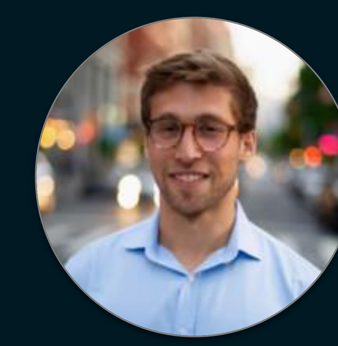
Improving Inventory Placement for Walmart E-Commerce

MIT Faculty Advisor: Stephen C. Graves
Walmart Partner: Samuel Smith
Walmart, Hoboken, NJ, USA; February – August 2019


An V. Luong


Jonah A. Adler

Problem and Scope

Problem we are trying to solve

1. Walmart is expanding its E-Commerce business to support Next-Day shipping
2. Current inventory placement ("mirror profiling") algorithm is extremely simplistic and is a "best guess"

Figure 1. Walmart's acquisition of jet.com has been an attempt to improve inventory management and to take on Amazon

Goal of Capstone Project

1. Build an inventory placement algorithm that minimizes shipping costs
2. Produce a modular product that can adapt to changing business constraints

Data Description

Data

- Utilized 11 different datasets
- Preprocessed and aggregated to focus on our project scope for replenishable, non-perishable items

Scale of Problem Space

- ~150,000 products
- 6 fulfillment centers across U.S.
- 42,000 zip codes and 3,007 counties
- $(2^6)^{150{,}000} \rightarrow (2^6)^{1800}$ possible allocations
- 52-week simulated shipping costs and capacity usage

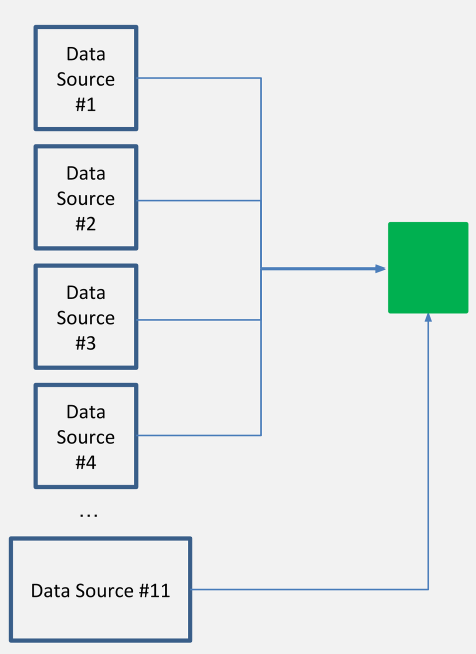


Figure 2. Consolidating and cleaning Walmart's numerous data sources

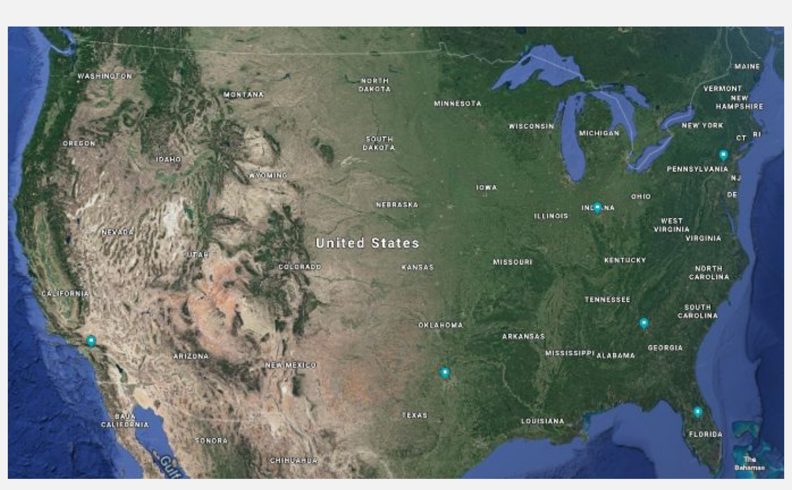
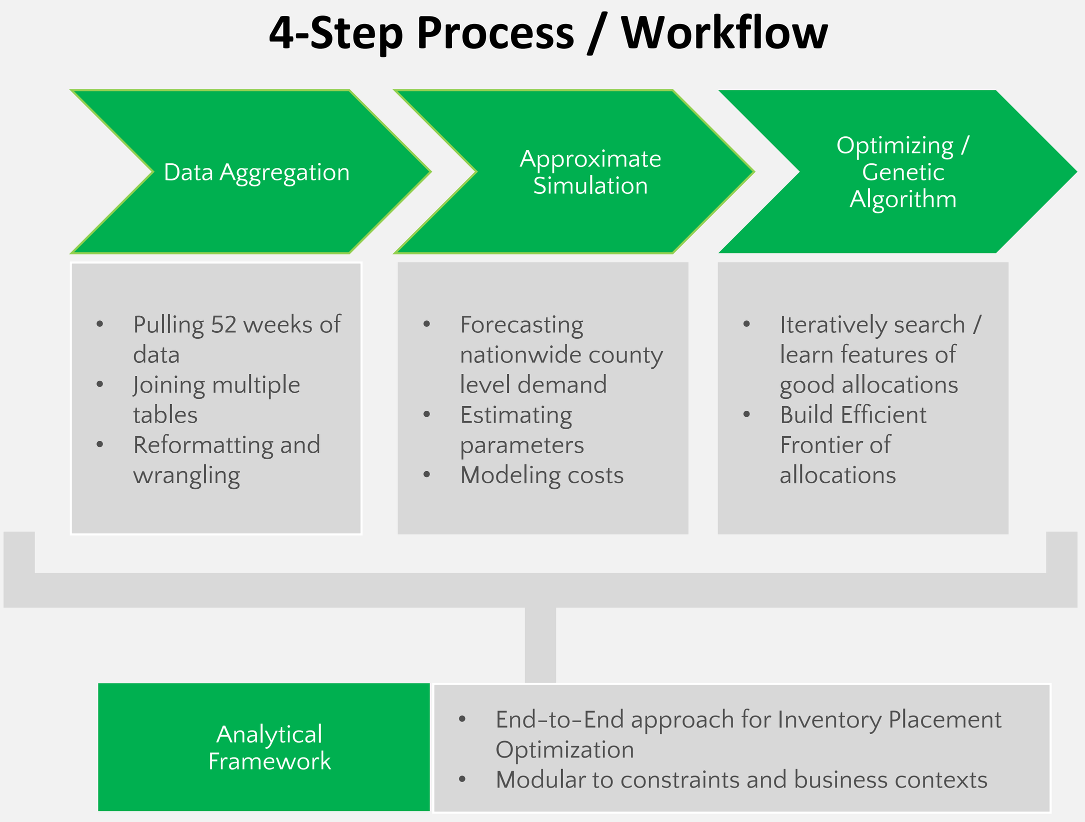


Figure 3. Locations of Walmart's fulfillment centers in the U.S.

Methodology

4-Step Process / Workflow

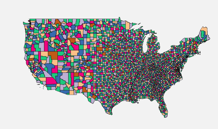


4 main evaluation criteria to consider for inventory allocation selection:

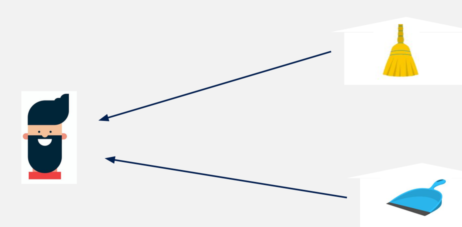
1. Shipping Costs
2. Warehouse Inventory / Capacity (overstocks)
3. Service Level and Stockouts
4. Shipping Speed

Simulating Walmart Supply Chain

1. Outbound Shipping

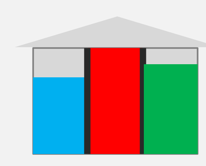


- Demand is predicted at the U.S. county level per subcategory
- Outbound shipping cost is approximated as a linear relationship between distance and weight
  - $c_i = \beta_0 + \beta_1 \text{distance}_i + \beta_2 \text{weight}_i$
  - Regression on current Fedex quotes (mean error: $1.20, MAPE: 10%)
- Split shipment rate is assessed on a random sample of historical customer carts. Final shipping cost is adjusted to account for split shipment rate.



2. Warehouse Inventory

- Inventory Levels are tracked by total volume
- Average fraction of items in the "Red Zone" (over 75% of max cap) is recorded as sim output



3. Service Level

- Walmart's reorder policy consists of a weekly review with an order up to level (OUTL) to maintain a product specific service level.
- We maintain service levels by "stocking" by the same policy
- In order to get subcategory level OUTL's (Walmart service levels are at the item level) we need to aggregate carefully:

L = Lead Time, μ_D = Mean demand, σ_D = std deviation of demand, Z_α = Z score for service level alpha

$$\text{OUTL}_{item} = L * \mu_D + \sqrt{L} Z_\alpha \sigma_D$$

$$\text{OUTL}_{sub} = \sum \text{OUTL}_{item} = L_{sub} * \sum \mu_D + \sqrt{L_{sub}} Z_{\alpha_{sub}} \sqrt{\sum \sigma_D^2}$$

4. Shipping Speed

Even if a mirror profile is cheap in terms of shipping costs and capacity, if it means that many customers have to wait more than 2 days for a product, then it is unacceptable.

1. We utilize Information from FedEx as to what distances ground shipping can travel in two days.
2. We asses what percentage of nationwide demand each mirror profile can reach in two days
3. We say that mirror profiles under a certain threshold (currently 80%) of coverage are not acceptable

Simulation Tool

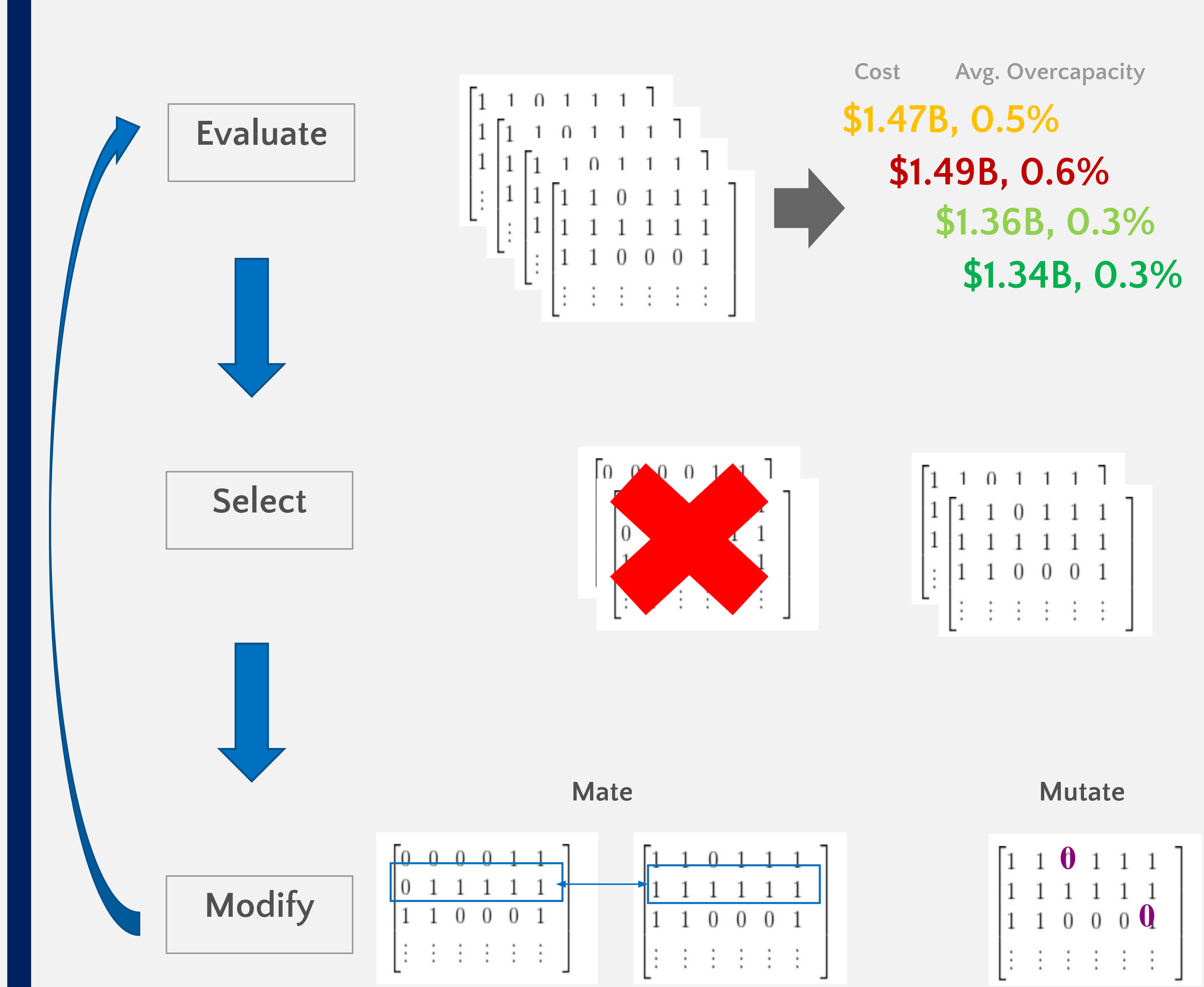
In summary, we built a simulation that can evaluate any candidate inventory allocation and output corresponding characteristics.

Our simulation runs in ~0.5 seconds.

Optimization using Genetic Algorithm

Genetic Algorithm is based on natural selection:

1. Does not rely on gradients
2. Explores a large solution space
3. Applicable to our complex objective function



Results

Initial Algorithmic Attempts

As we tried to optimize inventory allocation, we tried random search, local search, and reinforcement learning. However, none of those algorithms provided tractable and helpful results

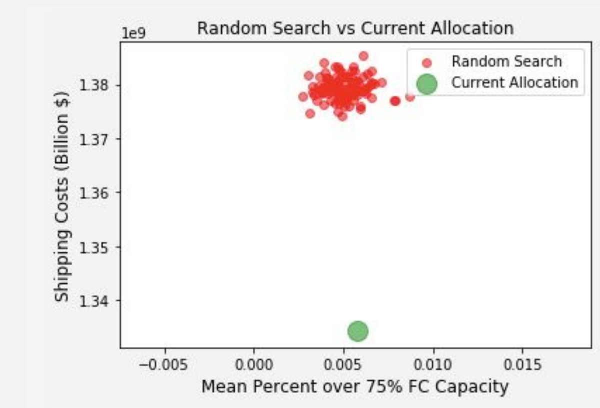


Figure 4. Local search for this problem did not provide improvements over the baseline

Genetic Algorithm Results

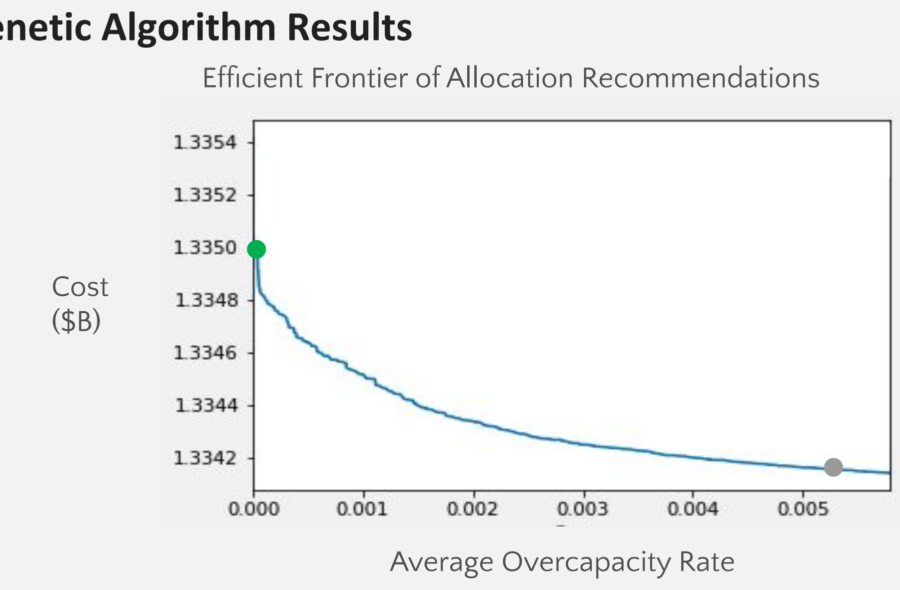


Figure 5. Efficient frontier for shipping cost and FC capacity for Walmart eCommerce products annually

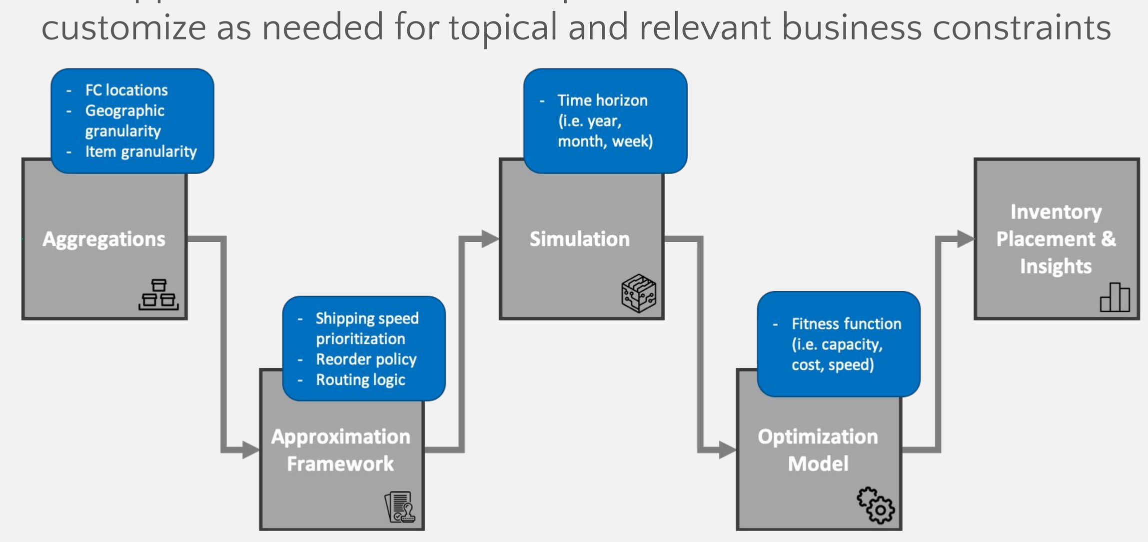
Overcapacity can be **eliminated** with a 0.06% increase in shipping cost

Capacity is best cost-effectively conserved by stocking **low volume** items in **more FC's**

- In the Zero-Overcapacity recommendation one less cubic foot of item volume -> 2.5x increased probability of being stocked everywhere

Modular Analytical Pipeline

Our approach has also been implemented such that Walmart can customize as needed for topical and relevant business constraints



Conclusions and Recommendations

More data-focused inventory placements

- Using this model we have developed, Walmart can decrease costs associated with running a giant E-Commerce business
- We have also provided heuristic directions on how to stock items based on volume
- ***We have built a modular, ready-to-use, customizable analytical pipeline that should be ready to be updated for specific Walmart concerns related to inventory allocation***

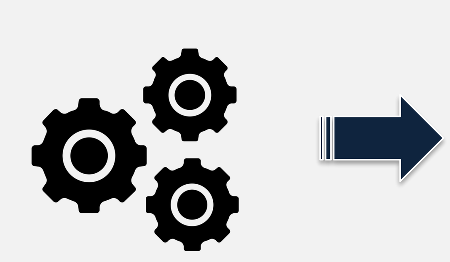


Figure 6. Improving inventory allocation will lower capacity concerns at FCs, which will make delivering on customer expectations less uncertain

Next Steps for Implementation

1. Familiarize with assumptions and methodology of analytical pipeline
2. Apply relevant and topical business constraints
3. Use output to educate allocation decisions