump"}(DRINKER \bowtie_{DLicNo=DLicNo} LIKES)$
$Result \leftarrow \Pi_{BarName}(BAR \bowtie_{BNO=BNO} (SERVES - SERVES \bowtie_{BeerName=BeerName} DonaldLikeBeer))$

(.10) $BarInTowson \leftarrow \Pi_{BNO,BarName}\sigma_{BCity="Towson"} BAR$
$BarInTimonium \leftarrow \Pi_{BNO}\sigma_{BCity="Timonium"} BAR$
$BeerInTimonium \leftarrow \Pi_{BeerName}(BarInTimonium \bowtie_{BNO=BNO} SERVES)$
$Result \leftarrow \Pi_{BarName}(BarInTowson - \Pi_{BNO,BarName}((BAR \bowtie_{BNO=BNO} SERVE \bowtie_{BeerName=BeerN}$
$BeerInTimonium)))$

(.11) $DonaldLikeBeer \leftarrow \Pi_{BeerName}\sigma_{DName=\imath DonaldTrump"} DRINKER \bowtie_{DLicNo=DLicNo} LIKES$
$IvankaLikeBeer \leftarrow \Pi_{BeerName}\sigma_{DName=\imath IvankaTrump"} DRINKER \bowtie_{DLicNo=DLicNo} LIKES$
$BothLikeBeer \leftarrow DonalLikeBeer \cap IvankaLikeBeer$
$Result \leftarrow \Pi_{BeerName}(BothLikeBeer \bowtie_{BeerName=BeerName} SERVES)$

(.12) $NumBeers \leftarrow \rho_{NumBeers(BNO,NumBeerName)} {}_{BNO}\mathcal{G}_{\mathbf{count}\,BeerName}(SERVES)$
$Results \leftarrow \Pi_{name,city,state}({}_{BNO}\mathcal{G}_{\mathbf{max}\,NumBeerName}(NumBeers) \bowtie_{BNO=BNO} BAR)$

(.13) $NumDrinkerLikesBeers \leftarrow \rho_{NumDrinkerLikesBeers(DLicNo,NumBeerName)} {}_{DLicNo}\mathcal{G}_{\mathbf{count}\,BeerName}(LIK$
$Result \leftarrow \Pi_{DName,Age}({}_{DLicNo}\mathcal{G}_{\mathbf{min}}(NumBeerName) \bowtie_{BNO=BNO} DRINKER)$

(.14) $BeerTrumpLikes \leftarrow \Pi_{BeerName}(\sigma_{DName="DonaldTrump"} DRINKER \bowtie_{DLicNo=DLicNo} LIKES)$
$DrinkerLikeTrumpBeer \leftarrow LIKES \bowtie_{BeerName=BeerName} BeerTrumpLikes$
$Result \leftarrow \Pi_{DName,PoliticalParty}(DRINKER - DrinkerLikeTrumpBeer)$

(.15) $BeerTrumpLikes \leftarrow \Pi_{BeerName}(\sigma_{DName="DonaldTrump"} DRINKER \bowtie_{DLicNo=DLicNo} LIKES)$
$DrinkerLikeEveryTrumpBeer \leftarrow LIKES \div BeerTrumpLikes$
$Result \leftarrow \Pi_{DName,PoliticalParty}(DrinkerLikeEveryTrumpBeer \bowtie_{DLicNo=DLicNo} DRINKER)$

(.16) $PeopleSufferCoVid \leftarrow \Pi_{BeerName}(\sigma_{EstimatedStartDate<DataOfPurchase \wedge EstimatedEndDate>DateOfPurc}$
$COVID\_DIAGNOSIS \bowtie_{DlicNo=DLicNo} BEER\_PURCHASE)$

(.17) $TrumpVisit \leftarrow DRINKER \bowtie_{DLicNO=DLicNO} VISIT$
$Result \leftarrow \Pi_{BarName}\sigma_{COUNT(BNO)>1}(TrumpVisit \bowtie_{BNO=BNO} BAR)$

(.18) $BarIvankaVisit \leftarrow DRINKER \bowtie_{DName="IvankaTrump"} VISIT$
$BarIvankaVisitDuringCovid \leftarrow \sigma_{DataOfVisit>EStinatedStartDate \wedge DateOfVisit<EstimatedEndDate}$
$BarIvankaVisit \bowtie_{DLicNO=DLicNo} COVID\_DIAGNOSIS$
$DrinkerVisitSameIvanks \leftarrow VISIT \bowtie_{BNO=BNO \wedge DataOfVisit=DateOfVisit} BarIvankaVisitDuring$
$Result \leftarrow \Pi_{Dname,Phone} DRINKER \bowtie_{DLinNo=DLicNo} DrinkerVisitSameIvanks$

(.19) $CovidVisit \leftarrow \sigma_{DataOfVisit>EStinatedStartDate \wedge DateOfVisit<EstimatedEndDate} COVID\_DIAGNOSIS$
$VISIT$
$AllVisit \leftarrow DRINKER \bowtie_{DLicNo=DLincNo} VISIT$
$Result = \Pi_{Dname,Phone}((\Pi_{BNO,DateOfVisit} CovidVisit) \bowtie_{BNO=BNO \wedge DataOfVisit=DateOfVisit} AllVisit)$

(.20) $CovidVisit \leftarrow \sigma_{DataOfVisit>EStinatedStartDate \wedge DateOfVisit<EstimatedEndDate} COVID\_DIAGNOSIS$
$VISIT$
$Result \leftarrow \Pi_{DName,BarName,EstimatedStartDate,EstimatedEndDate}(BAR \bowtie_{BNO=BNO}$
$CovidVisit \bowtie_{DLicNo=DLicNo} DRINKER)$

(.21) $NumAllVisit \leftarrow \rho_{NumAllVisit(DLicNo,BNO,NumVisit)} {}_{DLicNo}\mathcal{G}_{\mathbf{count}\,BNO} VISIT$

$Biden \leftarrow \Pi_{DLicNo}\sigma_{DName="JoeBiden"}DRINKER$
$NumBidenVisit \leftarrow \Pi_{BNO,NumVisit}(Biden \bowtie_{DLicNo=DLicNo} NumAllVisit)$
$Person \leftarrow \Pi_{DLicNo}(NumAllVisit \div NumBidenVisit)$
$Reuslt \leftarrow \Pi_{Dname,Age}(Person \bowtie_{DLicNo=DLicNo} DRINKER)$

(.22) $AllDrinkerVaccined \leftarrow DRINKER \bowtie_{DLicNo=DLicNo} COVID\_VACCINE$
$AllDrinkerTestCovidOnDiffDay \leftarrow \sigma_{DateOfVaccine \neq DateOfDiagnosis}((\Pi_{DLicNo,DateOfVaccine}AllDri$
$COVID\_DIAGNOSIS)$
$Result \leftarrow \Pi_{DName,Age}((\Pi_{DLicNo}AllDrinkerTestCovidOnDiffDay) \bowtie_{DLicNo=DLicNo}$
$DRINKER)$

(.23) $AllBeerInBatBar \leftarrow \sigma_{BarName="BatBar}BAR \bowtie_{BNO=BNO} SERVES$
$PersonBuyAllBeerAtBatBar \leftarrow \Pi DLicNo(BEER\_PURCHASE \div (\Pi_{BNO,BeerName}AllBeerInBat$
$Result \leftarrow \Pi_{DName,Age}(PersonBuyAllBeerAtBatBar \bowtie_{DLicNo=DLicNo} DRINKER)$

(b) Relation Calculus

i. 2.1

$$\{t|\exists d, i \in DRINKER($$
$$\exists v, vi \in VISIT($$
$$d[DLicNo] = v[DLicNo]$$
$$\wedge i[DName] = "IvankaTrump"$$
$$\wedge i[DLicNo] = vi[DLicNo]$$
$$\wedge v[DateOfVisit] = vi[DateOfVisit]$$
$$\wedge v[BNO] = vi[BNO]$$
$$\wedge t[DName] = d[DName]$$
$$\wedge t[PoliticalParty] = d[PoliticalParty]$$
$$))\}$$

ii. 2.2

$$\{t|\exists b \in BAR($$
$$b[BState] = "MD"$$
$$\wedge \neg b[BCity] = "Baltimore"$$
$$\wedge \neg(\exists s \in SERVES($$
$$\wedge s[Serves] = "BudLite"$$
$$\wedge s[BNO] = b[BNO])$$
$$\wedge t[BarName] = b[BarName]$$
$$))\}$$

iii. 2.3

$$\{t|\exists d \in DRINKER($$
$$v \in VISIT($$
$$b \in BAR($$
$$l \in LIKE($$
$$d[DLicNo] = v[DLicNo]$$
$$\wedge v[BNO] = b[BNO]$$
$$\wedge l[DLicNo] = d[DLicNo]$$
$$\wedge b[BCity] = "Georgetown"$$
$$\wedge d[Age] < 30$$
$$\wedge l[BeerName] = "ButLite"$$
$$\wedge \neg l[BeerName] = "MillerLit"$$
$$\wedge t[DName] = d[DName])))\}$$

iv. 2.4

$$\{t|\exists d, da \in DRINKER($$
$$\exists v, va \in VISIT($$
$$d[DLicNo] = v[DLicNo]$$
$$\wedge d[DName] = "DonaldTrump"$$
$$\wedge da[DLicNo] = va[DLicNo]$$
$$\wedge v[BNO] = va[BNO]$$
$$\wedge t[DName] = d[Dname]$$
$$\wedge t[Age] = d[Age]))\}$$

v. 2.9

$$\{t|\exists d \in DRINKER($$
$$\exists l \in LIKES($$
$$\exists s \in SERVES($$
$$\neg(\exists d \in DRINKER($$
$$d[DLicNo] = l[DLicNo]$$
$$\wedge d[DName] = "DonaldTrump")$$
$$\wedge l[BeerName] = s[BeerName]))$$
$$\wedge t[BarName] = b[BarName])\}$$

vi. 2.10

$$\{t|\exists bto \in BAR($$
$$bto[BCity] = "Towson"$$
$$\wedge\neg(\exists bit \in BAR($$
$$bti[BCity] = "Timonium"$$
$$\wedge\exists sto, sti, \in SERVES($$
$$sto[BNO] = bto[BNO]$$
$$\wedge sti[BNO] = bti[BNO]$$
$$\wedge sto[BeerName] = sti[BeerName])))$$
$$\wedge t[BarName] = bto[BarName])\}$$