

Instacart Market Basket Analysis

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The dataset is a relational set of files describing customers' orders over time. We are working with below 3 datasets:

1. Order_products_prior.csv
2. Products.csv
3. Departments.csv

Packages required:

- Arules
- readr
- Plyr

Data Pre-processing:

Used read_csv function to load the datasets into R. Order_products_prior dataset looks like below:

```
> head(order_products_prior)
  order_id product_id add_to_cart_order reordered
1         2       33120                 1         1
2         2       28985                 2         1
3         2       9327                  3         0
4         2       45918                 4         1
5         2       30035                 5         0
6         2       17794                 6         1

> head(products)
  product_id product_name aisle_id department_id
1          1 Chocolate Sandwich Cookies      61      19
2          2 All-Seasons Salt      104      13
3          3 Robust Golden Unsweetened Oolong Tea      94       7
4          4 Smart Ones Classic Favorites Mini Rigatoni with vodka Cream Sauce      38       1
5          5 Green Chile Anytime Sauce          5      13
6          6 Dry Nose Oil          11      11

> head(products)
# A tibble: 6 x 4
  product_id product_name aisle_id department_id
  <dbl> <chr> <dbl> <dbl>
1         1 Chocolate Sandwich Cookies      61      19
2         2 All-Seasons Salt      104      13
3         3 Robust Golden Unsweetened Oolong Tea      94       7
4         4 Smart Ones Classic Favorites Mini Rigatoni with vodka Cream Sauce      38       1
5         5 Green Chile Anytime Sauce          5      13
6         6 Dry Nose Oil          11      11
```

Order_products_prior dataset contains below fields:

- Order_id
- Product_id
- Add_to_cart_order
- Reordered

The products.csv file contains below fields:

- Product_id
- Product_name
- Aisle_id
- Department_id

The departments.csv file contains the below fields:

- Department_id
- Department

We merged order_products_prior and products dataset to get the corresponding product name and grouped the item names by order_id and store in transactionData and convert it to transaction object.

```
transactions as itemMatrix in sparse format with
3214875 rows (elements/itemssets/transactions) and
291600 columns (items) and a density of 3.381286e-05
```

most frequent items:

Banana	Bag of Organic Bananas	Organic Strawberries	Organic Baby Spinach	Organic Hass Avocado
444134	372129	256230	235489	191943
(Other)				
30198196				

element (itemset/transaction) length distribution:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
176763	200371	215192	225877	228550	226274	216798	200868	182823	163882	145703	129726	115236	101690	89355	78800	68917	60533
19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
52999	45961	40215	34705	30186	25930	22501	19418	16690	14326	12364	10650	8969	7611	6628	5636	4946	4107
37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54
3476	2993	2547	2164	1772	1518	1336	1102	999	858	711	604	498	453	363	325	236	223
55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72
194	171	151	119	110	83	78	74	64	53	48	39	34	29	36	23	11	13
73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90
25	16	17	11	10	11	6	6	7	3	3	5	6	3	2	2	3	1
91	92	93	94	95	98	99	100	102	105	110	111	112	113	114	119	139	150
2	1	2	1	3	2	3	1	4	2	1	2	1	1	1	1	1	1

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.00	4.00	8.00	9.86	13.00	150.00

includes extended item information - examples:

	labels
1	#2
2	#2 Coffee Filters
3	#2 Cone White Coffee Filters

Frequent itemsets for products in orders dataset. You have to output product names and not just product id

From transaction Data object tr, we can run summary(tr) which gives very useful information about the transaction object.

We can get frequent product items by running eclat command on the transaction object.

The parameters used for frequent product items are:

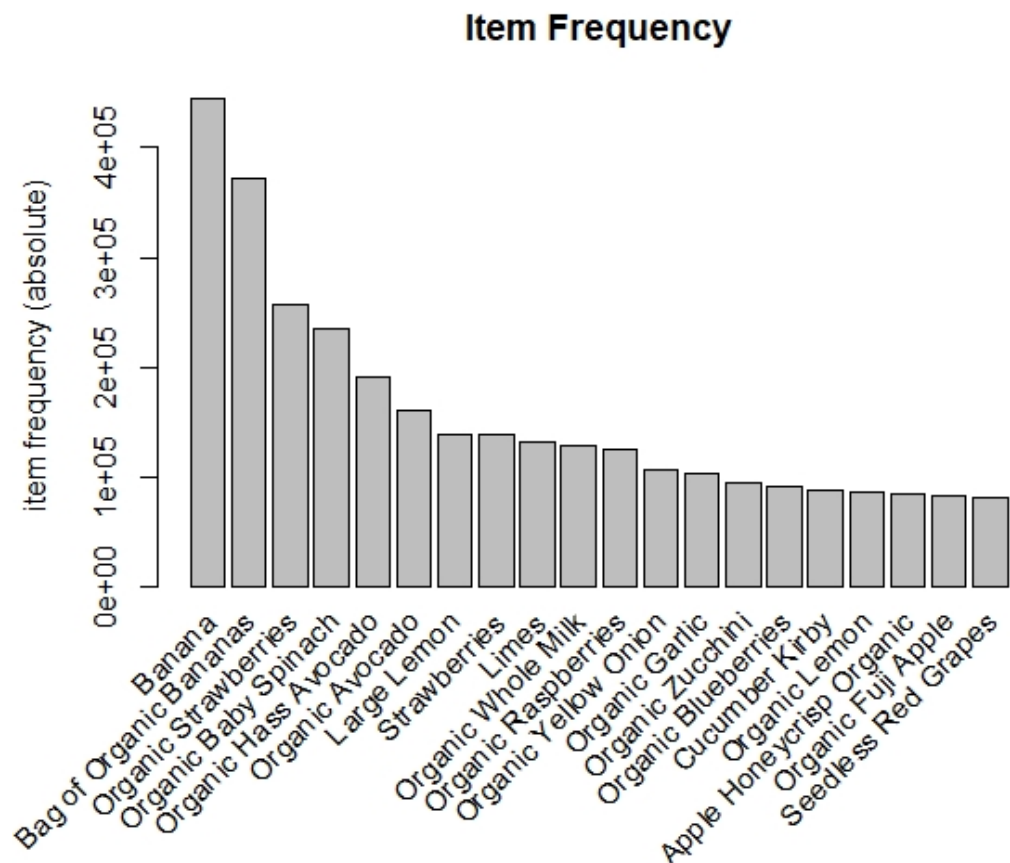
Support: 0.03

Maxlen: 15

The frequent products look like below:

	items	support	count
[1]	{Banana}	0.13814969	444134
[2]	{Bag of Organic Bananas}	0.11575225	372129
[3]	{Organic Strawberries}	0.07970139	256230
[4]	{Organic Baby Spinach}	0.07324982	235489
[5]	{Organic Hass Avocado}	0.05970465	191943
[6]	{Organic Avocado}	0.05021844	161446
[7]	{Large Lemon}	0.04311210	138600
[8]	{Limes}	0.04095525	131666
[9]	{Organic Raspberries}	0.03879311	124715
[10]	{Strawberries}	0.04294226	138054
[11]	{Organic Whole Milk}	0.03990357	128285
[12]	{Organic Yellow Onion}	0.03300439	106105
[13]	{Organic Garlic}	0.03219130	103491

We can see the frequent items graphically by using the item frequency plot.



Association rules for products in orders dataset. You have to output product names and not just product id

Next step is to mine the rules using the APRIORI algorithm. The function `apriori()` is from package `arules`. The `apriori()` takes the transaction object on which mining to be applied along with parameter values of support and confidence.

The parameters for `item_rules` are :

Support: 0.001

Confidence: 0.5

The first 20 rules for frequent product items look like below:

	lhs	rhs	support	confidence	lift	count
[1]	{Country Stand Juice}	=> {Medium Pulp}	0.001090245	1	917.22539	3505
[2]	{Medium Pulp}	=> {Country Stand Juice}	0.001090245	1	917.22539	3505
[3]	{Chocolate Chip Walnut}	=> {Cookies}	0.001055718	1	701.63138	3394
[4]	{Twin Pack}	=> {Take & Bake}	0.001005016	1	995.00929	3231
[5]	{Take & Bake}	=> {Twin Pack}	0.001005016	1	995.00929	3231
[6]	{Twin Pack}	=> {French Baguettes}	0.001005016	1	995.00929	3231
[7]	{French Baguettes}	=> {Twin Pack}	0.001005016	1	995.00929	3231
[8]	{Take & Bake}	=> {French Baguettes}	0.001005016	1	995.00929	3231
[9]	{French Baguettes}	=> {Take & Bake}	0.001005016	1	995.00929	3231
[10]	{2 Huge Rolls = 5 Regular Rolls Towels/Napkins}	=> {Select-A-Size Paper Towels}	0.001302383	1	579.98827	4187
[11]	{2 Huge Rolls = 5 Regular Rolls Towels/Napkins}	=> {White}	0.001302383	1	457.63345	4187
[12]	{Three Cheese}	=> {Pizza Poppers}	0.001001594	1	998.40839	3220
[13]	{Pizza Poppers}	=> {Three Cheese}	0.001001594	1	998.40839	3220
[14]	{Deliciously Hydrating Watermelon Water}	=> {Cold-pressed}	0.001258525	1	794.58107	4046
[15]	{Cold-pressed}	=> {Deliciously Hydrating Watermelon Water}	0.001258525	1	794.58107	4046
[16]	{Ginger Root Beer}	=> {Naturally Flavored Zero Calorie Soda}	0.001221509	1	614.11175	3927
[17]	{Ginger Root Beer}	=> {Caffeine Free}	0.001221509	1	511.35279	3927
[18]	{Sunkissed in the Mediterranean}	=> {Wild Non-Pareil Capers}	0.001091800	1	915.91880	3510
[19]	{Wild Non-Pareil Capers}	=> {Sunkissed in the Mediterranean}	0.001091800	1	915.91880	3510
[20]	{Organic Snack Mix Bunnies Snack Mix}	=> {Organic}	0.001038921	1	47.54537	3340

Frequent itemsets for departments in orders dataset. You have to output product names and not just product id

We merged order_products_prior, products and departments dataset to get the corresponding department names of the items purchased per order and grouped the departments names by order_id and store in transactionData1 and convert it to transaction object tr1.

From transaction Data object tr1, we can run summary(tr1) which gives very useful information about the transaction object.

```
transactions as itemMatrix in sparse format with
3214875 rows (elements/itemsets/transactions) and
22 columns (items) and a density of 0.2152805

most frequent items:
  produce dairy eggs   beverages      snacks      frozen      (Other)
2409320    2177338    1457351    1391447    1181018    6609725

element (itemset/transaction) length distribution:
sizes
  1      2      3      4      5      6      7      8      9     10     11     12     13     14     15     16     17     18
287949 395701 468955 488113 447455 367284 279920 198390 130101 78397  41778  19579  7880  2589   651   108   22    3

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000  3.000  4.000  4.736  6.000 18.000

includes extended item information - examples:
labels
1 alcohol
2 babies
3 bakery
```

We can get frequent product items by running eclat command on the transaction object.

The parameters used for frequent departments are:

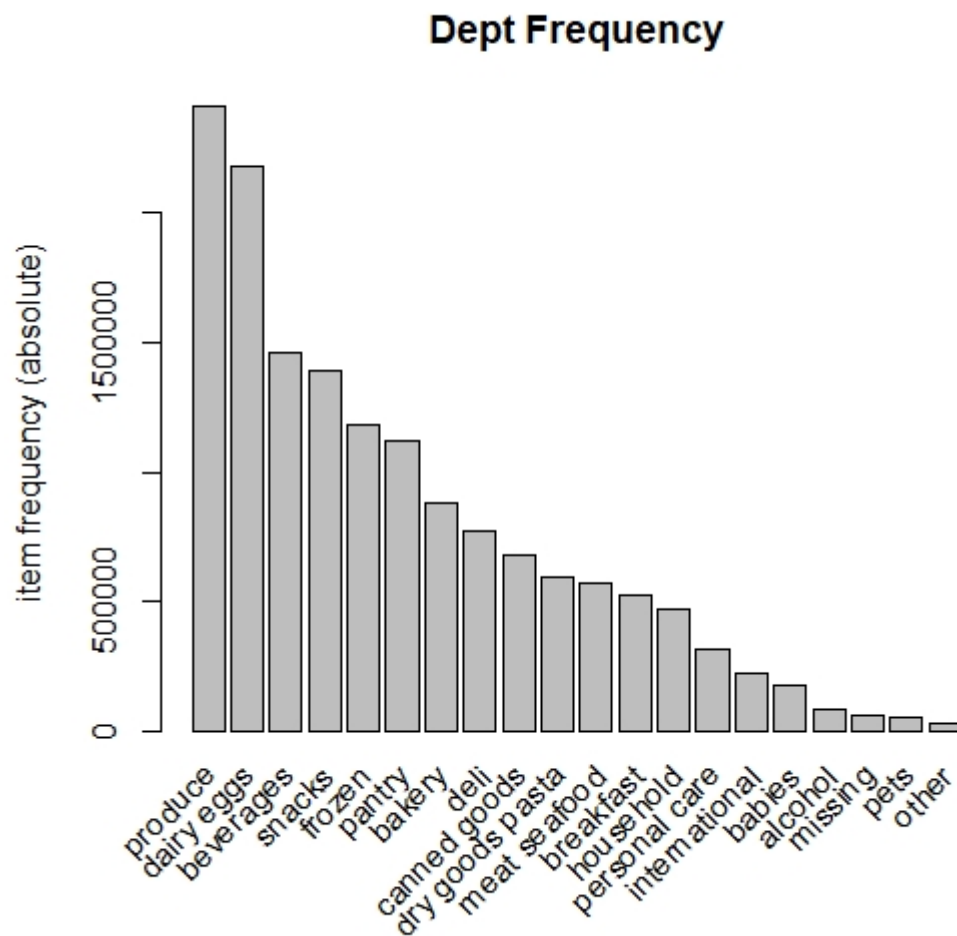
Support: 0.2

Maxlen: 15

The frequent departments look like below:

	items	support	count
[1]	{deli,produce}	0.2060590	662454
[2]	{bakery,produce}	0.2289678	736103
[3]	{bakery,dairy eggs}	0.2249972	723338
[4]	{dairy eggs,pantry,produce}	0.2324585	747325
[5]	{pantry,produce}	0.2869402	922477
[6]	{dairy eggs,pantry}	0.2692615	865642
[7]	{dairy eggs,frozen,produce}	0.2425799	779864
[8]	{frozen,produce}	0.2981183	958413
[9]	{dairy eggs,frozen}	0.2833796	911030
[10]	{beverages,dairy eggs,produce}	0.2611629	839606
[11]	{beverages,produce}	0.3335635	1072365
[12]	{beverages,dairy eggs}	0.3207378	1031132
[13]	{beverages,snacks}	0.2291035	736539
[14]	{dairy eggs,produce,snacks}	0.2704659	869514
[15]	{produce,snacks}	0.3372616	1084254
[16]	{dairy eggs,snacks}	0.3225478	1036951
[17]	{dairy eggs,produce}	0.5504833	1769735
[18]	{produce}	0.7494288	2409320
[19]	{dairy eggs}	0.6772699	2177338
[20]	{snacks}	0.4328153	1391447
[21]	{beverages}	0.4533150	1457351
[22]	{frozen}	0.3673605	1181018
[23]	{pantry}	0.3477249	1117892
[24]	{bakery}	0.2742116	881556
[25]	{deli}	0.2396050	770300
[26]	{canned goods}	0.2119227	681305

We can see the frequent departments graphically by using the item frequency plot.



Association rules for departments in orders dataset. You have to output product names and not just product id

Next step is to mine the rules using the APRIORI algorithm. The function `apriori()` is from package `arules`. The `apriori()` takes the transaction object on which mining to be applied along with parameter values of support and confidence.

The parameters for `department_rules` are :

Support: 0.07

Confidence: 0.5

The rules for frequent departments look like below:

	lhs	rhs	support	confidence	lift	count
[1]	{canned goods,dairy eggs,pantry}	=> {produce}	0.08483067	0.9217936	1.229995	272720
[2]	{dairy eggs,deli,pantry}	=> {produce}	0.08249123	0.9169900	1.223585	265199
[3]	{dairy eggs,dry goods pasta,pantry}	=> {produce}	0.07342867	0.9137443	1.219254	236064
[4]	{canned goods,dairy eggs,frozen}	=> {produce}	0.08240383	0.9130381	1.218312	264918
[5]	{canned goods,dairy eggs,snacks}	=> {produce}	0.08535977	0.9123281	1.217365	274421
[6]	{bakery,dairy eggs,deli}	=> {produce}	0.07833026	0.9085897	1.212376	251822
[7]	{dairy eggs,deli,frozen}	=> {produce}	0.09052856	0.9073162	1.210677	291038
[8]	{dairy eggs,dry goods pasta,snacks}	=> {produce}	0.07973343	0.9068887	1.210107	256333
[9]	{bakery,canned goods}	=> {produce}	0.07238664	0.9068781	1.210092	232714
[10]	{canned goods,pantry}	=> {produce}	0.09871053	0.9064324	1.209498	317342
[11]	{meat seafood,pantry}	=> {produce}	0.07578273	0.9050391	1.207638	243632
[12]	{canned goods,dairy eggs}	=> {produce}	0.15367409	0.9040459	1.206313	494043
[13]	{dairy eggs,dry goods pasta,frozen}	=> {produce}	0.07794984	0.9035153	1.205605	250599
[14]	{dairy eggs,meat seafood}	=> {produce}	0.12915774	0.9014228	1.202813	415226
[15]	{beverages,canned goods,dairy eggs}	=> {produce}	0.07813679	0.9012985	1.202647	251200
[16]	{deli,pantry}	=> {produce}	0.09426494	0.9000567	1.200990	303050
[17]	{dairy eggs,deli,snacks}	=> {produce}	0.10425724	0.8996680	1.200472	335174
[18]	{dairy eggs,frozen,pantry,snacks}	=> {produce}	0.07424363	0.8994555	1.200188	238684
[19]	{dry goods pasta,pantry}	=> {produce}	0.08325549	0.8982468	1.198575	267656
[20]	{meat seafood,snacks}	=> {produce}	0.07954275	0.8972348	1.197225	255720