



MEETUP

RECOMMENDATION SYSTEMS

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AGENDA



Problem Statement



Exploratory data analysis



Types of recommender Systems



Our Approach for meetups

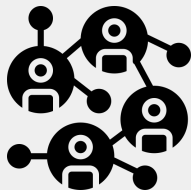


Potential benefits for meetup.com



PROBLEM STATEMENT

MEETUP



Social networking ecosystem bringing people together for teaching, learning and exploring areas of interest

CHALLENGES



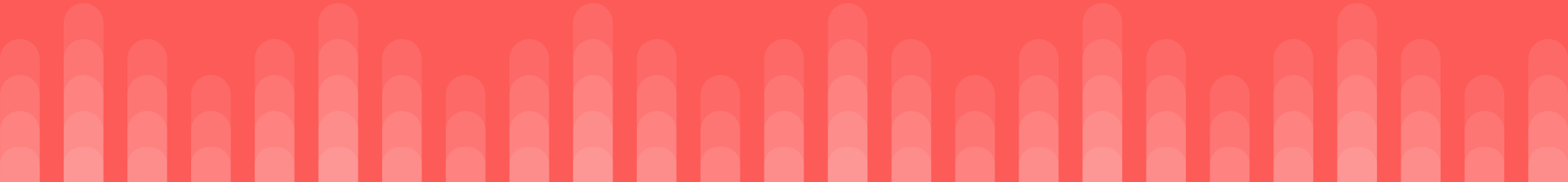
- Meetups unable to target users effectively
- Customers without personalized recommendations based on interests
- Groups devoid of intelligence on user interests

PROJECT AIM

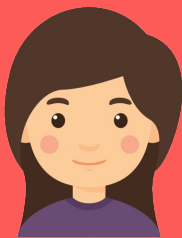
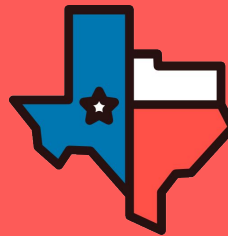


- Build custom recommendations for members
- Improve member experience and advocacy of the Meetups org

DATA GATHERING AND EXPLORATORY ANALYSIS



DATASET - MEETUP API



299,630
Members

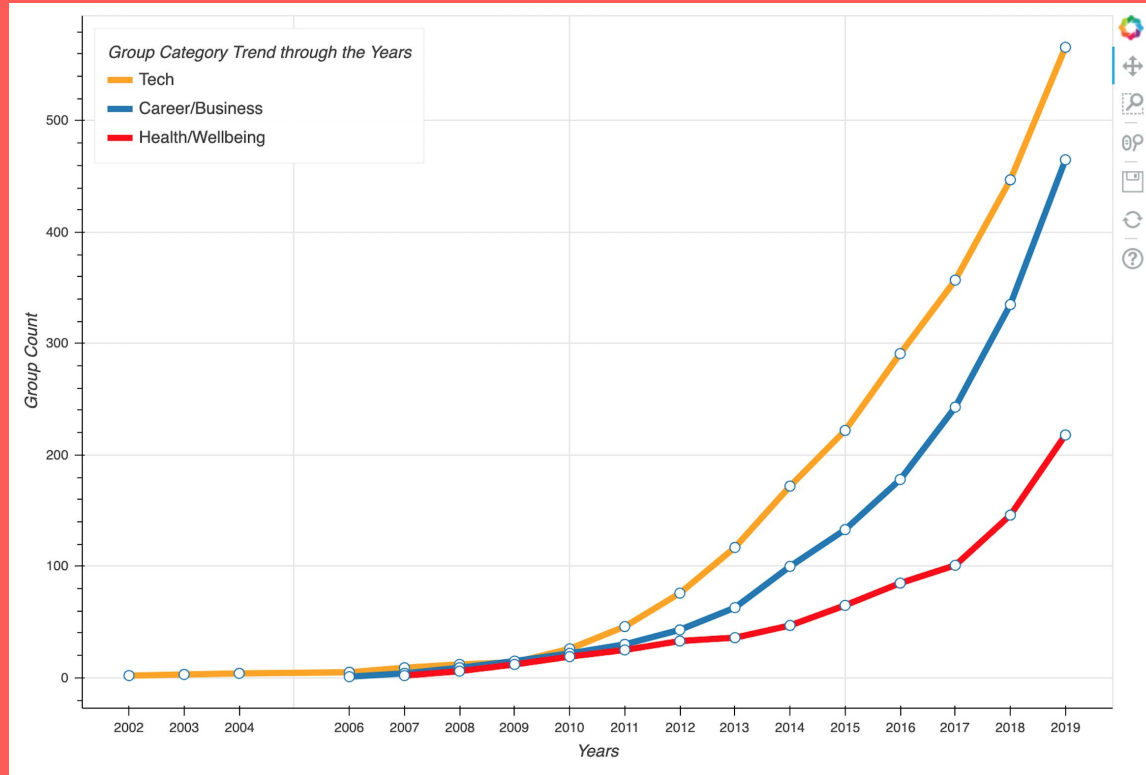


2,891
Groups

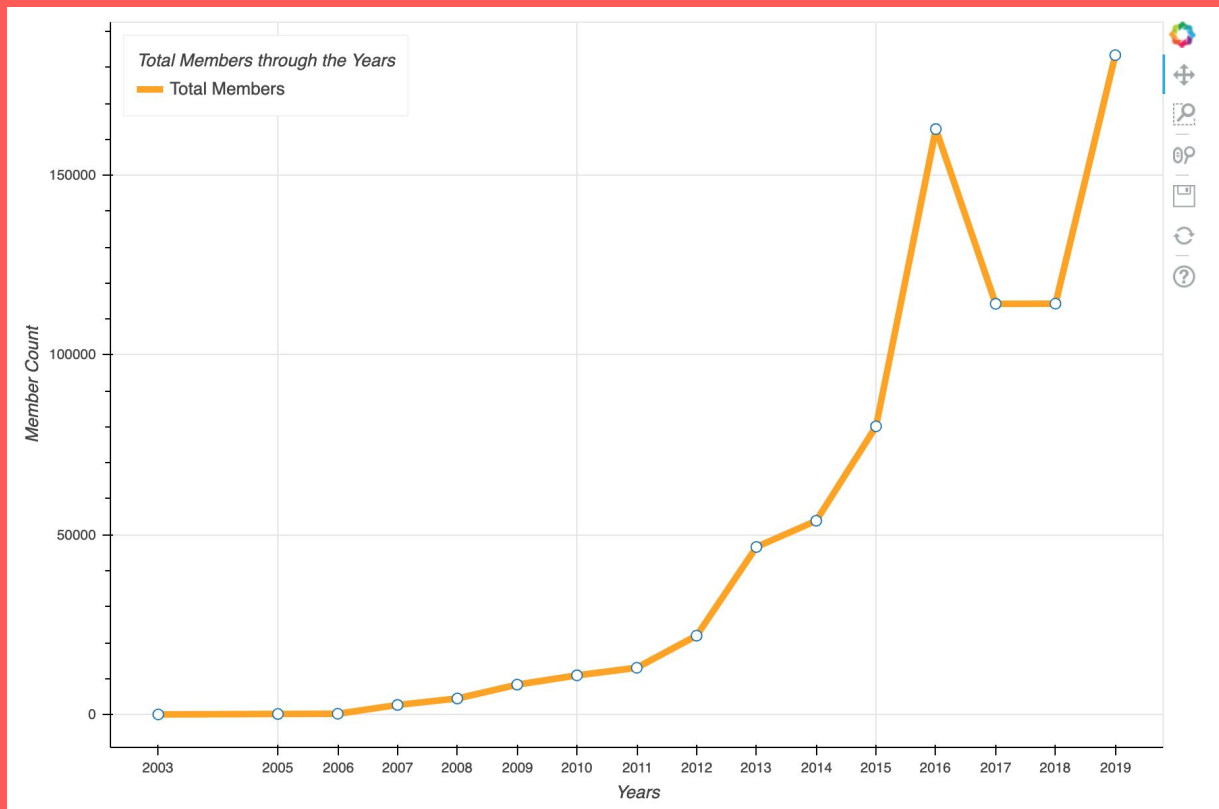


35,629
Events

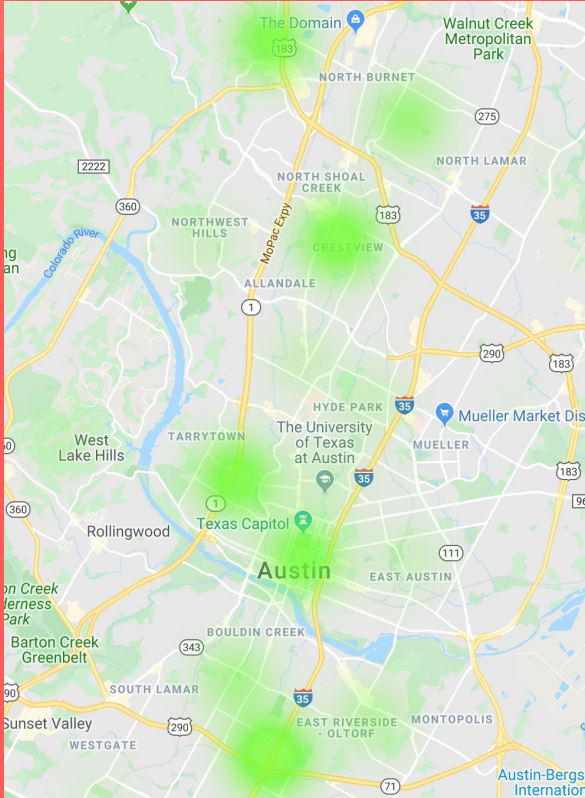
GROUP CATEGORIES



MEMBERS



EVENTS



RECOMMENDATION SYSTEMS



Leverage Recommendation systems to provide a robust customer experience and deeper engagement



POPULARITY BIAS

COLD START



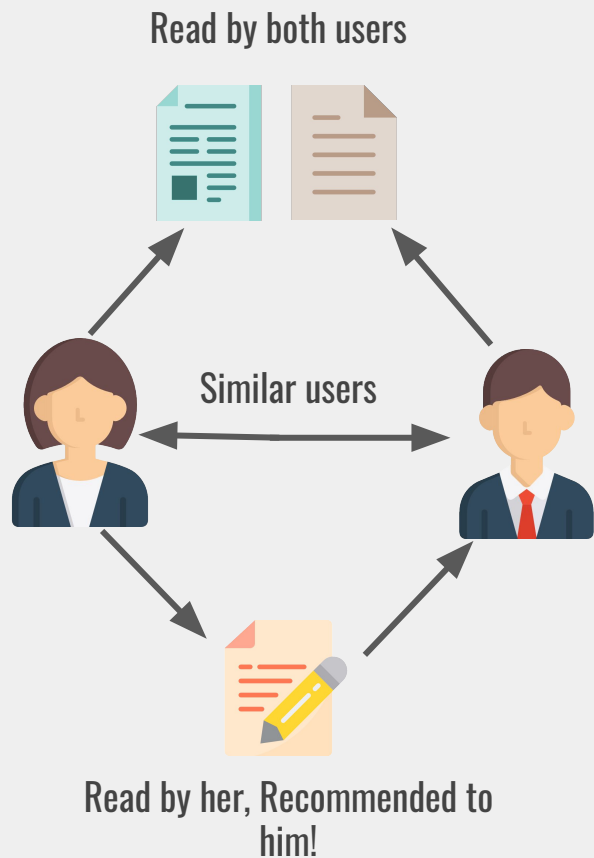
SCALABILITY

SPARSITY

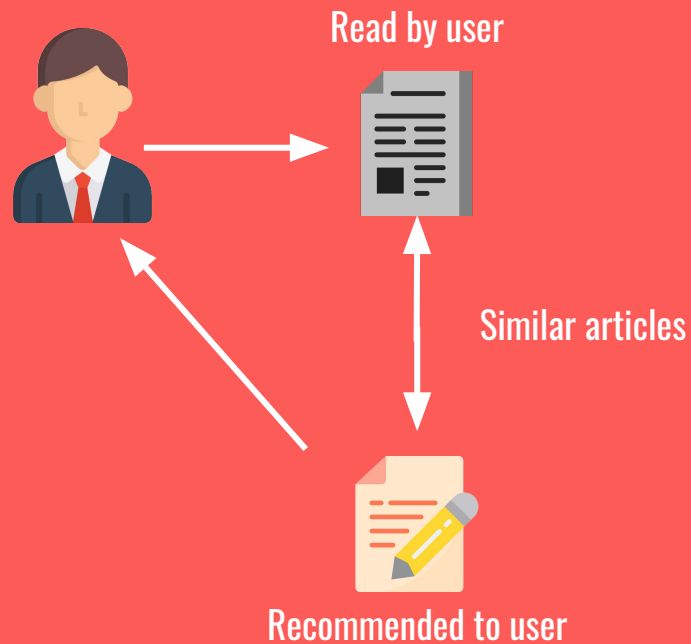
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TYPES OF RECOMMENDER SYSTEMS

COLLABORATIVE FILTERING



CONTENT BASED



COLLABORATIVE FILTERING



TECHNIQUES



ADVANTAGES



DISADVANTAGES

MEMORY BASED APPROACH

Find similar users based on cosine similarity or pearson correlation and take weighted average of ratings

Easy creation and explainability of results

Performance reduces when data is sparse hence non-scalable

MODEL BASED APPROACH

Use Machine Learning to find user ratings of unrated items, eg., PCA, SVD, Neural Nets, Matrix Factorization

Dimensionality reduction deals with missing/sparse data

Inference is intractable because of hidden/latent features

MEMORY-BASED APPROACH



STEPS TAKEN

- Leveraged RSVP count as an implicit score
- Filtered users with RSVP count greater than two
- Removed similar users who are part of only one group together



CHALLENGES

- Only 18% of the users have an RSVP count greater than two for a group
- May not be as meaningful to target other users
- 20% of users are part of only one group
- Possibility of getting new recommendations from similar users/groups becomes challenging

MEMORY-BASED APPROACH



PROCESS

- User based and Item based collaborative filtering
- Cosine similarity & Pearson Correlation as similarity metrics
- Top 5 recommendations listed for a given user



OBSERVATIONS

- User based and item-based recommendations with similar results
- Pearson correlation and cosine similarity computed differ slightly, but not much (possibly due to sparse data)



NEXT STEPS

- Consider robust models which can work with sparse data
- Provide related recommendations over and above similar user circle/groups

POPULAR GROUPS



Dragon's Lair Events
Meetup



Kontenders Poker of
Austin



Austin Dance Lessons
and Social Events



Austin Dance Social
Meetup



PrimeTime

CURRENT GROUPS



Austin Dance Social
Meetup

RECOMMENDATIONS



Austin Dance Social Meetup



Austin Salsa Bachata Dance
and Social Events



Austin Argentine Tango and Social Events

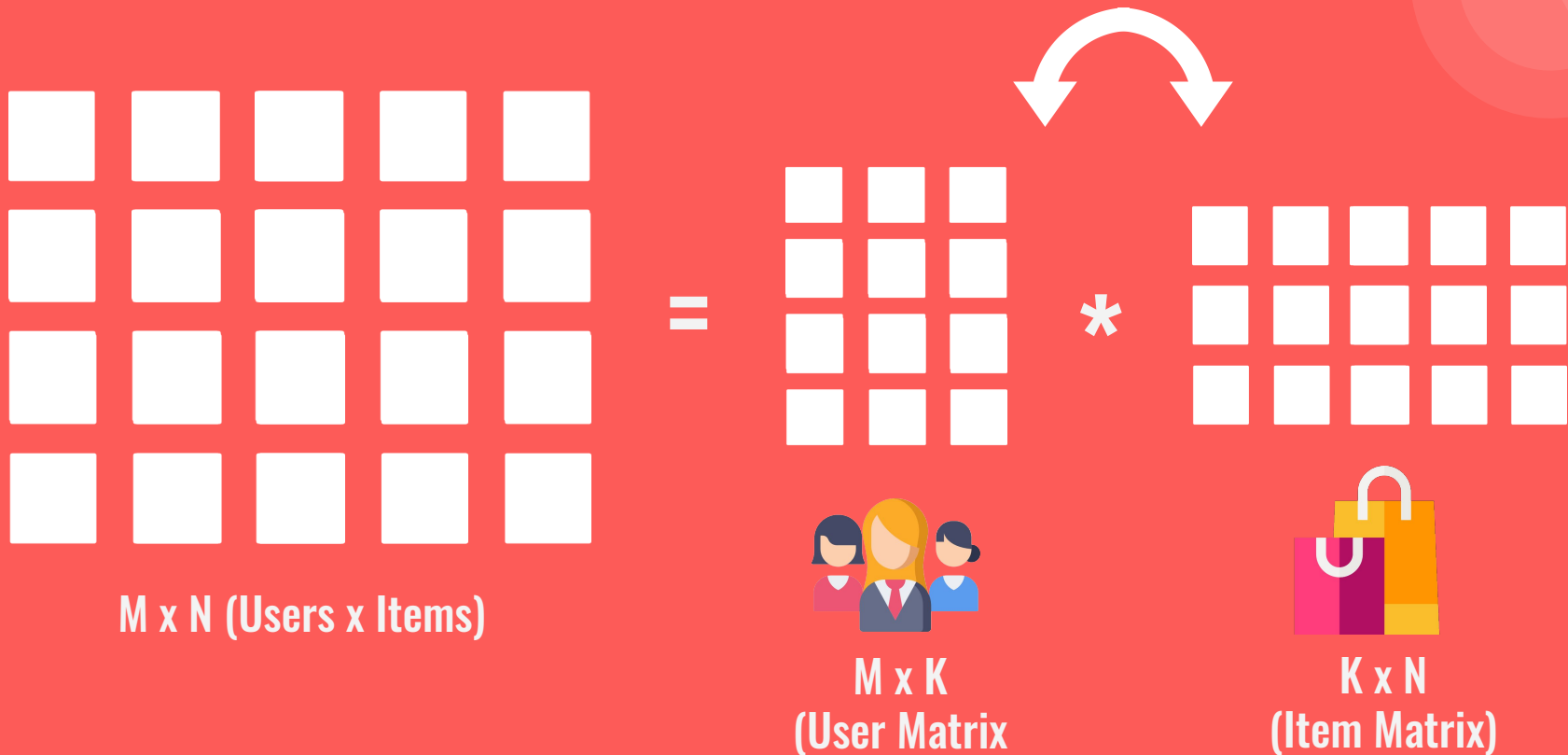


Austin Kizomba Dance and Social
Events



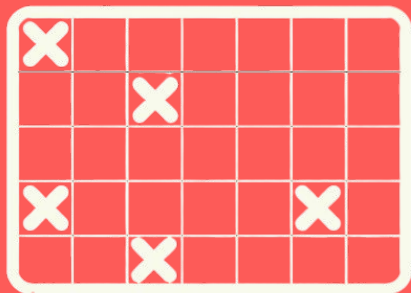
Austin Swing Dance and Social Events

MATRIX FACTORIZATION USING ALS

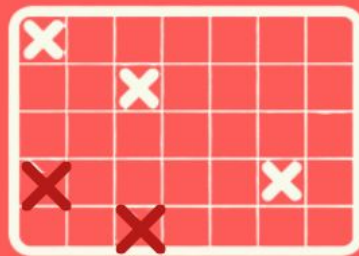


APPROACH

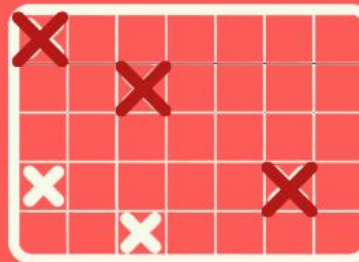
Original



Train



Test



IMPLICIT FEEDBACK: RSVP



Members RSVP for events organized by groups to indicate their intent to attend

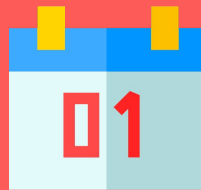
- For each member and group, we calculated the ratio:

Total Number of Events RSVP'd for in the Group

Total Number of Events Organized by the Group

- This ratio was used as an implicit feedback signal in the ALS recommender systems

IMPLICIT FEEDBACK: TIMDELTA



TimeDelta in this case is the difference (in months) between the last visited event and the time a member joined the group.

- For each member and group, if the timedelta is high, it indicates a long-term interest in the group for the member
- This difference was used as a second implicit feedback signal in the ALS recommender systems

EXAMPLE USER: WHAT WE KNOW





IMPLICIT FEEDBACK: RSVP

	Austin International Travel
	Austin AI Developers Group
	Austin Deep Learning
	Austin Big Data AI
	Austin Data Science
	Austin International Travel Club
	Data on Tap
	Austin Women Over 50
	Women in Data Science - ATX
	Austin Solo Female Travel Group



IMPLICIT FEEDBACK: TIMEDELTA

	Austin Sierra Club Outings
	Austin Data Science
	Queer Adventures of Austin
	Guided Hikes on BCP
	Austin ACM SIGKDD
	Austin Big Data AI
	Austin R User Group
	Austin LGBT Socials
	Austin Lesbian Mixers
	Austin Data Geeks

LOGISTIC MATRIX FACTORIZATION



- This model takes a similar approach to ALS by splitting the observation matrix into the user matrix and item matrix
- Since this is a Non-negative Matrix Factorization, we can use the log-loss as our cost function. It treats it as a binary classification problems where we the probability that a member is part of a group or not

COMPARE RECOMMENDATION SYSTEMS

- Since we masked some portion of the testing dataset, we can evaluate the performance of our recommender systems
- Essentially, we need to check if the order of recommendations given for each of the user matches the events and corresponding groups that they ended up being a part of. This is evaluated using the AUC metric
- As a benchmark, we also calculated what the mean AUC would have been if we had simply recommended the most popular items. Popularity tends to be hard to beat in most recommender system problems, so it makes a good comparison

ALS: RSVP

Model AUC: 0.761
Baseline AUC: 0.837

ALS: TimeDelta

Model AUC: 0.809
Baseline AUC: 0.859

Logistic: RSVP

Model AUC: 0.738
Baseline AUC: 0.725

CONTENT BASED

Content Based Recommendation Systems are born from the idea of using the content of each item for recommending purposes

It is easier to make a more transparent system since we use the same content to explain the recommendations. However, they tend to over-specialize and recommend items similar to those already consumed



PAST GROUP

Austin Wine
Enthusiasts

RECOMMENDATIONS

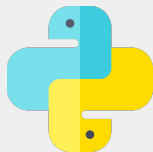
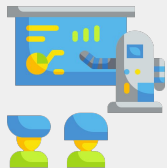
Austin Wine Tastings
Austin Texas Wine Society
Jazz Theory and its Practical Applications
Austin Burgundy Wine Meetup
Austin Food and Wine Lovers

MEETUP GROUP RECOMMENDATION FOR A MSBA GRADUATE STUDENT



RACHEL MEADE

CURRENT GROUPS



Austin Big Data AI

Women in Data Science - ATX

Austin Women in Technology

Austin AI Developers Group

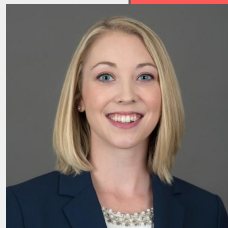
Austin Startup and Tech Mixer

Data on Tap

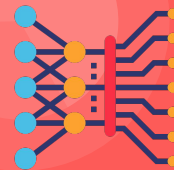
Association of Industry Analytics - Austin

Austin ACM SIGKDD

PyLadies ATX



RECOMMENDATIONS



Austin Deep Learning

Austin Data Science

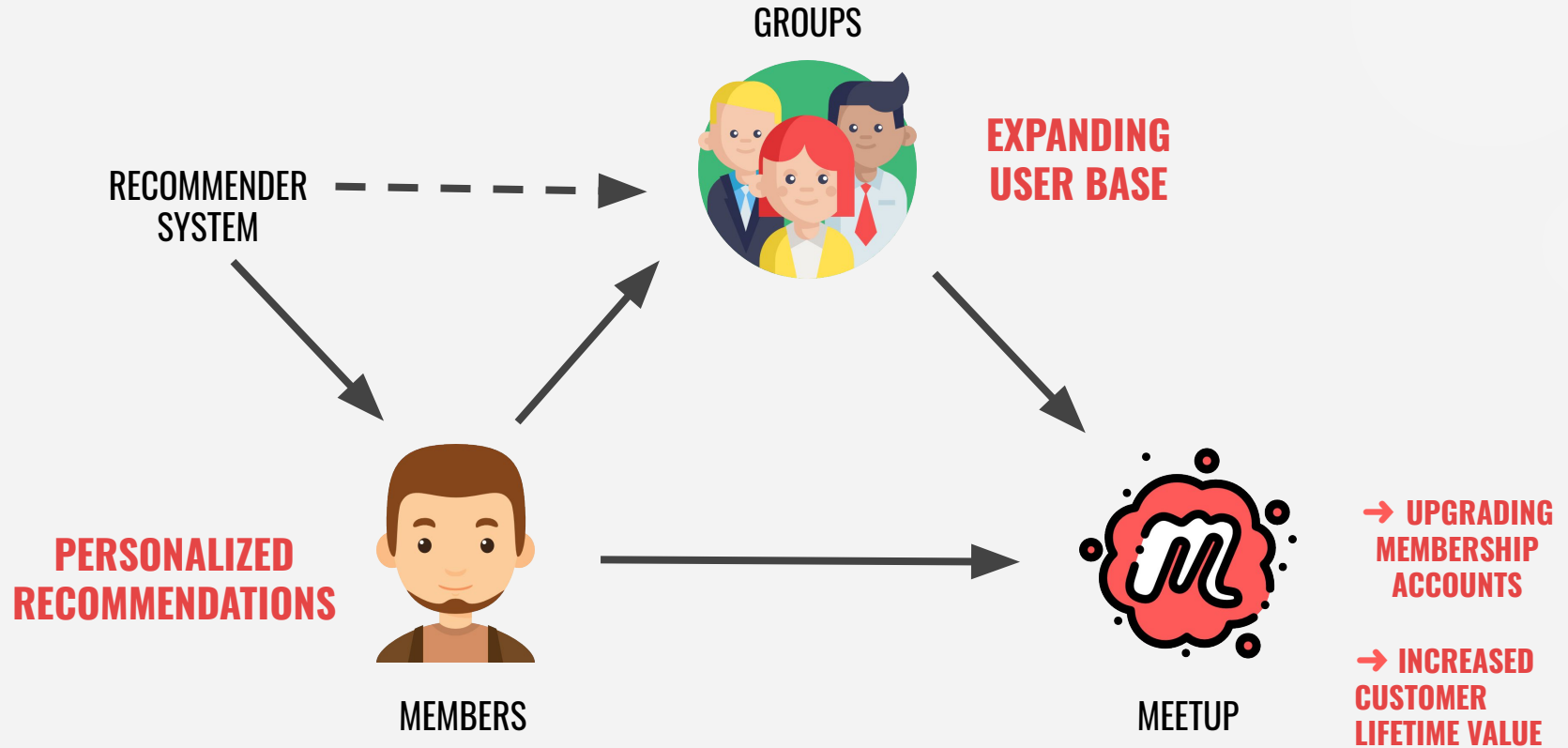
Austin Python Meetup

Healthcare Predictive Analytics

Austin Data Geeks



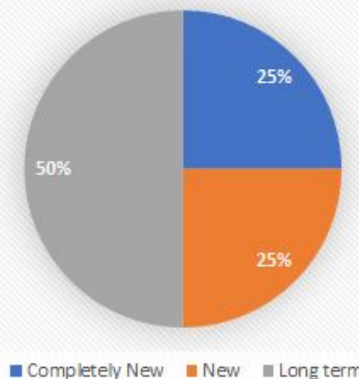
MEETUP: ECOSYSTEM



MEETUP: REVENUE MODEL

GROUP FEES	\$180/Year
BASIC PLAN	\$14.99
UPGRADE PLAN	\$19.99
INCREASE IN REVENUE	\$5.00

Percentage Split of Groups



CALCULATIONS

Assume that we can get 50% of groups falling in the “Completely New” and “New” categories to increase their revenues by upgrading the plans.

This would amount to 25% of the total number of groups.

of groups in Austin = 2900

Number of groups to upgrade = $0.25 \times 2900 = 725$

Revenue increase per month = $\$5 \times 725 = \$3,625$

Potential Annual Revenue = \$43,500

of groups around the world = 225,000

*Austin represents only 1.3% of the total groups



QUESTIONS?

REFERENCES

1. <https://en.wikipedia.org/wiki/Meetup>
2. <https://techboomers.com/t/what-is-meetup-how-it-works>
3. <https://drive.google.com/file/d/1wllvd4a2nzkmgHOy9WqpqFzBA9596nHW/view?usp=sharing>
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5. <http://cs229.stanford.edu/proj2014/Christopher%20Aberger.%20Recommender.pdf>