

```
In [26]: using JuMP, Gurobi, LinearAlgebra, CSV, DataFrames, Pkg, Distances, Random,
```

```
In [27]: items = CSV.read("items.csv",DataFrame; header=1);
sales = CSV.read("sales.csv",DataFrame; header=1);
side = CSV.read("sideinformation.csv",DataFrame; header=1);
```

```
In [100]: Q = [50,100, 150, 200, 250, 300]
merged = innerjoin(items, sales, on = :item_nbr)
first(merged, 5);
```

## 2.b.i

```
In [86]: dbf = merged[joined_data.date .== "14/08/2017", :];
dbf2 = merged[joined_data.date .== "15/08/2017", :];
d_np = dbf[dbf.perishable .== 0, :].unit_sales;
e_p = dbf[dbf.perishable .== 1, :].unit_sales;
d_np_15 = dbf2[dbf2.perishable .== 0, :].unit_sales;
e_p_15 = dbf2[dbf2.perishable .== 1, :].unit_sales;
p_p = dbf[dbf.perishable .== 1, :].price;
p_np = dbf[dbf.perishable .== 0, :].price;
c_p = dbf[dbf.perishable .== 1, :].cost;
c_np = dbf[dbf.perishable .== 0, :].cost;
n_p = nrow(dbf[dbf.perishable .== 1, :])
n_np = nrow(dbf[dbf.perishable .== 0, :]);
```

```
In [87]: function optimize_values(Q; solver_output = 0)
model = Model(with_optimizer(Gurobi.Optimizer))
set_optimizer_attribute(model, "OutputFlag", solver_output)

@variable(model, s_np[i=1:n_np]>=0, Int)
@variable(model, t_p[j=1:n_p]>=0, Int)
@variable(model, phi[i=1:n_np])
@variable(model, theta[j=1:n_p])

@constraint(model, [j=1:num_p], t_p[j] <= (1/20*Q))
@constraint(model, [i=1:num_np], s_np[i] <= (1/20*Q))
@constraint(model, [j=1:num_p], theta[j] <= e_p[j])
@constraint(model, [j=1:num_p], theta[j] <= t_p[j])
@constraint(model, [i=1:num_np], phi[i] <= d_np[i])
@constraint(model, [i=1:num_np], phi[i] <= s_np[i])
@constraint(model, [i=1:num_np, j=1:n_p], sum(s_np[i] for i=1:n_np) + sum(t
@objective(model,Max, sum(p_p[j]*theta[j] - c_p[j]*t_p[j] for j=1:n_p)+ sum
JuMP.optimize!(model)
obj_val = JuMP.objective_value(model)
return obj_val
end
```

```
Out[87]: optimize_values (generic function with 1 method)
```

```
In [88]: profit = 0
for i in Q
    profit = profit + optimize_values(i)
end
println("Average Profit: ", profit/length(Q))
```

```
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Average Profit: 508.2975666666666
```

## 2.b.ii

```
In [90]: dbf = merged[joined_data.date .== "15/08/2017", :]
d_np = dbf[dbf.perishable .== 0, :].unit_sales;
e_p = dbf[dbf.perishable .== 1, :].unit_sales;
p_p = dbf[dbf.perishable .== 1, :].price;
p_np = dbf[dbf.perishable .== 0, :].price;
c_p = dbf[dbf.perishable .== 1, :].cost;
c_np = dbf[dbf.perishable .== 0, :].cost;
n_p = nrow(dbf[dbf.perishable .== 1, :])
n_np = nrow(dbf[dbf.perishable .== 0, :]);
```

```
In [91]: profit = 0
for i in Q
    profit = profit + optimize_values(i)
end
println("Average Profit: ", profit/length(Q))
```

```
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Average Profit: 460.2348866666667
```

## 2.b.iii

The approach used below judges the five nearest neighbors as those which are most similar in terms of holiday status and oil price (isHoliday, oilPrice). Both are an effort to indicate days with similar economic and consumer patterns.

```
In [92]: side[!,:dt]=Date.(side.date, "dd/mm/yyyy");
side[!,:oil_p]=(side[!,:oilPrice].-minimum(side[!,:oilPrice]))./(maximum(si
#obtaining the most recent 100 days
recent=subset(side, :dt => ByRow( >=(Date(2017,8,15)-Dates.Day(100))));
oil_p_15 = subset(recent, :date => ByRow(isequal("15/08/2017"))[:, 3]);
hol_15 = subset(recent, :date => ByRow(isequal("15/08/2017"))[:, 2]);
#calculating euclidean distance
side.dist = ((oil_p_15 .- side.oil_p).^2 + (hol_15 .- side.isHoliday).^2).^
#finding the 5 "nearest" neighbors
dist_sorted = sort!(side, [:dist]);
fiveNN_dates = dist_sorted[:, :date][2:6, :]
```

```
Out[92]: 5x1 Matrix{String}:
"3/06/2017"
"14/08/2017"
"12/03/2017"
"2/05/2017"
"2/06/2017"
```

```
In [93]: #subsetting data to five nearest dates
df2 = joined_data[isin(fiveNN_dates).(merged.date), :];
df2_p = df2[df2.perishable == 1, :];
df2_np = df2[df2.perishable == 0, :];
```

```
In [94]: #subsetting data to five nearest dates for sales records and splitting into
knn_1 = sales[sales[:, :date] .== fiveNN_dates[1], :];
knn_2 = sales[sales[:, :date] .== fiveNN_dates[2], :];
knn_3 = sales[sales[:, :date] .== fiveNN_dates[3], :];
knn_4 = sales[sales[:, :date] .== fiveNN_dates[4], :];
knn_5 = sales[sales[:, :date] .== fiveNN_dates[5], :];
#obtaining unit_sales for all five neighbors
items.knn_demand_1 = knn_1[:, 5];
items.knn_demand_2 = knn_2[:, 5];
items.knn_demand_3 = knn_3[:, 5];
items.knn_demand_4 = knn_4[:, 5];
items.knn_demand_5 = knn_5[:, 5];
d_np = Matrix(items[items.perishable .== 0, :][:, Not(1:6)]);
e_p = Matrix(items[items.perishable .== 1, :][:, Not(1:6)]);
p_p = items[items.perishable .== 1, :].price;
p_np = items[items.perishable .== 0, :].price;
c_p = items[items.perishable .== 1, :].cost;
c_np = items[items.perishable .== 0, :].cost;
n_p = nrow(items[items.perishable .== 1, :]);
n_np = nrow(items[items.perishable .== 0, :]);
```

```

In [97]: function optimize_values(Q; solver_output = 0)
           model = Model(with_optimizer(Gurobi.Optimizer))
           set_optimizer_attribute(model, "OutputFlag", solver_output)

           K = 5
           @variable(model, s_np[i=1:n_np]>=0, Int)
           @variable(model, t_p[j=1:n_p]>=0, Int)
           @variable(model, phi[i=1:n_np, k=1:K])
           @variable(model, theta[j=1:n_p, k=1:K])

           @constraint(model, [j=1:n_p], t_p[j] <= (1/20*Q))
           @constraint(model, [i=1:n_np], s_np[i] <= (1/20*Q))

           @constraint(model, [j=1:n_p, k=1:K], theta[j, k] <= e_p[j, k])
           @constraint(model, [j=1:n_p, k=1:K], theta[j, k] <= t_p[j])

           @constraint(model, [i=1:n_np, k=1:K], phi[i, k] <= d_np[i, k])
           @constraint(model, [i=1:n_np, k=1:K], phi[i, k] <= s_np[i])

           @constraint(model, [i=1:n_np, j=1:n_p], sum(s_np[i] for i=1:num_np) + s
           @objective(model, Max, sum(1/K*sum(p_p[j]*theta[j, k] - c_p[j]*t_p[j] for
           sum(1/K*sum(p_np[i]*phi[i, k] - c_np[i]*phi[i, k] for i=1:n_np) for k=1

           JuMP.optimize!(model)
           obj_val = JuMP.objective_value(model)
           return (obj_val, JuMP.value.(s_np), JuMP.value.(t_p), JuMP.value.(theta
end

```

Out[97]: optimize\_values (generic function with 1 method)

```

In [96]: profit = 0
           actual_profit = 0
           for i in Q
               vals = optimize_values(i)
               obj_value = vals[1]
               opt_s = vals[2]
               opt_t = vals[3]
               profit = profit + obj_value
               ac_prof = sum(p_p[j]*min(e_p_15[j], opt_t[j]) - c_p[j]*opt_t[j] for j=1:
               sum(p_np[i]*min(d_np_15[i], opt_s[i]) - c_np[i]*min(d_np_15[i], opt_s[i]
               actual_profit = actual_profit + ac_prof
           end
           println("Average Optimized Profit: ", profit/length(Q))
           println("Average Actual Profit: ", actual_profit/length(Q))

```

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Average Optimized Profit: 384.325
Average Actual Profit: 333.22822

```

## 2.b.iv

Throughout this course we have demonstrated the empirical dominance of optimization based machine learning as opposed to heuristic methods. We would expect the same performance differential in this setting. Thus, with optimization based machine learning methods we'd expect the profit to be even higher.