15.072: Advanced Analytics Edge Fall 2021 Homework 4: From Predictions to Prescriptions

a.i)

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)
             2.312e+00 3.317e-02
                                  69.712
                                            <2e-16 ***
linc
            -2.351e-01 3.147e-03 -74.711
                                            <2e-16 ***
Week_Num
            4.771e-03 2.832e-05 168.495
                                            <2e-16 ***
bseason2
             2.167e-03 3.757e-03
                                   0.577
                                            0.564
             2.182e-03 3.762e-03
                                   0.580
                                            0.562
bseason3
bseason4
            1.750e-03 3.770e-03
                                   0.464
                                            0.643
            1.315e-03 3.782e-03
                                   0.348
                                            0.728
bseason5
                                  13.336
                                            <2e-16 ***
bseason6
             5.064e-02 3.797e-03
             5.318e-02 3.816e-03
                                  13.936
                                            <2e-16 ***
bseason7
                                            <2e-16 ***
bseason8
            4.891e-02 3.838e-03
                                  12.744
                                            <2e-16 ***
bseason9
            5.253e-02 3.863e-03
                                  13.600
bseason10
             5.409e-02 3.891e-03
                                  13.903
                                            <2e-16 ***
             2.517e-03 3.922e-03
                                   0.642
bseason11
                                            0.521
bseason12
             1.423e-01 3.956e-03
                                  35.974
                                            <2e-16 ***
             1.410e-01 3.993e-03 35.317
bseason13
                                            <2e-16 ***
```

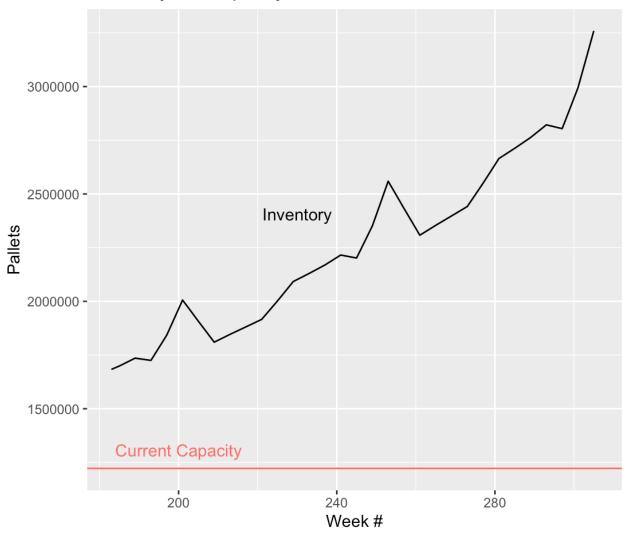
```
his<-his%>%mutate(lsale = log(Sales/Population),saleper = Sales/Population,
linc = log(Income), bseason = as.factor(Season))
train <- his%>%filter(Year <=2013)
test<-his%>%filter(Year ==2014)
mod <- lm(lsale~linc+Week_Num+bseason, data = train)
summary(mod)
```

a.ii)

It is important to note that none of these estimates are causal and can only be interpreted as correlation. A one percent increase in income per capita is associated with a 0.235% decrease in sales per capita. Another week away from the beginning of 2012 is associated with a .477% increase in sales per capita. Using season 2 as an example, being in season 2 is associated with a .217% increase in sales per capita. All other seasons can be interpreted the same was a 100*coefficient increase in sales per capita.

a.iii) Out-of-sample performance: $R^2 = 0.777$, MAE = 0.163, RMSE = 0.209

b.i) Inventory vs. Capacity Over Time



b.ii) **Shortage = 166.674%**

 $percent_cap_short <- (inv_df[123,3]-current_cap)/(current_cap)*100$

c.i)

Decision Variables:

 $b_i = 1$ if DC_i is chosen, 0 otherwise

 $u_i = 1 if DC_i$ is serves $County_j$, 0 otherwise

 $c_i = the \ capacity \ utilized \ of \ DC_i$

Inputs:

 $FixedCost_i = fixed\ cost\ of\ constructing\ DC_i$ $VariableCost_i = variable\ cost\ of\ constucting\ DC_i\ per\ sqft$ $d_{ij} = distance\ from\ DC_i\ to\ county_j$ $CapacityDC_i = maximum\ capacity\ of\ DC_i$ $x_{it} = predicted\ demand\ of\ county\ j\ in\ week\ t$

$$\begin{split} \operatorname{Min_{b,u,c}} & \sum_{i} FixedCost_{i}b_{i} + \sum_{i} VariableCost_{i}c_{i} + \sum_{i} \sum_{j} \sum_{t} \left(\frac{1.55}{20}\right) d_{ij}x_{jt}u_{ij} \\ & b_{i} = 1 \ \forall \ i = 1,2,3 \\ & c_{i} = 1,200,000 \ \forall \ i = 1,2 \\ & c_{i} = 900,000 \ \forall \ i = 3 \end{split} \\ & \sum_{j} u_{ij} = 1 \ \forall \ j \\ & u_{ij} \leq b_{i} \ \forall \ i,j \\ & c_{i} = 1,200,000 \ \forall \ i = 1,2 \\ & 0 \leq c_{i} \leq CapacityDC_{i}b_{i} \end{split}$$

$$& \sum_{j} u_{ij} \leq CapacityDC_{i}\left(\frac{5}{13.5}\right) \forall \ i \\ & c_{i} \leq 1,200,000b_{i} \forall \ i \\ & u_{ij}, b_{i} \in \{0,1\} \end{split}$$

model = Model(with optimizer(Gurobi.Optimizer, Gurobi.Env()))

set_optimizer_attribute(model, "OutputFlag", 0)

 $n = size(county_tot_d,1)$

- @variable(model, b[i=1:20], Bin)
- @variable(model, u[i=1:20,j=1:n], Bin)
- @variable(model, c[i=1:20]>=0)
- @constraint(model, [i=1:3], b[i]==1)
- @constraint(model, [i=1:2], c[i]==1200000)
- @constraint(model, [i=3], c[i]==900000)
- @constraint(model, [j=1:n], sum(u[:,j])== 1)

```
(a) constraint(model, [i=1:20, j=1:n], u[i,j] \le b[i])
       @constraint(model, [i=1:20], c[i]*(5/13.5) >= sum(df[j]*u[i,j] for j=1:n))
       @constraint(model, [i=1:20], c[i] <= b[i] * 1200000)
       @objective(model, Min, sum(variable cost[i]*c[i] for i=1:20) + sum(fixed cost[i]*b[i]
       for i=1:20) +
         sum(sum((1.55/20)*d mat[i,j]*county tot d[j,:d pallets sum]*u[i,j] for j=1:n) for
       i=1:20)
       optimize!(model)
d.i) In addition to the 3 original DCs, there will also be DCs at Kalamazo, Lancaster,
Scranton, Syracuse, Toledo.
     b=value.(b)
Providence = 57
Richmond = 122
Youngstown = 120
Kalamazo = 222
Lancaster = 41
Scranton = 27
Syracuse = 60
Toledo = 116
       sum(u, dims=2)
Construction Cost = $556,050,072.64
Transportation Cost = $197,324,788.82
       construction cost = sum(variable cost[i]*c[i] for i=1:20) + sum(fixed cost[i]*b[i] for
       i=1:20)
       transpo cost = sum(sum((1.55/20)*d mat[i,j]*county tot d[j,:d pallets sum]*u[i,j] for
      i=1:n) for i=1:20)
Cheapest DC's w/ capacity (in sqft)
   Providence = 1,200,000
   Richmond = 1,200,000
   Youngstown = 900,000
   Bangor = 1,200,000
   Burlington = 1.200.000
   Dover = 1,200,000
```

d.ii)

d.iii)

e.i)

```
Kalamazoo = 700237.0249
   Worcester = 1,200,000
Construction Costs = $517,077,966.49
Transportation Costs = $505,919,172.89
       mod1 = Model(with optimizer(Gurobi.Optimizer, Gurobi.Env()))
       set optimizer attribute(mod1, "OutputFlag", 0)
       n = size(county tot d,1)
       @variable(mod1, c[i=1:20] \ge 0)
       @variable(mod1, b[i=1:20], Bin)
       (a) constraint(mod1, [i=1:2], c[i]==1200000)
       (a) constraint(mod1, [i=3], c[i]==900000)
       @constraint(mod1, [i=1:3], b[i]==1)
       @constraint(mod1, [i=1:20], c[i]<=b[i]*1200000)
       @constraint(mod1, sum(c[i]*(5/13.5) for i=1:20) >= sum(df[i] for i=1:n))
       @objective(mod1, Min, sum(fixed cost[i]*b[i] for i=1:20) + sum(variable cost[i]*c[i]
       for i=1:20)
       optimize!(mod1)
       mod2 = Model(with optimizer(Gurobi.Optimizer, Gurobi.Env()))
       set optimizer attribute(mod2, "OutputFlag", 0)
       n = size(county tot d,1)
       @variable(mod2,u[i=1:20,j=1:n], Bin)
       b = value.(b)
       c = value.(c)
       @constraint(mod2, [j=1:n], sum(u[:,j])== 1)
       @constraint(mod2, [i=1:20, j=1:n], sum(df[j]*u[i,j] for j=1:n) \leq 1.001*c[i]*5/13.5)
       @objective(mod2, Min,
       sum(sum(1.55/20*d mat[i,j]*county tot d[i,:d pallets sum]*u[i,j] for j=1:n) for
       i=1:20)
       optimize!(mod2)
```

e.ii) In the baseline solution, which first optimizes for construction cost and then generates transportation costs, the solution reflects the priorities. Construction cost is lower in the

second model because it is explicitly minimizes it first. However, this comes at the cost of higher transportation costs. In part d, we were only concerned with the overall cost and thus that was decreased, and transportation costs were significantly less.

R-Code Appendix

```
library(tidyverse)
library(Metrics)
library(zoo)
his = read.csv("/Users/bennetthellman/Desktop/OneDrive - Massachusetts Institute of
Technology/AE/HWs/HW4/Dartboard historical-1.csv");
fut = read.csv("/Users/bennetthellman/Desktop/OneDrive - Massachusetts Institute of
Technology/AE/HWs/HW4/Dartboard future.csv.crdownload");
dc = read.csv("/Users/bennetthellman/Desktop/OneDrive - Massachusetts Institute of
Technology/AE/HWs/HW4/Dartboard dcs.csv");
#dc<-dc%>%mutate(County.Name = Location)
#mdf = merge(his, dc, by.x = "State.Name", by.y = "Location", all.x = TRUE)
his<-his%>%mutate(lsale = log(Sales/Population), saleper = Sales/Population,
          linc = log(Income), bseason = as.factor(Season))
train <- his%>%filter(Year <=2013)
test<-his%>%filter(Year == 2014)
mod <- lm(lsale~linc+Week Num+bseason, data = train)
summary(mod)
summary(mod)$r.squared
pred <- predict(mod, newdata=test)</pre>
#OSR^2
1 - sum((pred - test$lsale)^2) / sum((mean(train$lsale) - test$lsale)^2)
#OMAE
mae(test$lsale, pred)
#ORMSE
rmse(test$lsale, pred)
fut<-fut%>%mutate(linc = log(Income), bseason = as.factor(Season))
fut$forecast <- exp(predict(mod, newdata=fut))*fut$Population</pre>
#b
inv df <- fut %>% group by(Week Num) %>% summarize(tot d= sum(forecast)) %>%
 mutate(inv = (rollapply(data = tot d, FUN=sum, width=8, align="left", fill=NA)/1000))
#Claire Sailard helped me with this function
current cap<- dc%>%summarise(tot pallets cap = sum(5*Current Size/(13.5)))
ggplot(main = "Inventory vs. Capacity Over Time")+geom line(aes(x = Week Num, y = inv),
data = inv df) + geom hline(aes(vintercept=1222222, color = "red")) +
 geom text(aes(200,1222222,label = "Current Capacity", vjust = -1, color = "red")) +
geom text(aes(230,2322222,label = "Inventory", vjust = -1))+
```

```
labs(x ="Week #", y="Pallets", title="Inventory vs. Capacity Over Time")+
theme(legend.position = "none")+xlim(183,306)

#bi
percent_cap_short <- (inv_df[123,3]-current_cap)/(current_cap)*100
percent_cap_short

#exportation
fut$d_pallets = fut$forecast/1000
write.csv(fut,'/Users/bennetthellman/Desktop/OneDrive - Massachusetts Institute of Technology/AE/HWs/HW4/pred_d.csv')
```

Julia Code Appendix