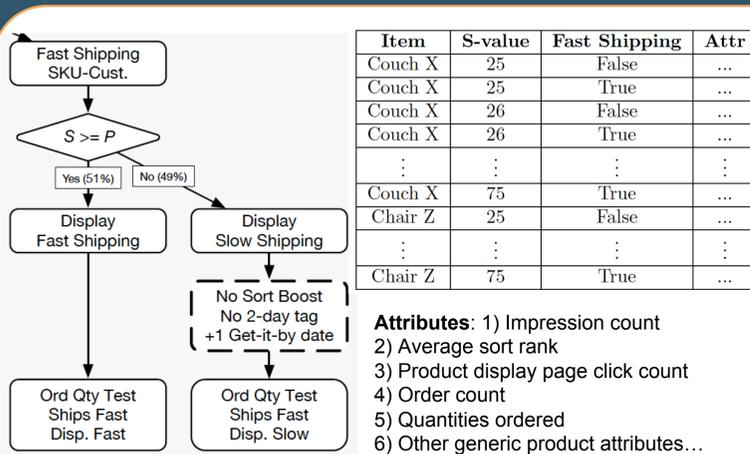




Overview and Objectives

- 1) Estimate the average boost in sales on different scopes
- 2) Measure the marginal effect of sales boost: how the sales boost changes as the portion of products offered with fast shipping increases.
- 3) Identify key product characteristics that will make the product sales more sensitive to fast shipping.

Experimental Design



Treatment Effect Definition

- $Y_i(t_i)$: observed outcome for the chosen treatment \rightarrow number of orders (numord), the quantity ordered (qtyord), etc.
 - t_i : the treatment \rightarrow fast shipping flag (0 or 1)
 - x_i : covariates used for heterogeneity (i.e., the variable that interacts with the treatment) \rightarrow S-value
 - w_i : other parameters that might affect our response variables \rightarrow generic product attributes like previous sales, rating, price, etc.
- We assume the outcome Y is linear in the treatment vector, and we assume the following structure for our target quantity τ (heterogeneous treatment effect):

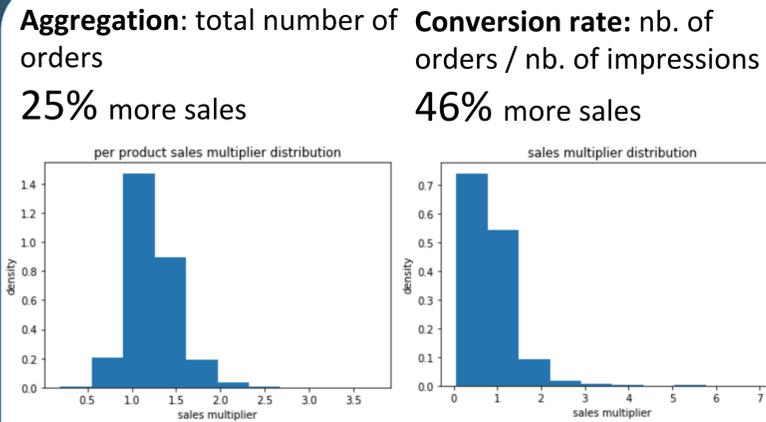
$$Y = H(X, W)T + g(X, W, \epsilon)$$

$$T = f(X, W, \eta)$$

$$\tau(t_1, t_0, x) = E[H(X, W) | X = x](t_1 - t_0)$$

Here η and ϵ are noise factor added, and H, g, f are functions.

Task 1: average boost in sales

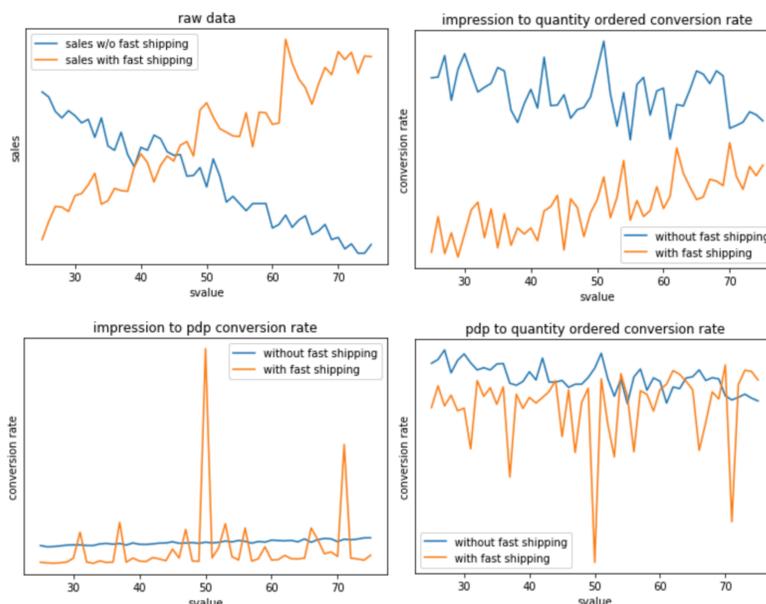


Issues: Not factoring in the increase product exposure due to the sort-boost effect of fast-shipping.

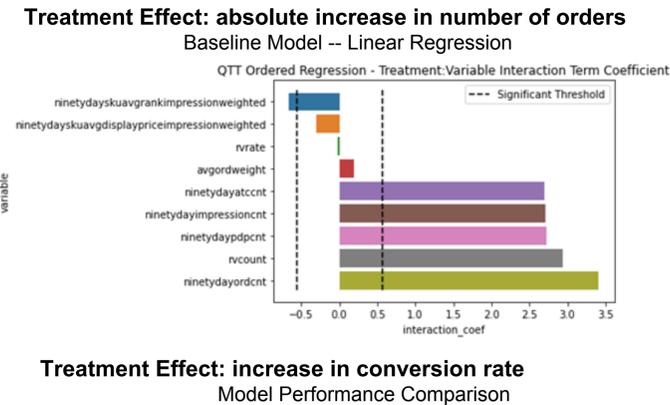
Issues: Only 30% products receive sales boost under this framework. Estimate only applies to these products.

Task 2: impact of S-value

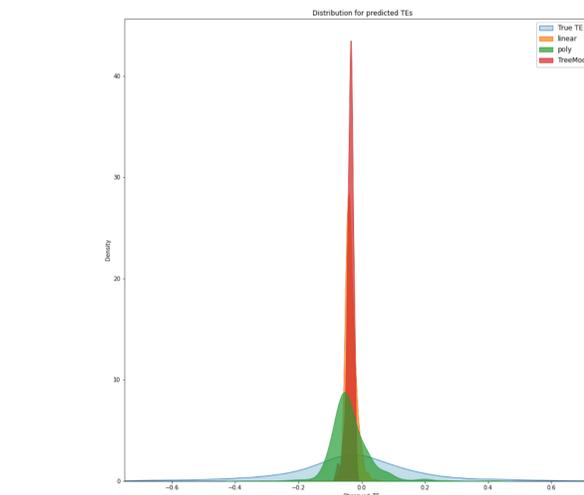
How various quantities of interest change as S-value changes:



Task 3: important product features



Variable	Model	MSE Score	95% Confidence Interval Accuracy
$TE(\log(\frac{N_{fast}}{N_{total}}))$	Causal Forest	0.097	15.8%
$TE(\log(\frac{N_{impression}}{N_{total}}))$	Causal Forest	0.087	17.2%
$TE(\log(\frac{N_{impression}}{N_{total}}))$	LinearDRL with Polynomial Feature	0.06	42%



Coefficient Results

Variable	point_estimate	stderr	zstat	pvalue	ci_lower	ci_upper
ninetydayskuavgrankimpressionweighted	-0.004	0.018	-0.2	0.841	-0.033	0.026
ninetydayskuavgrankimpressionweighted	0.014	0.056	0.254	0.8	-0.077	0.105
rvrate	-0.02	0.019	-1.043	0.297	-0.052	0.012
avgordweight	0.006	0.016	0.4	0.689	-0.02	0.033
ninetydayordcnt	-0.023	0.017	-1.324	0.186	-0.051	0.006
ninetydayskuavgrankimpressionweighted	-0.014	0.03	-0.462	0.644	-0.063	0.035
ninetydayskuavgrankimpressionweighted	0.01	0.022	0.432	0.666	-0.027	0.046
ninetydayskuavgrankimpressionweighted	-0.004	0.006	-0.642	0.521	-0.013	0.006
ninetydayskuavgrankimpressionweighted	0.004	0.008	0.56	0.576	-0.008	0.017
ninetydayskuavgrankimpressionweighted	0.022	0.034	0.635	0.526	-0.034	0.078
ninetydayskuavgrankimpressionweighted	-0.013	0.028	-0.461	0.645	-0.059	0.033
ninetydayskuavgrankimpressionweighted	-0.029	0.026	-1.096	0.273	-0.071	0.014
rvrate	-0.002	0.015	-0.11	0.913	-0.027	0.023
rvrate	-0.004	0.01	-0.413	0.68	-0.021	0.013
avgordweight	-0.001	0.006	-0.187	0.852	-0.012	0.009

Key findings: For popular products, adding fast shipping label won't have a significant contribution in boosting conversion rate.

Conclusion

Aggregation-based approach:

1. 25% increase in sales.
2. We can expect that order number and quantities sold scale linearly as s-value increases.

Conversion rate-based approach:

1. 46% more sales for products whose conversion rates does not degrade with fast-shipping.
2. The effect of fast-shipping has a much larger impact on the conversion rate from product display page clicks to quantities ordered, than the conversion rate from the impression to product display page clicks. The conversion rate from impression to quantities ordered with fast-shipping increases as s-value increases.
3. For popular products, adding fast shipping label won't have a significant contribution in boosting conversion rate.

Acknowledgements

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Reference

1. Chipman, H. et al. "BART: Bayesian Additive Regression Trees." *The Annals of Applied Statistics* 4 (2010): 266-298.
2. Wager, S. and S. Athey. "Estimation and Inference of Heterogeneous Treatment Effects using Random Forests." *Journal of the American Statistical Association* 113 (2015): 1228 - 1242.
3. EconML: Python SDK, developed by the ALICE team at MSR New England
4. GRF: Generalized Random Forest, a pluggable package for forest-based statistical estimation and inference.