MEETUP

RECOMMENDATION SYSTEMS

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

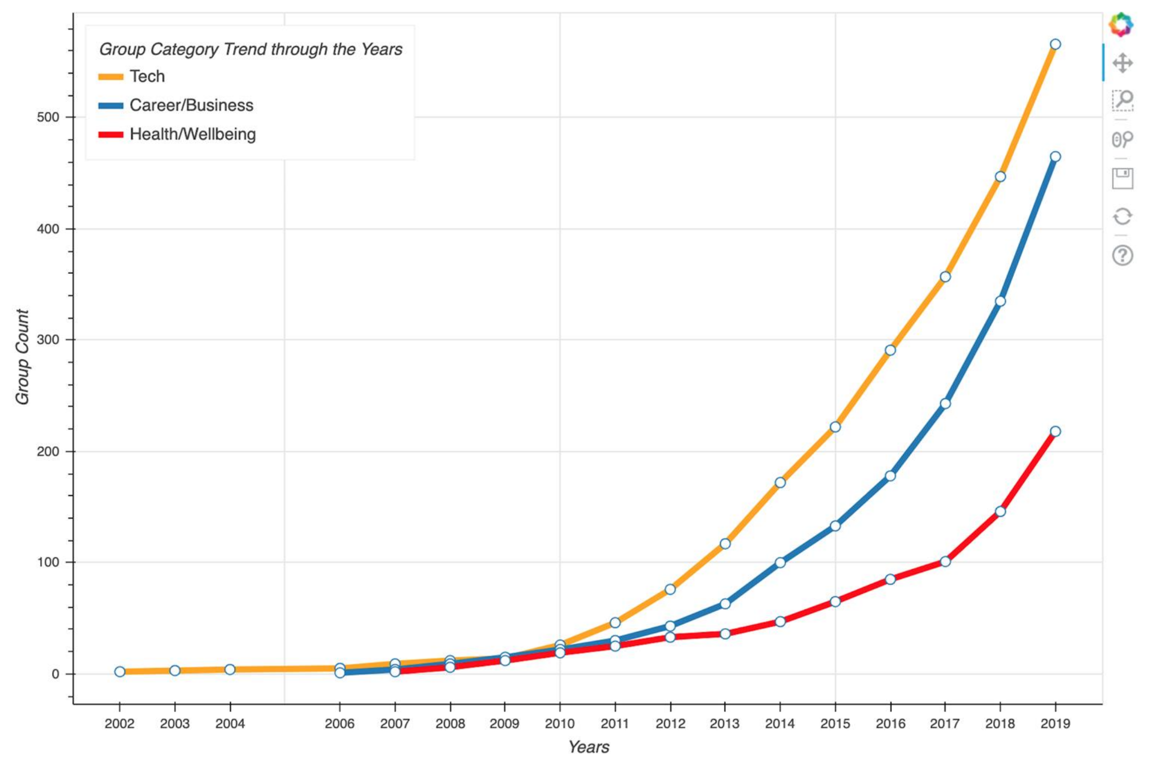
DATASET - MEETUP API

299,630
Members

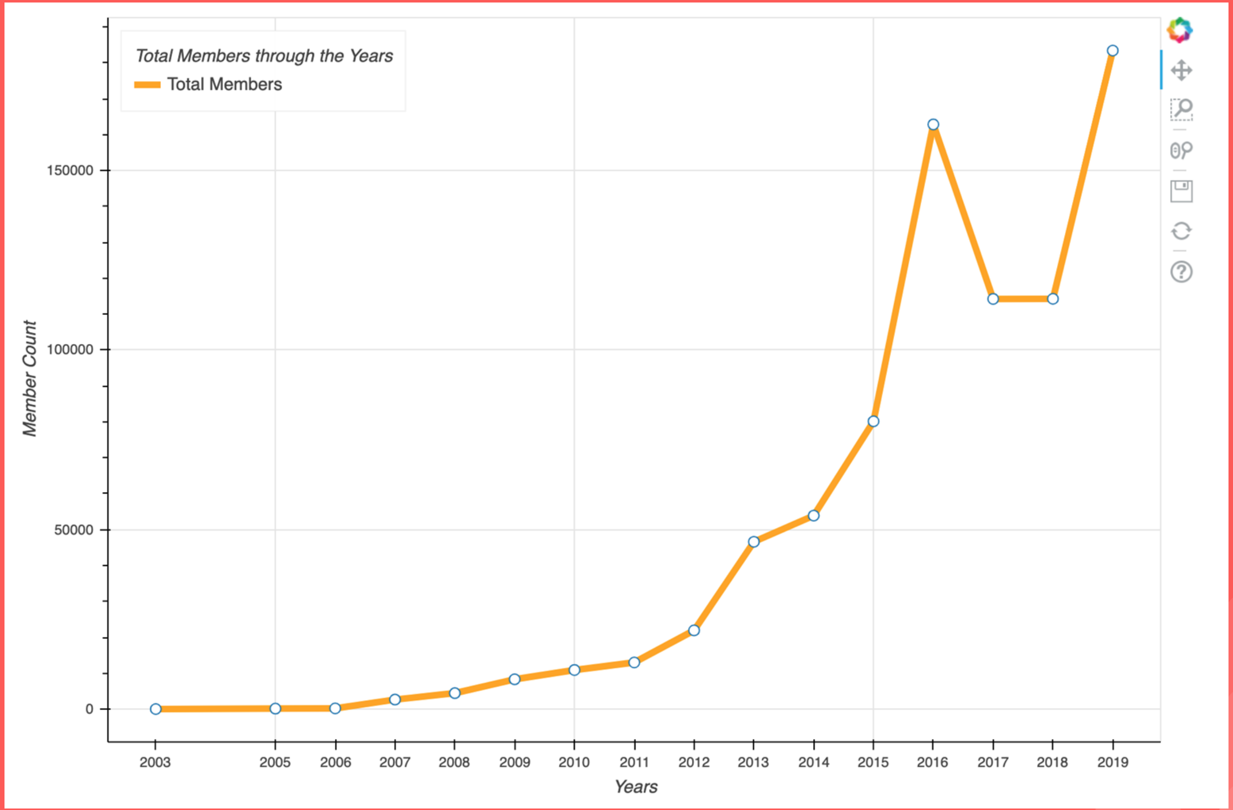
2,891
Groups

35,629
Events

GROUP CATEGORIES

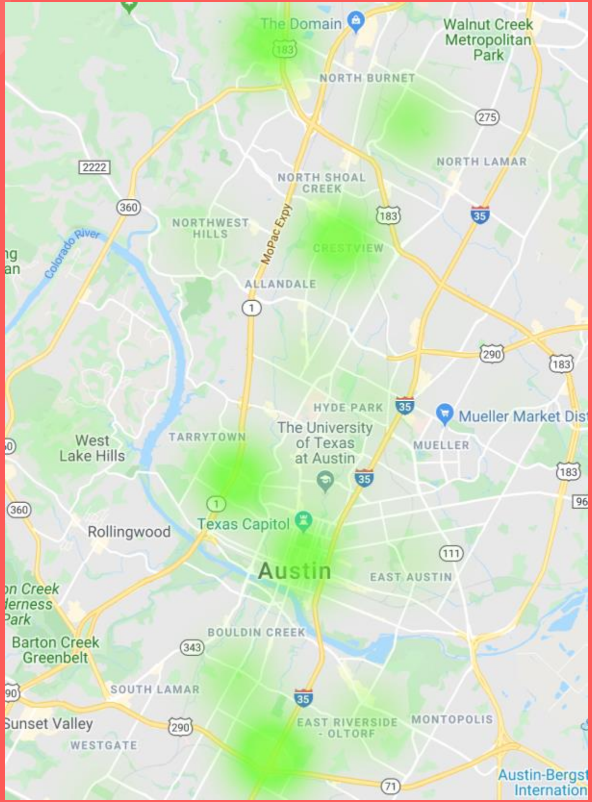


MEMBERS



Total Members through the Years
Total Members
Member Count
150000
100000
50000
0
2003
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
Years

EVENTS


The Domain
Walnut Creek
Metropolitan
Park
NORTH BURNET
NORTH LAMAR
NORTH SHOAL
CREEK
NORTHWEST
HILLS
MoPac Expy
Colorado River
CRESTVIEW
ALLANDALE
HYDE PARK
Mueller Market Dist
The University
of Texas
at Austin
MUELLER
TARRYTOWN
West
Lake Hills
Texas Capitol
Rollingwood
Austin
EAST AUSTIN
Barton Creek
Greenbelt
BOULDIN CREEK
SOUTH LAMAR
Sunset Valley
WESTGATE
EAST RIVERSIDE
- OLTORF
MONTOPOLIS


dance class
facebook groups
class facebook
Austin TX
dance lesson
feel free
first time
dance classes
Tony Mogadam
Time End
Come join
End Time
meetupstatic photos
board game
meetup
member
Tai Chi
Argentine Tango
Join us
DANCE U2
Two Step
Salsa Bachata
kids teens

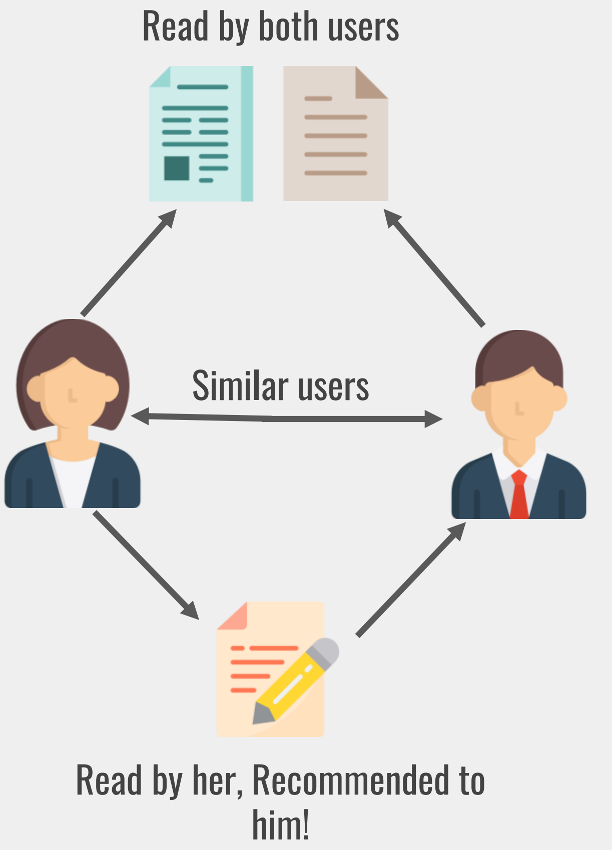
RECOMMENDATION SYSTEMS

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

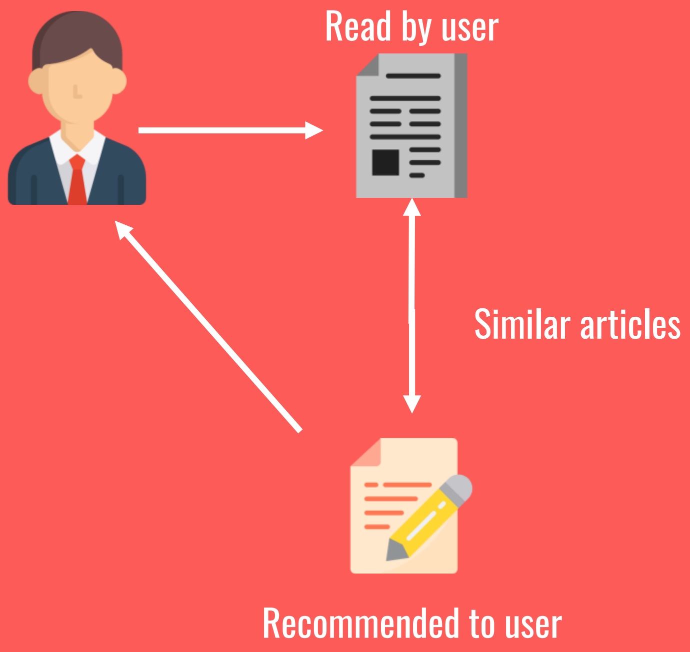
- POPULARITY BIAS
- COLD START
- SCALABILITY
- SPARSITY

TYPES OF RECOMMENDER SYSTEMS

COLLABORATIVE FILTERING



CONTENT BASED



COLLABORATIVE FILTERING

	MEMORY BASED APPROACH	MODEL BASED APPROACH
TECHNIQUES	Find similar users based on cosine similarity or pearson correlation and take weighted average of ratings	Use Machine Learning to find user ratings of unrated items, eg., PCA, SVD, Neural Nets, Matrix Factorization
ADVANTAGES	Easy creation and explainability of results	Dimensionality reduction deals with missing/sparse data
DISADVANTAGES	Performance reduces when data is sparse hence non-scalable	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

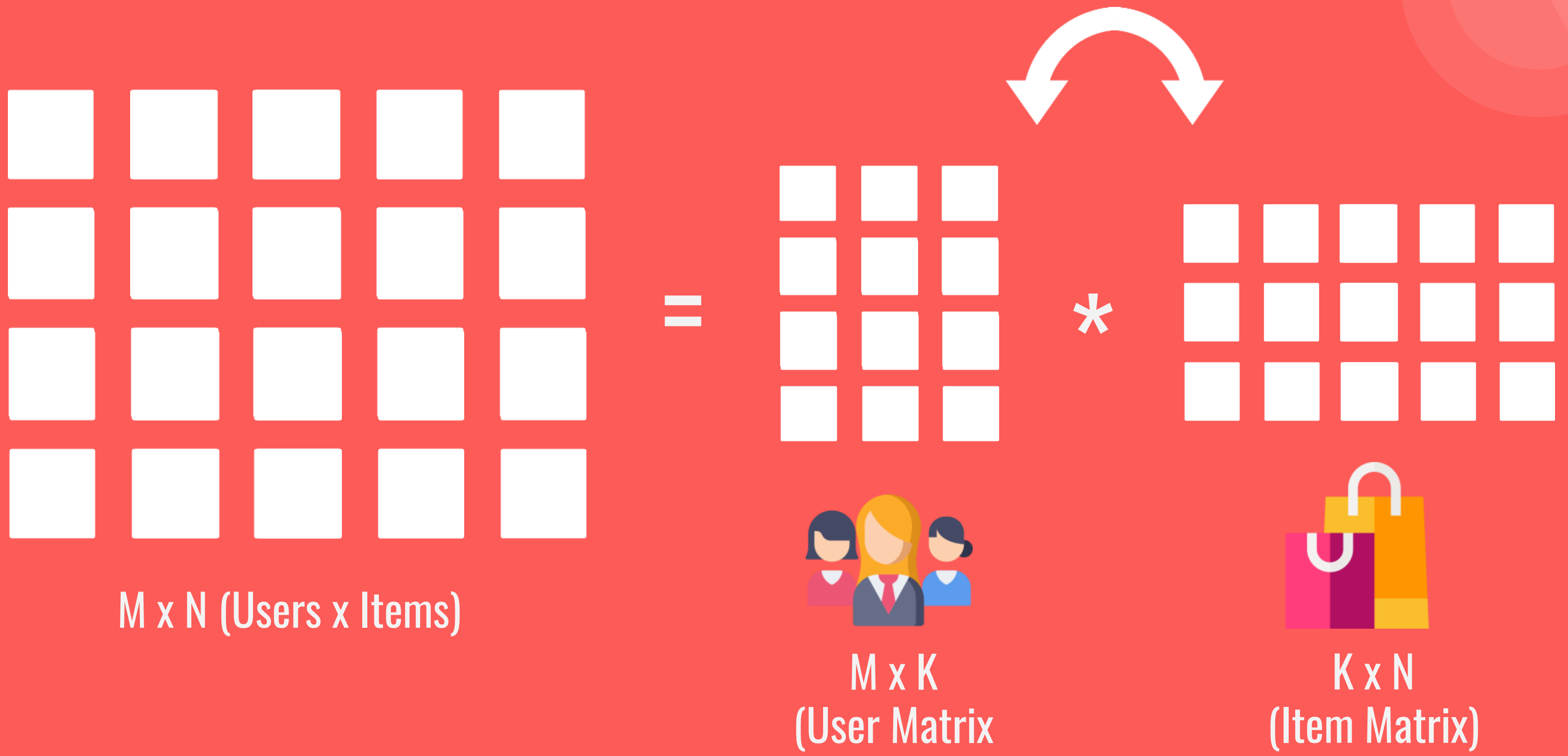
CURRENT GROUPS

- Austin Dance Social Meetup

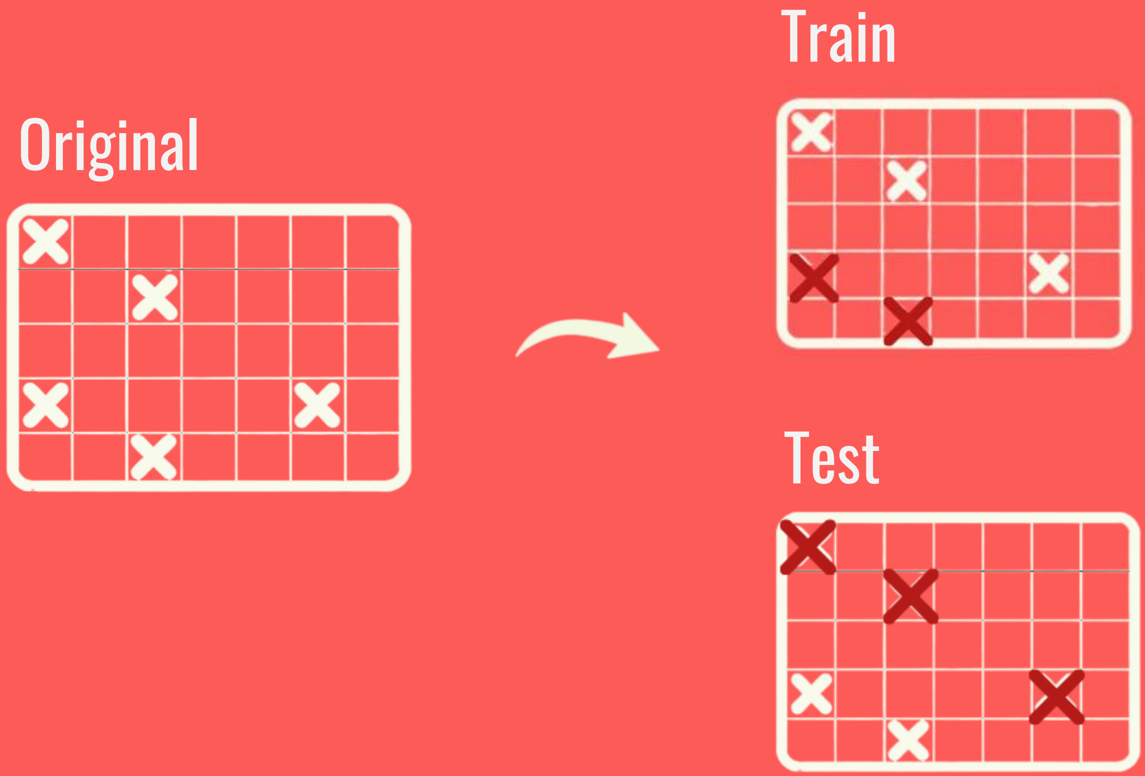
RECOMMENDATIONS

- 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

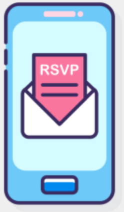
MATRIX FACTORIZATION USING ALS



APPROACH



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:

$$\frac{\textit{Total Number of Events RSVP'd for in the Group}}{\textit{Total Number of Events Organized by the Group}}$$

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

IMPLICIT FEEDBACK: TIMEDELTA

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

USER

Current Groups

Austin Data Science
Austin Tech Debates
Data Science Salon
Austin's Algorithm Meetup
Data on Tap

Austin Sierra Club Outings
Austin LGBT Socials
Queer Adventurers of Austin
Austin LGBTQ Hikers!

Austin Instant Pot Goodness
Rewild Community Meetup
Travelling Texans Over 50

RSVP

Austin Data Science
Travelling Texans Over 50

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	ALS: TimeDelta	Logistic: RSVP
Model AUC: 0.761 Baseline AUC: 0.837	Model AUC: 0.809 Baseline AUC: 0.859	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

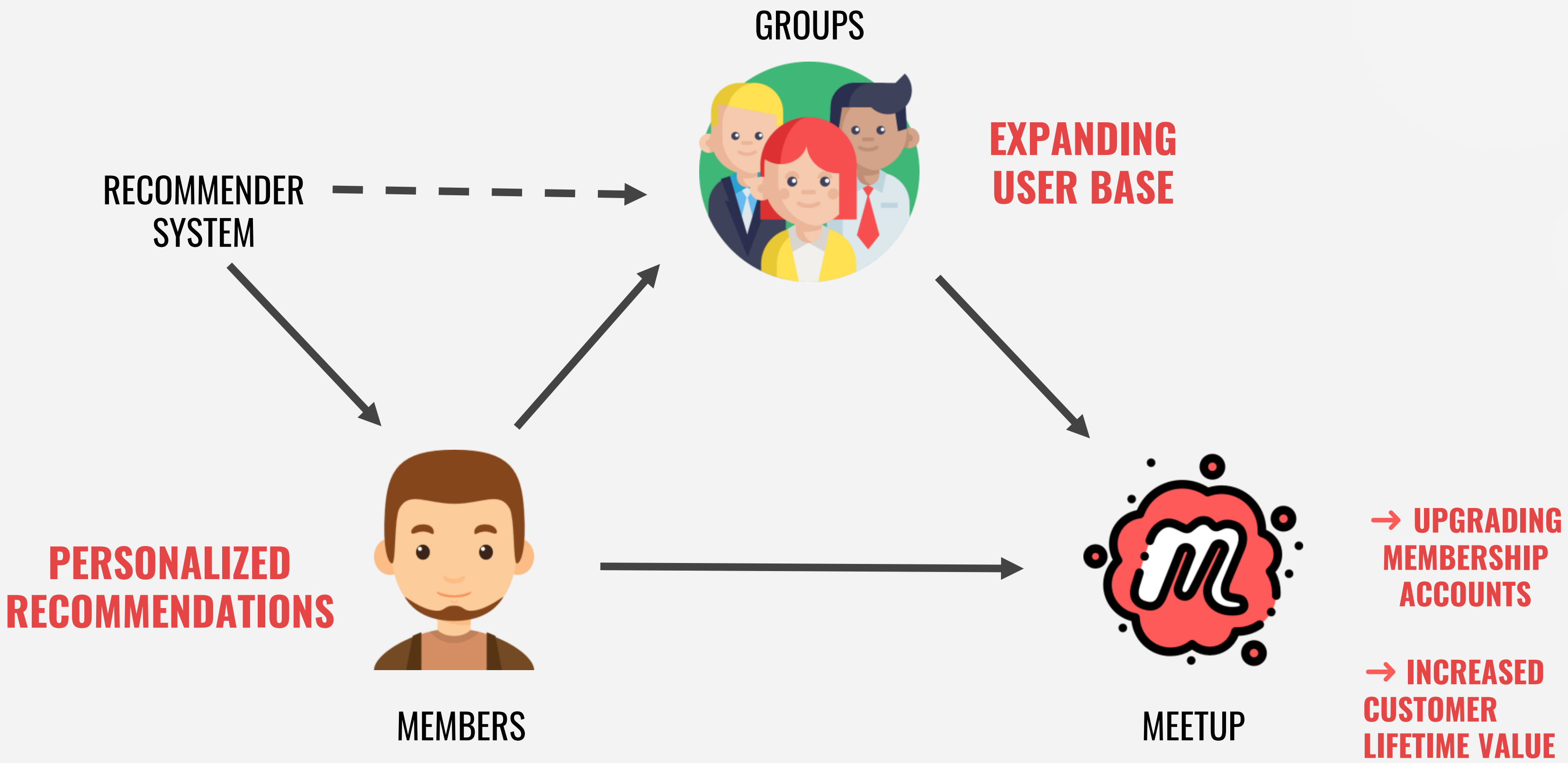
Austin Data Science

Austin Python Meetup

Healthcare Predictive Analytics

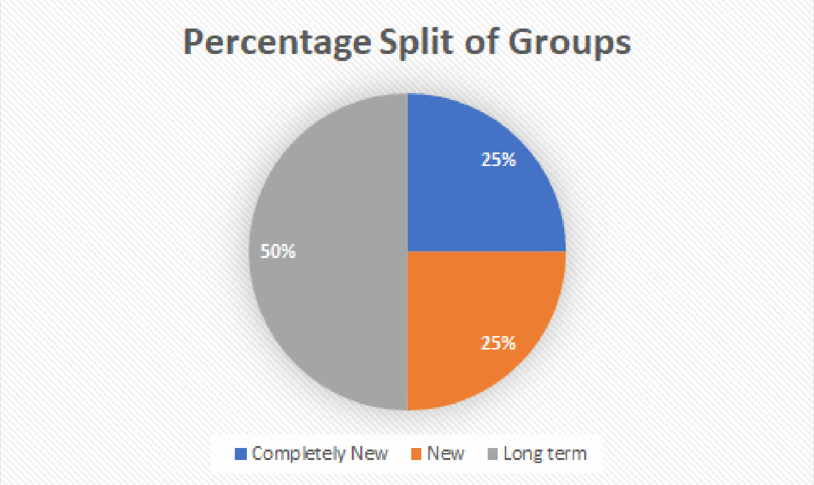
Austin Data Geeks

MEETUP: ECOSYSTEM



MEETUP: REVENUE MODEL

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



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*2900 = 725
Revenue increase per month = $5*725 = $3,625
Potential Annual Revenue = $43,500

# of groups around the world = 225,000
*Austin represents only 1.3% if the total groups

QUESTIONS?

REFERENCES

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5. http://cs229.stanford.edu/proj2014/Christopher%20Aberger,%20Recommender.pdf