Springboard Data Science Intensive

Instacart Market Basket Competition

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Ryan Alexander Alberts

Retail eCommerce & Operations Strategy

Previous

COO, MyToolStore.com (eCommerce retailer)

Market Strategist, Pearce Properties

Education

MIT | Supply Chain Management

Columbia | English Literature

Optimization

JMP, Gurobi, Excel

Systems Design

ERP & CRM (NetSuite), SQL

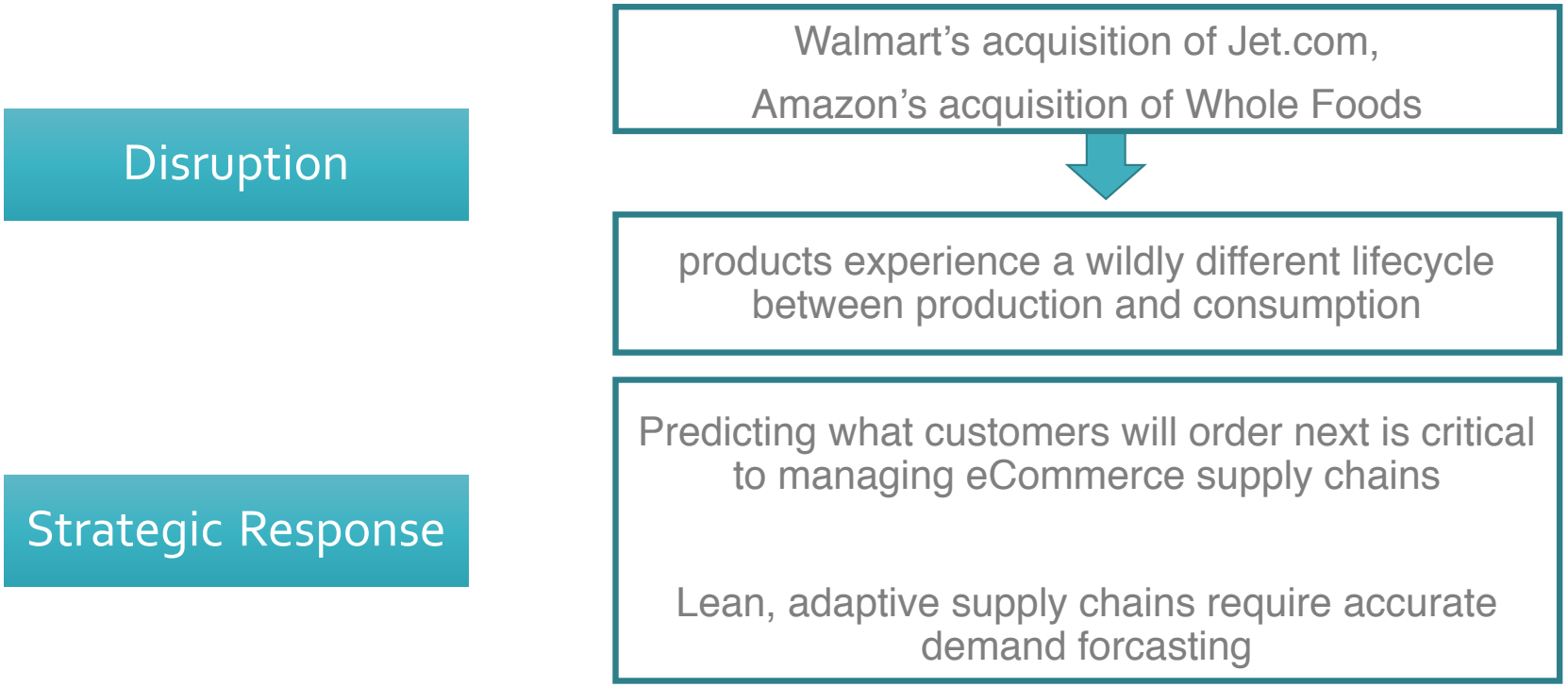
Data Visualization

Tableau, Seaborn, Matplotlib

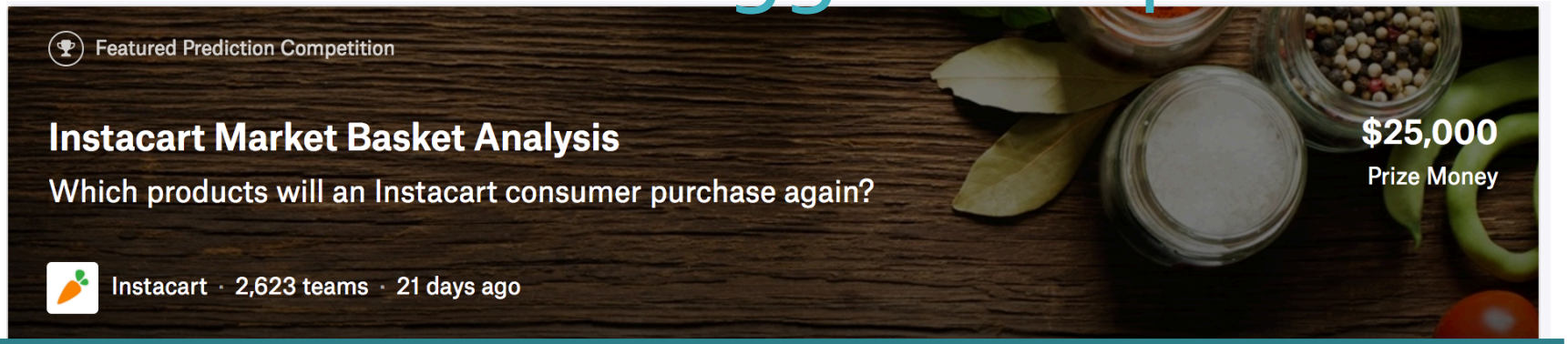
Data Science

Python, APIs, EDIs

Introduction: Retail eCommerce



Introduction: Kaggle Competitions



Top Platform for Data Science Competitions

Attacks real-world problems using anonymized data from public & private institutions

Extensive public repositories of:

- Machine-learning & Predictive Modelling techniques

- Over 500k Data Scientists
- 2M+ machine-learning models
- Over 200 competitions hosted
- $10,000 – $30,000 typical Prize Money
- Collaborative, global user community

Introduction: Instacart

Instacart is a pure-play eCommerce grocer

$25,000 prize for the top-three demand-forecasting models

The Data:

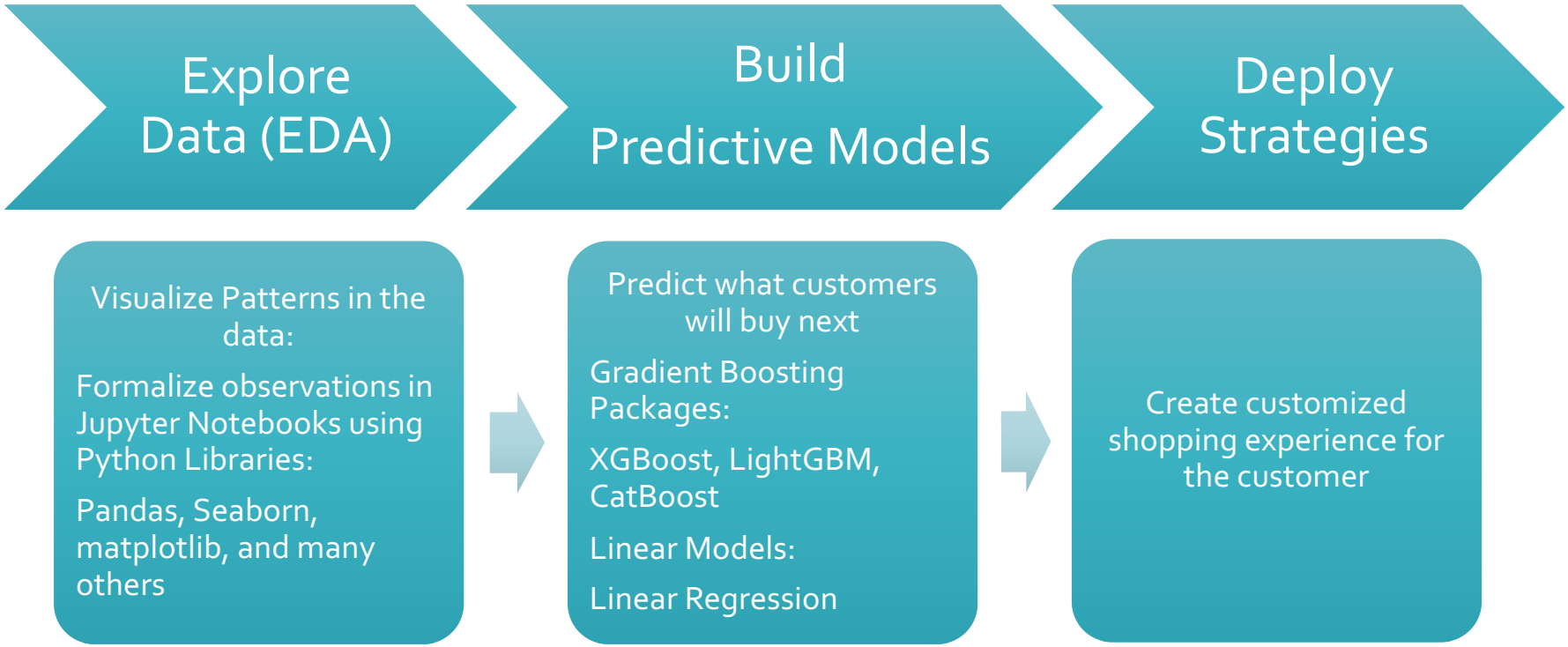
- 3M orders
- 206k customers
- Clean & well-wrangled
- Customer & Order History

Evaluative Metric: Mean F1 Score:

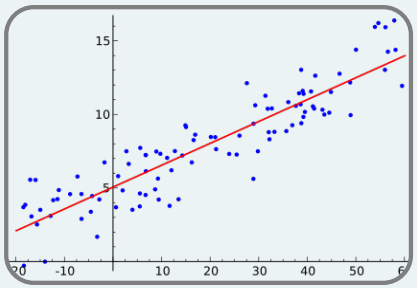
```
2 * (precision * recall) /
   (precision + recall)
```

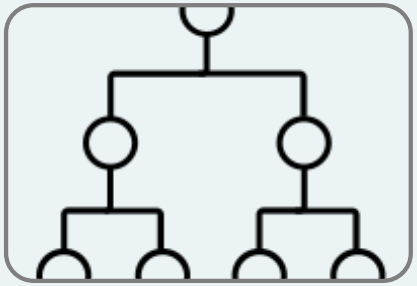
https://www.kaggle.com/c/instacart-market-basket-analysis

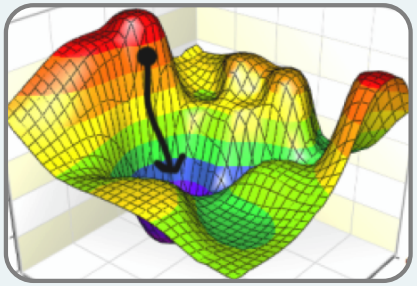
Methodology

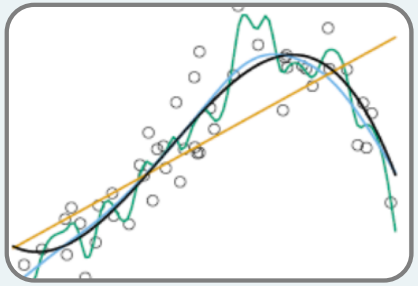


Models









Logistic Regression

Used to assess feature importance according to its ability to predict binary outcomes

Decision Trees

Method of classifying observations by weighing feature importance, closely analogous to how humans actually make decisions

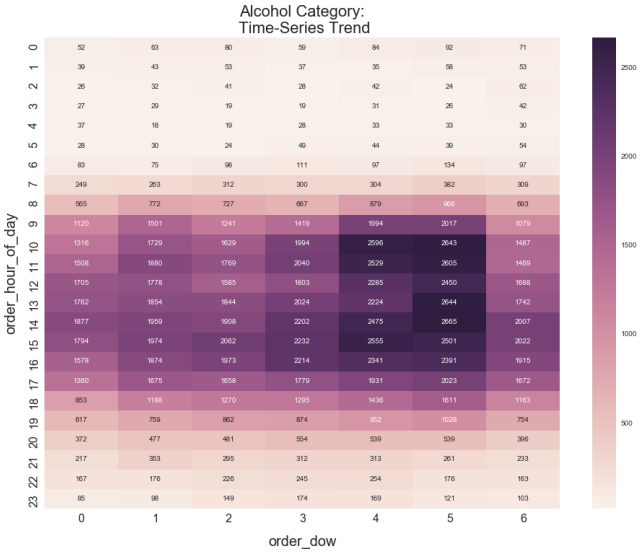
Gradient Boosting

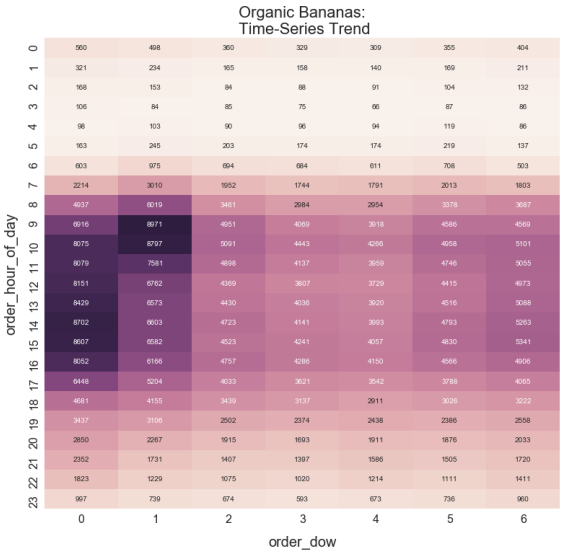
Sequential, dependent parameter analysis using many decision trees to assess feature importance

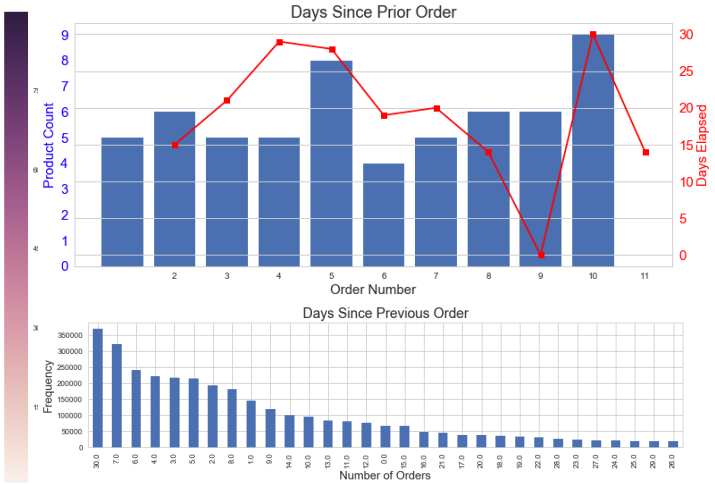
Ensemble Methods

Combining output of several models. Empirically, most of the winning models in Data Science competitions are ensembles

Exploring the Data



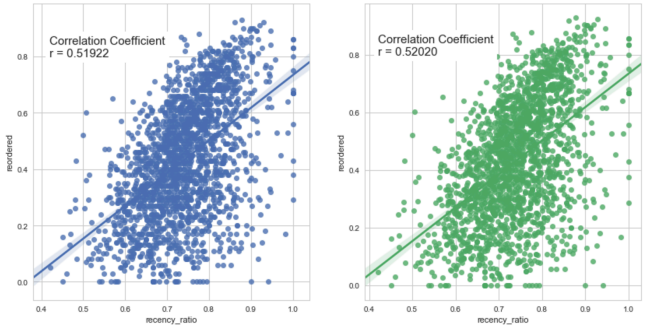


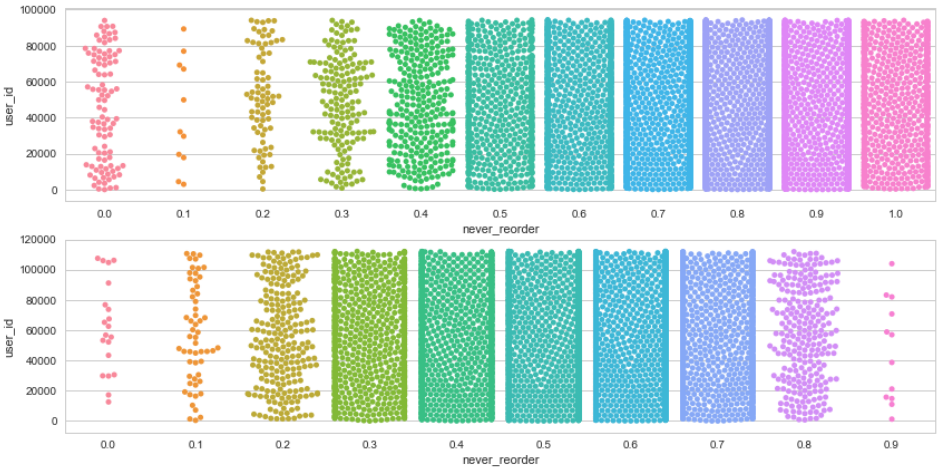


Exploring the Data (cont'd.)

In [144]:
```
from scipy import stats
fig, ax = plt.subplots(1, 2, figsize=(14,7))
r = stats.pearsonr(t['recency_ratio'][:200], t['reordered'][:200])
r = np.round(r, decimals=2)
bbox_props = dict(fc="w", ec="w", lw=2)
ax[0].text(.42, .8, "Correlation Coefficient\nr = 0.51922",
           size=15,
           bbox=bbox_props)
ax[1].text(.42, .8, "Correlation Coefficient\nr = 0.52020",
           size=15,
           bbox=bbox_props)

t = pd.DataFrame(recent_four.groupby('user_id').mean()).reset_index()
u = t.copy()
t['reordered'] = np.round(t['reordered'], decimals=2)
sns.regplot(x="recency_ratio", y="reordered", data=t[:2000], ax=ax[0]);
sns.regplot(x="recency_ratio", y="reordered", data=u[:2000], ax=ax[1]);
```





Finding Patterns in the Data

```
In [20]: # TEST SET


print 'Processing recency features --Approx. 40min -- ...\n'
sequence                        = pd.DataFrame(TEST__user_orders.groupby(['user_id',
                                                                          'product_id',
                                                                          'order_number']
                                                                        ).size()
                                               ).reset_index()
del TEST__user_orders
sequence                        = sequence.drop([0], axis=1)

basket_by_order                 = pd.DataFrame(sequence.groupby(['user_id',
                                                                 'order_number']
                                                               ).size()
                                               ).reset_index()
basket_by_order.rename(columns  ={0 :'order_size'}, inplace=True)
sequence                        = sequence.merge(basket_by_order,
                                                 on=['user_id',
                                                     'order_number'],
                                                 how='left')

recent_four                     = pd.DataFrame(sequence.groupby(['user_id','product_id'
                                                                 ]
                                                               )['order_number'
                                                                ].apply(lambda x:
                                                                        x.nlargest(4).values))

print 'Processing frequency features...\n'
```

```
In [97]: #m = pd.DataFrame(TEST__user_orders.groupby('user_id')['order_number'].max()).reset_index()
#m.rename(columns     ={'order_number' : 'prior_orders'}, inplace=True)
#recent_four = recent_four.merge(m, on='user_id', how='left')
#recent_four['recency_ratio'] = ( recent_four['most_recent']  / recent_four['prior_orders'] ).astype(np.float32)
recent_four = recent_four.merge(TEST__user_orders[['user_id',
                                                   'product_id',
                                                   'reordered']], on=['user_id',
                                                                      'product_id'], how='left')

recent_four
```

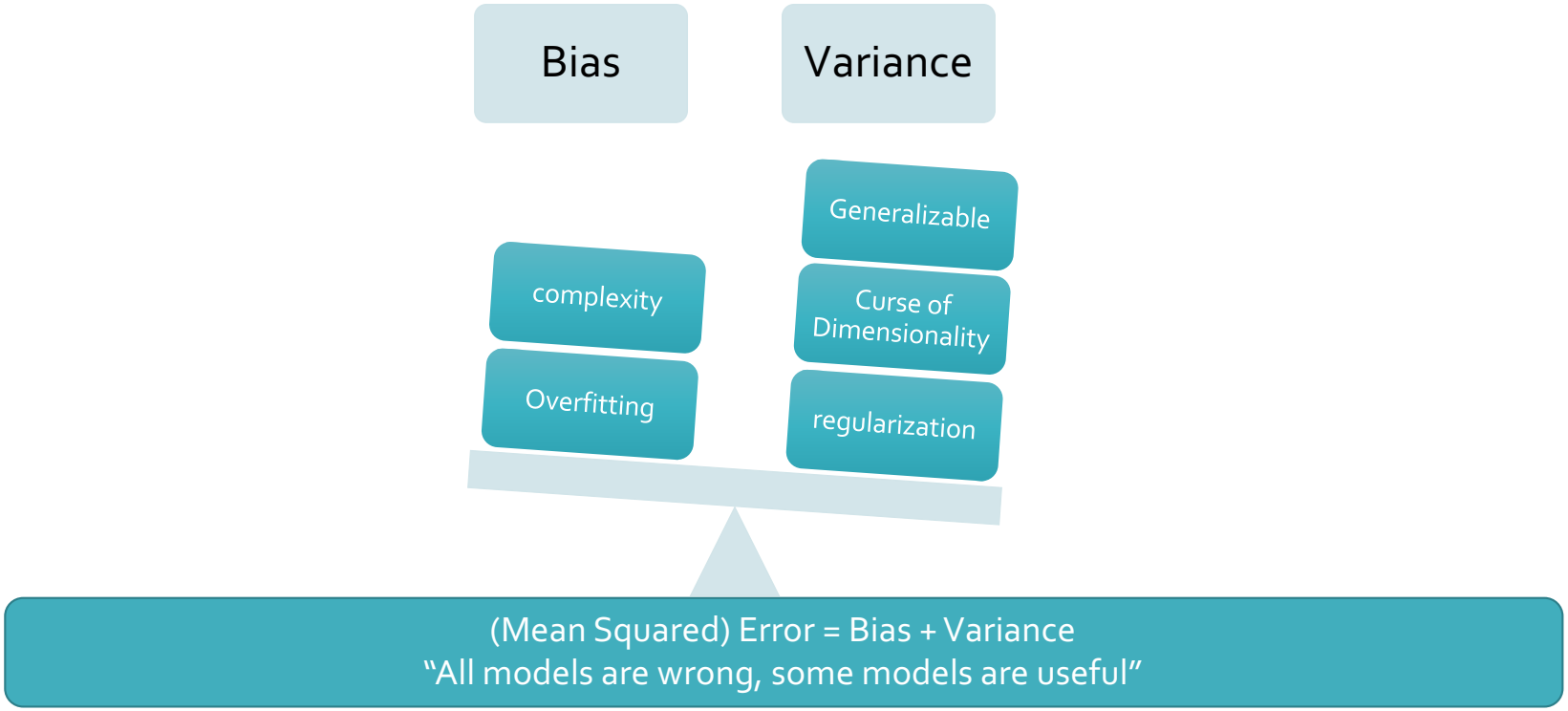
Out[97]:

_id	product_id	order_number	most_recent	second_most_recent	third_most_recent	fourth_most_recent	never_reorder	avg_no_reorder	recency_ratio	reordered
3	248	[2]	2	-1	-1	-1	1	0.424242	0.166667	0
3	1005	[10]	10	-1	-1	-1	1	0.424242	0.833333	0
3	1819	[7, 6, 4]	7	6	4	-1	0	0.424242	0.583333	0
3	1819	[7, 6, 4]	7	6	4	-1	0	0.424242	0.583333	1
3	1819	[7, 6, 4]	7	6	4	-1	0	0.424242	0.583333	1
3	7503	[3]	3	-1	-1	-1	1	0.424242	0.250000	0
3	8021	[2]	2	-1	-1	-1	1	0.424242	0.166667	0
3	9387	[7, 6, 5, 4]	7	6	5	4	0	0.424242	0.583333	0
3	9387	[7, 6, 5, 4]	7	6	5	4	0	0.424242	0.583333	1
3	9387	[7, 6, 5, 4]	7	6	5	4	0	0.424242	0.583333	1
3	9387	[7, 6, 5, 4]	7	6	5	4	0	0.424242	0.583333	1
3	9387	[7, 6, 5, 4]	7	6	5	4	0	0.424242	0.583333	1
3	12845	[4]	4	-1	-1	-1	1	0.424242	0.333333	0
3	14992	[7, 6]	7	6	-1	-1	0	0.424242	0.583333	0
3	14992	[7, 6]	7	6	-1	-1	0	0.424242	0.583333	1
3	15143	[1]	1	-1	-1	-1	1	0.424242	0.083333	0

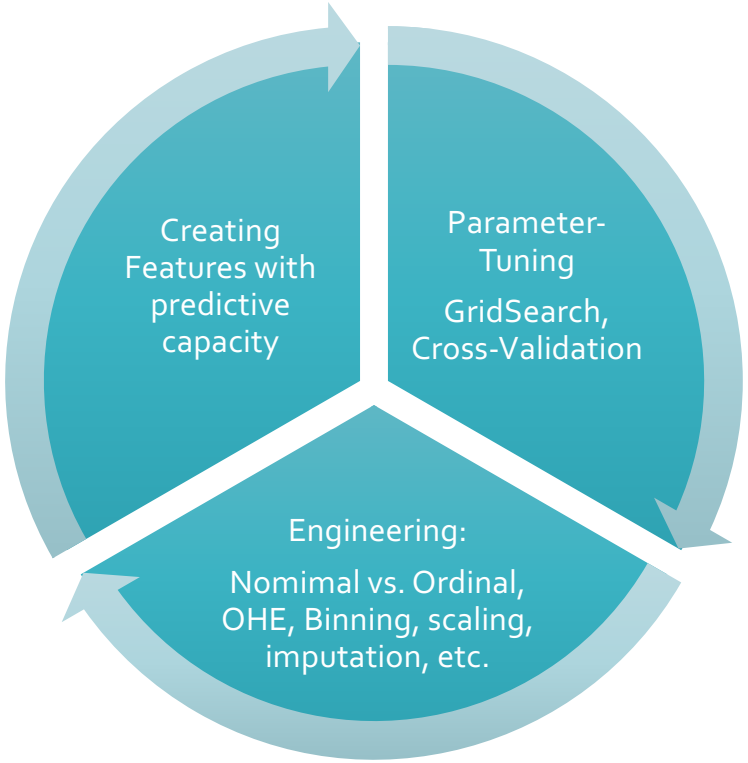
Example: Recent order behavior matters more

Use domain knowledge to isolate meaningful patterns → Engineer a feature that captures the pattern → Build feature set and feed into model

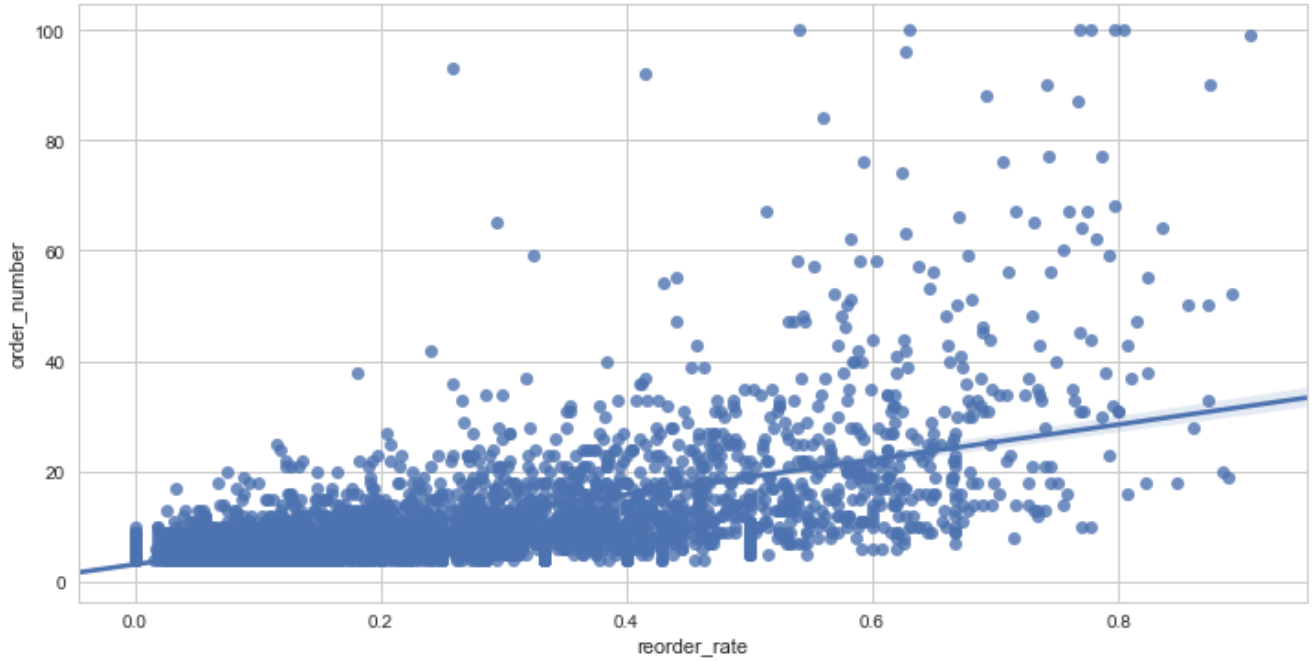
Feature Engineering & Parameter-Tuning



Feature Engineering & Parameter-Tuning



When No Prediction is the Best Prediction



Optimizing F-Measures for Binary Classifier

```
try:
    test_df = test_df.drop(['usr_threshold'], axis=1)
except:
    pass

class F1Optimizer():
    def __init__(self):
        pass

    @staticmethod
    def get_expectations(P, pNone=None):
        expectations = []
        P = np.sort(P)[::-1]

        n = np.array(P).shape[0]
        DP_C = np.zeros((n + 2, n + 1))
        if pNone is None:
            pNone = (1.0 - P).prod()

        DP_C[0][0] = 1.0
        for j in range(1, n):
            DP_C[0][j] = (1.0 - P[j - 1]) * DP_C[0, j - 1]

        for i in range(1, n + 1):
            DP_C[i, i] = DP_C[i - 1, i - 1] * P[i - 1]
            for j in range(i + 1, n + 1):
                DP_C[i, j] = P[j - 1] * DP_C[i - 1, j - 1] + (1.0 - P[j - 1]) * DP_C[i, j - 1]

        DP_S = np.zeros((2 * n + 1,))
        DP_SNone = np.zeros((2 * n + 1,))
        for i in range(1, 2 * n + 1):
            DP_S[i] = 1. / (1. * i)
            DP_SNone[i] = 1. / (1. * i + 1)
        for k in range(n + 1)[::-1]:
            f1 = 0
            f1None = 0
            for k1 in range(n + 1):
                f1 += 2 * k1 * DP_C[k1][k] * DP_S[k + k1]
                f1None += 2 * k1 * DP_C[k1][k] * DP_SNone[k + k1]
            for i in range(1, 2 * k - 1):
                DP_S[i] = (1 - P[k - 1]) * DP_S[i] + P[k - 1] * DP_S[i + 1]
                DP_SNone[i] = (1 - P[k - 1]) * DP_SNone[i] + P[k - 1] * DP_SNone[i + 1]
            expectations.append([f1None + 2 * pNone / (2 + k), f1])

        #print '\nexpectations', np.array(expectations[::-1])

        return np.array(expectations[::-1]).T

    @staticmethod
    def maximize_expectation(P, pNone=None):
        expectations = F1Optimizer.get_expectations(P, pNone)
        ix_max = np.unravel_index(expectations.argmax(), expectations.shape)
        max_f1 = expectations[ix_max]
        predNone = True if ix_max[0] == 0 else False
        best_k = ix_max[1]
```

Basket Size: Predicting HOW MANY is as important as WHICH products a customer will buy next

Problem: How do you rank the predictions, and what threshold do you use?

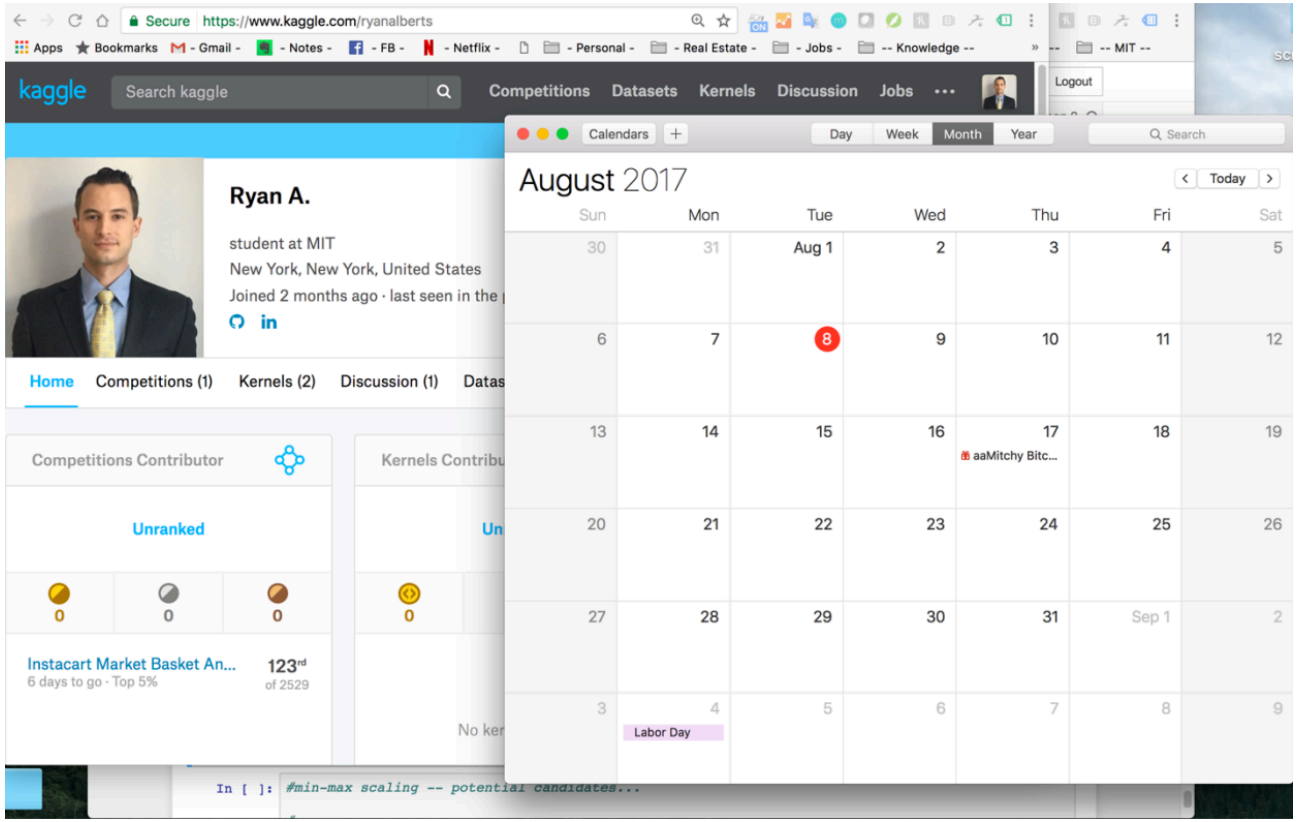
Solution: Maximize the expected F1 Score and rank product matrix

Conclusions & Recommendations

Use Predictions from the model to:

- Refine search recommendations for users while they are shopping
- More effectively manage inventory
- Create targeted merchandizing campaigns
- More effectively engage customers with personalized content

Thank you!


Secure https://www.kaggle.com/ryanalberts
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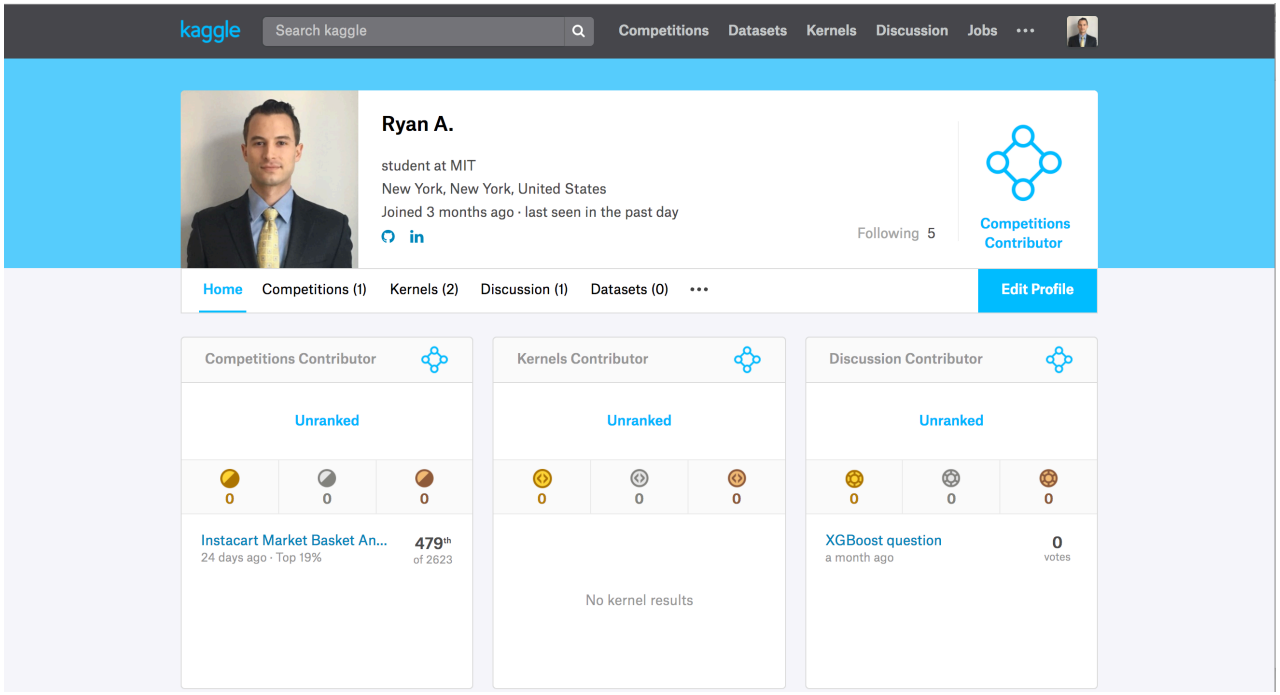
Datasets
Kernels
Discussion
Jobs
Logout
Ryan A.
student at MIT
New York, New York, United States
Joined 2 months ago · last seen in the
Home
Competitions (1)
Kernels (2)
Discussion (1)
Competitions Contributor
Unranked
Instacart Market Basket An...
6 days to go · Top 5%
123rd
of 2529
Calendars
Day
Week
Month
Year
Search
August 2017
Today
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Labor Day
In [ ]: #min-max scaling -- potential candidates...

...Final Rank*



* Competition ended after the start of my Master's program, so I made the decision to stop work on the project August 8th.