instacart
basket analysis

Elizabeth Naameh
lizzynaameh@ucla.edu
Data Scientist

Client:

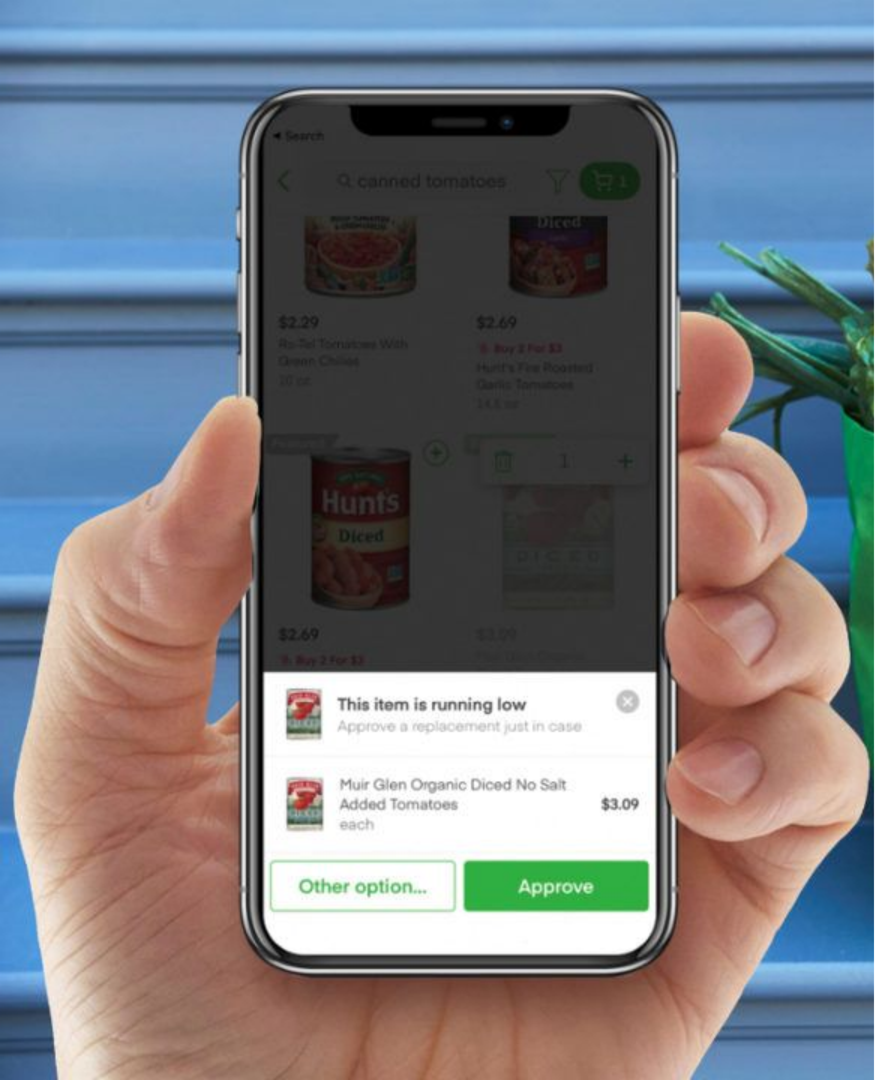
Instacart is an online grocery delivery service and app.

Goal:

Predict which products will be in a user's next order.

Product:

A classification model that predicts whether a user will reorder a product from their purchase history in their next order.



Data:

The dataset is anonymized and contains a sample of over 3 million grocery orders from more than 200,000 Instacart users.

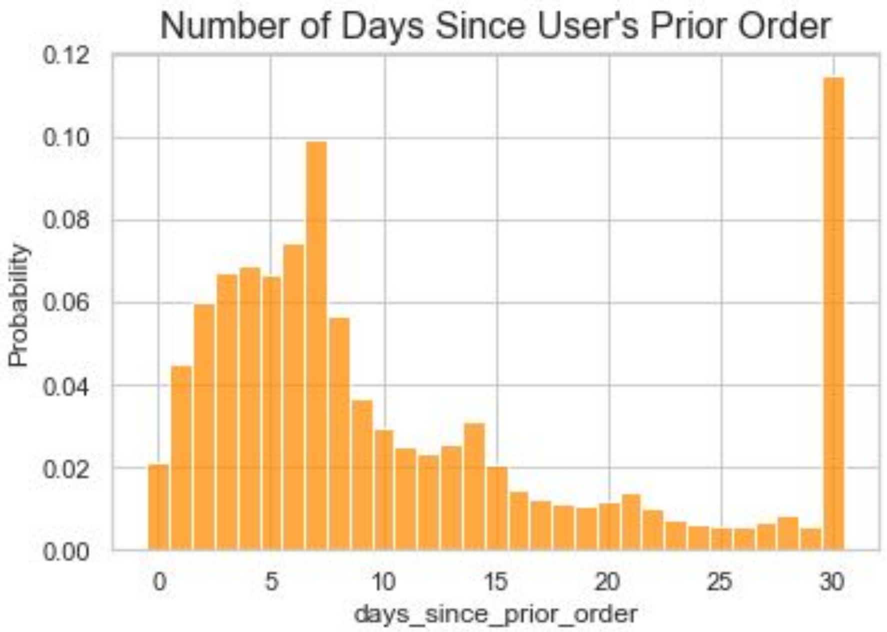
Dictionary available here.

Tools Used:

- Numpy & Pandas for data processing
- Seaborn for visualization
- Scikit-learn for machine learning

Exploratory Data Analysis

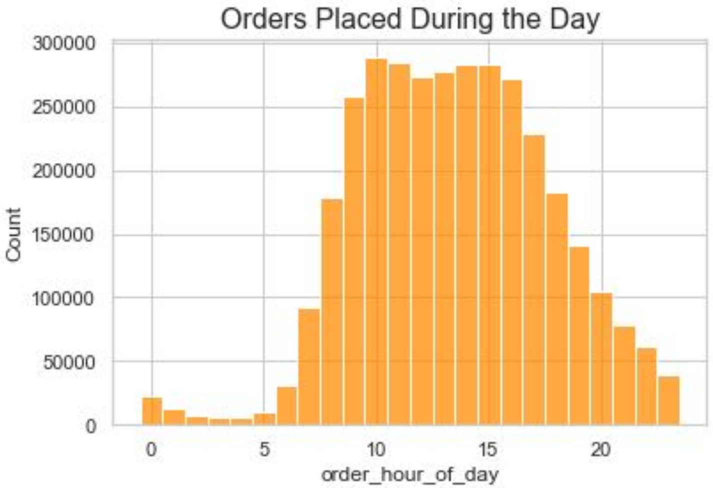
Users tend to make place orders on a weekly basis or more frequently.

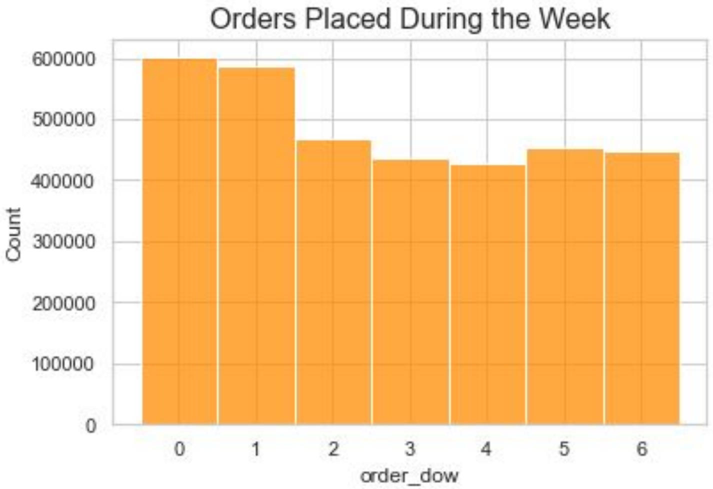


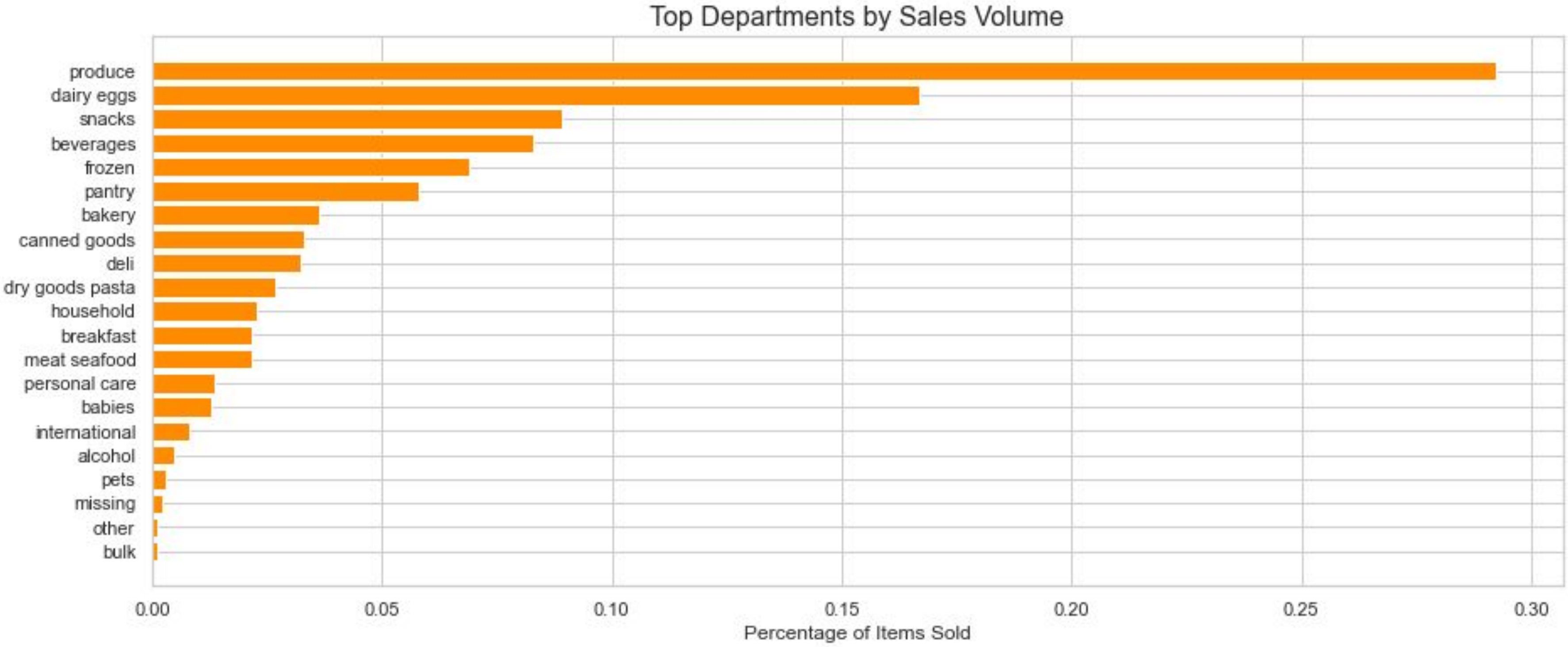
Findings

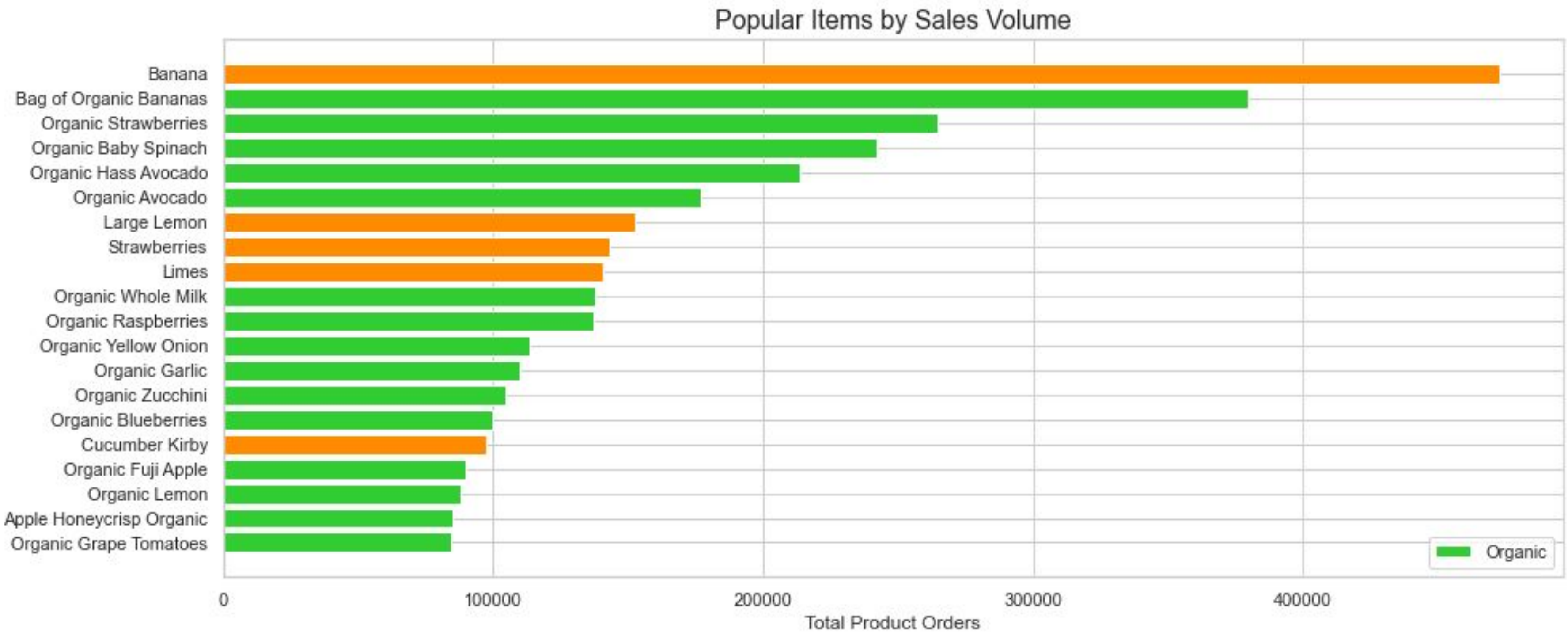
Peak shopping hours are between 10am and 4p.

Peak shopping days are Saturday and Sunday (coded 0, 1).






Top Departments by Sales Volume
produce
dairy eggs
snacks
beverages
frozen
pantry
bakery
canned goods
deli
dry goods pasta
household
breakfast
meat seafood
personal care
babies
international
alcohol
pets
missing
other
bulk
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Percentage of Items Sold


Popular Items by Sales Volume
Banana
Bag of Organic Bananas
Organic Strawberries
Organic Baby Spinach
Organic Hass Avocado
Organic Avocado
Large Lemon
Strawberries
Limes
Organic Whole Milk
Organic Raspberries
Organic Yellow Onion
Organic Garlic
Organic Zucchini
Organic Blueberries
Cucumber Kirby
Organic Fuji Apple
Organic Lemon
Apple Honeycrisp Organic
Organic Grape Tomatoes
🟩 Organic
0
100000
200000
300000
400000
Total Product Orders

Goal: Use user’s purchase history to predict whether a product will appear in their next order.

Creamy
Ground
Sparkling
Cheddar
Drink
Strawberry
Baby
Wild
Peach
Broccoli
Light
Mineral
Dark
Red
Raw
Grape
Turkey
Vanilla
Unsweetened
Sugar
Chip
Milk
Thin
Salt
Tomato
Yogurt
Greek
Seedless
Natural
Low
Green
Cauliflower
Style
Raspberry
Peanut
Smoothie
Large
Hass
Medium
Grapefruit
Pure
Gluten
Avocado
Mild
Tea
Celery
Plain
Free
Soft
Honeycrisp
Coffee
Lowfat
Tortilla
Food
Pepper
French
Chunk
Stick
Beef
Salsa
Spread
Frozen
Whole
Mushroom
Liquid
Almond
Bacon
Olive
Sausage
Apple
Ice
Brown
Small
Cream
Vegetable
Bag
Half
Protein
Pea
Sweet
Spinach
Bean
Black
Romaine
Raisin
Premium
Roll
Vitamin
Ginger
Muffin
Macaroni
Granola
Grain
Shredded
Heart
Organic
Fuji
Cinnamon
Blueberry
Mix
Carrot
Soda
Lime
Stage
Paper
Boneless
Pear
Rice
Cucumber
Roasted
Salad
Cookie
Yellow
Orange
Virgin
Onion
Sea
Fruit
Berry
Mint
Water
Total
Pack
Broth
Blend
Italian
Nut
Squash
Corn
AA
Fresh
Spring
Oat
Tomatoes
Cherry
Pretzel
Baked
Bar
Nonfat
Butter
Juice
Wheat
Bread
Lemon
Soup
Bell
Basil
Grade
Honey
Cereal
String
Strawberries
Reduced
Smoked
Hummus
Slice
Egg
Cracker
Snack
Sauce
Extra
Garlic
Sliced
Hot
Cheese
Fat
Waffle
Original
Kale
Cup
Bunch
Zucchini
Coconut
Pizza
Breast
Potato
Pasta
Mini
Mango
Oil
Classic
Lettuce
Sour
English
Uncured
Banana
Chocolate
White
Chicken
Blueberries
Raspberries
Unsalted
Breakfast
Cilantro
Skinless
Mozzarella
Parmesan
Salted
Strained

Optimize for the Best Shopping Experience

Precision: % of products we predict to be reordered that actually are.

Low precision means users see suggested products they are actually not interested in.

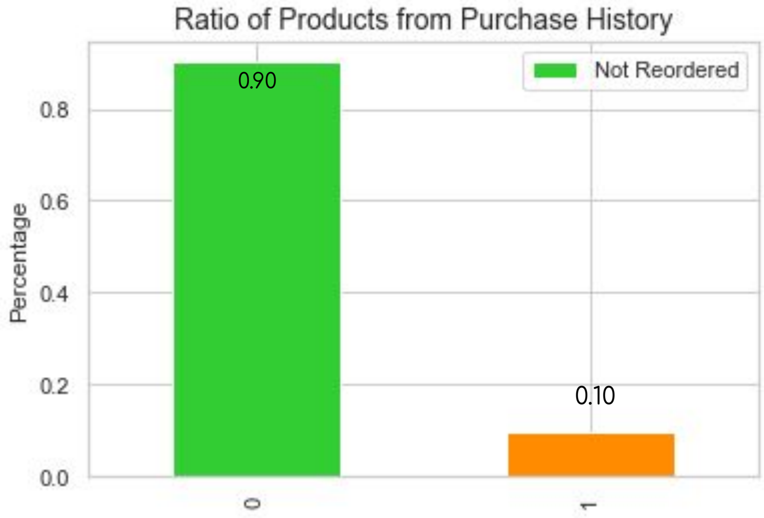
Recall: % of products that are actually reordered that we predicted.

Low recall means our model is missing out on showing products that our user is interested in.

Balance to keep suggestions relevant and promote purchases.

Baseline Model

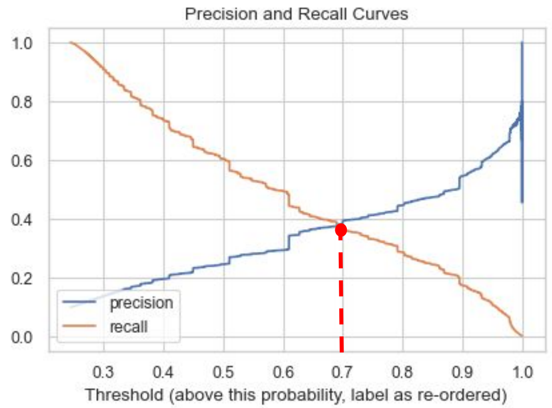
- Correct for class imbalance
- **Feature 1:** user's total number of orders for product
- **Feature 2:** percent of user's prior orders that included a given product

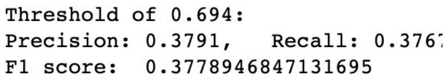


Tuning Our Baseline Model

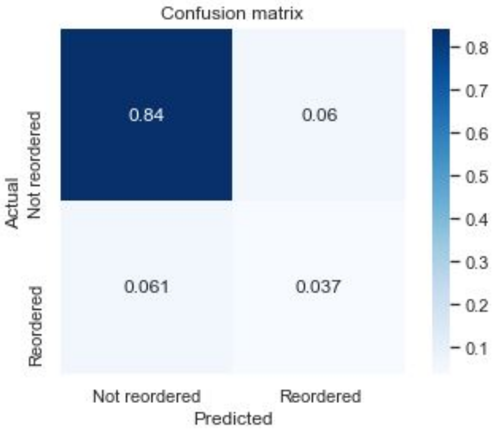
- **Model:** Logistic Regression using a 20-20-60 train-validate-test split
- Tune for optimum threshold
- Maximize for F1 score, balance precision and recall

F1 = 0.38



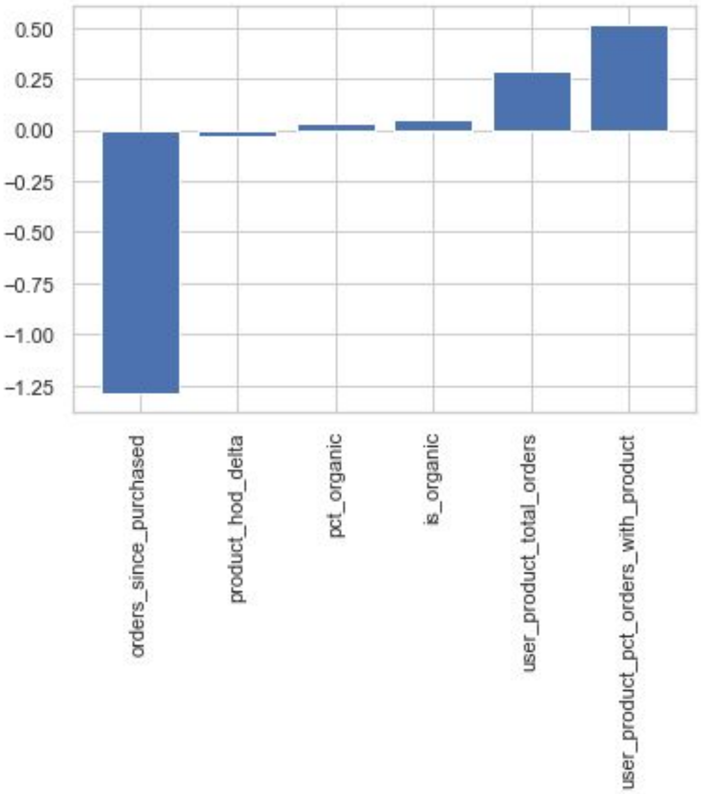


```
Threshold of 0.694:
Precision: 0.3791,    Recall: 0.376
F1 score:  0.3778946847131695
```



Feature Engineering

- Number of orders since user last purchased product
- Average difference between current order time and typical order time for product
- Percentage of user's prior products that are organic
- Product is organic
- User's total count of product orders
- Percent of user's prior orders that include product

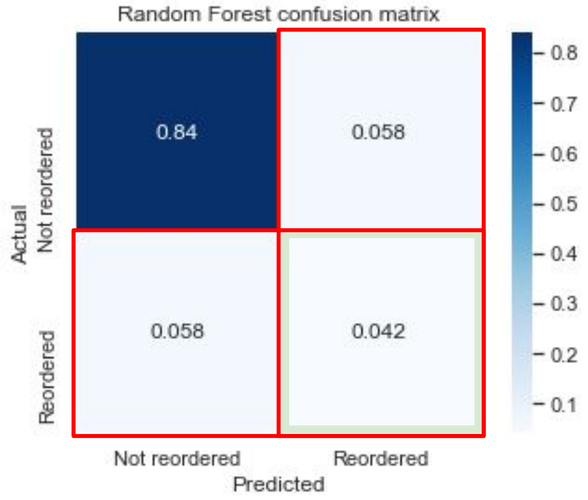


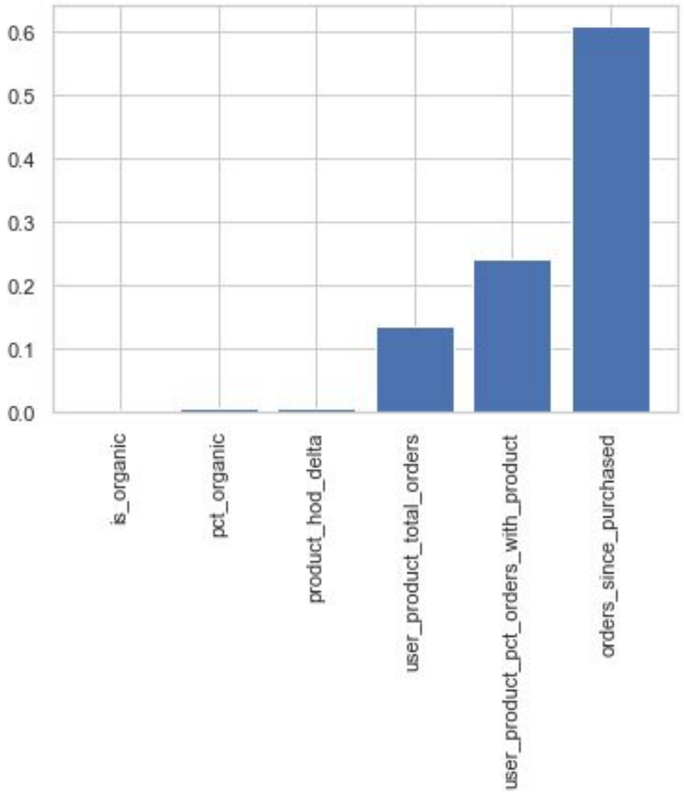
Final Model

Random Forest using an 80-20 train-holdout split.

```
Precision: 0.4179,   Recall: 0.4162
```

F1 = 0.42

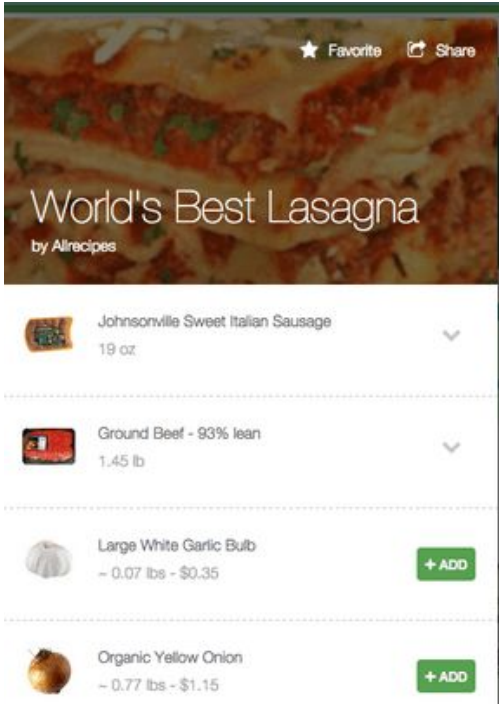




Conclusions & Future Work

Our model can serve as the basis for a **recommendation system**.

- Engineer more predictive features.
    - Buying velocity, time-series data
    - Aisle/category information
    - Customer segmentation
- Reduce memory usage.
- Try more sophisticated modeling techniques.
    - XGboost
    - Gradient Boosting Machines
- Extend functionality: Recommend recipes to users that align with their purchase history.



World's Best Lasagna
by Allrecipes

Johnsonville Sweet Italian Sausage
19 oz

Ground Beef - 93% lean
1.45 lb

Large White Garlic Bulb
~ 0.07 lbs - $0.35

Organic Yellow Onion
~ 0.77 lbs - $1.15