11.12.2018

R-Ladies Helsinki
1st meetup - welcome!

Program

18.00 Welcome
18.10 Intro to R-Ladies and community
18.30 Data Science & R in Omnichannel customer experience creation
19.15 Introducing and discussing the future of R-Ladies Helsinki and program
19.30 Networking

R-LADIES GLOBAL

Community and Vision

Original slides in
http://bit.ly/2utaAUT

Worldwide organization that promotes **gender diversity** in the **R** community via meetups and mentorship in a **friendly** and **safe** environment

Original slides in http://bit.ly/2utaAUT

Our mission

More women/non-binary

- coders
- developers
- speakers
- leaders

More awesome people developing R packages and being part of the R community.

Original slides in http://bit.ly/2utaAUT

2012

2013

2014

2015

2016

San Francisco
(USA)

R-Ladies was born

Taipei
(Taiwan)

Twin Cities
(USA)

London
(UK)

October 2012

August 2014

Ap

Original slides in
http://bit.ly/2utaAUT

R-Ladies Growth

9.12.2018

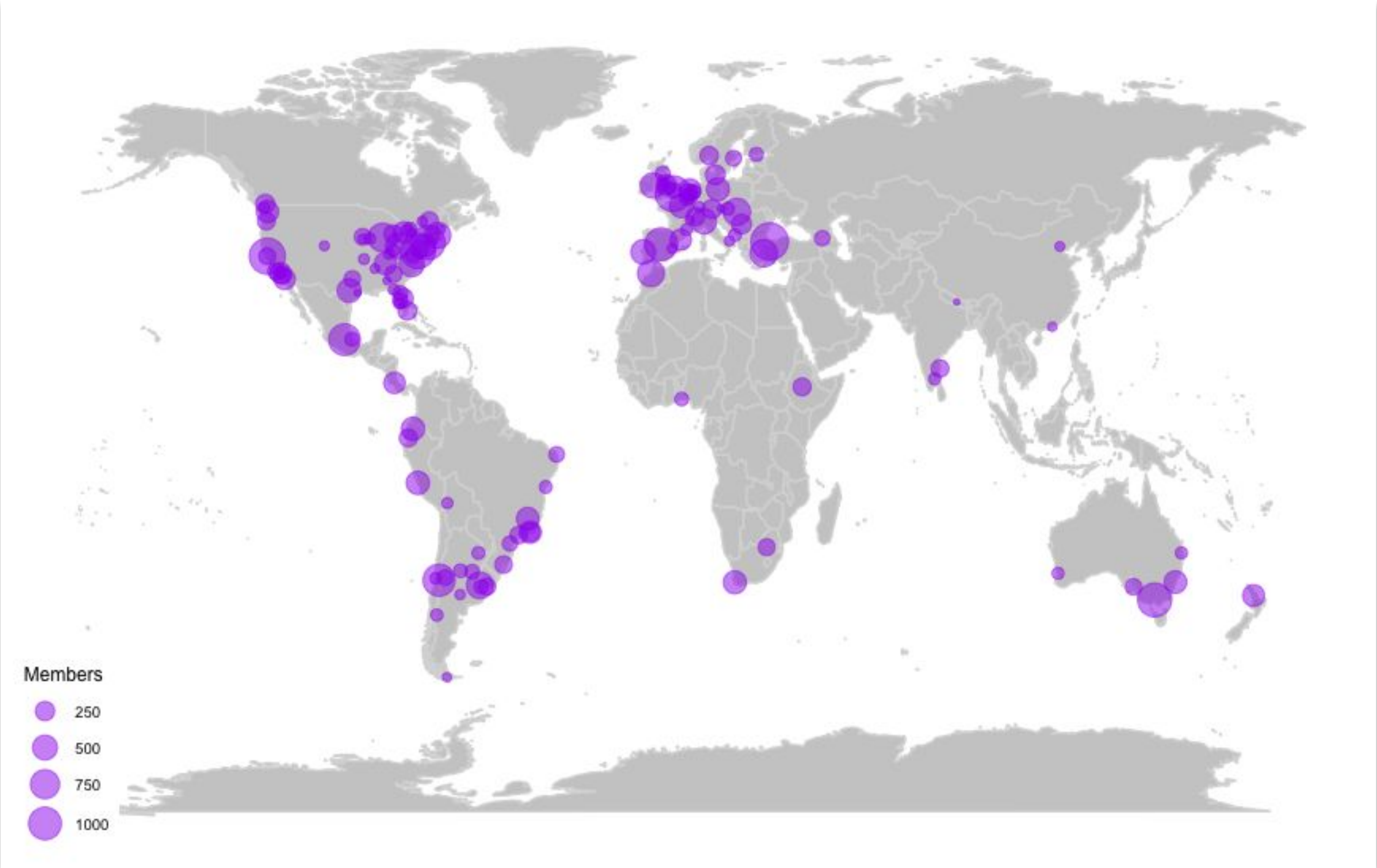
40+
countries

125+
cities

33000+
members

Original slides in
http://bit.ly/2utaAUT

Meetup members by each chapter 9.12.208



Made with 💜 by [Daniela Vázquez](), modified by [Eija-Leena Koponen]()

R-Ladies Events

R-Ladies Istanbul

2016 **September**

Number of R-Ladies = 1300 members
Meet-ups = 21
Organizer = Hazel Kavili

- 25 - 30 people attended once a month since
- Hands-on sessions
- dplyr, ggplot2, Statistics 101, Markdown, R programming 101, Data Cleaning and two Data analysis talks

IMPACT

Many beginners learnt a lot about using R and we developed a good community for women.

R-Ladies Helsinki

2018 September

Number of R-Ladies = 87 members
Meet-ups = This is the 1st!
Organizer = Eikku & Suvi

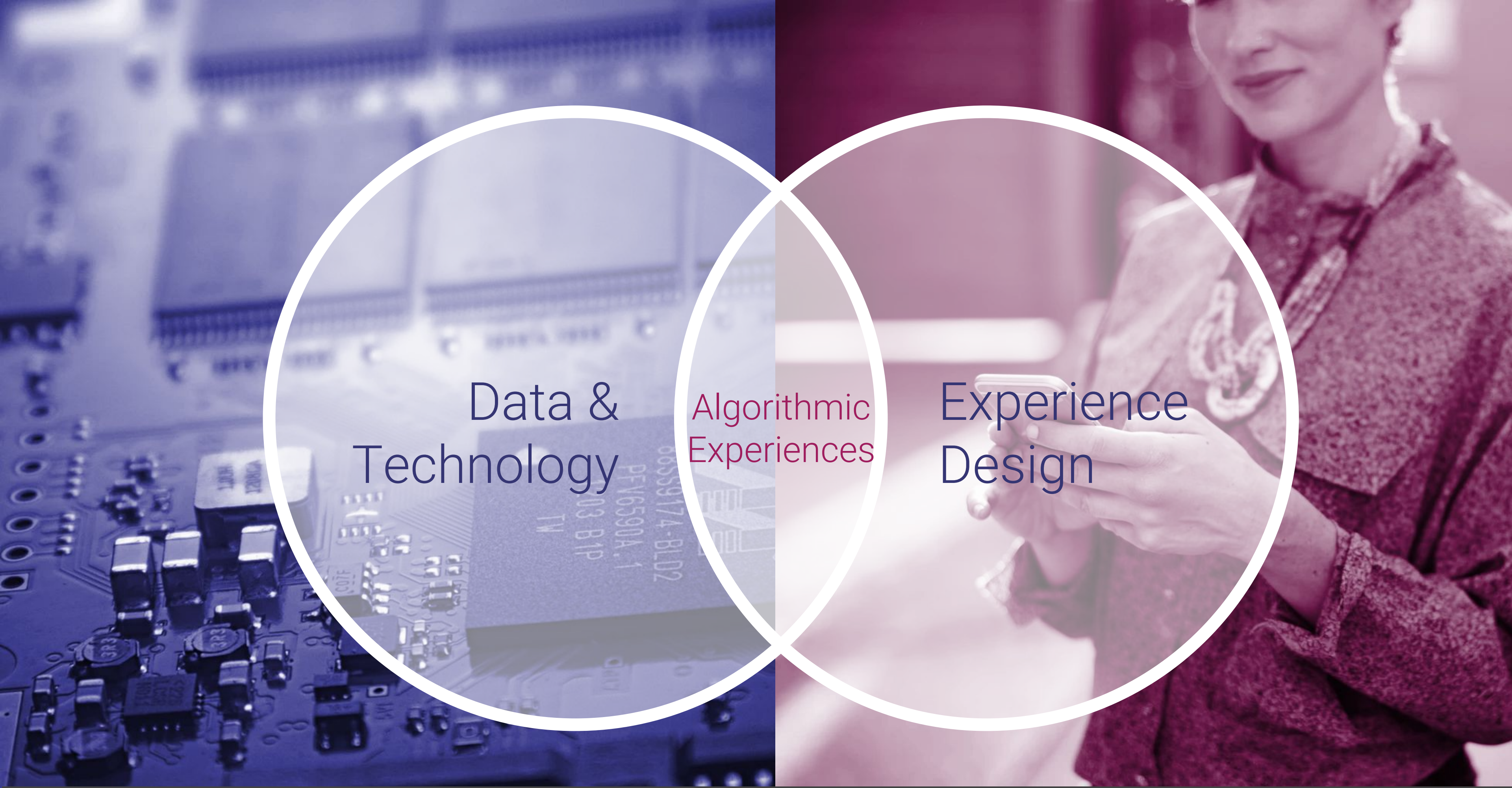
WHAT TO EXPECT?

Community
Meetups
Support
Peers
Professional growth

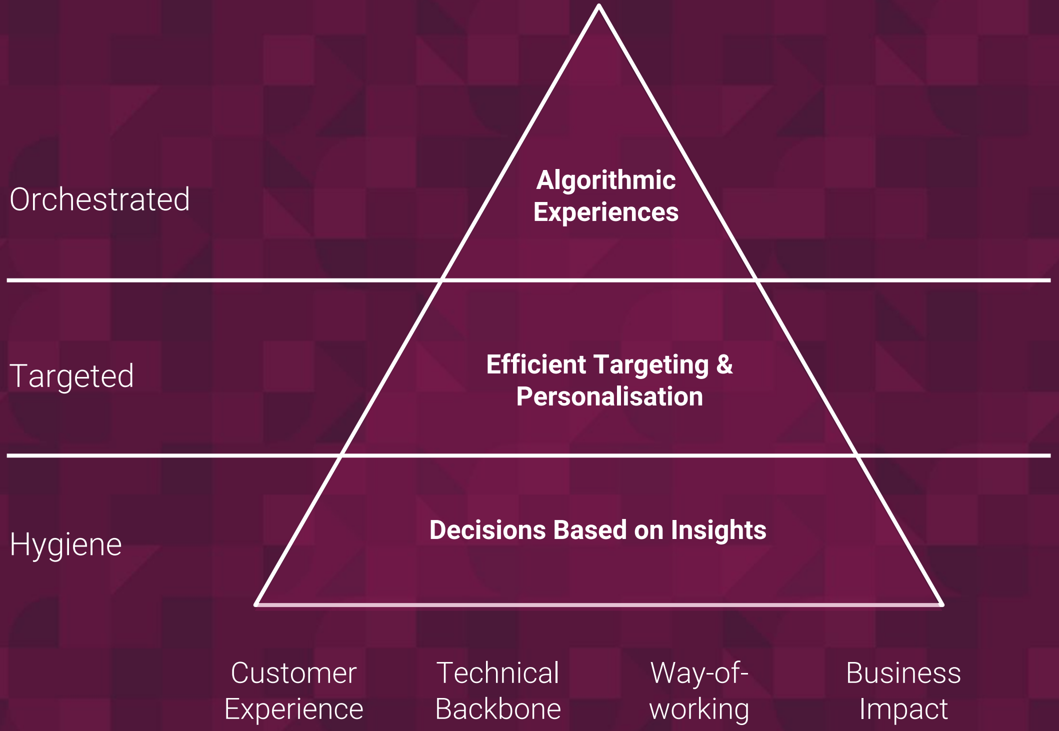
Algorithmic experiences

Future-proofing customer engagement

Saija Ekman



Avaus facts: 150 experts // 4 offices // Revenue 2017: 16,1 MEUR

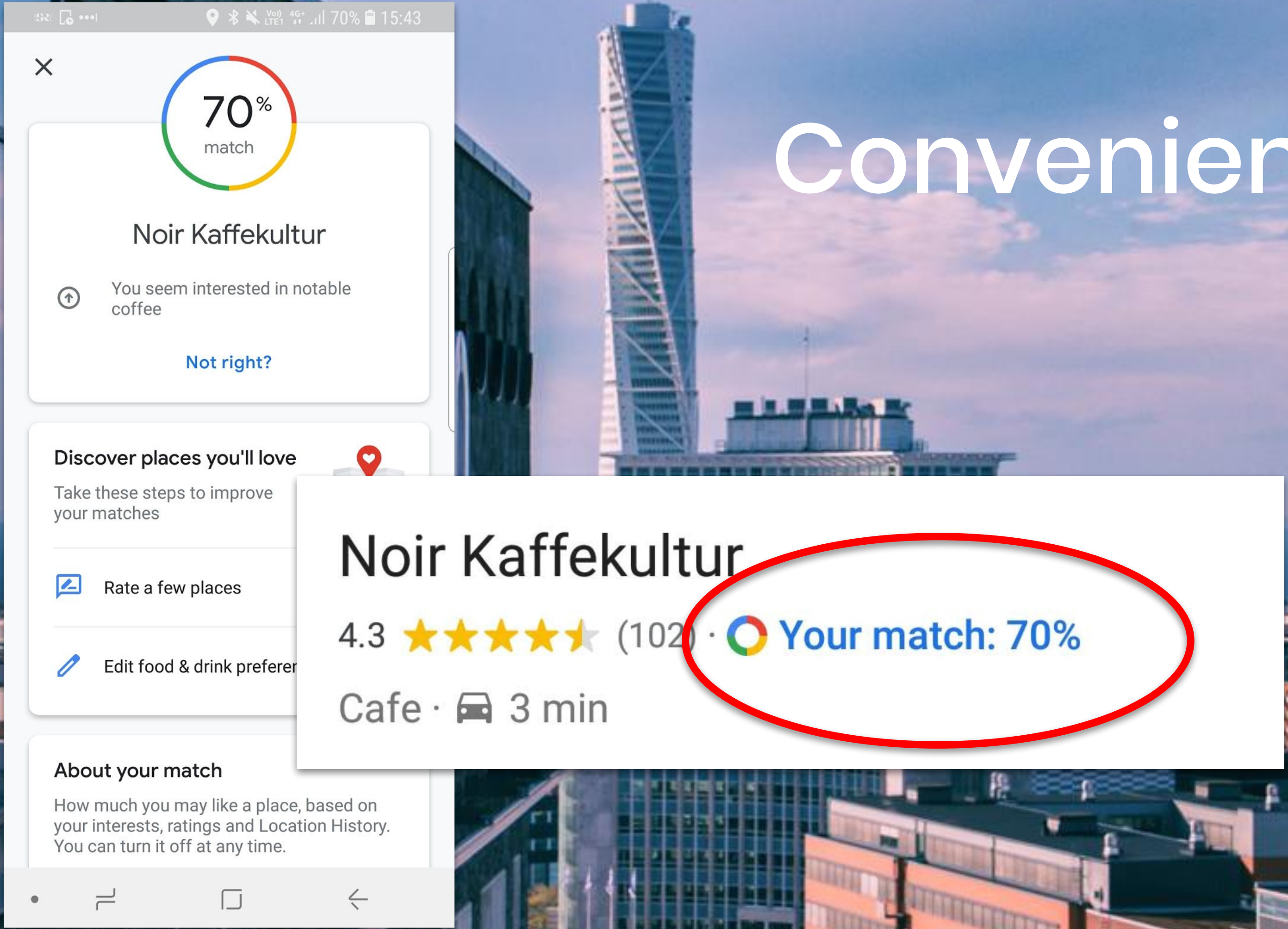


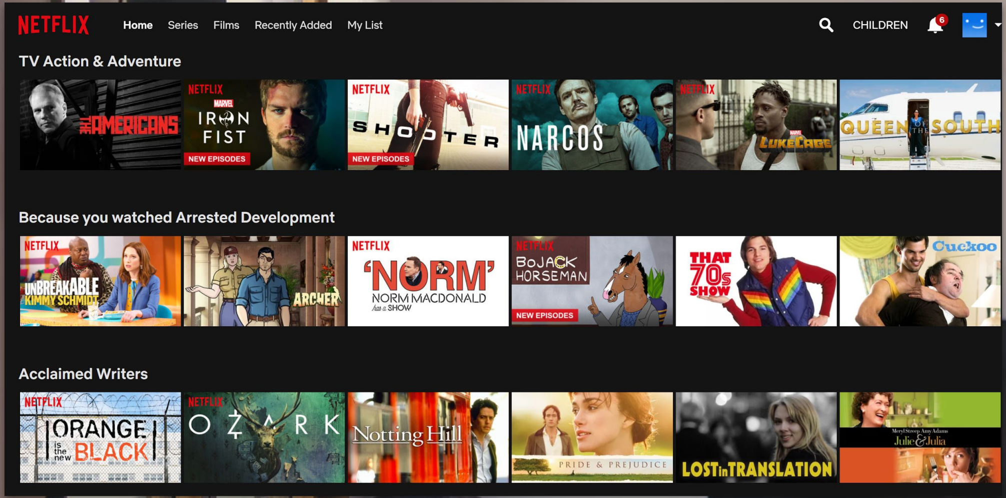
The journey towards algorithmically orchestrated experiences

What are algorithmic experiences?


ALMOST **EVERYTHING** WE TOUCH WILL BE **DRIVEN BY ALGORITHMS**
NARROW DOWN CHOICE
INCREASED AWARENESS
LOOK FOR INSPIRATION
DELEGATE MUNDANE TASKS
SUPPORT DECISIONS

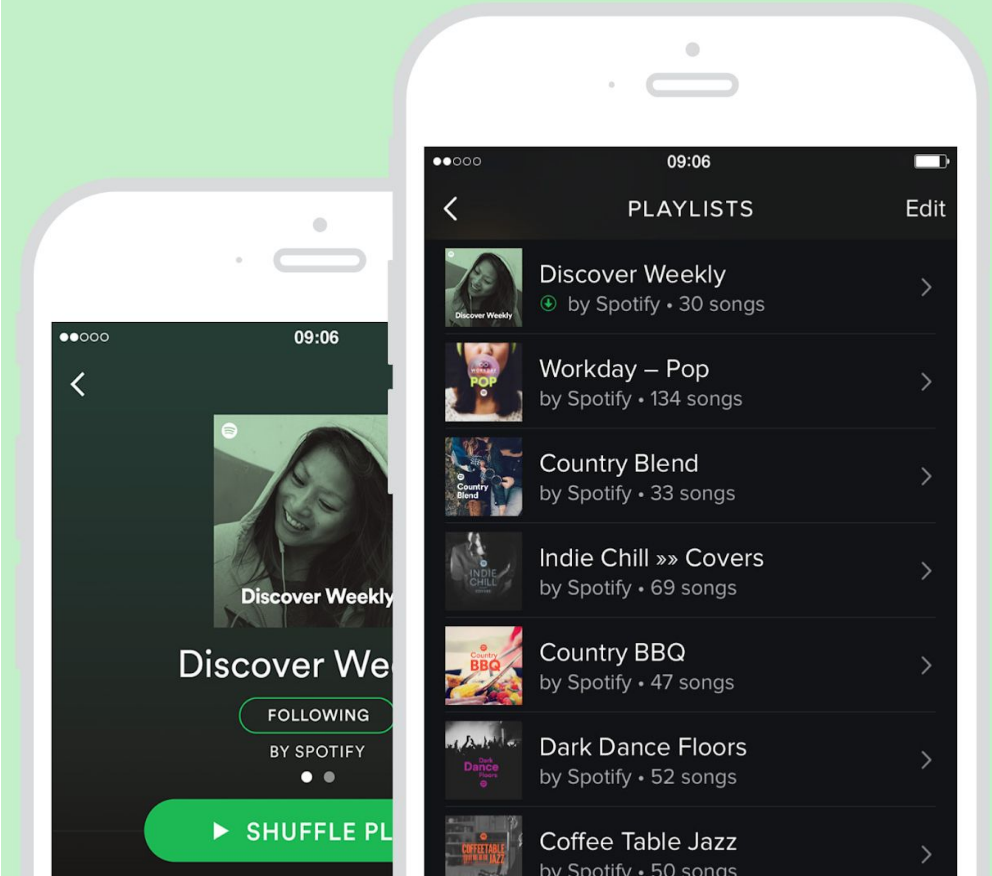
Convenience!





Glue

(don’t mess with my algo!)



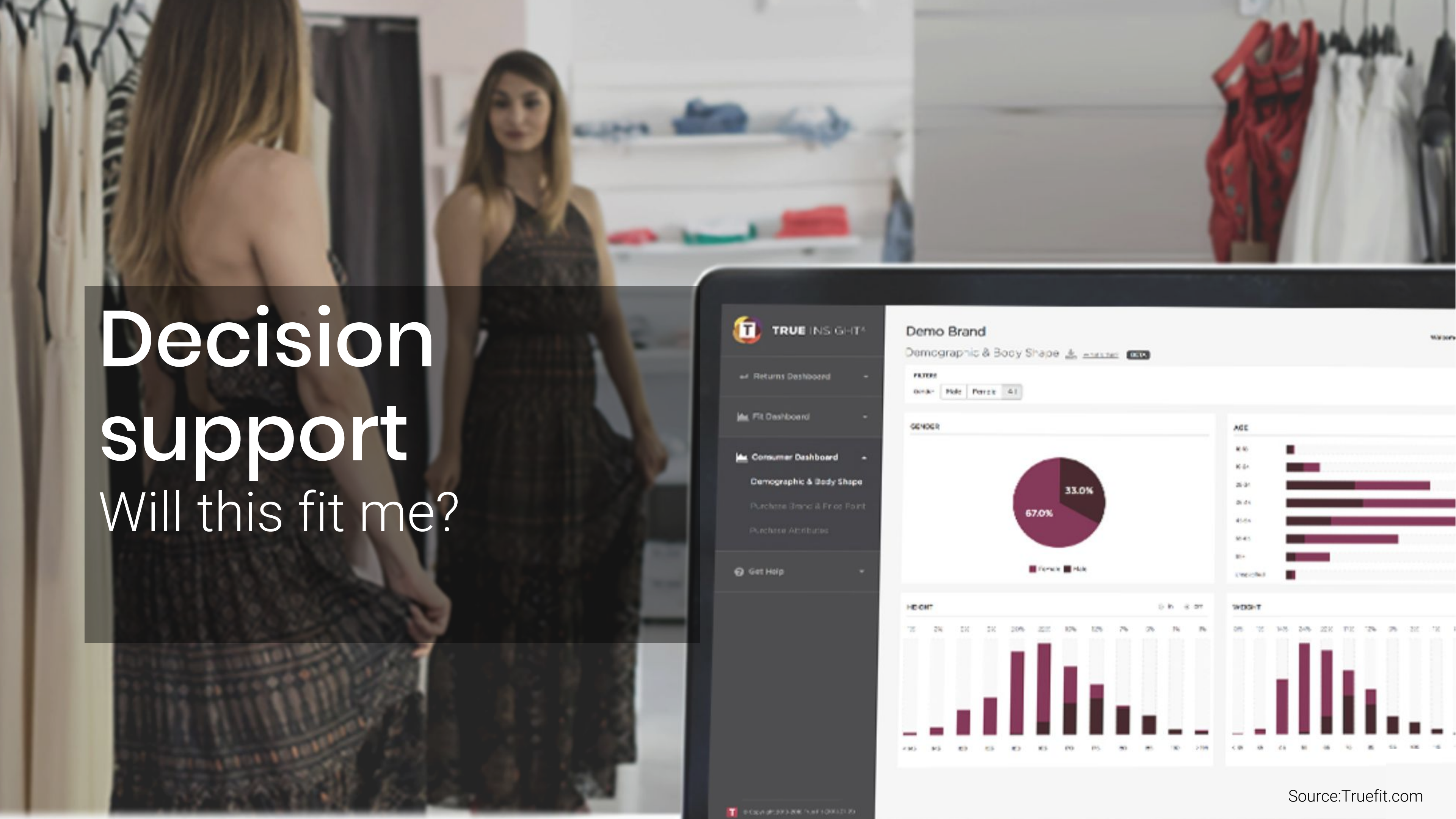
Exploration

Serendipity and taste

Source: Spotify.com

Decision support

Will this fit me?



Source:Truefit.com

Marketing and Sales Efficiency

>5-8x ROI

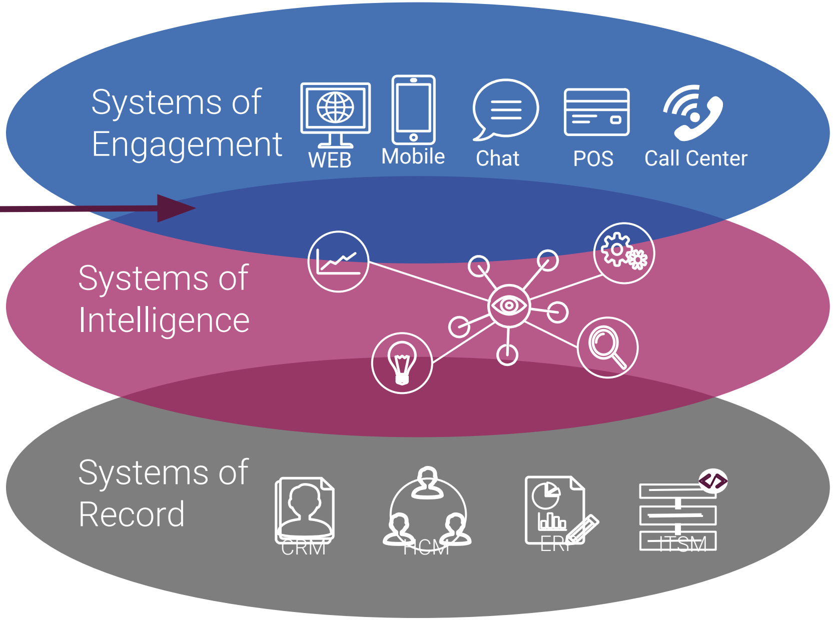
Source: McKinsey & Company

How?

Tech Backbone:

Systems of Engagement and Systems of intelligence

This is where the magic happens!



Experience Technologies: Martech & Adtech

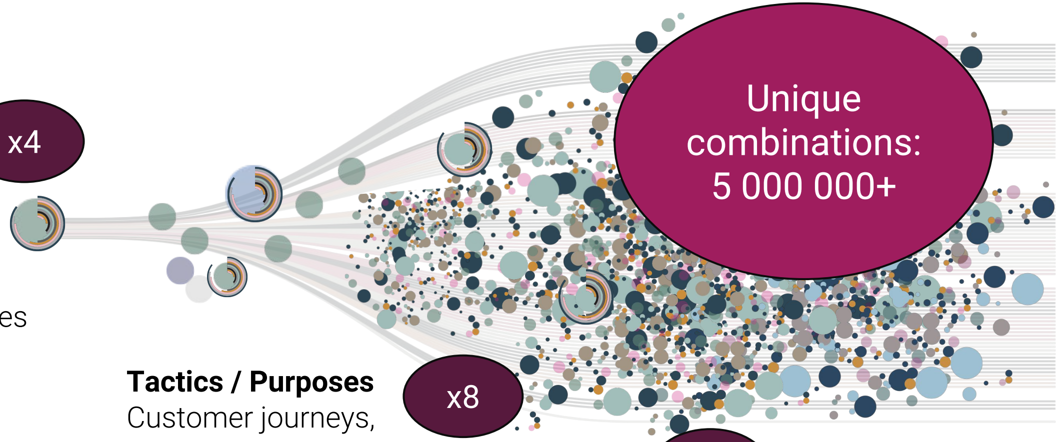
“Big Brain” Analytics

Enterprise backbone: Your data

Big Brain?

Complexity requires us to let analytics do the decisioning

Example of 1:1 Omnichannel marketing:



x4
Strategic brand/ content concepts
Targeted e.g. for strategic focus areas, such as movers, retirees

x8
Tactics / Purposes
Customer journeys, customer interactions, campaign activities

x5
Context
Location, situation, behaviour

x4
Content variants
Tone of voice / personality segmentation

x1000
Offers
Products, campaigns, actions, discounts

x10
Distribution / Channels
Online, offline, app, in-store, TV web, social, sms, display etc

N Possible variants per customer (hypothesis)

Typical “big-brain” application areas

Offer management

What makes a great offer?

Recommendation engines

How to give data back to consumers?

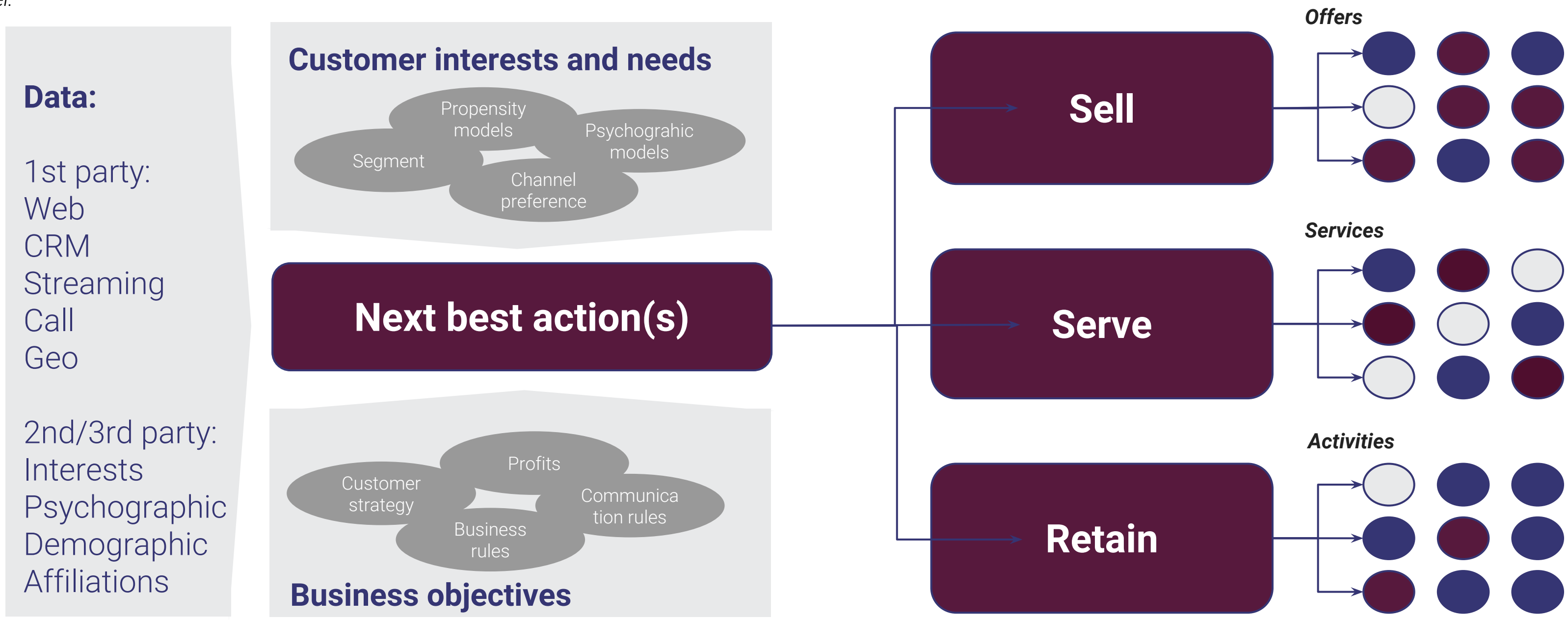
Next best action modeling

If given a 1:1 meeting with your customer - what do you talk about?

From rule-based to **algorithmic**

If given a 1:1 moment with your customer - what do you say?

Example of next best action model:



Thank you!

R as a tool in Omnichannel Marketing

Eija-Leena Koponen

WHO AM I?

Statistician - Data Scientist

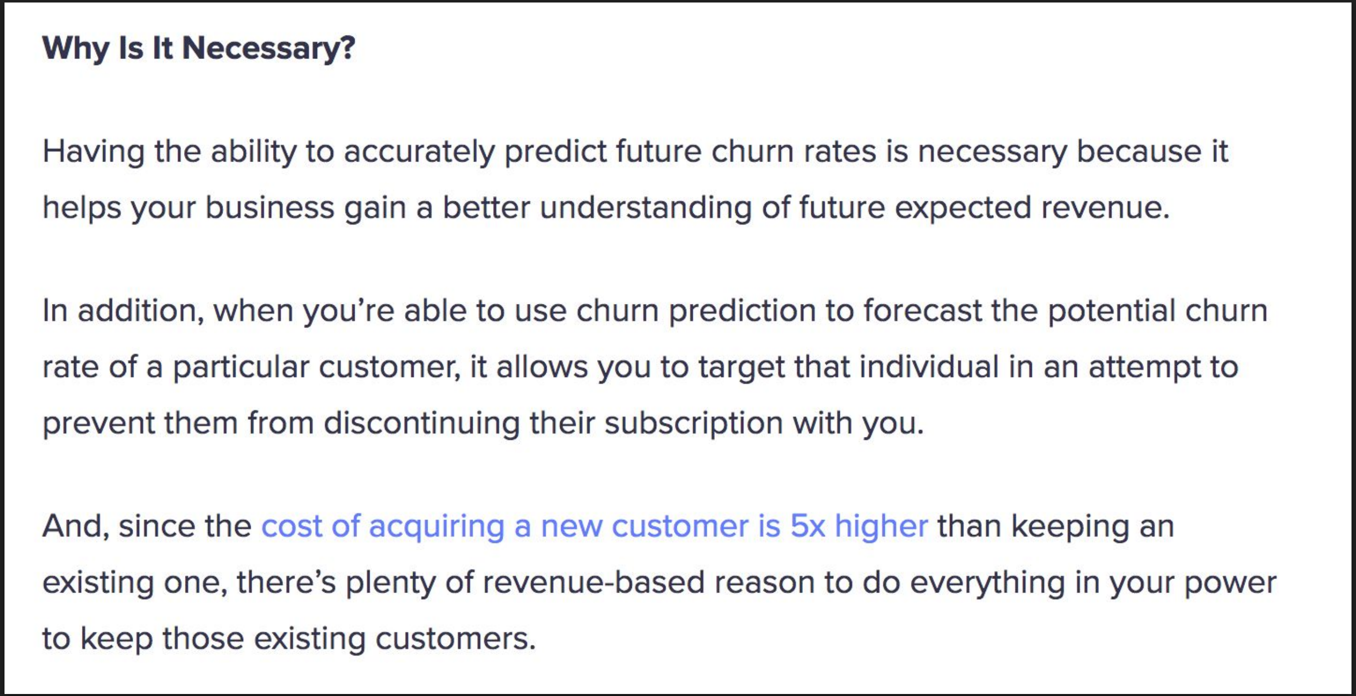
Worked in ministry, consulting, freelancing, startup, university ...

.. in banking, telco, unemployment statistics, customer analytics, real estate, legal tech, education, retail.

Popular models in marketing

- Churn
- CLV
- NBO/A
- Segmen-tation

Churn prediction = when or whether customer leaves



Why Is It Necessary?

Having the ability to accurately predict future churn rates is necessary because it helps your business gain a better understanding of future expected revenue.

In addition, when you're able to use churn prediction to forecast the potential churn rate of a particular customer, it allows you to target that individual in an attempt to prevent them from discontinuing their subscription with you.

And, since the cost of acquiring a new customer is 5x higher than keeping an existing one, there's plenty of revenue-based reason to do everything in your power to keep those existing customers.

https://baremetrics.com/academy/churn-prediction-can-improve-business

Churn algos in R

Logistic regression

glm {stats}

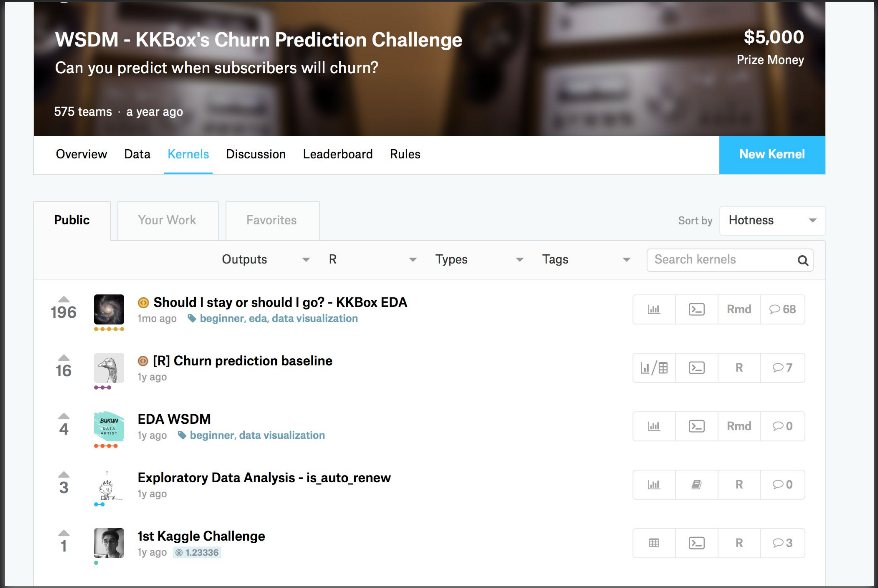
Tree models

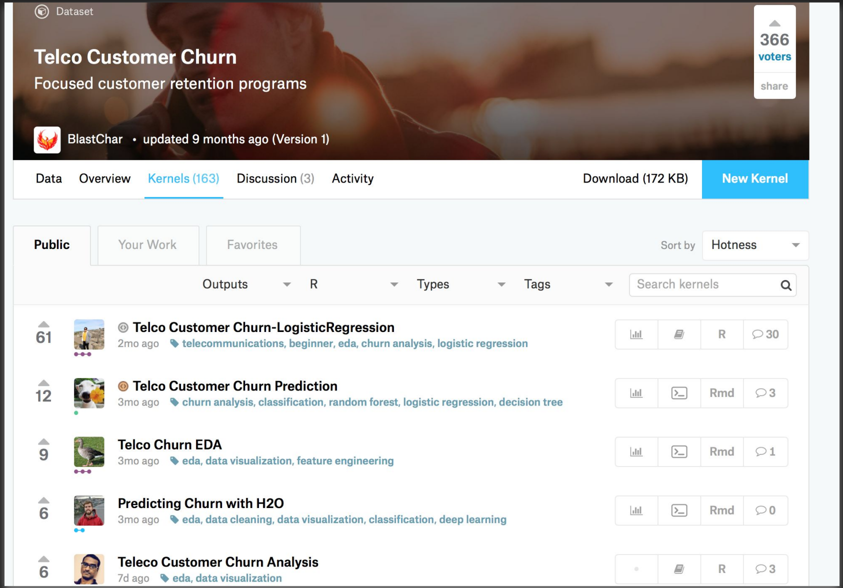
rpart{rpart}, train{randomForest} - ensemble of trees, xgb.train{xgboost} - boosted trees, gbm

Survival analysis

{survival}, {survminer}

Inspiration for own work





https://www.kaggle.com/

CLV =customer lifetime value

"Lifetime Value is the predicted amount a customer will spend on your product or service throughout the entire relationship, hence – "lifetime." This metric can help you move from transaction-based thinking to focusing on the long-term value of repeat business."
https://baremetrics.com/academy/lifetime-value-ltv

CLV algos in R

Churn

Revenu /cost prediction:

- Regression
- Buy ’Til You Die’=BTYD
- Recency-Frequecy-Monetary Value (RFM)

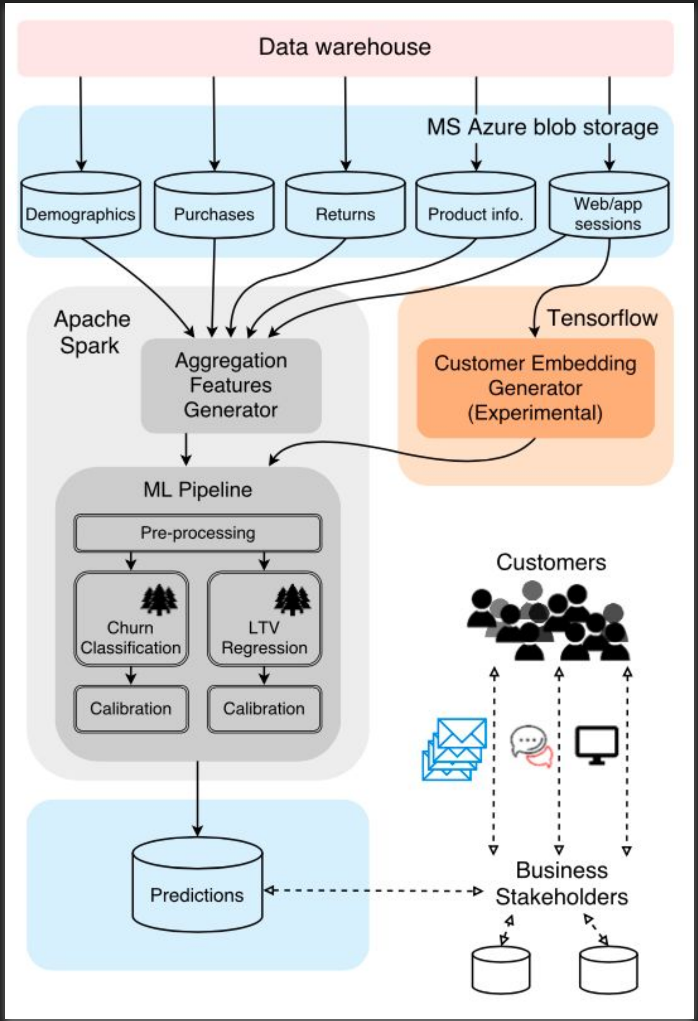
Loads of data and personalisation

Current Model & Architecture at ASOS

Currently, ASOS deploys a random forest model by Apache Spark. It has gathered customers' demographics, purchases, returns, product information, and utilizes manually created features. In the machine learning pipeline, two models were trained: churn classification and CLTV regression. After calibration, the whole system delivers predictions to business stakeholders.

Recent developments by ASOS is to use embeddings to capture information from web/app sessions as features in the current model. This part is discussed later.

https://medium.com/syncedreview/customer-lifetime-value-prediction-using-embeddings-53f54e2ac59d



Current Model & Arch

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gathered customers' demograph
and utilizes manually created fe
models were trained: churn clas
calibration, the whole system de

Recent developments by ASOS i
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later.

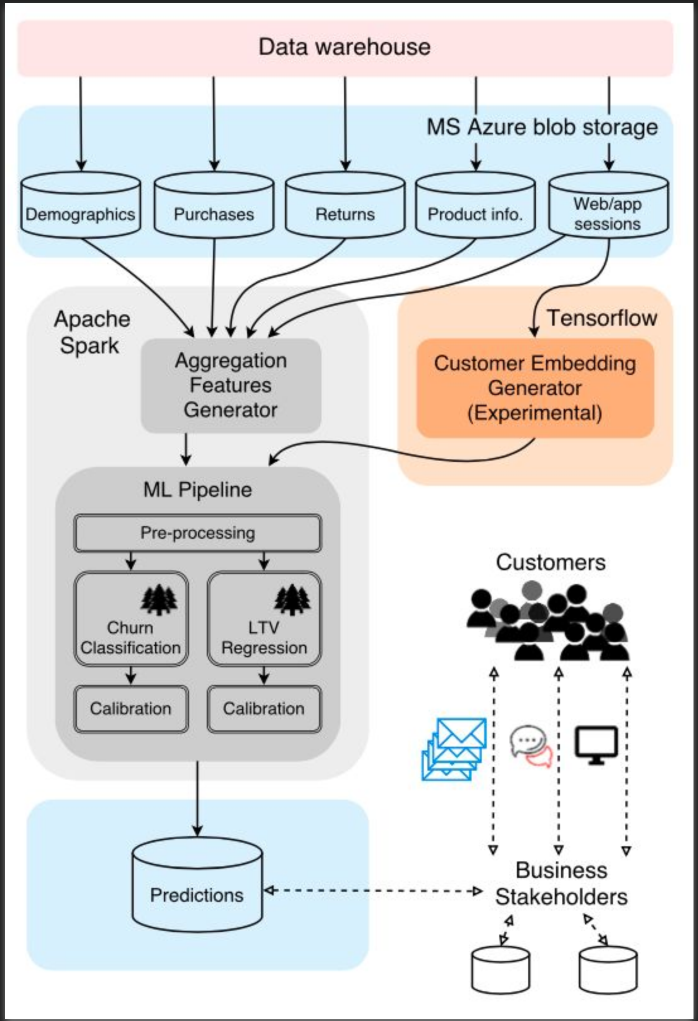
https://medium.com/s
value-prediction-using-embeddings-55f54e2ac59d

Table 1: Feature importance by data class.

Data class	Overall Importance
Customer demographics	0.078
Purchases history	0.600
Returns history	0.017
Web/app session logs	0.345

Table 2: Individual feature importance (top features).

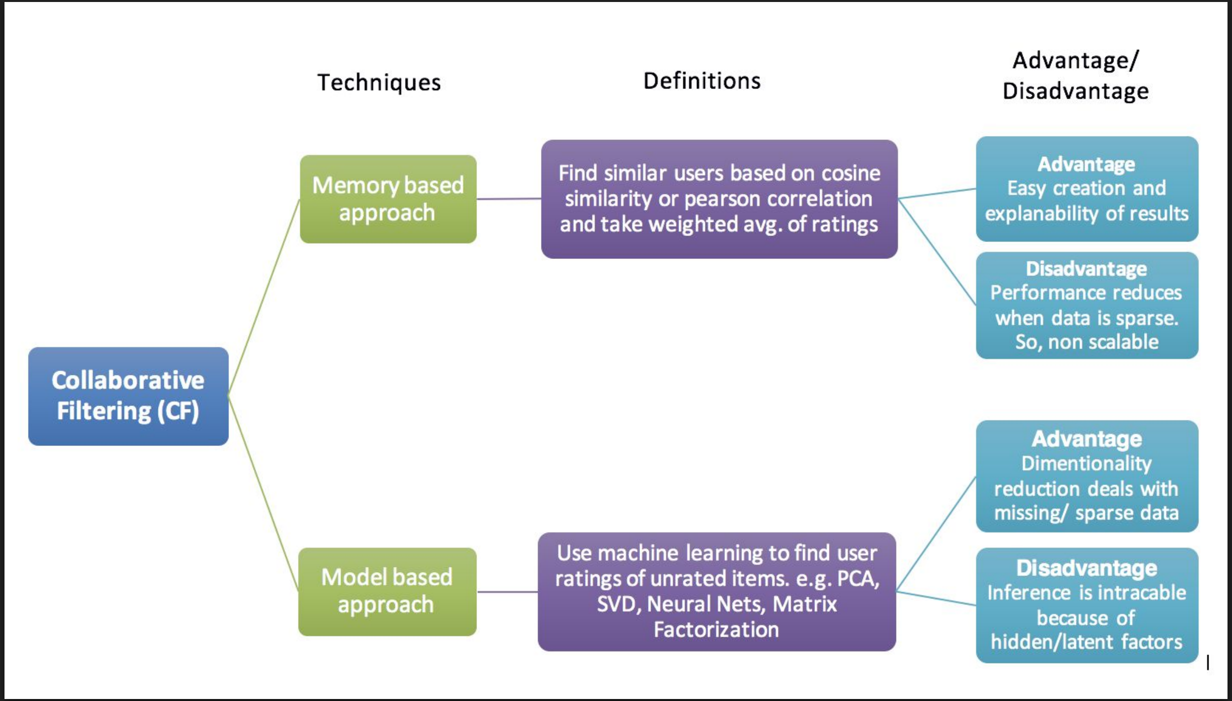
Feature Name	Importance
Number of orders	0.206
Standard deviation of the order dates	0.115
Number of session in the last quarter	0.114
Country	0.064
Number of items from new collection	0.055
Number of items kept	0.049
Net sales	0.039
Days between first and last session	0.039
Number of sessions	0.035
Customer tenure	0.033
Total number of items ordered	0.025
Days since last order	0.021
Days since last session	0.019
Standard deviation of the session dates	0.018
Orders in last quarter	0.016
Age	0.014
Average date of order	0.009
Total ordered value	0.008
Number of products viewed	0.007
Days since first order in last year	0.006
Average session date	0.006
Number of sessions in previous quarter	0.005



NBO/A =next best offer/action

“NBO has its origins in Amazon.com’s early use of so-called recommendation software (or collaborative filtering, in engineering-speak) to spur shoppers toward a “next best offer” based on site page visits and, of course, actual purchases.” https://www.cooladata.com/blog/next-best-offer-customer-based-predictive-datas-new-frontier/

NBO/A in R



https://towardsdatascience.com/various-implementations-of-collaborative-filtering-100385c6dfe0

Medium | Artificial Intelligence

Become a member

MEMBER FEATURE STORY

How Does Spotify Know You So Well?

A software engineer explains the science behind personalized music recommendations

Sophia Ciocca Follow

Oct 10, 2017 · 9 min read ★

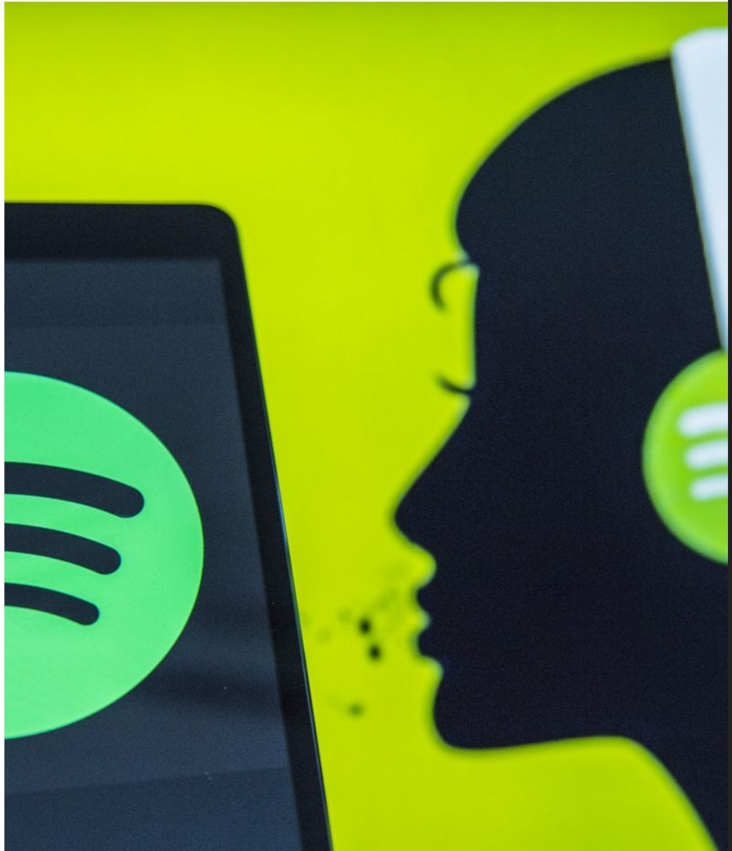


Photo by studioEAST/Getty Images

https://medium.com/s/story/spotifys-discover-weekly-how-machine-learning-finds-your-new-music-19a41ab76efe

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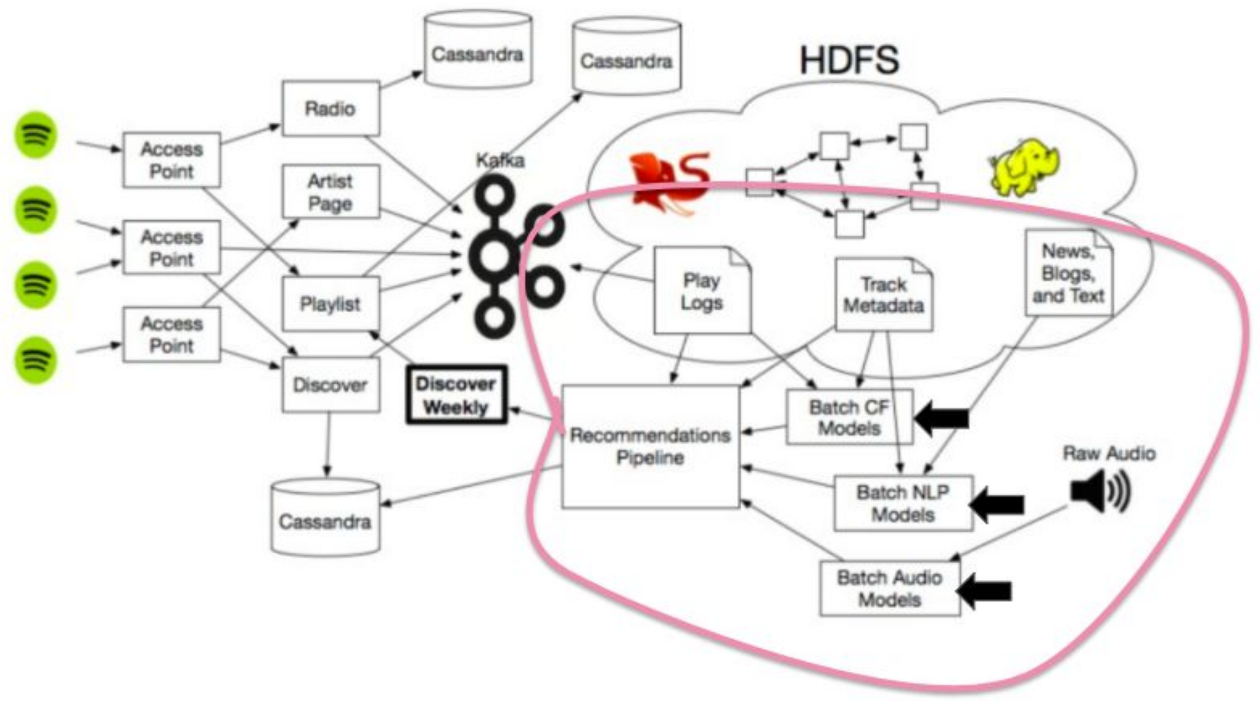


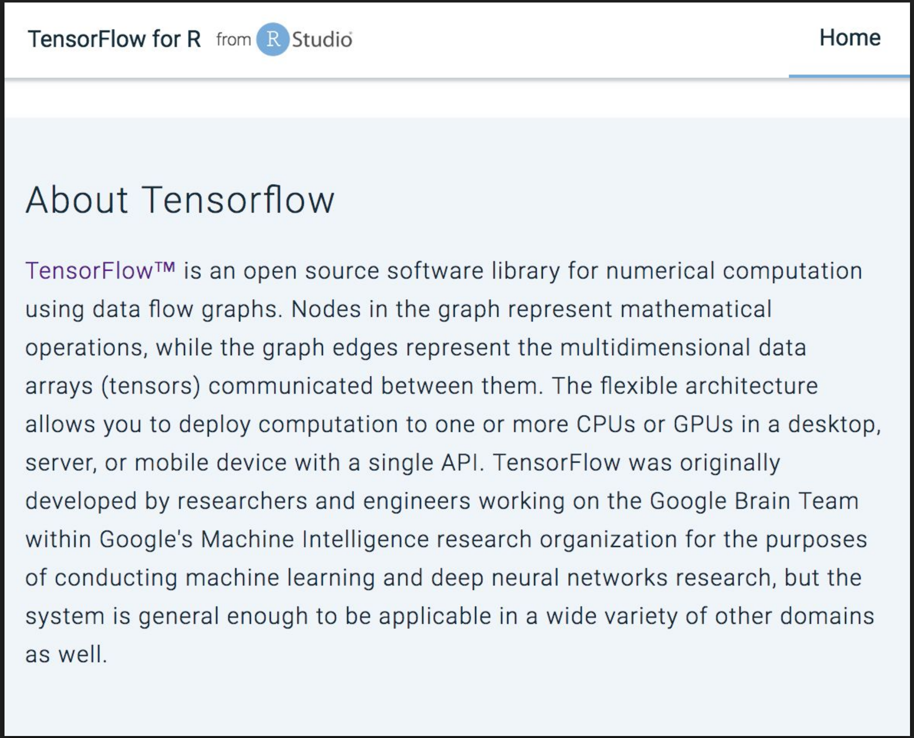
https://medium.com/s/story/spotifys-discover-weekly-how-machine-learning-finds-your-new-music-19a41ab76efe

Photo by studioEAST/Getty Images

Other inspiration

https://www.kaggle.com/philippsp/book-recommender-collaborative-filtering-shiny

https://blogs.rstudio.com/tensorflow/posts/2018-09-26-embeddings-recommender/


TensorFlow for R from RStudio

Home

About Tensorflow

TensorFlow™ is an open source software library for numerical computation using data flow graphs. Nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) communicated between them. The flexible architecture allows you to deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API. TensorFlow was originally developed by researchers and engineers working on the Google Brain Team within Google's Machine Intelligence research organization for the purposes of conducting machine learning and deep neural networks research, but the system is general enough to be applicable in a wide variety of other domains as well.

Segmentation = knowing your customer groups

Towards Data Science Follow Sign

DATA SCIENCE MACHINE LEARNING PROGRAMMING VISUALIZATION AI PICKS CONTRIBUTE

How to cluster your customer data—with R code examples

Clustering customer data helps find hidden patterns in your data by grouping similar things for you. For example you can create customer personas based on activity and tailor offerings to those groups.

Outlier AI Follow

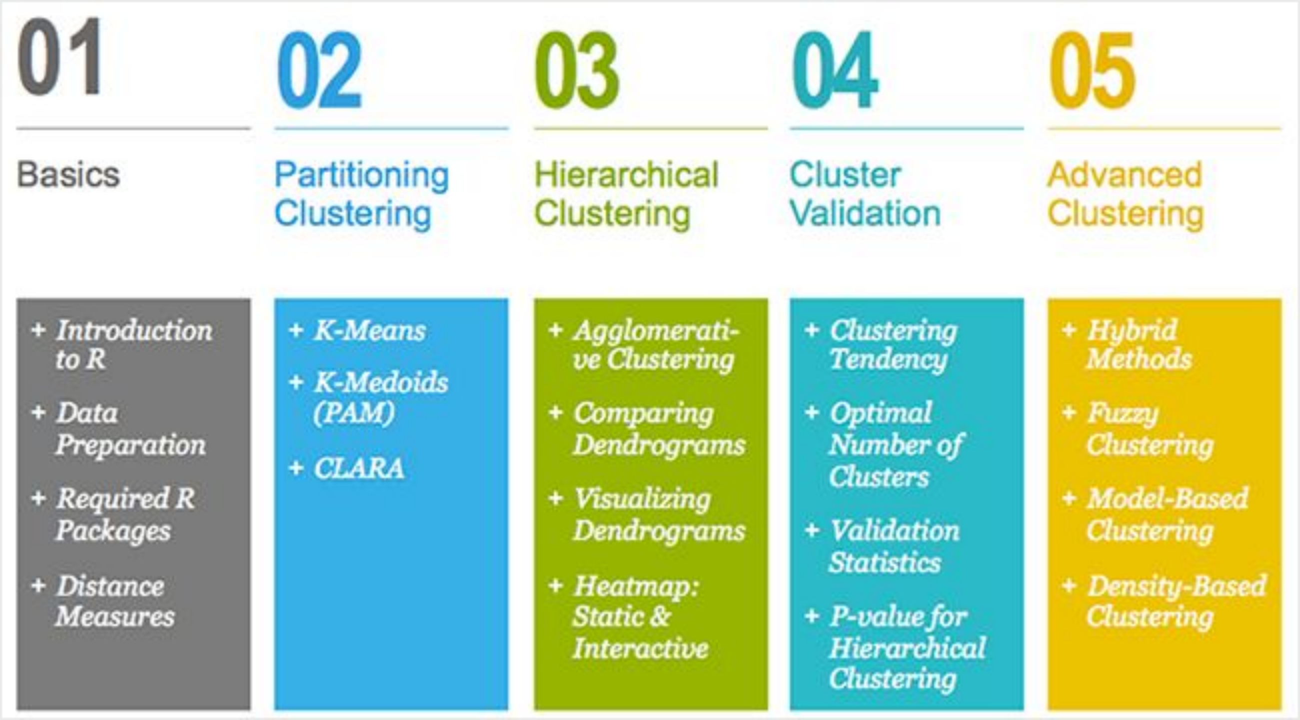
Jun 13, 2017 · 8 min read

https://towardsdatascience.com/how-to-cluster-your-customer-data-with-r-code-examples-6c7e4aa6c5b1

Segmentation in R

{cluster}

dendograms



How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did

Kashmir Hill Forbes Staff
Welcome to The Not-So Private Parts where technology & privacy collide

Every time you go shopping, you share intimate details about your consumption patterns with retailers. And many of those retailers are studying those details to figure out what you like, what you need, and which coupons are most likely to make you happy. Target TGT -1.31%, for example, has figured out how to data-mine its way into your womb, to figure out whether you have

https://www.forbes.com/sites/kashmirhill/2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/#7f1eee436668

R-Ladies Helsinki future ?

2019

January

FUTURE EVENTS

21.1.2019 **R DevOps** by Seija Sirkiä at Houston Analytics

Feb 2019 **R introductory workshop** by Suvi Vasama at Frantic

YOU ARE WELCOME TO CONTRIBUTE!

Introductory Workshop in February 2019

- **Target audience**
  - Beginners with no or very little experience in R and/ or data science
  - More experienced coders encouraged to attend as tutors and supporters
- **Main goals**
  - Gentle introduction into R and data science
  - Networking and having a good time
- **Tentative Outline**
  - Importing and preprocessing data
  - Introduction to common data science methods through practical examples
  - One example together followed by a hands-on exercise independently or in groups

How can you help?

Support

Local Chapters :

- FREE venue
- Sponsorship for food and drink
- Speakers

Advocate

- R-Ladies directory
- Opportunities e.g. conferences, jobs etc

Inspire

Raise your voice

- Join R-Ladies
- Code Share
- Inspire and support others
- Teach
- Blog
- Tweet

THANK YOU!

Website: rladies.org
Twitter: @RLadiesGlobal
Email: info@rladies.org