Instacart Market Basket Analysis

Which products will an Instacart consumer purchase again?

Boriss Siliverstovs

July 21, 2017

Roadmap

- Motivation
- Data
- Results
- Conclusions

- Data are provided by Instacart
 - Online retail grocery shop in US
 - Founded in 2012
 - Present in 1,200 cities in 25 states (March 2017)
 - Valued at approximately 3.4 bln USD (March 2017)
- Data contain ordering history of Instacart customers
 - Questions: Which products will a consumer
 - and to their cart during the next order?
 Its for the first time?
 - o purchase again?
- Given a sequence of prior orders which products will be re-ordered in the next order?

Running Kaggle competition (August 14, 2017 - Final submission deadline)

- Data are provided by Instacart
 - Online retail grocery shop in US
 - Founded in 2012
 - Present in 1,200 cities in 25 states (March 2017)
 - Valued at approximately 3.4 bln USD (March 2017)
- Data contain ordering history of Instacart customers
 - Questions: Which products will a consumer

Given a sequence of prior orders which products will be re-ordered in the next order?

- Data are provided by Instacart
 - Online retail grocery shop in US
 - Founded in 2012
 - Present in 1,200 cities in 25 states (March 2017)
 - Valued at approximately 3.4 bln USD (March 2017)
- Data contain ordering history of Instacart customers
 - Questions: Which products will a consumer
 add to their cart during the next order?
 try for the first time?
 purchase again?
- Given a sequence of prior orders which products will be re-ordered in the next order?

- Data are provided by Instacart
 - Online retail grocery shop in US
 - Founded in 2012
 - Present in 1,200 cities in 25 states (March 2017)
 - Valued at approximately 3.4 bln USD (March 2017)
- Data contain ordering history of Instacart customers
 - Questions: Which products will a consumer
 - add to their cart during the next order?
 - try for the first time?
 - purchase again?
- Given a sequence of prior orders which products will be re-ordered in the next order?

- Data are provided by Instacart
 - Online retail grocery shop in US
 - Founded in 2012
 - Present in 1,200 cities in 25 states (March 2017)
 - Valued at approximately 3.4 bln USD (March 2017)
- Data contain ordering history of Instacart customers
 - Questions: Which products will a consumer
 - add to their cart during the next order?
 - try for the first time?
 - purchase again?
- Given a sequence of prior orders which products will be re-ordered in the next order?

- Data are provided by Instacart
 - Online retail grocery shop in US
 - Founded in 2012
 - Present in 1,200 cities in 25 states (March 2017)
 - Valued at approximately 3.4 bln USD (March 2017)
- Data contain ordering history of Instacart customers
 - Questions: Which products will a consumer
 - add to their cart during the next order?
 - try for the first time?
 - purchase again?
- Given a sequence of prior orders which products will be re-ordered in the next order?

Running Kaggle competition (August 14, 2017 - Final submission deadline)

- Data are provided by Instacart
 - Online retail grocery shop in US
 - Founded in 2012
 - Present in 1,200 cities in 25 states (March 2017)
 - Valued at approximately 3.4 bln USD (March 2017)
- Data contain ordering history of Instacart customers
 - Questions: Which products will a consumer

Given a sequence of prior orders which products will be re-ordered in the next order?

Table: A typical consumer order

Product	Reordered
Chocolate Sandwich Cookies	1
Dry Nose Oil	0
Pure Coconut Water With Orange	1
Green Chile Anytime Sauce	0

Table: (Correct) prediction

Product	Reordered
Chocolate Sandwich Cookies	1
Pure Coconut Water With Orange	1

(Online) retailers do

- Complement/substitute shopping lists of customers
 - by sending (accurate) personalised reminders
- Time-saving shopping activity
 - Increase customer turnover
- Better management of inventories
- Allow dynamic pricing
 - by offering personalised price tags/coupons
- Boost sales/revenues/market share

- The Kaggle competition prize
- Built up a reputation



(Online) retailers do

- Complement/substitute shopping lists of customers
 - by sending (accurate) personalised reminders
- Time-saving shopping activity
 - Increase customer turnover
- Better management of inventories
- Allow dynamic pricing
 - by offering personalised price tags/coupons
- Boost sales/revenues/market share

- The Kaggle competition prize
- Built up a reputation



(Online) retailers do

- Complement/substitute shopping lists of customers
 - by sending (accurate) personalised reminders
- Time-saving shopping activity
 - Increase customer turnover
- Better management of inventories
- Allow dynamic pricing
 - by offering personalised price tags/coupons
- Boost sales/revenues/market share

- The Kaggle competition prize
- Built up a reputation



(Online) retailers do

- Complement/substitute shopping lists of customers
 - by sending (accurate) personalised reminders
- Time-saving shopping activity
 - Increase customer turnover
- Better management of inventories
- Allow dynamic pricing
 - by offering personalised price tags/coupons
- Boost sales/revenues/market share

- The Kaggle competition prize
- Built up a reputation



Data

- 206,209 customers
- 49,688 products
 - 21 departments
 - 134 aisles
- 3,421,083 orders
 - 3,214,874 orders in the prior set
 - 206,209 orders in the postprior set
 - 131,209 orders in the train set
 - 75,000 orders in the test set (stored in Kaggle)

Data features

- Product-specific
- User-specific
- User-Product-specific
- Train/Test-specific

Data features: Product-specific

- How many times a product was ordered
- How many times a product was re-ordered
 - Product re-order ratio
- How many times a product was ordered for the first time
- How many times a product was ordered for the second time
 - Re-order propensity of a product

Data features: User-specific

- Number of orders made by user
- Number of all products ever ordered by user
 - Average basket size
- Number of distinct products ever ordered by user
- DOW/HOD orders are typically made
- Average ordering frequency in days
- Average share of re-ordered products in each order

Data features: User-Product-specific

- How many times user ordered product
- Share of orders with a product in total number of orders
- Share of orders with a product since this product was ordered for the first time
- How many orders/days ago a product was ordered last time
- Average position in ordering cart

Data features: Train/Test-specific

- Days since the last order in prior
- Day of week order was made
- Hour of day order was made

Table: A typical consumer order

Product	Reordered
Chocolate Sandwich Cookies	1
Dry Nose Oil	0
Pure Coconut Water With Orange	1
Green Chile Anytime Sauce	0

Table: (Correct) prediction

Product	Reordered
Chocolate Sandwich Cookies	1
Pure Coconut Water With Orange	1

Ordering habits of a user

Basket size

Share of re-ordered product

Investigate their variation with data features

Table: A typical consumer order

Product	Reordered
Chocolate Sandwich Cookies	1
Dry Nose Oil	0
Pure Coconut Water With Orange	1
Green Chile Anytime Sauce	0

Table: (Correct) prediction

Product	Reordered
Chocolate Sandwich Cookies	1
Pure Coconut Water With Orange	1

Ordering habits of a user:

- Basket size
- Share of re-ordered products

Investigate their variation with data features

Table: A typical consumer order

Product	Reordered
Chocolate Sandwich Cookies	1
Dry Nose Oil	0
Pure Coconut Water With Orange	1
Green Chile Anytime Sauce	0

Table: (Correct) prediction

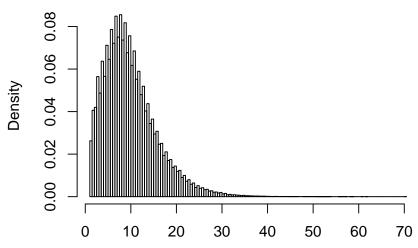
Product	Reordered
Chocolate Sandwich Cookies	1
Pure Coconut Water With Orange	1

Ordering habits of a user:

- Basket size
- Share of re-ordered products

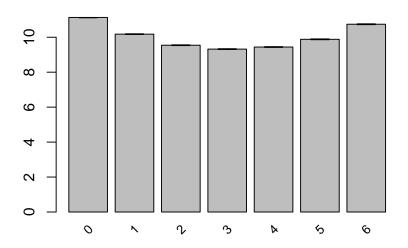
Investigate their variation with data features

Average basket size (across users)



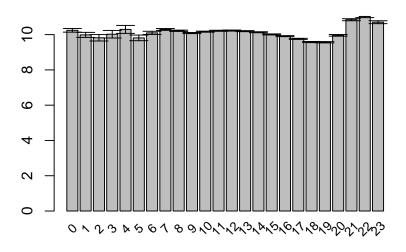
Data: basket size by DOW

Average basket size by DOW

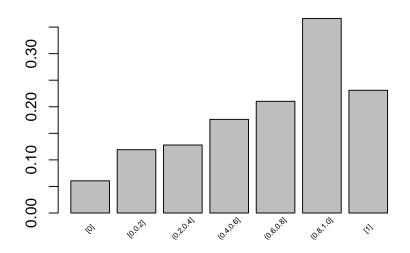


Data: basket size by HOD

Average basket size by HOD

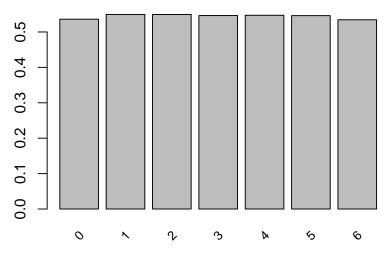


Share of re-ordered products



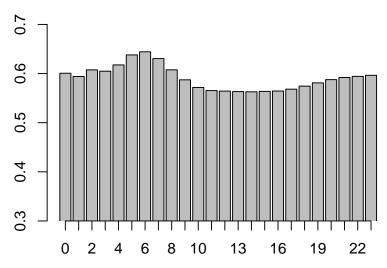
Data: Reorder share by DOW

Reorder share by DOW



Data: Reorder share by HOD

Reorder share by HOD



Evaluation metrics: mean F₁ score

F₁ score is the harmonic mean of:

- p precision: share of correct predictions in total number of predictions, \widehat{x}
- r recall: share of correct predictions in total number of outturns, x

$$p(x,\widehat{x}) = \frac{|x \cap \widehat{x}|}{|\widehat{x}|}$$
 $r(x,\widehat{x}) = \frac{|x \cap \widehat{x}|}{|x|}$

$$F_1$$
score = $2 * \frac{1}{\frac{1}{p} + \frac{1}{r}} = 2 * \frac{p * r}{p + r} \in [0, 1]$

At Kaggle: take average of individual F₁ scores



Benchmark models

- Repeat last order
- Repeat reordered items in last order
- Repeat reordered items in two last orders
- Repeat reordered items in three last orders
 - Kaggle Leadership Board:

```
F_1 score = 0.3586635 (1,074th place out of 1,716) F_1^{MAX} score = 0.4069657
```

Benchmark models

- Repeat last order
- Repeat reordered items in last order
- Repeat reordered items in two last orders
- Repeat reordered items in three last orders
 - Kaggle Leadership Board:

```
F_1 score = 0.3586635 (1,074th place out of 1,716)

F_1^{MAX} score = 0.4069657
```

Benchmark models

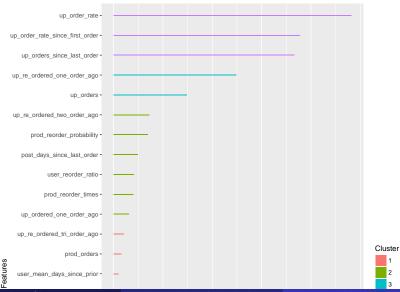
- Repeat last order (LB = 0.3276746)
- Repeat reordered items in last order (LB = 0.3276826)
- Repeat reordered items in two last orders
- Repeat reordered items in three last orders
 - Kaggle Leadership Board:

```
F_1 score = 0.3586635 (1,074th place out of 1,716)

F_1^{MAX} score = 0.4069657
```

- King of Kaggle competitions
 - Praised to be one of the most successful algorithms
- Provides feature importance
 - Product-specific
 - User-specific
 - User-Product-specific
 - Train/Test-specific





- Current stand:
 - My best LB score: 0.3797138 in TOP 33% (561 out of 1,716)
- Outlook
 - Think of more features to add
 - Compare benchmark and XGBoost
 - Predict those cases where benchmark beats XGBoost
 - User-specific thresholds
 - Apply alternative methods and their combinations:
 - Logistic regression
 - Random Forest
 - Gradient Boosting Machine (GBM)
- Not too late to join (Ends on Aug 14)!

- Current stand:
 - My best LB score: 0.3797138 in TOP 33% (561 out of 1,716)
- Outlook
 - Think of more features to add
 - Compare benchmark and XGBoost
 - Predict those cases where benchmark beats XGBoost
 - User-specific thresholds
 - Apply alternative methods and their combinations:
 - Logistic regression
 - Random Forest
 - Gradient Boosting Machine (GBM)
- Not too late to join (Ends on Aug 14)!

- Current stand:
 - My best LB score: 0.3797138 in TOP 33% (561 out of 1,716)
- Outlook
 - Think of more features to add
 - Compare benchmark and XGBoost
 - Predict those cases where benchmark beats XGBoost
 - User-specific thresholds
 - Apply alternative methods and their combinations:
 - Logistic regression
 - Random Forest
 - Gradient Boosting Machine (GBM)
- Not too late to join (Ends on Aug 14)!