# BABYLIST

## Email Metrics Project

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# Outlines

# 1 : How our email list(s) are growing/churning

# 2 : Churn, Factors, Worst/Best Cohort

# 3 :  Profit Prediction Model

# 4 :  Recommendations

## 1-1 : IMPORT CSV AND CREATE A LOCAL DATABASE.

Data description

From dim_user database, we got 1,500,000 users x 37 columns

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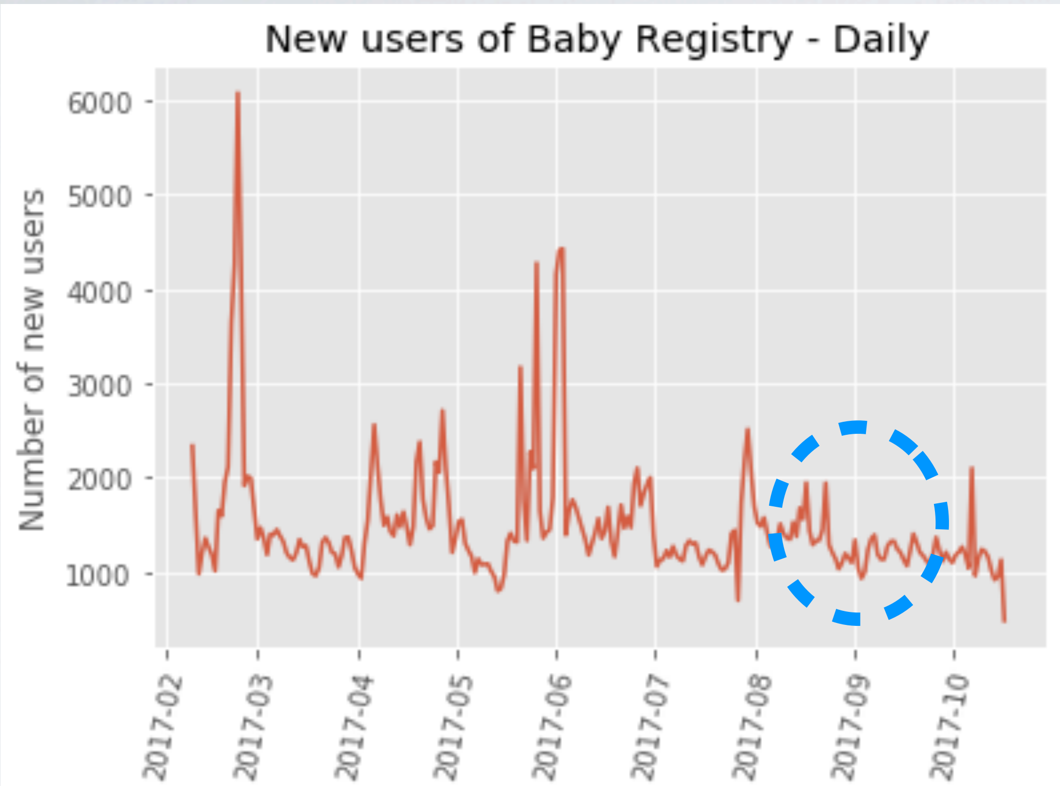
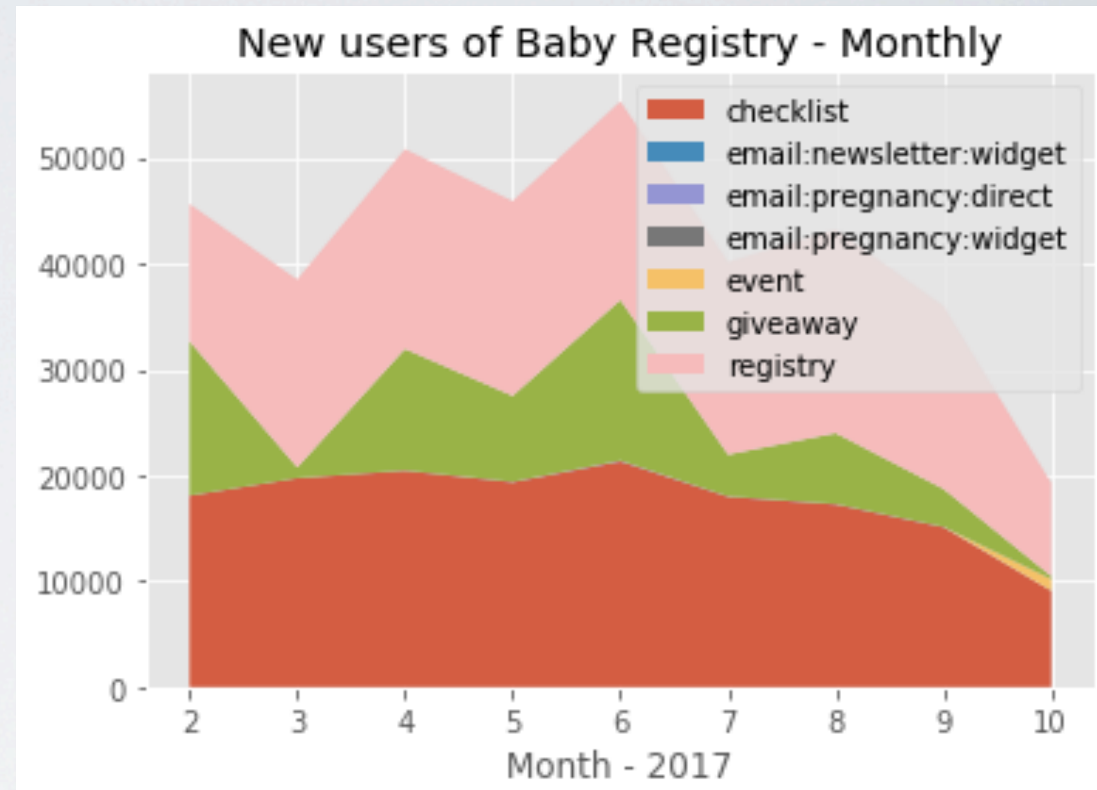
### Data overview

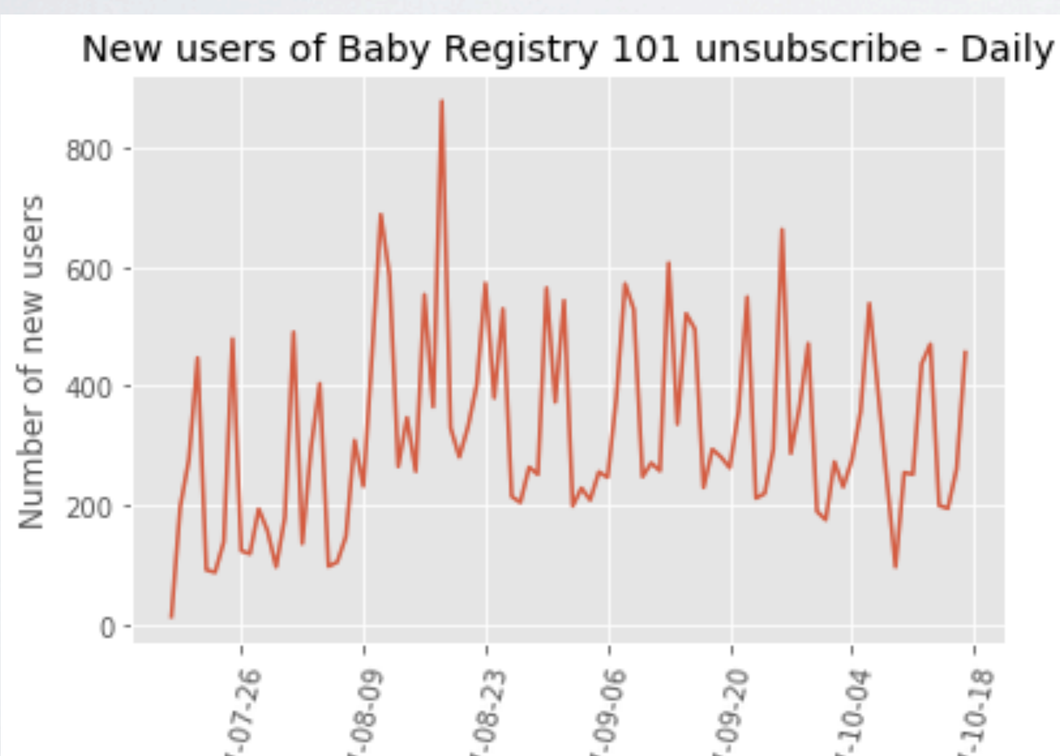
| 4 Email Lists | Email Related | Others |
| --- | --- | --- |
| Baby Registry 101 | 1.Subscribe_at | ID |
| Newsletter | 2.Delivered | Created_at |
| Pregnancy_weekly | 3.Open | Original_arrival_date |
| Sponsored | 4.Click | referrer |
| | 5.Unsubscribe_at | Source...etc |

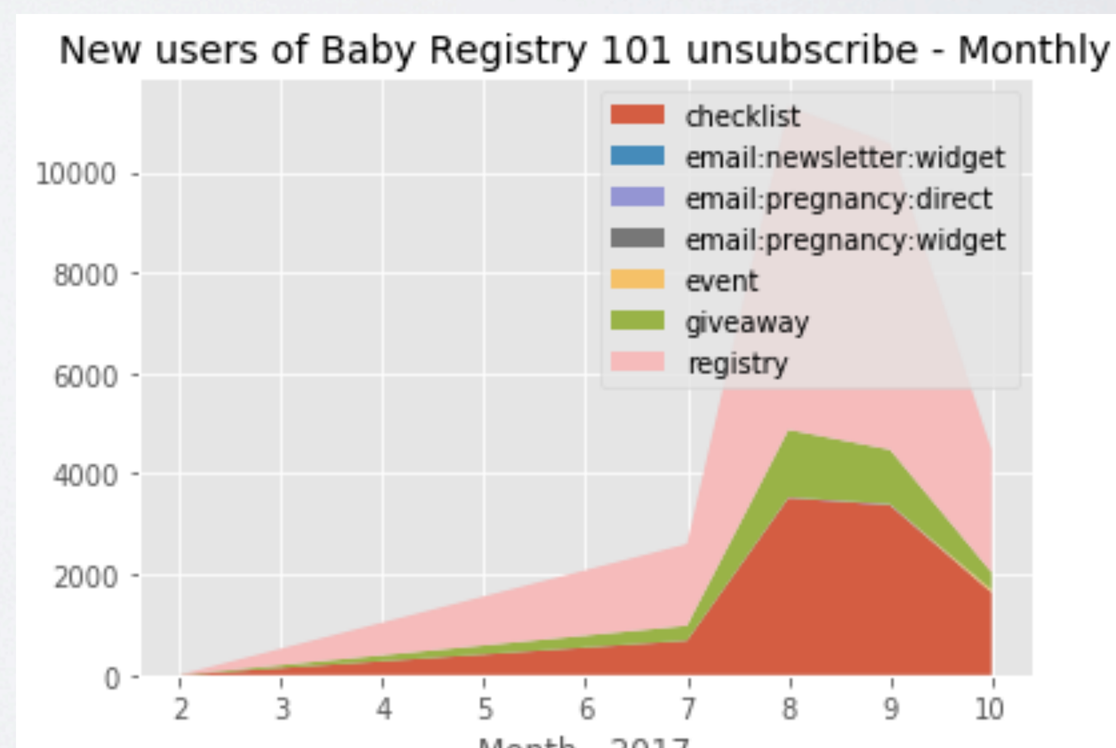
# 1-1 : IMPORT CSV AND CREATE A LOCAL DATABASE.

[Baby Registry 101] There is a stable growth in checklist. However, we see in September, there is a declining trend in this email list.



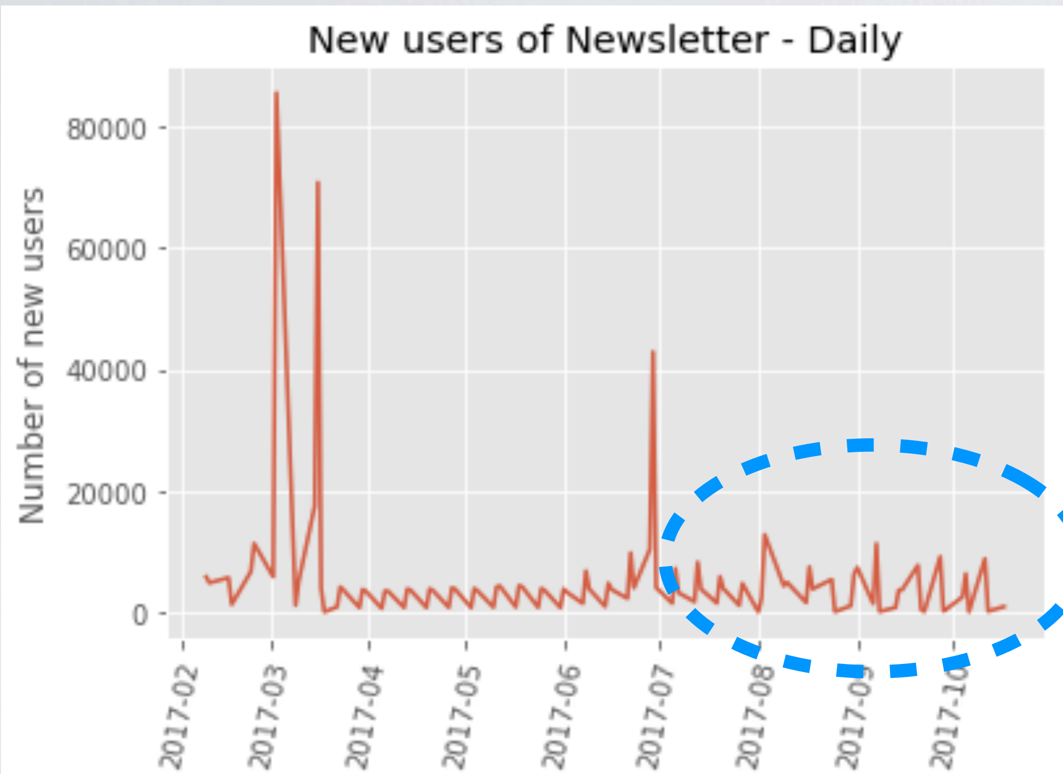



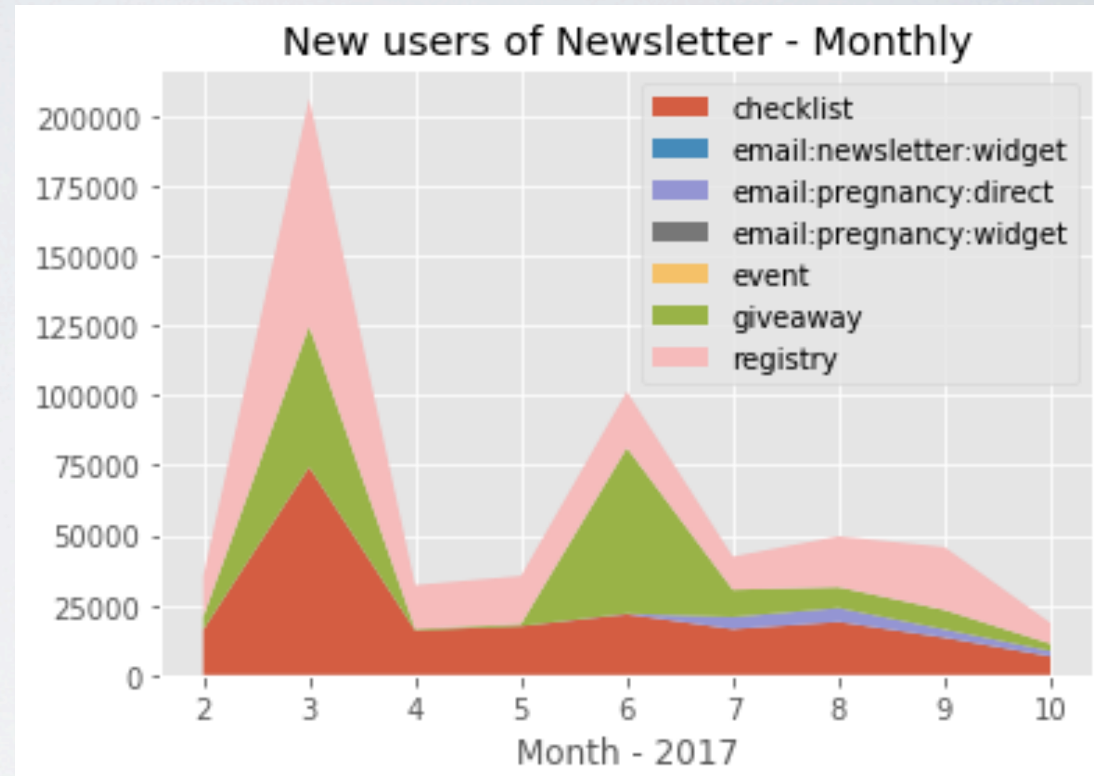



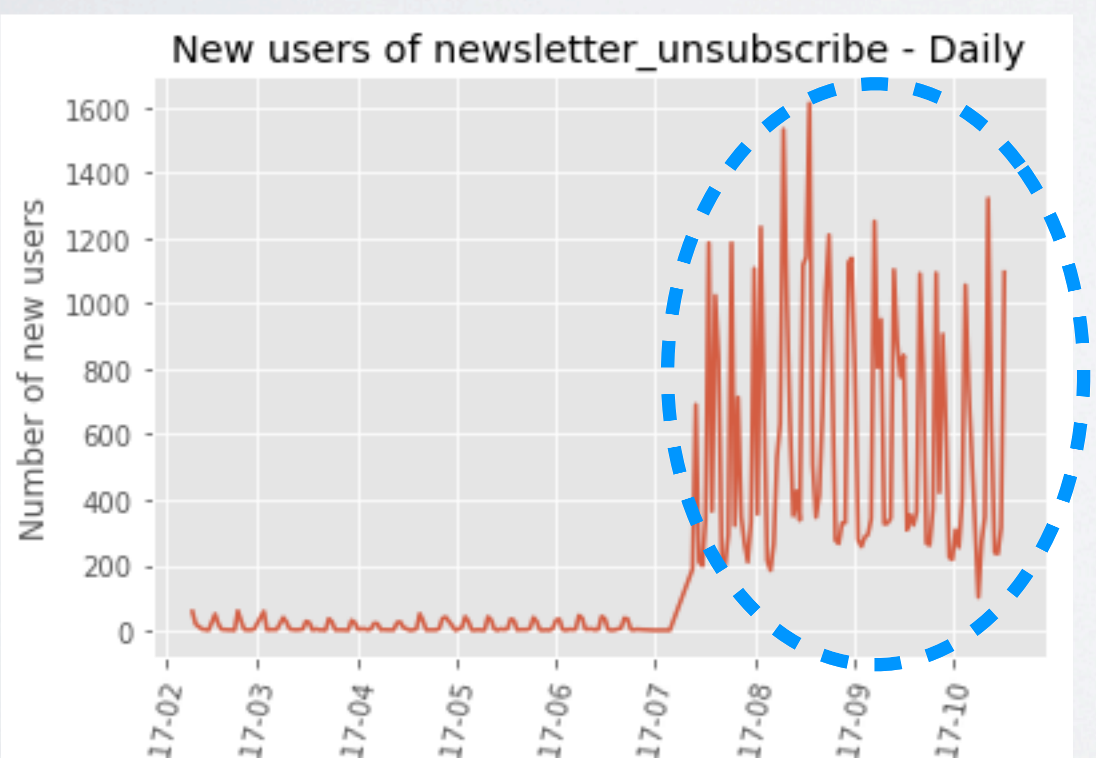



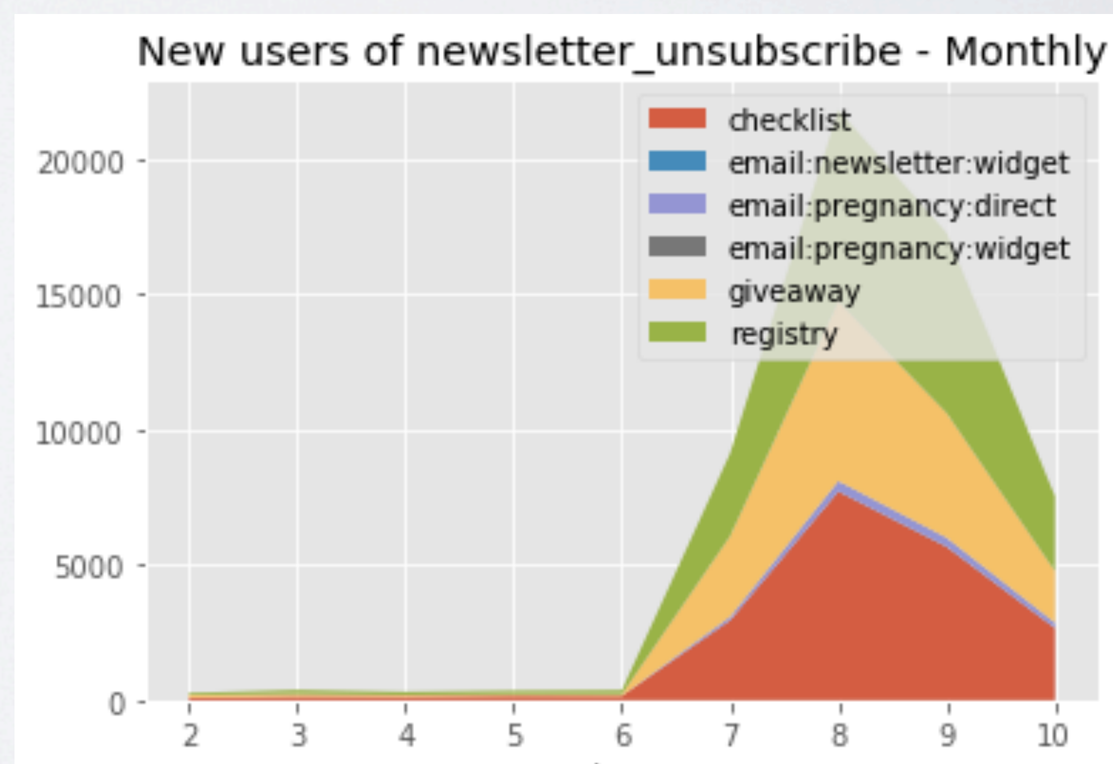
## 1-1 : IMPORT CSV AND CREATE A LOCAL DATABASE.

[Newsletter] We focus on data after 2017-08 and we can see the growth/churning source is mainly from registry/giveaway/checklist



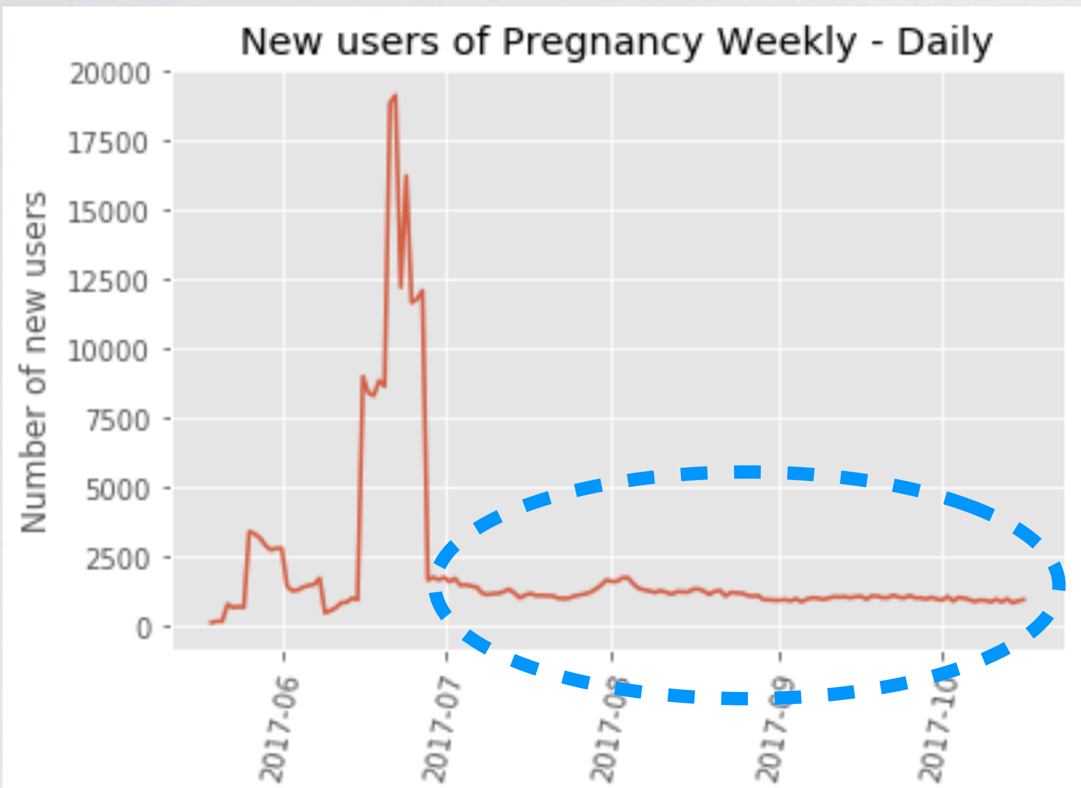



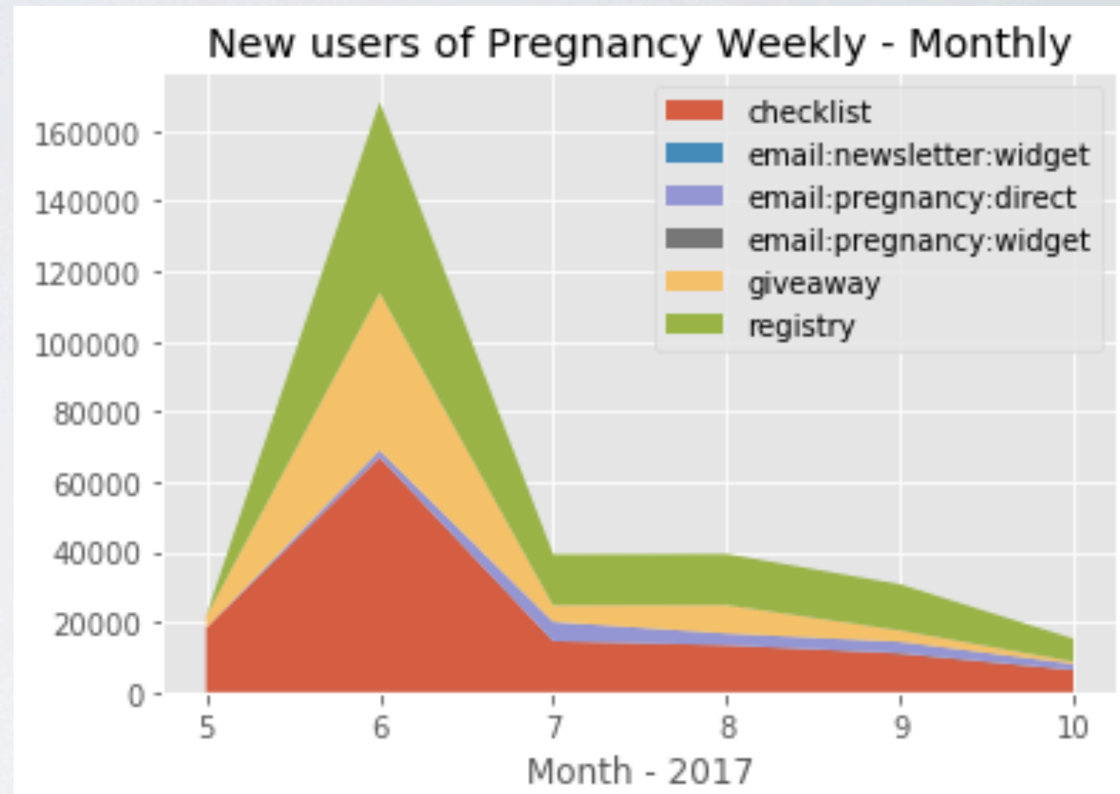



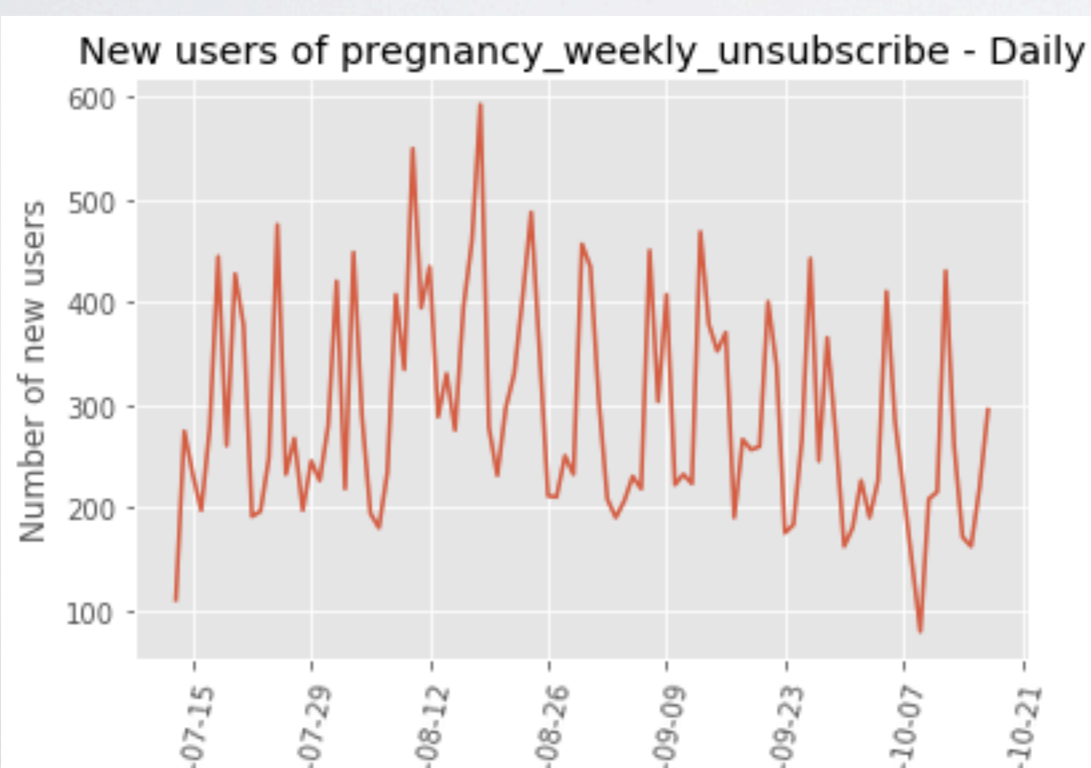



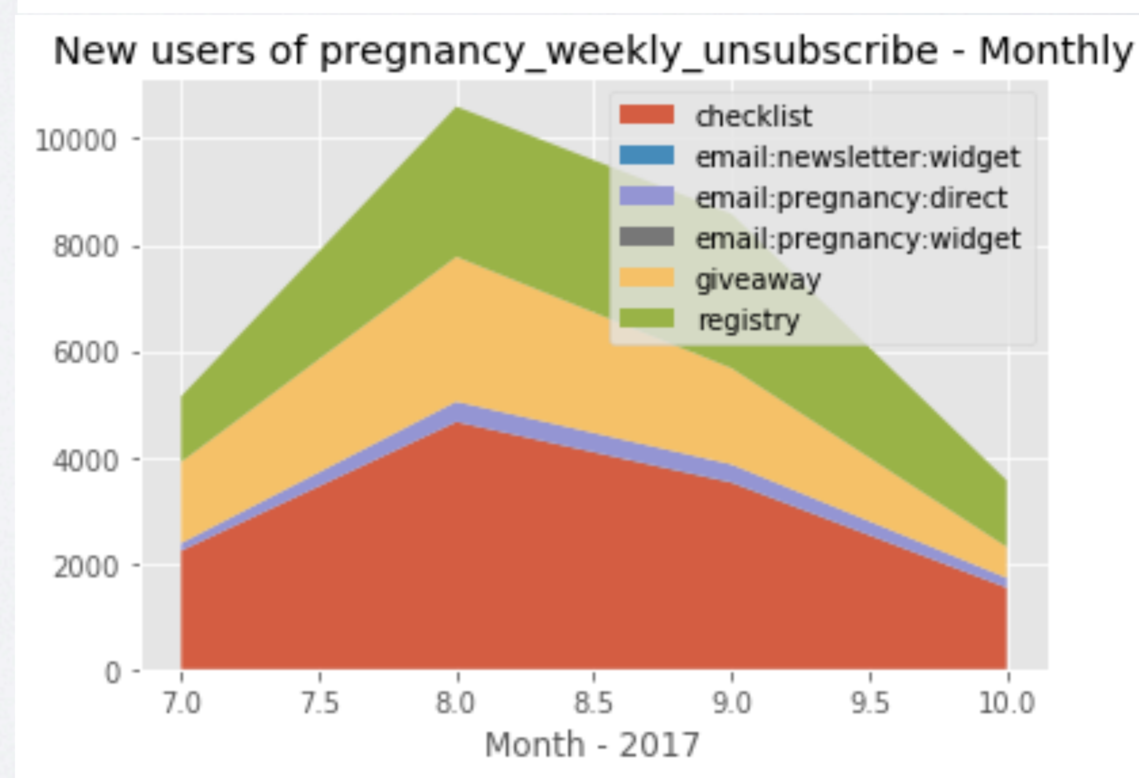
## 1-1 : IMPORT CSV AND CREATE A LOCAL DATABASE.

[Pregnancy Weekly] It is relatively stable and the growth/churning source is mainly from registry/giveaway/checklist



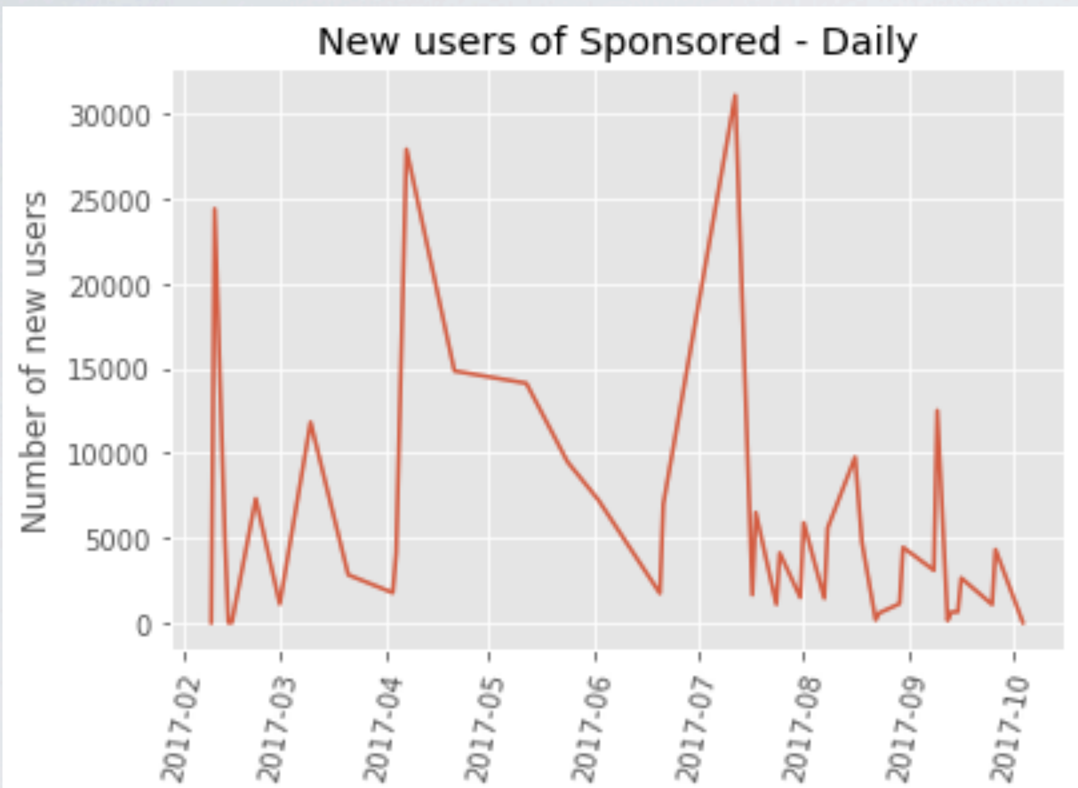



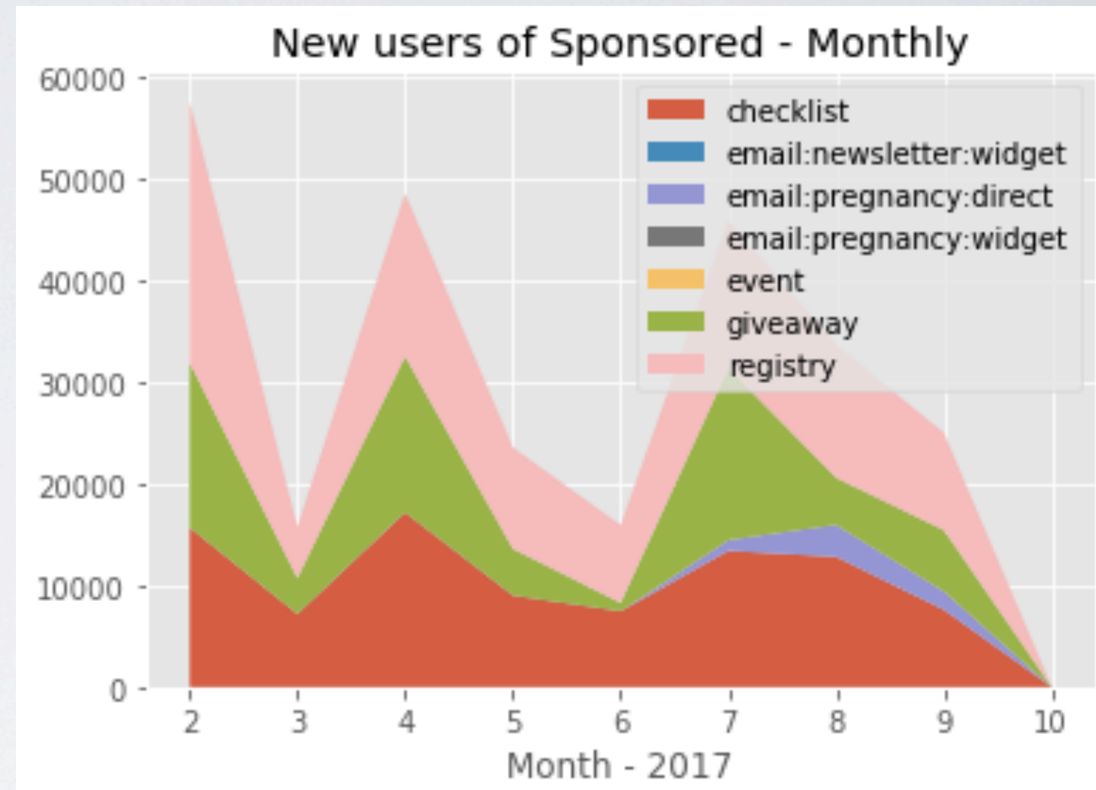



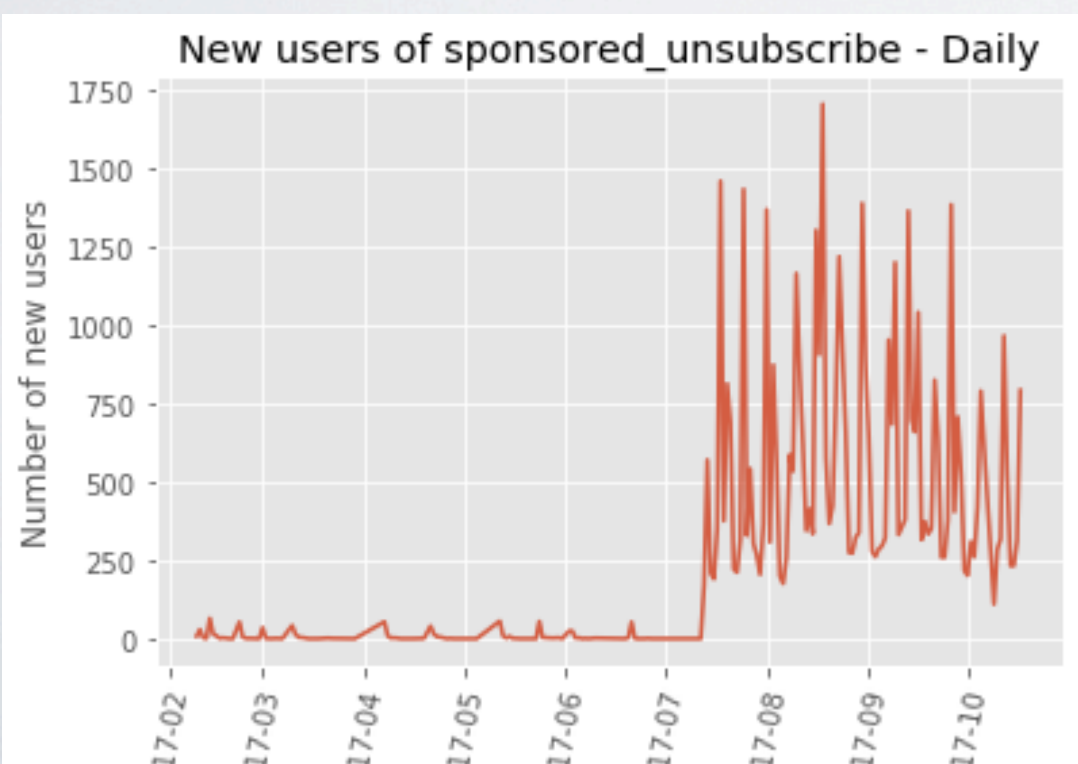



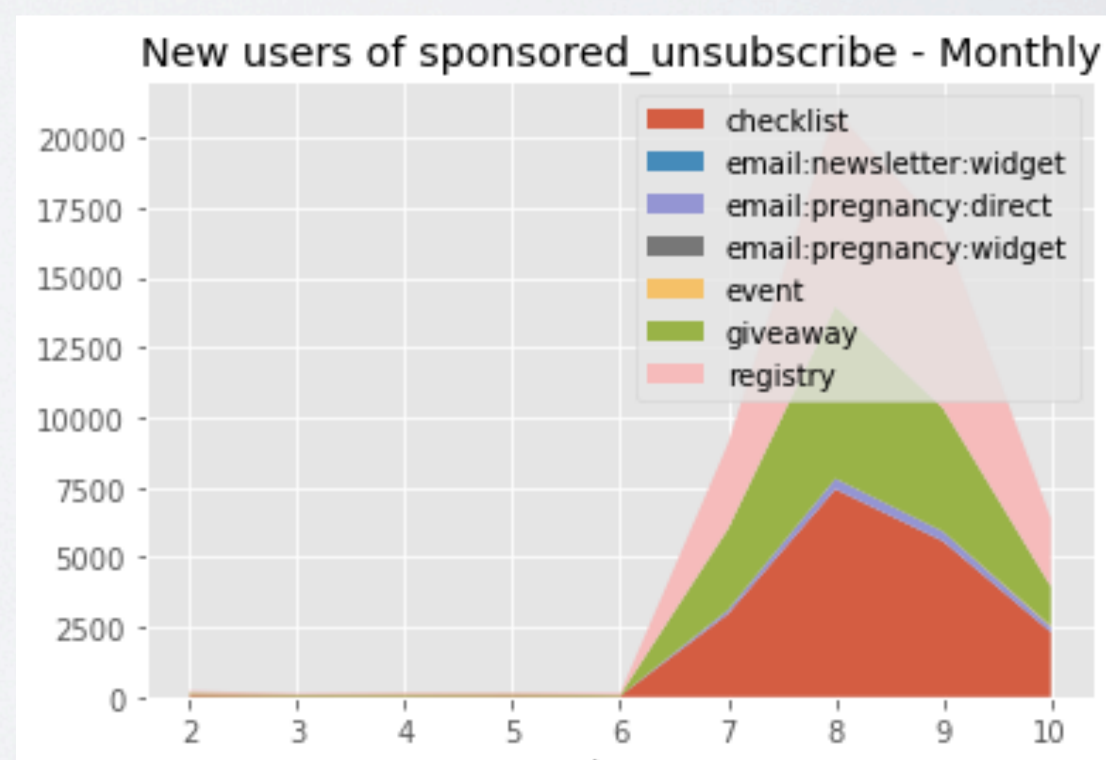
# 1-1 : IMPORT CSV AND CREATE A LOCAL DATABASE.

[Sponsored] This is a strategic e-mail list. We see a seasonal growth in this one.



# Outlines

# 1 : How our email list(s) are growing

**# 2 : Churn, Factors, Worst/Best Cohort**

# 3 :  Profit Prediction Model

# 4 :  Recommendations

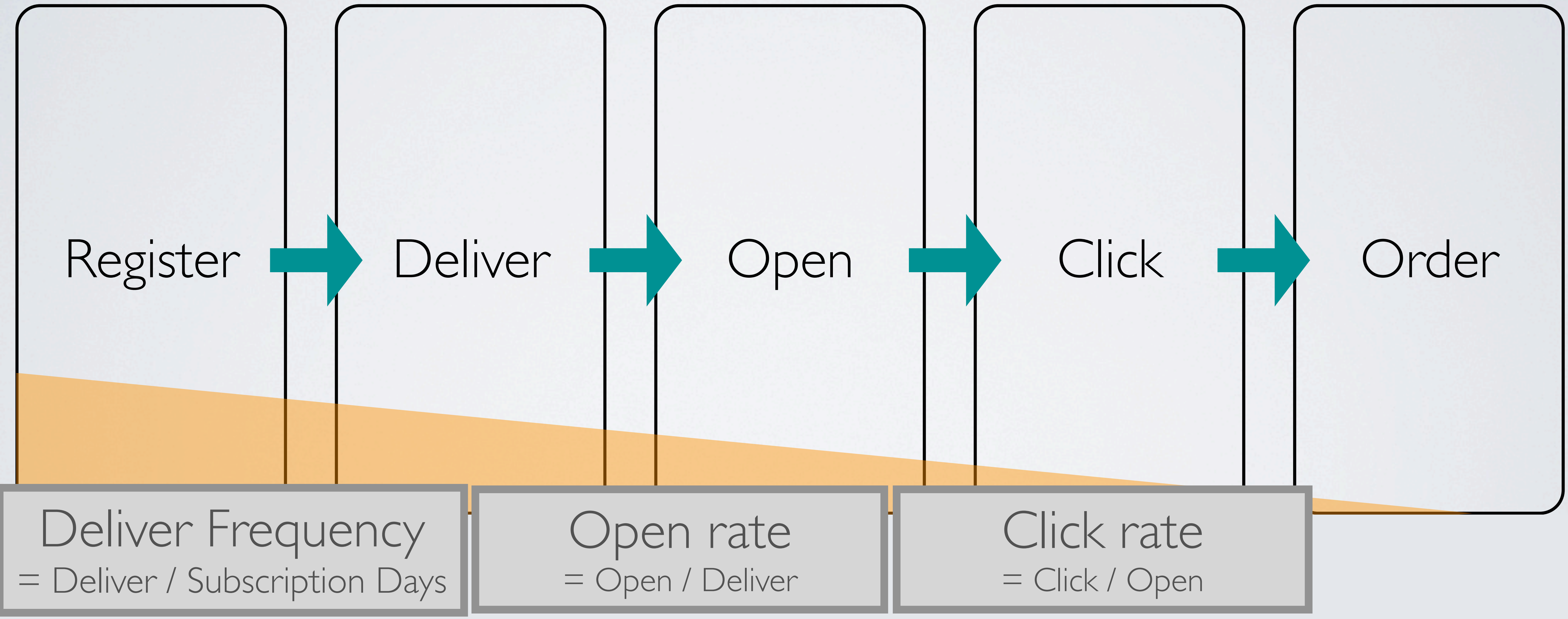
# EMAIL CHURN - RELATED QUESTIONS

- Can you describe how our email list(s) are churning?
- What factors correlate the most to churn? Due date?Source? Anything else?
- How would you describe our worst cohort?
- How would you describe our best cohort?

## 2 : CHURN, FACTORS, WORST/BEST COHORT

Users will unsubscribe email at any stage. We use "Deliver rate", "Open rate" and "Click rate" as our main parameters.

### Churn Process



## 2 : CHURN, FACTORS, WORST/BEST COHORT

Goal: We want to segment users and show their profile in different groups with machine learning model (unsupervised)

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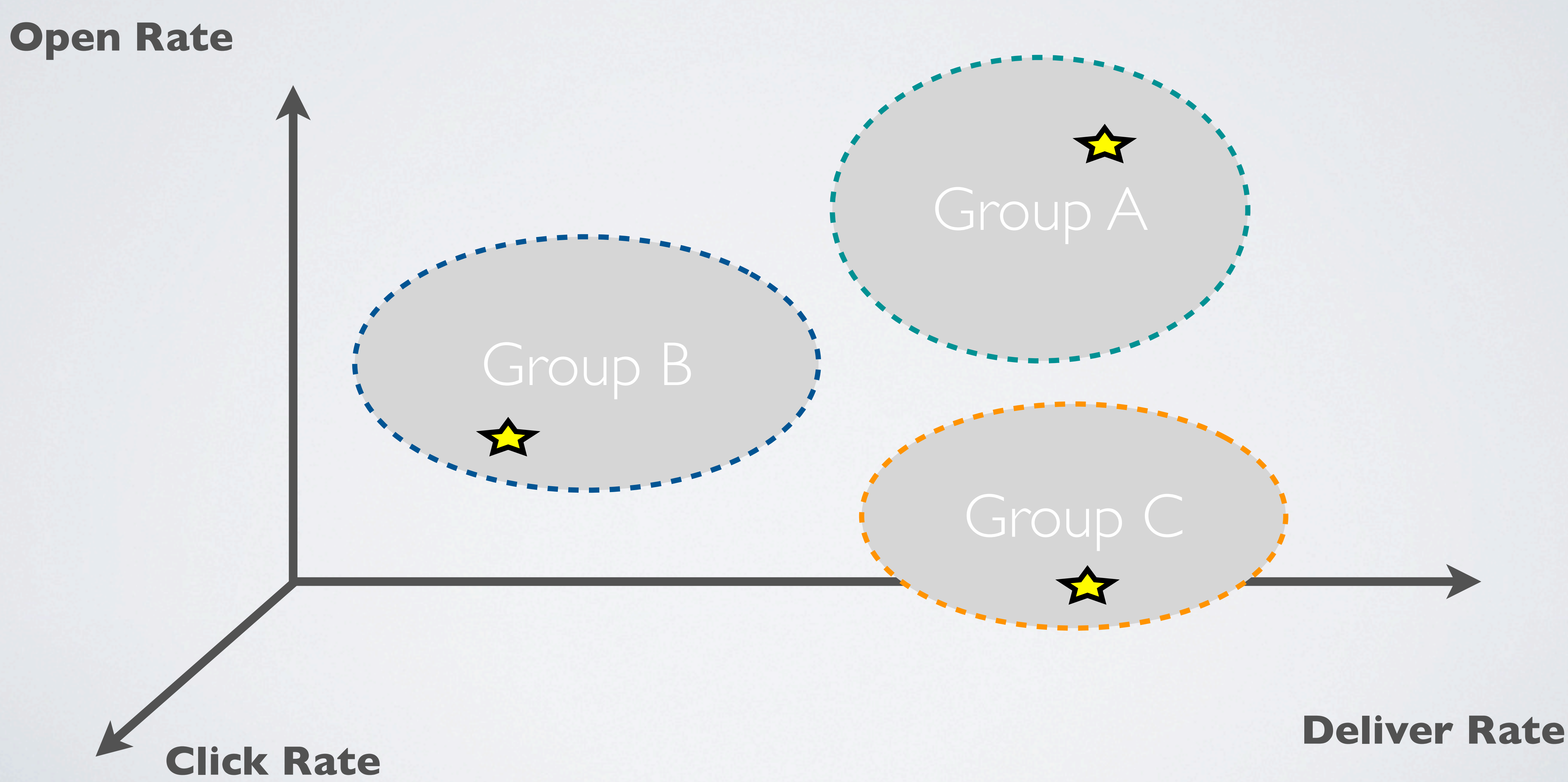
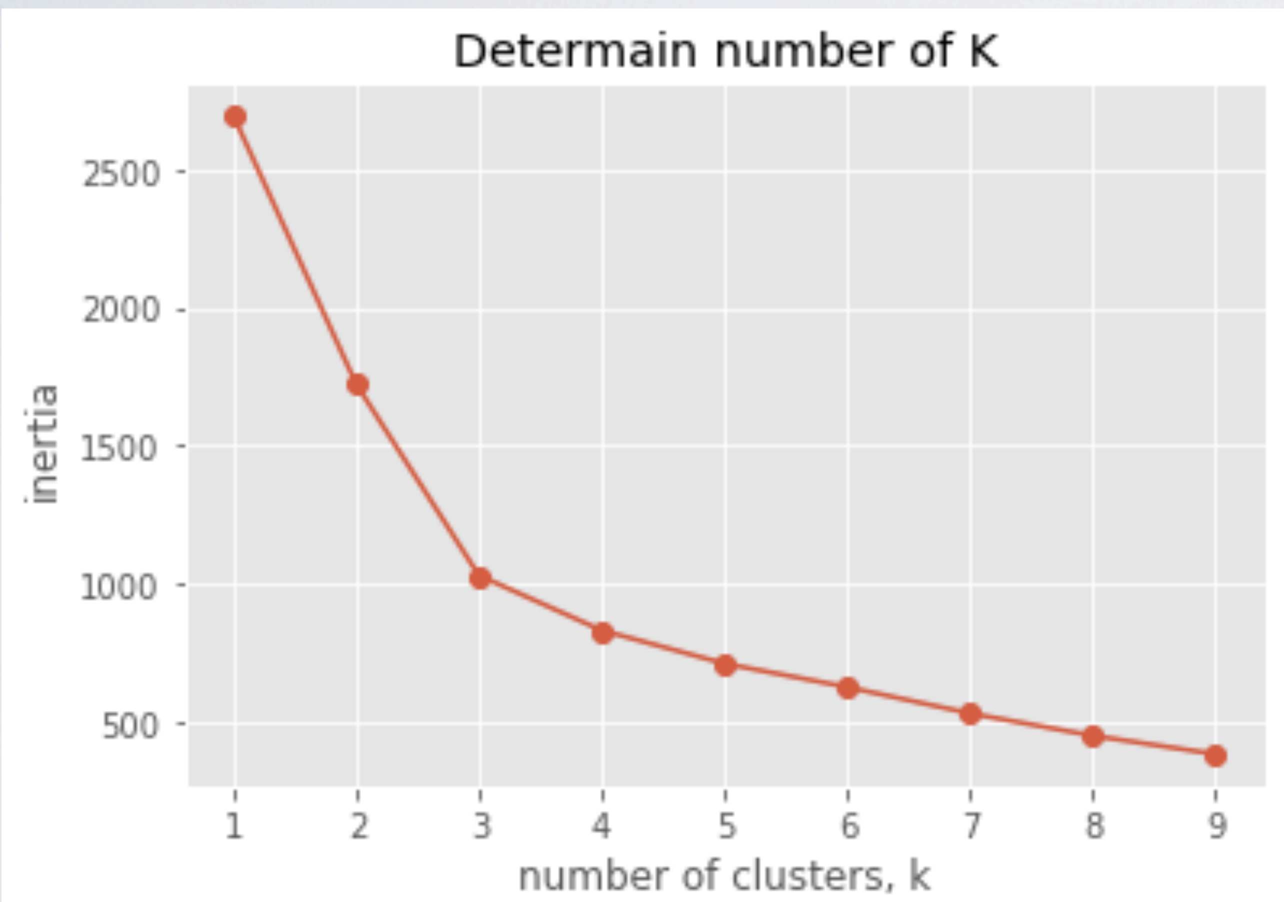
**Goal: Clustering (Expected)**

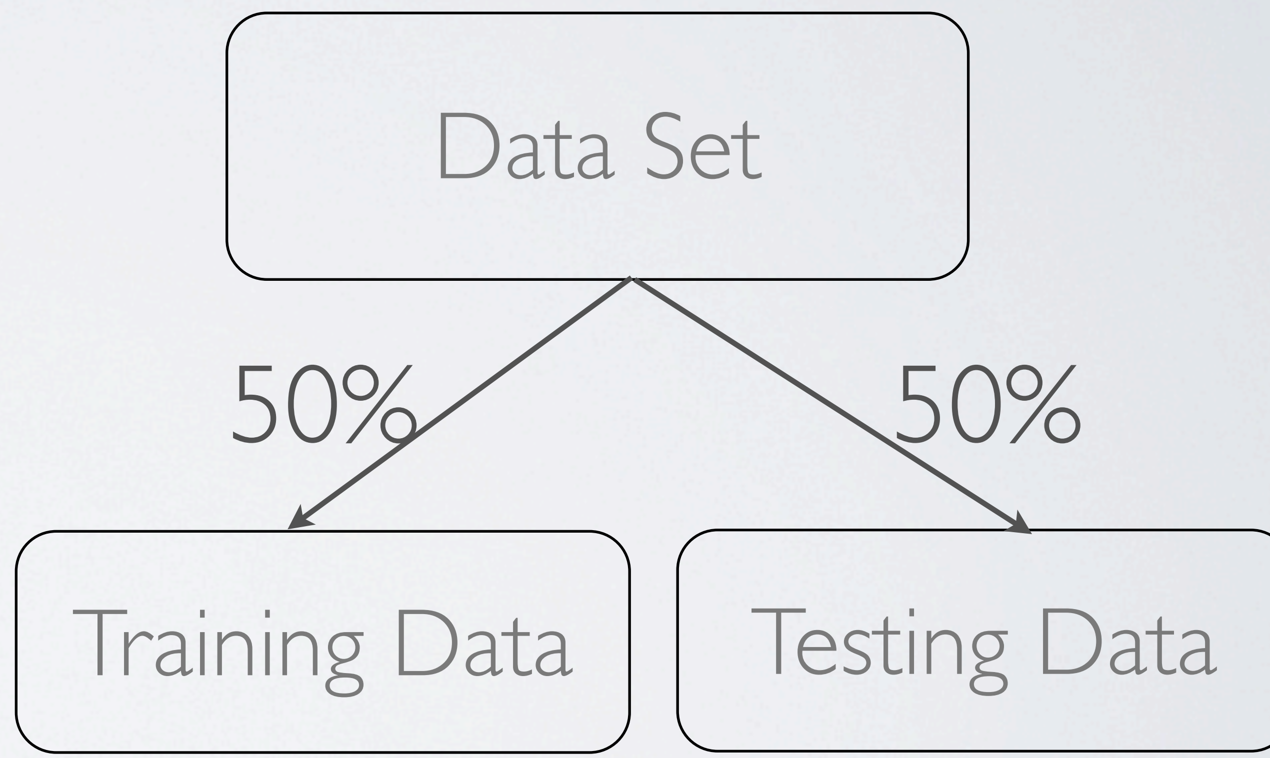



Source: Babylist - Email Metrics Project. Created by Peggy Lin

# Model Settings: KMENAS Model unsupervised model with K = 3; 50-50 Testing / Training Data Set




## Train-Test split




Deliver rate

Open rate

Click rate

Before modeling, we found several data need to be cleaned. I spent 50% of my time cleaning the data to make sure the quality of data

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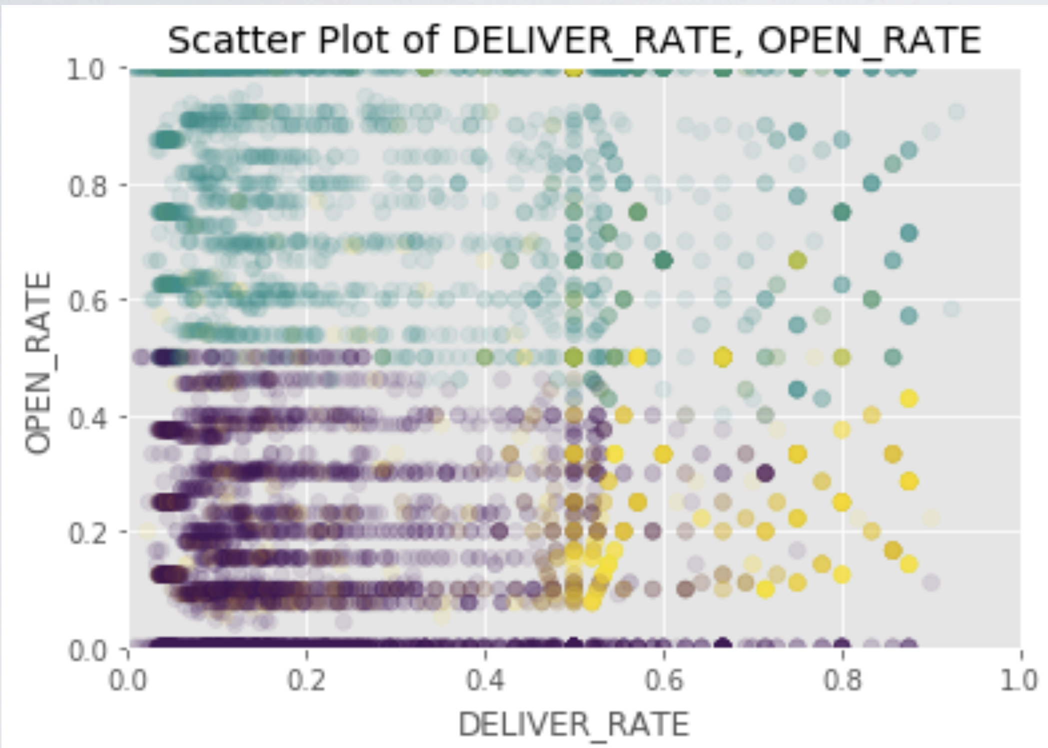
## Data Cleaning

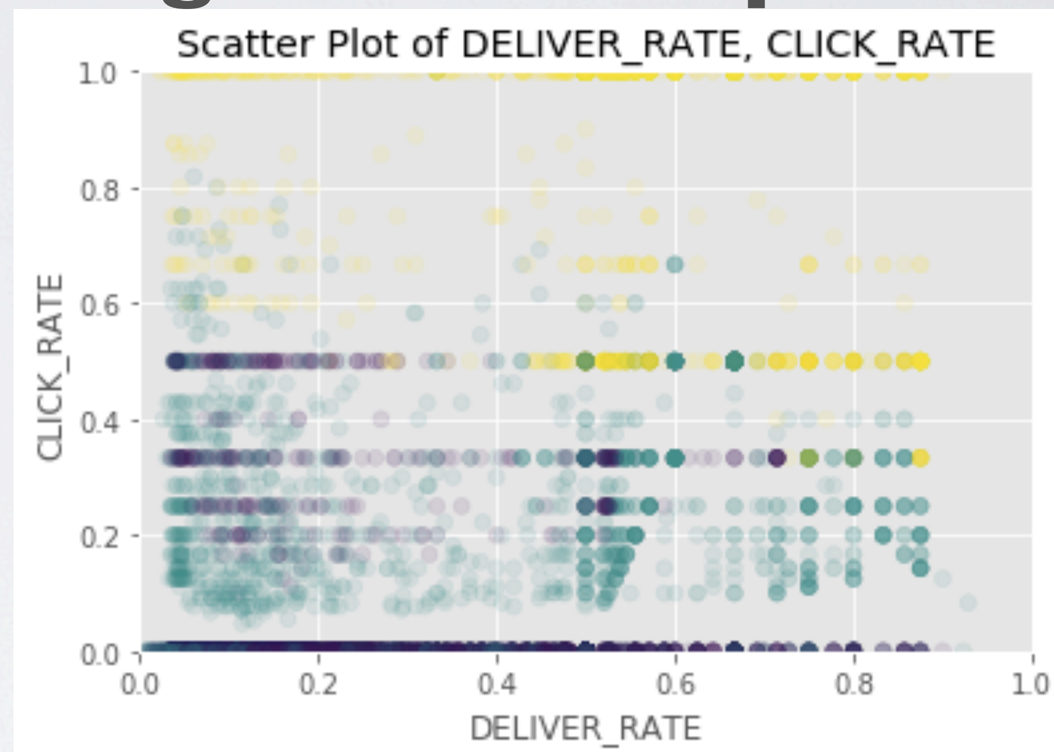
1. **Overwhelmed delivery**: Some users only register for 1 day, but got more than 10 times of delivery. We only keep deliver rate (deliver times / subscribe_days) < 1.
2. **No opened but clicked**: Some users didn't open an email, but click email. This may cause by some people using windows outlook, so they don't open the email but can click on the link. For those users, we make the open times = click times.
3. **Subscribe again**: Some users' subscribe_at date is later than unsubscribe date. We remove those with negative subscribe_days. Those might be still active users. (Unsubscribe email but then subscribe again)
4. **Arrival after 10 years**: Some people's baby may arrive before the year 2000 or after the year 2020. We only keep arrival date that makes more sense.

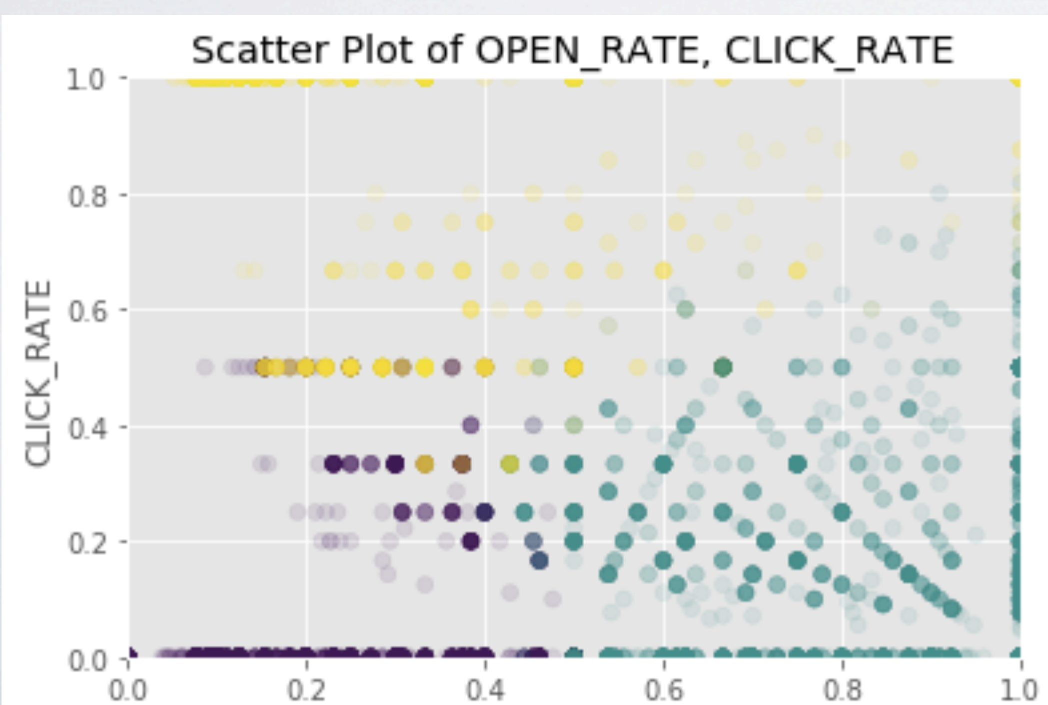
## 2 : CHURN, FACTORS, WORST/BEST COHORT

From machine learning model, we can cluster users into 3 different of groups and get their centroid position

# Machine learning model output




centroids

| | DELIVER_RATE | OPEN_RATE | CLICK_RATE |
|---|---|---|---|
| 0 | 0.228210 | 0.147665 | 0.030858 |
| 1 | 0.333370 | 0.817357 | 0.156528 |
| 2 | 0.552065 | 0.395322 | 0.908738 |

We found 3 types of users in Baby Registry 101.

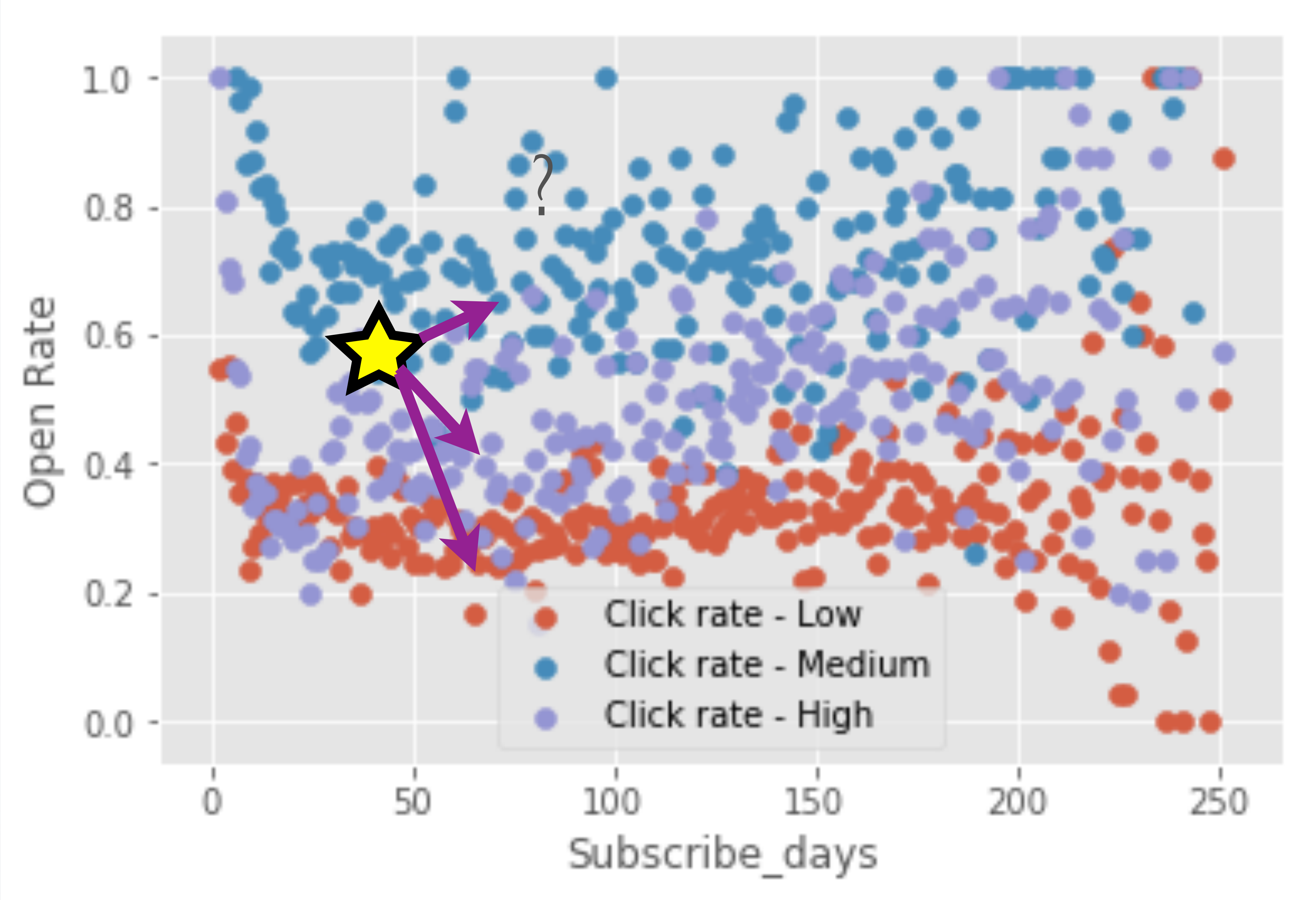
## User profile - Baby Registry 101

| Type of User | Type 1 | Type 2 | Type 3 |
|---|---|---|---|
| Deliver Frequency | 0.23 | 0.33 | 0.55 |
| Open Rate | 0.14 | 0.81 | 0.39 |
| Click Rate | 0.03 | 0.16 | 0.91 |
| Subscribe Days | 82 Days ☆ | 63 Days ☆ | 25 Days ☆ |
| Urgency | 126 | 122 ☆ | 108 ☆ |
| Source | Registry (55%)<br>Checklist (29%)<br>Giveaway(16%) | Registry (60%)<br>Checklist (28%)<br>Giveaway(12%) | Registry (57%)<br>Checklist (32%)<br>Giveaway(9%) |
| Transaction | 9 | 10 ☆ | 5 ☆ |

## 2 : CHURN, FACTORS, WORST/BEST COHORT

According to the classifier, we could determine relative marketing action plan for new users.

**Scatter plot of new users action plan**




Source: Babylist - Email Metrics Project. Created by Peggy Lin

# Outlines

# 1 : How our email list(s) are growing

# 2 : Churn, Factors & Worst/Best Cohort

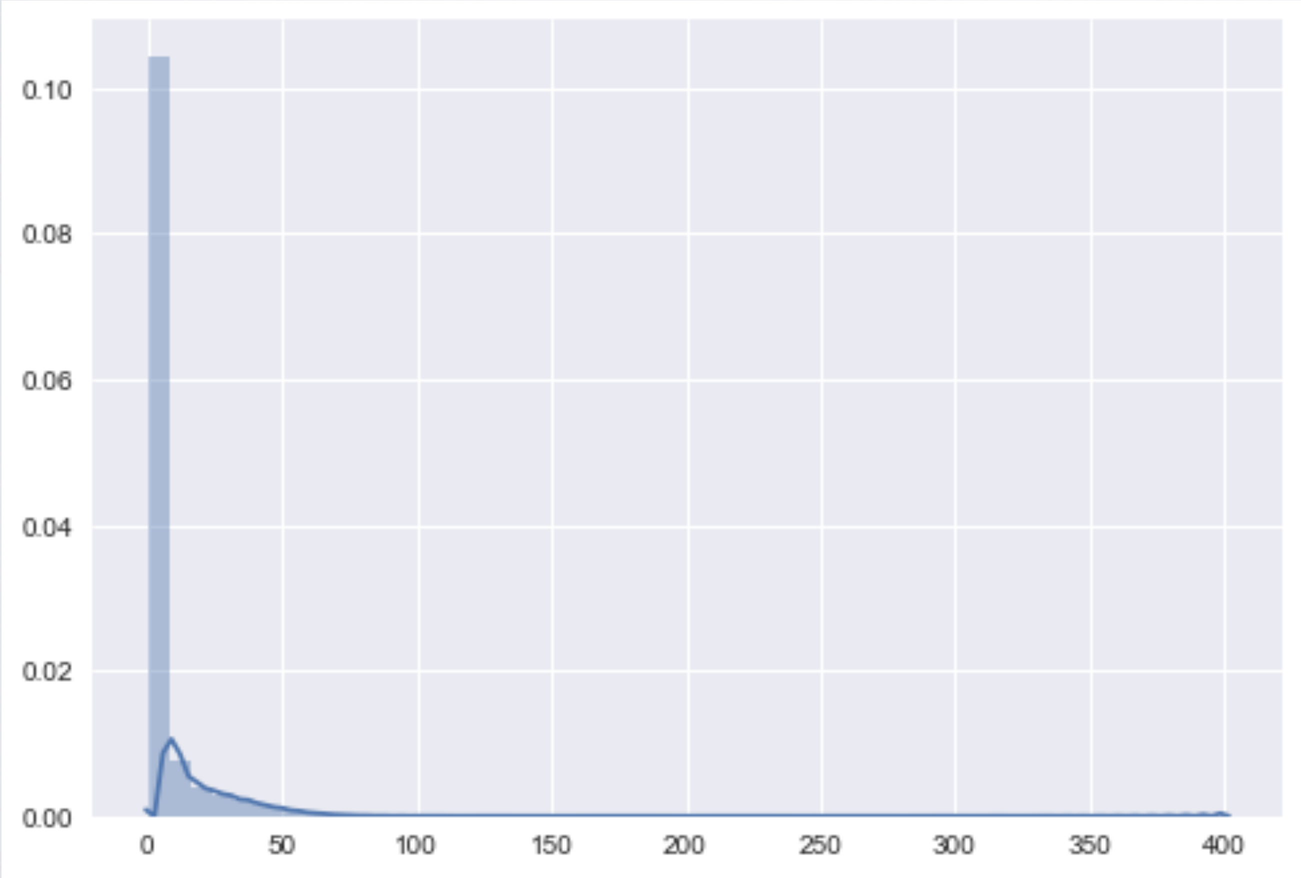
**# 3 : Profit Prediction Model**

# 4 : Recommendations

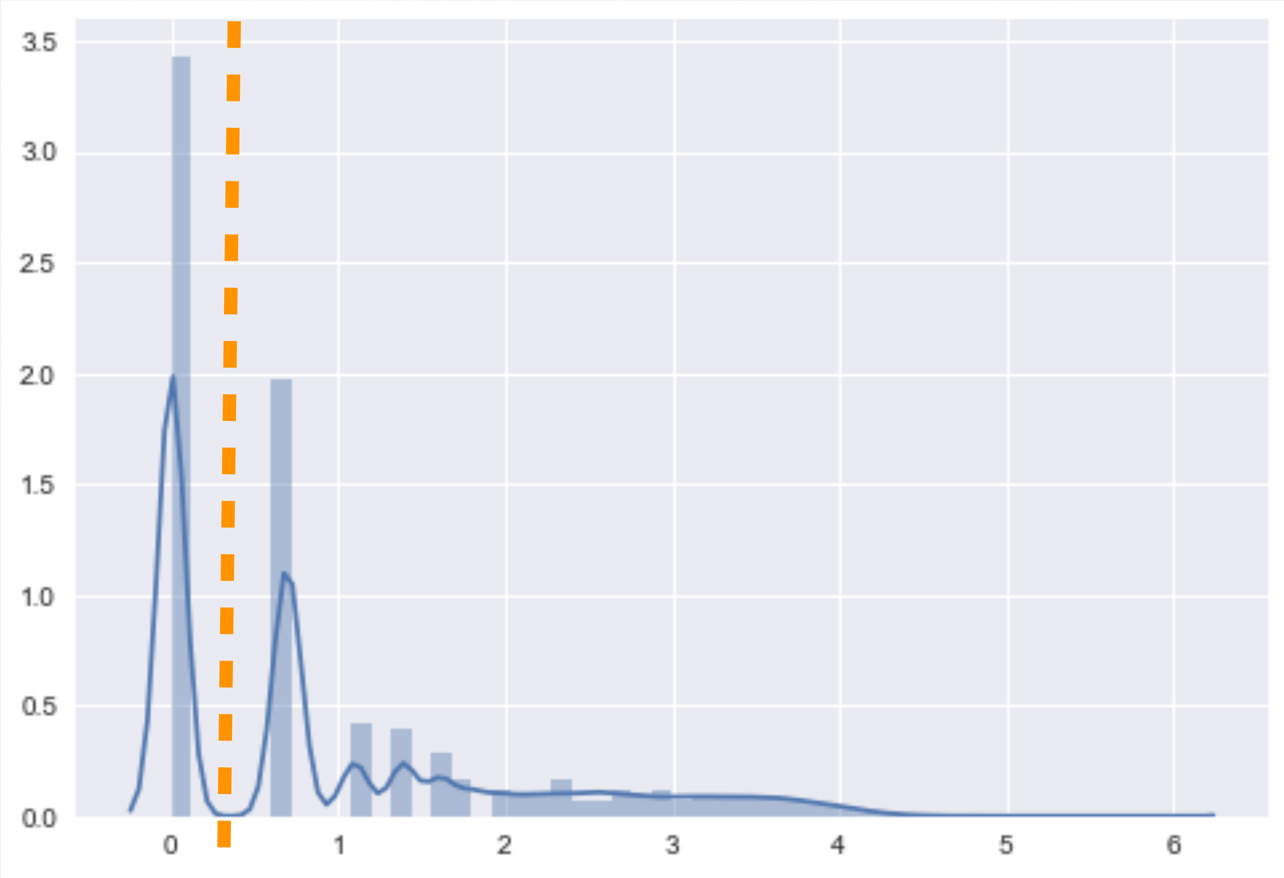
## 3: PROFIT/ NONPROFIT PREDICTION MODEL

GOAL: Build a model to predict if a user is brought profit or not base on the current information.

**Original transactional_delivered distribution**




**Transformed transactional_delivered distribution**




Source: Babylist - Email Metrics Project. Created by Peggy Lin

## 3: PROFIT/ NONPROFIT PREDICTION MODEL

Here, we set diversity, urgency, and life-time as model variables, and profit/ not profit as predictor

## Model Overview

| **Predictor** | **Variables** |
| --- | --- |
| Not Profit (Deliver = 0) | 1.Diversity : Subscribed E-mail lists |
| | 2.Urgency : Original arrival date until now |
| Profit (Deliver > 0) | 3.Life-time : How long did he/she be with us |

**Data**

Training Data (Model Building)
Testing Data (Accuracy Rate)

Source: Babylist - Email Metrics Project. Created by Peggy Lin

## 3: PROFIT/ NONPROFIT PREDICTION MODEL

We have 80% of accuracy and a great performance model to predict if our customer is profit or not.

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**Model accuracy result**

| Model | KNN | NB | Logistic regression | SVM |
|---|---|---|---|---|
| Accuracy Rate | 0.83 | 0.63 | 0.81 | N/A* |
| Run time | 143 secs | 0.27 secs | 1.82 secs | 5 hours |

Note: Due to time and resource limit, I did only one time model building. For more accurate model, I suggest using pipeline tuning model and n-fold cross validation

## Outlines

# 1 : How our email list(s) are growing

# 2 : Churn, Factors, Worst/Best Cohort

# 3 :  Average Lifetime

**# 4 :  Recommendations**

It would be great to have these recommendations in the future projects.

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**Recommendations**

1. **Data cleaning** : This data base is merged with other data base, thus I recommend to add more data cleaning before modeling.
2. **Add transaction features** : Add more transaction data, product information into the data, so we could group users base on this information.
3. **Profit prediction model** : It would be great to have a project for profit prediction model.

Thank you!