Programming for Big Data

Lecture 3

Data Processing with Spark



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Agenda

Preliminaries

- 1. Use Case: Personalisation
 - Sales and Marketing
 - Customer Segmentation
- 2. Machine Learning with Spark
 - Basic Data Types
 - Basic Statistics
 - Supervised
 - Unsupervised
 - Evaluation
 - PMML Publishing and Sharing
- 4. Summary

PRELIMINARIES

My Details

Name: Dr. Bojan Božić

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Details on SPARK labs:

https://ceadar.dit.ie/bojan.bozic/SPARK/

Final assignment will be published on webcourses.

Any Questions, Please email me!

Books and Resources

Mastering Spark

www.packtpub.com/big-data-and-business-intelligence/mastering-apache-spark

Apache Spark From Inception to Production

http://info.mapr.com/rs/mapr/images/Getting_Started_With_Apache_Spark.pdf

Spark Programming Guide

http://spark.apache.org/docs/latest/programming-guide.html

Course Details

Classes: Wednesday 18:30 - 21:30

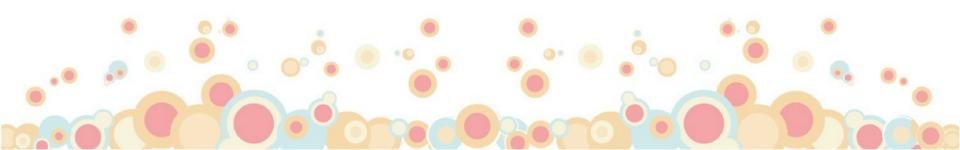
- 4 labs with 3 lab assignments (voluntary)
- Final assignment starts in last (4th) lab

Grading: Only final assignment is graded (100%)

Software



http://spark.apache.org/

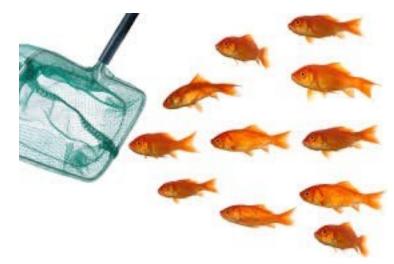


USE CASE: PERSONALISATION

From then to now...



Customer Acquisition:



The process of acquiring new leads, prospects and customers.

(CAQ - Customer Acquisition Cost)

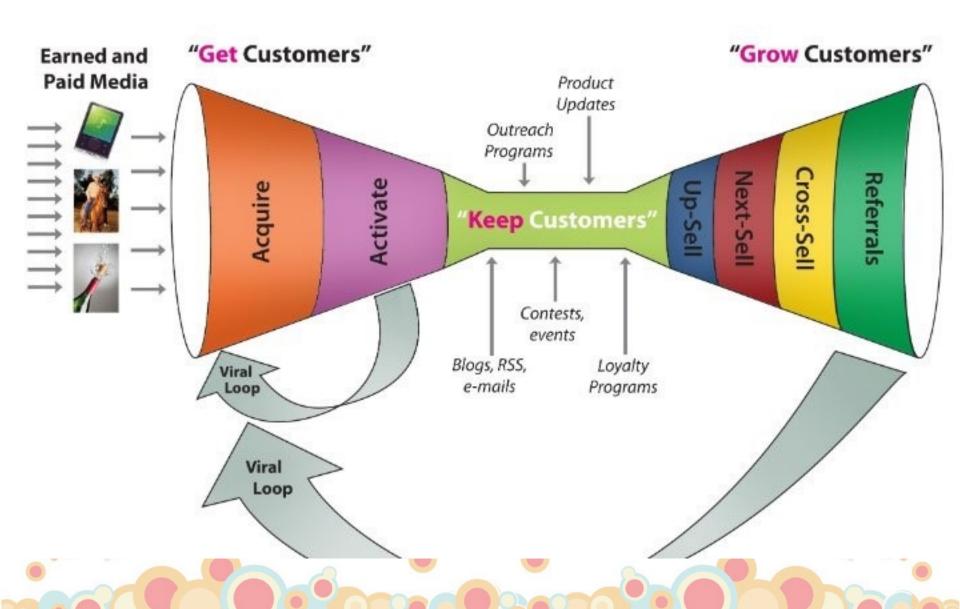
Customer Retention:

Using CRM we can improve customer retention by building brand loyalty and develop the customer by increasing share of wallet through upsell, cross-sell and referrals















Brand Touchpoints



HOW IS THIS DONE?

Customer Segmentation

Customer segmentation is the practice of dividing a customer base into groups of individuals that are similar in specific ways relevant to marketing, such as age, gender, interests and spending habits.

searchcrm.techtarget.com

Customer Segmentation is the subdivision of a market into discrete customer groups that share similar characteristics. Customer Segmentation can be a powerful means to identify unmet customer needs.

Bain and Company

Segmentation

Approaches:

1. RULE-BASED SEGMENTATION

Simple logic, user-focused, quick to define and execute

2. ALGORITHIMICALLY-BASED SEGMENTATION

More complex logic, typically different processing engine and analyst

Types:

1. BEHAVIOURAL SEGMENTATION

Demographic, geographic, technographic, psychographic

2. PREDICTIVE SEGMENTATION

Survival modelling, propensity modelling, Next Best Action

3. DYNAMIC SEGMENTATION

Mapping the migration of populations between segments

Rule-based Segmentation

- Usually SQL-based Spark
- (Supposedly) Simple logic
- Business user-focused
- Application:
 - Quick to define and execute
 - Can be difficult to maintain
 - Need updating and can go stale

Rule-based Segmentation

```
CREATE TABLE #WORKSHEETS (WorkId Int)
INSERT #WORKSHEETS
SELECT WorkId
                               = WORS.WORK ID
FROM
       CARS.DBO.WORS WorksheetsLeads
INNER
       JOIN CARS.DBO.LEAD Leads
                                           LEADS ON LEADS.LEAD_ID = WORS.LEAD_ID AND WORS.WORK_ID IS NOT NULL
INNER JOIN COM.DBO.CNTL ContactCenterLeads
                                                  CNTL ON LEADS.LEAD OldCode = CNTL.CNTL ID
G<sub>0</sub>
SELECT
    LeadId
                               = LEAD.LEAD ID,
   AffinityGroupId
                                   = CU.AFFINITY GROUP ID,
   CntlId
                               = CNTL.CNTL ID,
   CntlPrimaryId
                                   = CNTL.CNTL PrimaryID,
                               = CONVERT(Int, ISNULL(CNTL Type, 0)),
    CnttID
    CntcID
                               = CNTC.CNTC ID,
    Leads800
                               = CASE WHEN (PHONE.CNTS ID <> 7) THEN 1 ELSE 0 END,
    LeadsWarmTransfer
                                   = CASE WHEN (PHONE.CNRE_ID IS NOT NULL AND PHONE.CNTS_ID = 7) THEN 1 ELSE 0 END,
    LeadsWalkIn
                               = CASE WHEN (WORK.WORK ID NOT IN (SELECT WorkId FROM #WORKSHEETS) AND WORK.AGRA ID = CU.AFFINITY GROUP ID) THEN 1 ELSE 0 END,
                                   = CASE WHEN (CNTL.CNTL Type IN ('0', '1', '2', '3', '4', '5', '6', '7', '8') AND CNTL.AGRP ID = CU.OldId) THEN 1 ELSE 0 END,
    LeadsDistributed
   CntlDate
                               = CNTL.CNTL Datetime.
   WorkDate
                               = WORK.WORK CreatedDate,
    ResultYear
                               = CONVERT(varchar, DATEPART(YY, WORK.WORK CreatedDate), 101),
    ResultMonth
                               = CONVERT(varchar, DATEPART(MM, WORK.WORK CreatedDate), 101),
    ResultQuarter
                                   = CONVERT(varchar, DATEPART(QQ, WORK.WORK CreatedDate), 101)
FROM
       AIME. dbo. LEAD
                                           LEAD
LEFT
       JOIN AIME. dbo. AFFINITY GROUP
                                                  CU ON LEAD.AFFINITY_GROUP_ID = CU.AFFINITY_GROUP_ID
       JOIN CARS.dbo.WORK Worksheets
                                              WORK ON WORK, WORK ID = LEAD, CARS#WORK ID
LEFT
       JOIN CARS.dbo.COWS CodesWorksheetStatus
                                                  COWS ON WORK, COWS ID = COWS, COWS ID
LEFT
       JOIN AIME. DBO. DEALER
                                           DEALER ON LEAD. DEALER ID = DEALER. DEALER ID
LEFT
       JOIN CARS.DBO.EMPL Employees
                                               EMPL ON LEAD.CARS#EMPL ID = EMPL.EMPL ID
                                                  CNTL ON LEAD.COM#CNTL ID = CNTL.CNTL ID
LEFT
       JOIN COM.DBO.CNTL ContactCenterLeads
LEFT
       JOIN COM.DBO.CNRE ContactRequestEmailPhone PHONE ON PHONE.CNTL ID = CNTL.CNTL ID AND CNTL.AGRP ID = CU.OldId
       JOIN COM.DBO.CNRE ContactRequestEmailPhone EPHONE ON EPHONE.CNTL ID = CNTL.CNTL ID
WHERE WORK.WORK_CreatedDate <= '10/1/2014'
AND WORK.WORK CreatedDate >= '1/1/' + CONVERT(varchar, DATEPART(yy, DATEADD(YY, -1, '10/1/2014')), 101)
AND CU.AFFINITY GROUP ID = 11765
```

Algorithmically-based Segmentation

- Unsupervised (Noun) and Supervised (Verb)
- (Supposedly) complex logic
- Analyst focused
- Application:
 - More precise
 - Requires processing framework Spark

- Demographic
 - •Age, Background, Social Class, Economic Class...
- Geographic
 - Address, Current location
- Technographic (indicative of lifestyle)
 - Technology adoption Mobile, Tablet, Browser ...
 - Orbitz found Apple users spend 30% more a night
- Psychographic
 - The 4-Cs Cross Cultural Consumer Characterisation

Demographic

The socio-economic scale

Social grade	Description of occupation	Example
A	higher managerial, administrative or professional	Company director
В	intermediate managerial, administrative or professional	Middle manager
C1	supervisory, clerical, junior administrative or professional	Bank clerk
C2	skilled manual workers	Plumber
D	semi- and unskilled manual workers	Labourer
E	state pensioners with no other income, widows, casual and lowest grade earners	Unemployed

Geographic

ACORN

A. Agricult	ural areas
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- B. Modern family housing, higher incomes
- C. Older housing of intermediate status
- D. Poor quality older terraced housing
- E. Better-off council estates
- F. Less well-off council estates
- G. Poorest council estates
- H. Multi-racial areas
- I. High status non-family areas
- J. Affluent suburban housing
- K. Better-off retirement areas
- U. Unclassified

3% of UK population18% of UK population17% of UK population

4% of UK population

13% of UK population

9% of UK population

7% of UK population

4% of UK population

4% of UK population

16% of UK population

4% of UK population

1% of UK population

Psychographic

Aspirer

Succeeder

Explorer

Reformer

The 4Cs Cross Cultural Consumer Characterisation

Resigned	Rigid, strict, authoritarian and chauvinist values, oriented to the past and to Resigned roles. Brand choice stresses safety, familiarity and economy. (Older)
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Alienated, Struggler, disorganised - with few resources apart from physical/mechanical skills (e.g. car repair). Heavy consumers of alcohol, junk food and lotteries, also trainers. Brand choice involves impact and sensation.

Domestic, conformist, conventional, sentimental, passive, habitual. Part of **Mainstreamer** the mass, favouring big and well-known value for money 'family' brands. Almost invariably the largest 4Cs group.

Materialistic, acquisitive, affiliative, oriented to extrinsics ... image, appearance, charisma, persona and fashion. Attractive packaging more important than quality of contents. (Younger, clerical/sales type occupation)

Strong goal orientation, confidence, work ethic, organisation ... support status quo, stability. Brand choice based on reward, prestige - the very best . Also attracted to 'caring' and protective brands ... stress relief. (Top management)

Energy - autonomy, experience, challenge, new frontiers. Brand choice highlights difference, sensation, adventure, indulgence and instant effect - the first to try new brands. (Younger - student)

Freedom from restriction, personal growth, social awareness, value for time, independent judgement, tolerance of complexity, anti-materialistic but intolerant of bad taste. Curious and enquiring, support growth of new product categories. Select brands for intrinsic quality, favouring natural simplicity, small is beautiful.(Higher Education)

Technographic

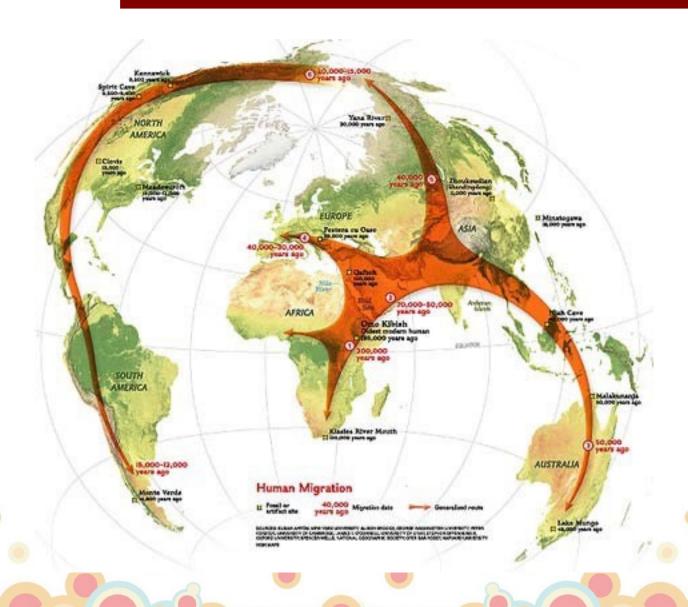
Primary motivation Career Entertainment Family (2596)(24%)(22%)High income Mouse Potatoes are Fast Forwards are time-New Age Nurturers are fechnology optimist (50%) underserved believers in dedicated to interactive strapped, driven, and technology for family entertainment. top users of technology. and education. especially on the PC. 13% 8% 9% Low income Digital Hopefuls are family-Gadget Grabbers are Techno-Strivers are oriented technology lovers: focused on low-cost, highup-and-coming believers Technology attitude a promising market for tech toys like MP3 players in technology for low-cost PCs. and portable game players. career advancement. 6% 7% 8% Technology pessimist (45%) High income Traditionalists are Media Junkies are visual Handshakers are suspicious of successful professionals TV lovers and interested technology in TV features like video with a low technology beyond the basics. on demand. tolerance. 6% 9% 5% Low income Sidelined Citizens are technophobes and technology laggards, the least receptive audience for any technology or digital channel.

25%

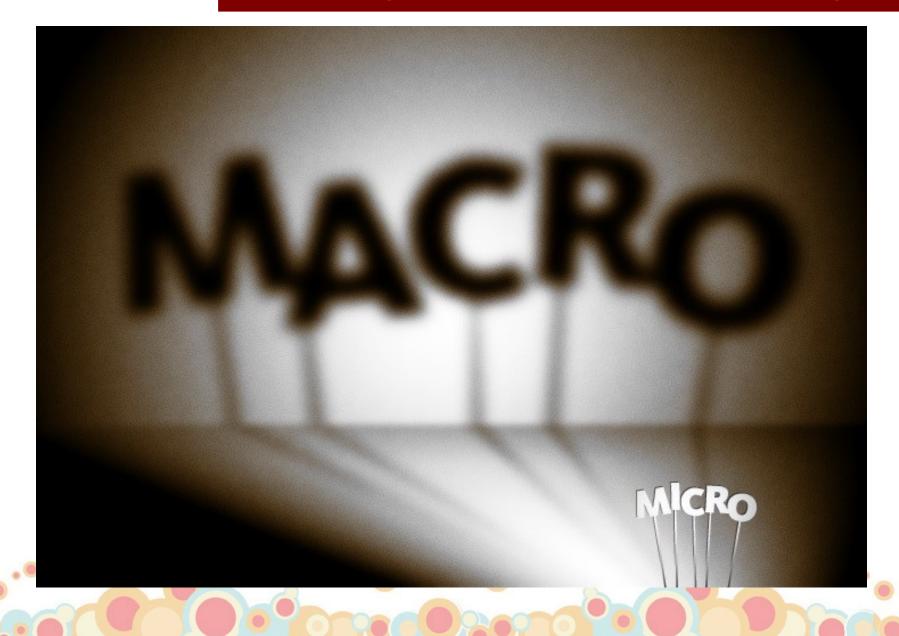
Predictive Segmentation

- Survival or Churn modelling
 - Mobile Phone Networks, Social Networks, Brands
 - Classification Algorithms churn / not churn
- Propensity modelling
 - Propensity / Likelihood of someone to buy
- Next Best Action
 - Offers, Cross sell, Up sell, Service Recovery

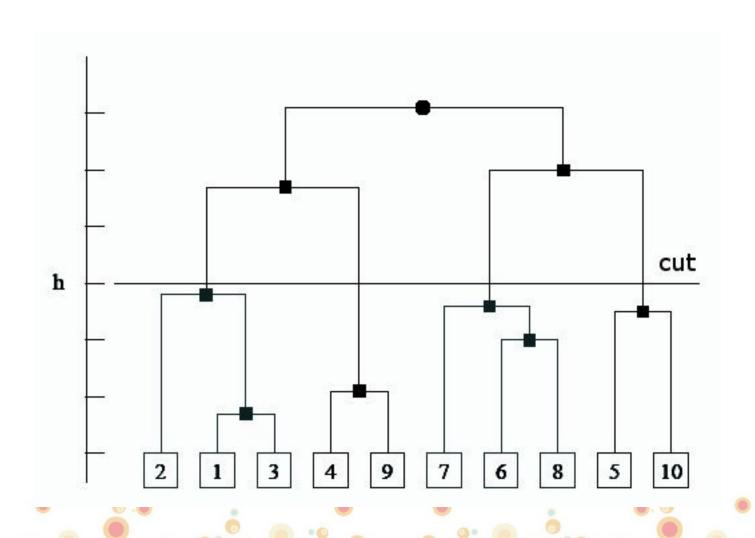
Dynamic Segmentation



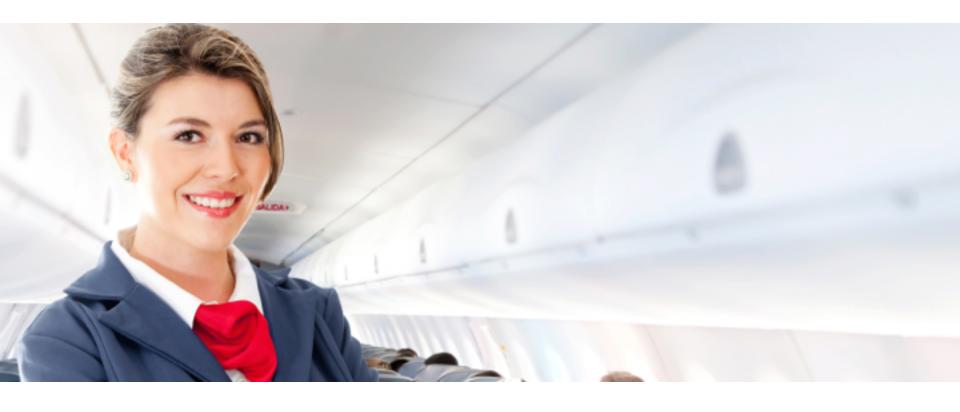
Segmentation Strategies



Segmentation Strategies



Personalisation



Automated Customer Engagement - NBA, Service Recovery

From the web - Amazon, Booking, Spotify, Hotels, RyanAir

To the real world - In Cabin, Airport Shopping

MACHINE LEARNING WITH SPARK



- MLIB Version 2.10s
- Comprehensive suite of algorithms
- One infrastructure to address a wide range of problems

- Basic Data Types
- Basic Statistics
- Supervised
 - Classification and Regression
- Unsupervised
 - Collaborative Filtering (Matrix Factorisation)
 - Clustering
 - Dimensionality Reduction
- Frequent Pattern Matching
- Evaluation
- PMML Publishing and Sharing

Data Types

- Local Vector
 - Vector on a single machine
 - Sparse and Dense Vector types
- Labelled point
 - Vector associated with a label/response
- Local Matrix
 - Dense and Sparse Matrices supported
- Distributed Matrix
 - RowMatrix, IndexedRow Matrix, Coordinate Matrix

- Data Statistics
 - Summary Statistics

val summary: MultivariateStatisticalSummary = Statistics.colStats(observations)
println(summary.mean)

Correlations

val correlation: Double = Statistics.corr(seriesX, seriesY, "pearson")

- Stratified Sampling splits automatically on a given level val approxSample = data.sampleByKey(withReplacement = false, fractions)
 - Hypothesis Testing
 - Random data generation

 $val\ u = normalRDD(sc, 1000000L, 10)$

Supervised

- Classification (Binary and Multinomial)
 - Linear SVM
 - Logistic Regression
 - Decision trees (random forests)

Regression

- Linear Regression (Linear least squares)
- Lasso (Support regularisation and feature selection)
- Ridge Regression (Addresses Co-linearity)
- Streaming linear regression (A version of online learning)
- Decision Tree Regression

Unsupervised

- Collaborative Filtering (Matrix Factorisation)
 - Supports user-item recommendation
 - Supports Implicit and Explicit Feedback

Clustering

- K-means
- Gaussian Mixture Models
- Latent Dirichlet allocation (Topic Modelling)
- Bisecting k-means, Streaming K-means

Dimensionality Reduction

- PCA
- SVD

Evaluation

Classification

- Confusion Matrix
- Precision (Positive Predictive Value)
- Recall (True Positive Rate)
- F-measure
- Receiver Operating Characteristic (ROC)
- Area Under ROC Curve

Regression

- Mean Squared Error (MSE)
- Root Mean Squared Error & Mean Absolute Error
- Coefficient of Determination (R2)

Publishing and Sharing

- PMML Format
 - An XML-based predictive model interchange format
 - Enabled publishing and sharing models (zementis, r, Oracle)

Models

- K-means
- Linear Regression Model
- Ridge Regression Model
- Lasso Model
- SVM Model
- Logistic Regression Model

SUMMARY

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 - Basic Statistics
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Further Reading

MLIB Release:

https://databricks.com/blog/2014/07/16/new-features-in-mllib-in-spark-1-0.html

Lasso Explained:

https://www.youtube.com/watch?v=qU1_cj4LfLY

Ridge Regression Explained:

http://www.ncss.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Ridge_Regression.pdf

Netflix Prise using Matrix Factorisation:

http://dx.doi.org/10.1007/978-3-540-68880-8_32

Gaussian Mixture Models

https://www.youtube.com/watch?v=Rkl30Fr2S38

Questions

