

NEGATIVE CUSTOMER REVIEWS

PREDICTIVE CLASSIFICATION MODEL

**PREPARED FOR OLIST
JUNE 17, 2021**

TODAY'S MODEL REVIEW

- Business Objective
- Visual Highlights
- Bad Review Model Solution
- Model Feature Importance
- Actionable Next Steps

PREDICTING BAD CUSTOMER REVIEWS

Business
Objective

Business Objective: Understand and predict bad customer reviews (scores 1 or 2) in order to try to minimize bad reviews and improve customer satisfaction.

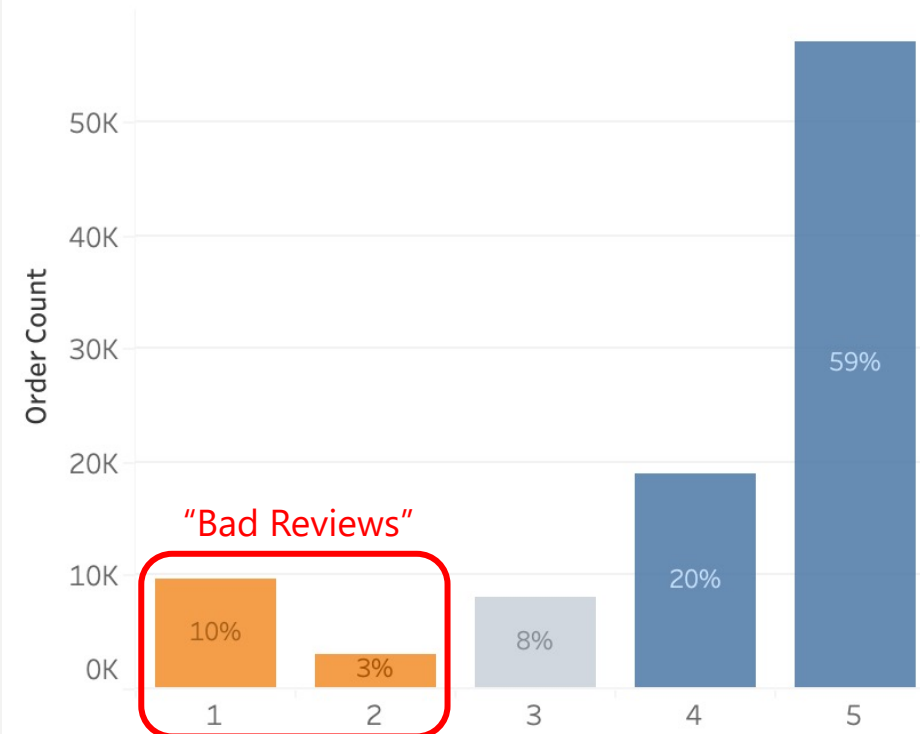
Requirements

- Understand dynamics that cause customers to leave a bad review
- Find the best prediction model to classify a bad review from a customer
- Deliverables should explain the relative influence of each predictor on the model
- Deliverables should suggest potential solutions to preventing bad customer reviews

Olist Customer Review Distribution

96,745 Orders | Jan 2017 - Aug 2018 | Delivered Status

Bad Review Ratings: 1 or 2 (13.2% Combined)

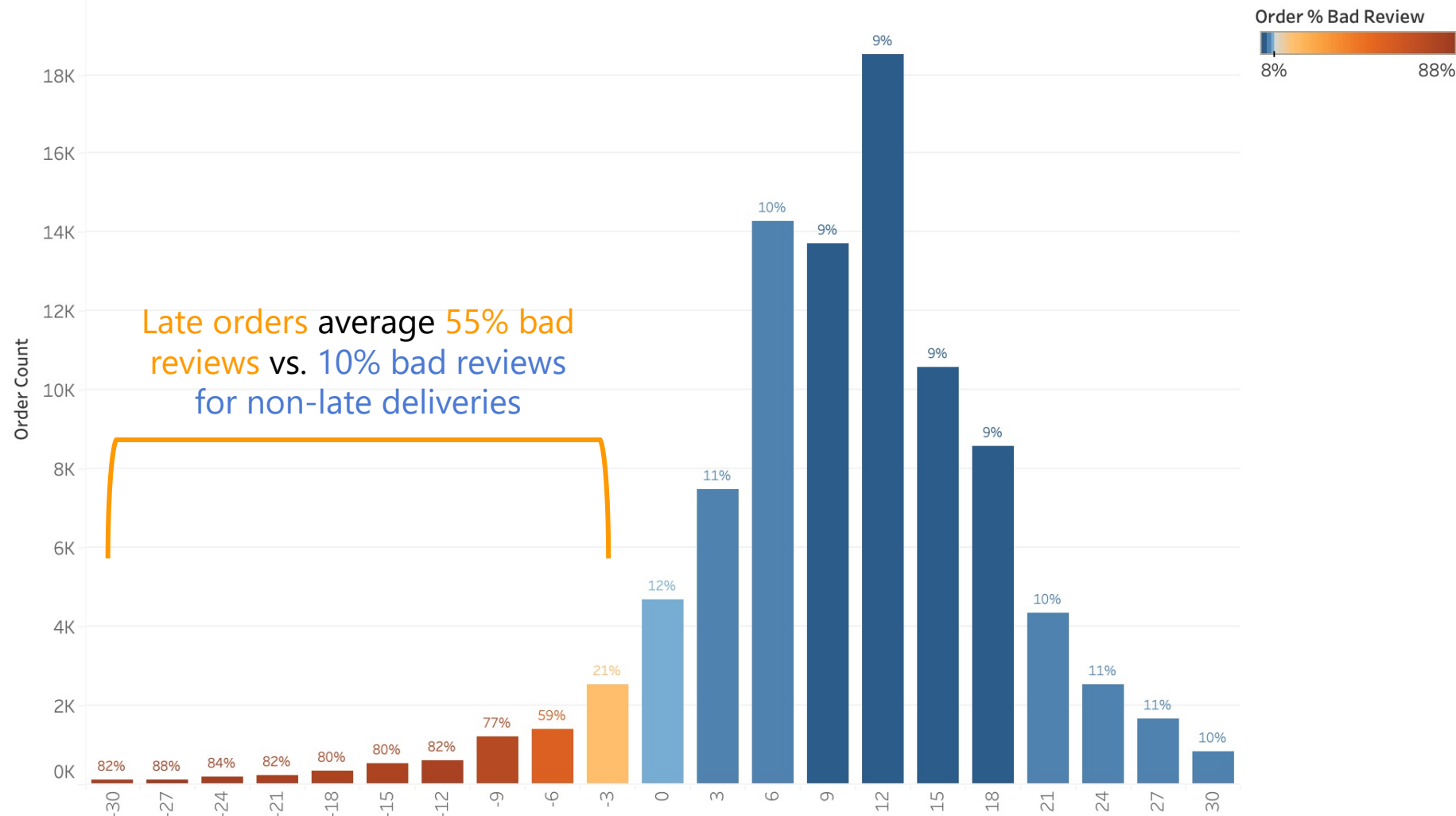


MEETING PROMISED DELIVERY DATES

Late
Delivery

Olist Delivered Days Late (vs. Promised Date)

94,469 Orders | Jan 2017 - Aug 2018 | Delivered Status | +/- 30 Days Variance

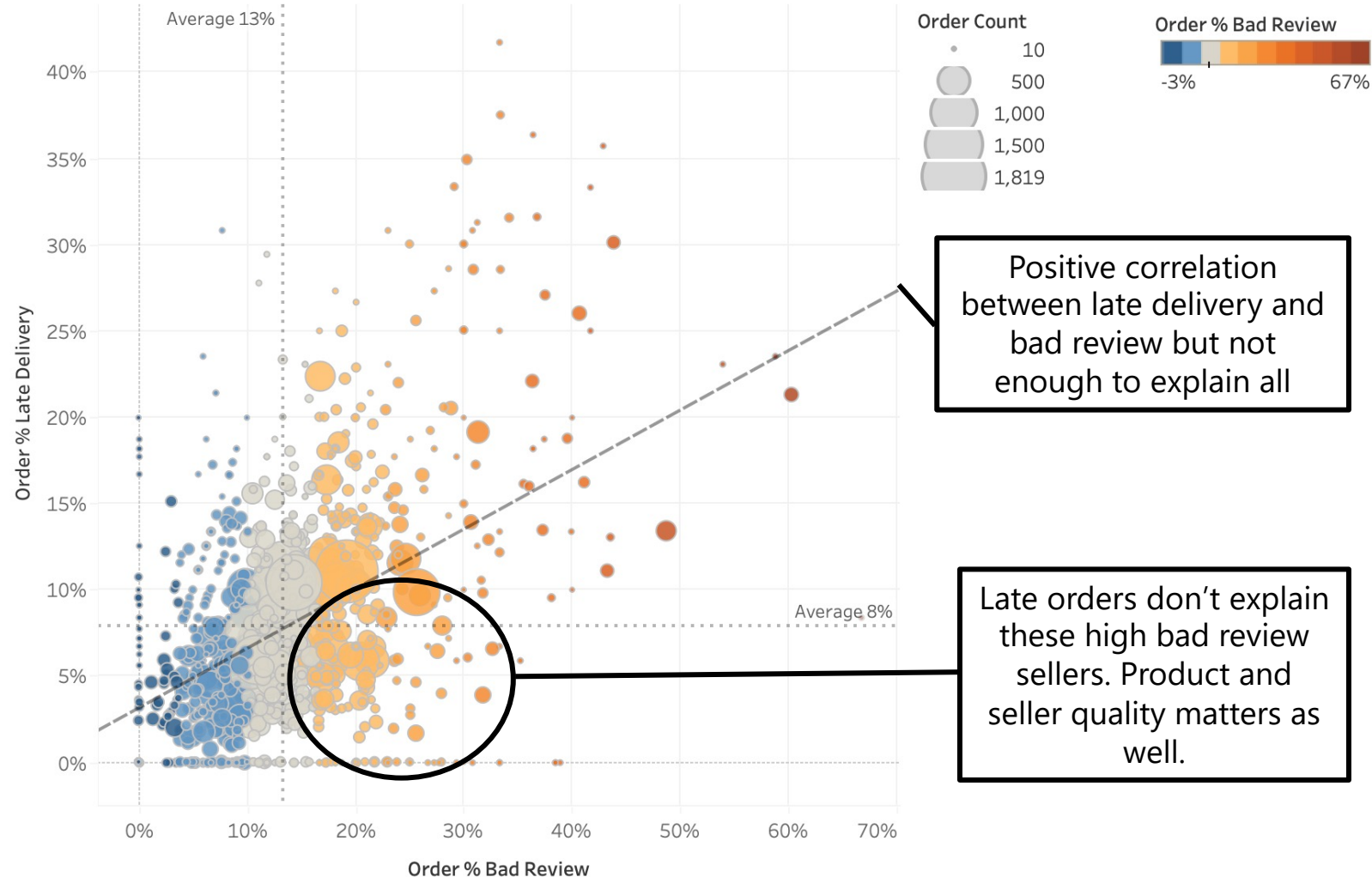


SELLER QUALITY MATTERS

Seller
Quality

Olist Sellers Bad Review % vs. Late Delivery %

96,745 Orders | Jan 2017 - Aug 2018 | Delivered Status | By Seller ID

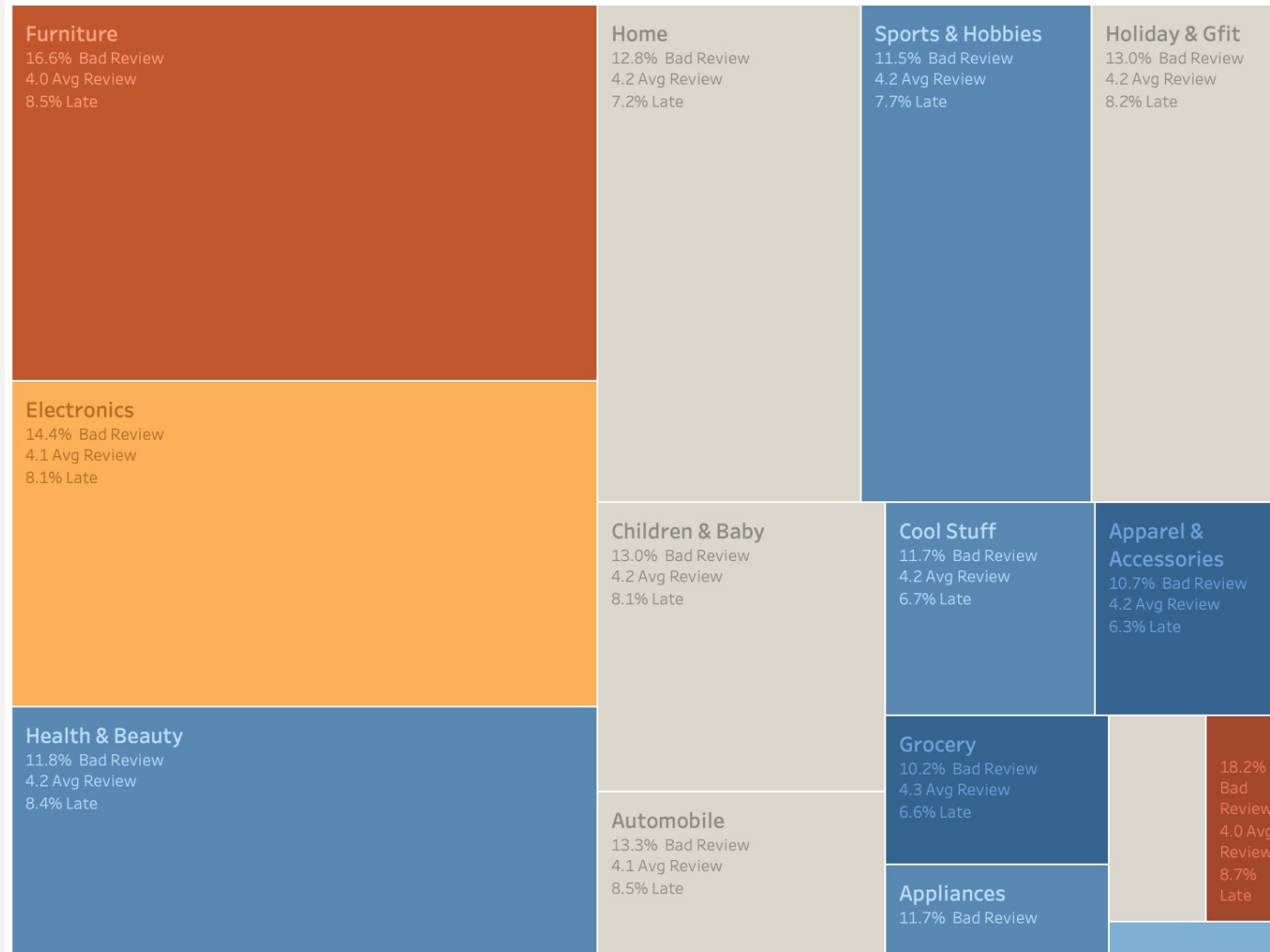


MARKETPLACE PRODUCT VARIETY

Product
Category

Olist Product Category Distribution

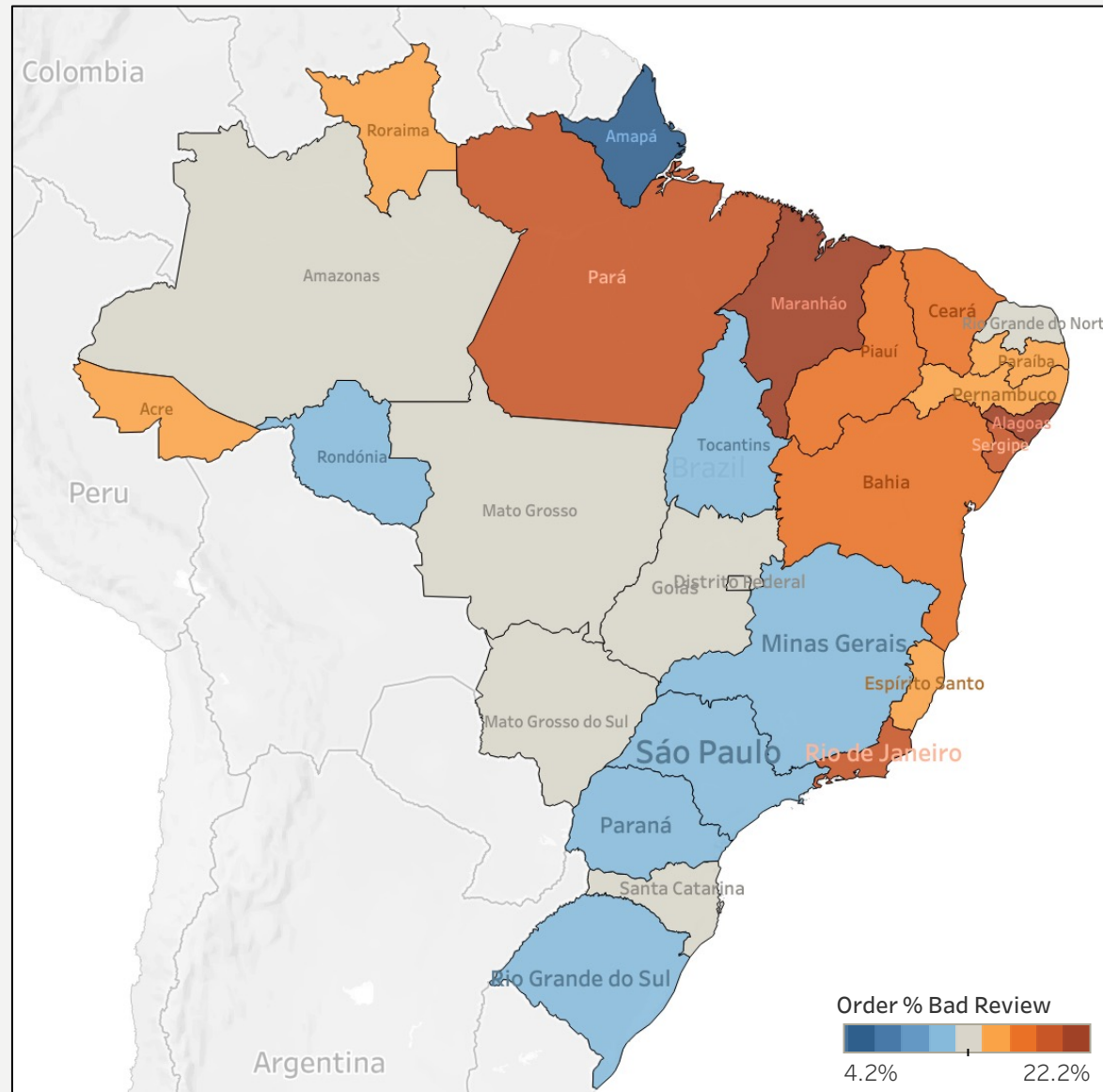
96,745 Orders | Jan 2017 - Aug 2018 | Delivered Status































The bad review rate (%) for each unique product varies substantially and many aren't meeting customer expectations

Product Id	Product Category Parent	Order % Bad Review	Order Count
fd0065af7f09af4b82a0ca8f3eed1852	Automobile	90.0%	10.0
6d2fde7d12bb6ff367dbda120ba8828e	Electronics	83.3%	12.0
cd46a885543f0e169a49f1eb25c04e43	Electronics	82.1%	28.0
b36f3c918c91478c4559160022d3f14e	Other	73.3%	15.0
b1d207586fca400a2370d50a9ba1da98	Other	71.4%	42.0
16bf176650a888512655cc94f61860e3	Holiday & Gfit	63.6%	11.0
89b121bee266dcd25688a1ba72eefb61	Electronics	59.6%	57.0
86ecc269de40ba13205e7beeee12f26f	Electronics	58.3%	12.0
25c38557cf793876c5abdd5931f922db	Children & Baby	55.3%	38.0
7b35ccd93a2184646c03b70326626923	Sports & Hobbies	55.0%	20.0
43ee88561093499d9e571d4db5f20b79	Furniture	53.8%	13.0
63085bb4366ded27bcb63cbb59b4103a	Children & Baby	53.8%	13.0
0cf41187284d7f099adc8415a743ebbd	Children & Baby	53.1%	32.0
fb01a5fc09b9b9563c2ee41a22f07d54	Electronics	52.2%	23.0
1dec4c88c685d5a07bf01dcb0f8bf9f8	Automobile	51.4%	35.0

REVIEWS VARY BY BRAZIL STATE



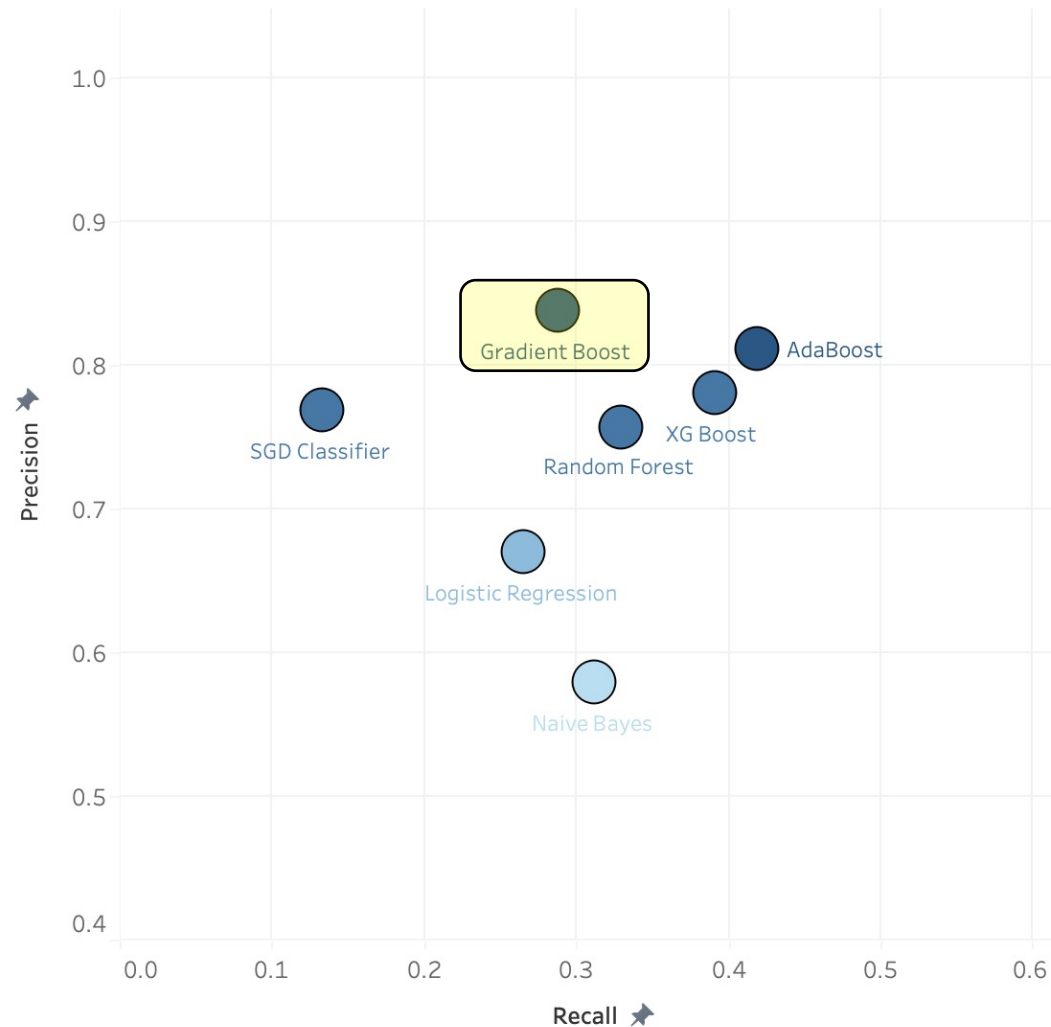
	Customer State	Order % Bad Review	Delivery Days	Order % Late	Product Index
	Acre	15.0%	21	3.8%	122
	Alagoas	22.2%	25	23.7%	164
	Amapá	6.0%	27	3.0%	49
	Amazonas	13.8%	26	4.1%	110
	Bahia	17.7%	19	13.8%	140
	Ceará	17.7%	21	15.3%	137
	Distrito Federal	13.5%	13	7.0%	109
	Espírito Santo	14.7%	16	12.2%	117
	Goiás	13.8%	16	8.0%	112
	Maranhão	20.5%	22	19.2%	165
	Mato Grosso	13.2%	18	6.6%	118
	Mato Grosso do Sul	13.4%	16	11.1%	108
	Minas Gerais	12.1%	12	5.5%	98
	Pará	18.8%	24	12.4%	149
	Paraíba	15.3%	20	11.0%	121
	Paraná	11.2%	12	4.8%	95
	Pernambuco	15.2%	18	10.7%	122
	Piauí	16.6%	19	15.6%	134
	Rio de Janeiro	18.9%	15	13.3%	148
	Rio Grande do Norte	13.6%	19	10.9%	117
	Rio Grande do Sul	12.1%	15	6.9%	104
	Rondônia	11.9%	19	2.9%	103
	Roraima	15.0%	30	12.5%	120
	Santa Catarina	13.5%	15	9.6%	110
	São Paulo	11.0%	9	5.7%	92
	Sergipe	19.3%	21	15.4%	148
	Tocantins	12.0%	18	12.4%	90
	Grand Total	13.2%	13	7.9%	111

MODEL PERFORMANCE COMPARISON

Model
Summary

Olist Prediction Model: Bad Customer Reviews

Precision - Recall Tradeoffs (20% Test Set)



Recommend Gradient Boost Model

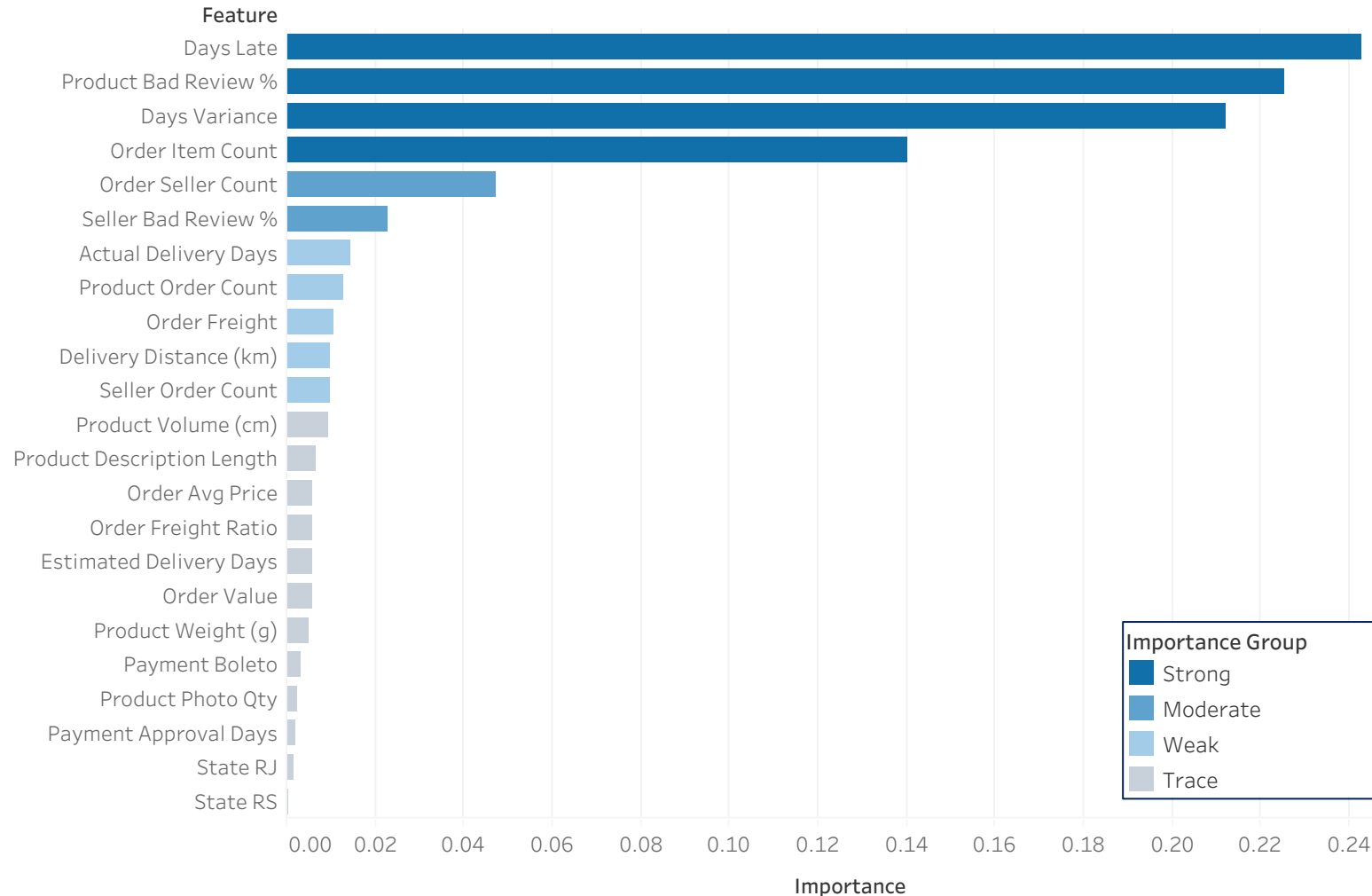
- Predicts bad reviews with 84% precision
- Captures 29% of bad reviews (recall)
- Even higher precision possible for lower recall (90% precision @ 12% recall)
- Understandable feature importance
- Model performs relatively efficiently

MODEL PREDICTOR IMPORTANCE

Gradient
Boost Model

Gradient Boost Bad Review Prediction Model

Relative Importance Of Features



Strong Impact

- Delivered days late
- Days variance (vs. estimated)
- Products avg. bad review rates
- Count of items on order

Moderate Impact

- Count of sellers on order
- Sellers avg. bad review rates

Weak Impact

- Actual delivery days
- Total orders for product
- Total orders for seller
- Freight on order
- Delivery distance in kilometers

NEXT STEPS

1. Define customer retention actions
2. Perform randomized trials on treatment/control groups
3. Measure ROI uplift from each action/experiment
4. Formalize high-performing actions into business

**Predictive capabilities may be expanded with broader customer data profiles.
Explore potential data such as:**

- Review Comment – Parse text sentiment to derive insight into customer complaints
- Customer Service – Incorporate Contacts/Call/Emails, Tickets, Website/App Usage
- Demographics – Credit Score, Income, Home Ownership, Household Size, Persona/Lifecycle, Time at Address, Other customer demographics
- Supplier – Incorporate supplier product, process, inventory and quality metrics

"In God we trust, all others bring data." – Edward Deming

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THANKS