CLIRS: Customer Loyalty Improvement Recommender System.

Developed for the Daniel Group (2013-2018)

presented by

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Research sponsored by

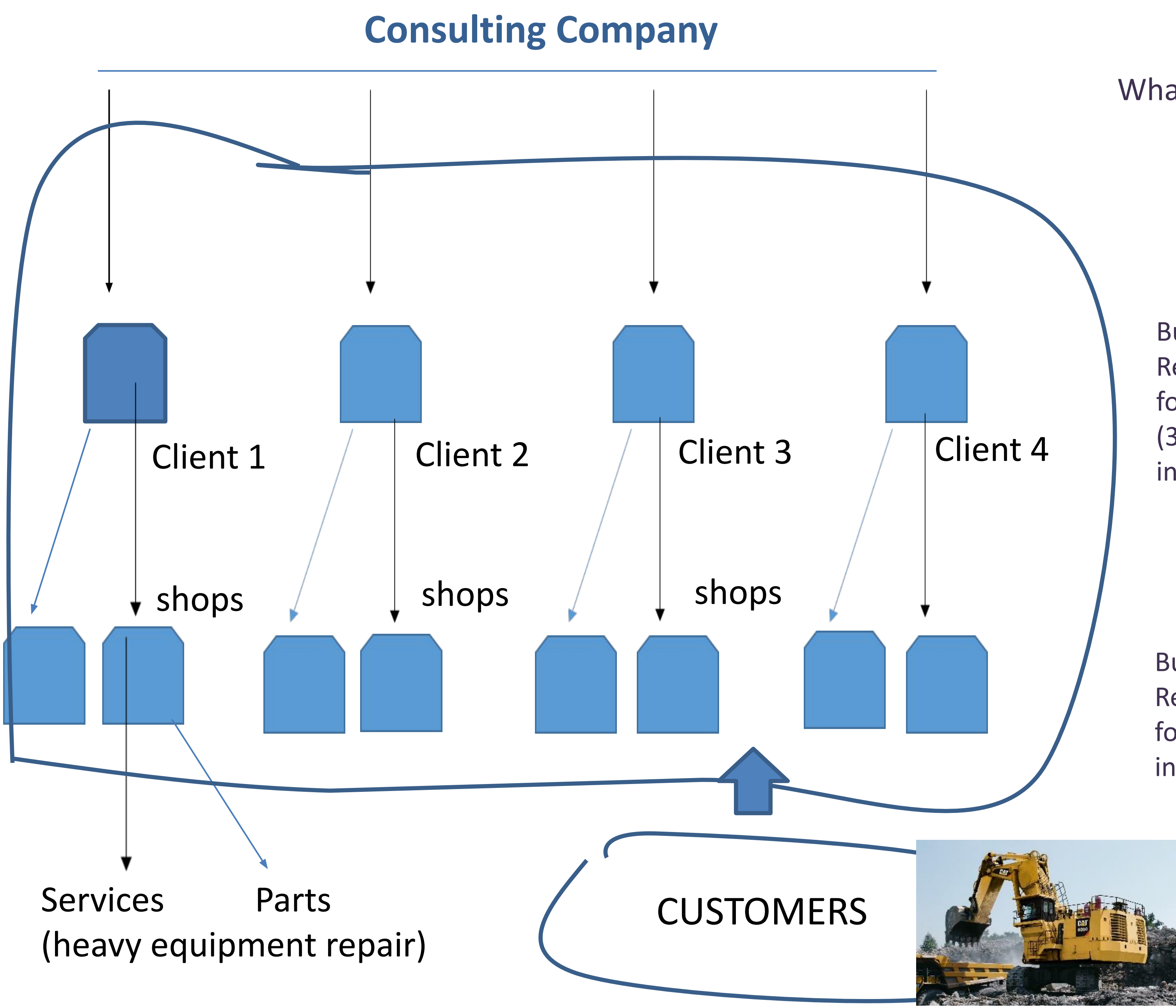
TheDanielGroup

NSF

What we had to do

Build
Recommender System
for each **client**
(34 clients) helping to
increase its revenue

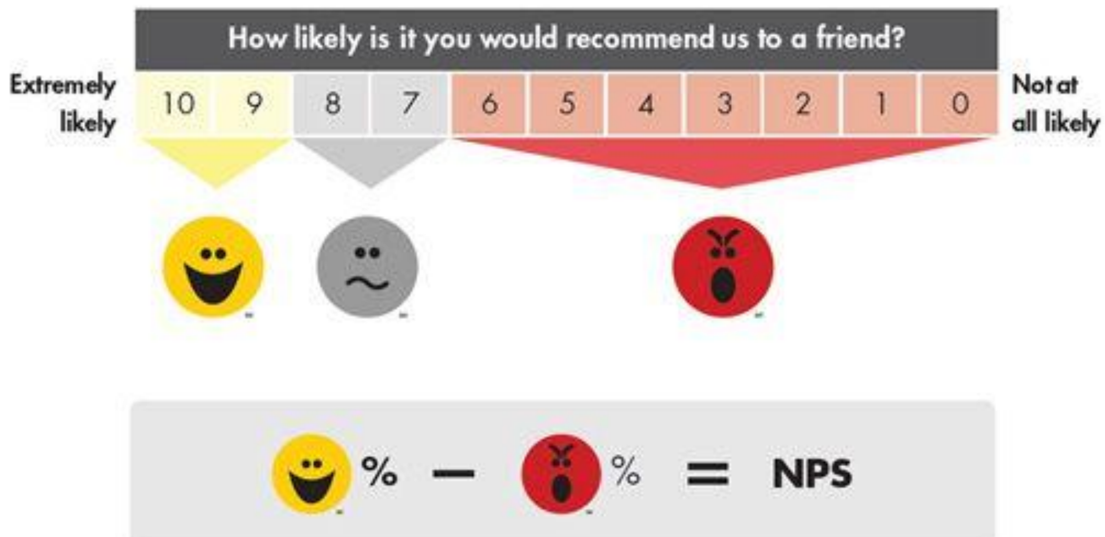
Build Personalized
Recommender System
for each **shop** helping to
increase its revenue



NPS is correlated with company revenue growth

Net Promoter Score (NPS) –

today's standard for measuring customer loyalty

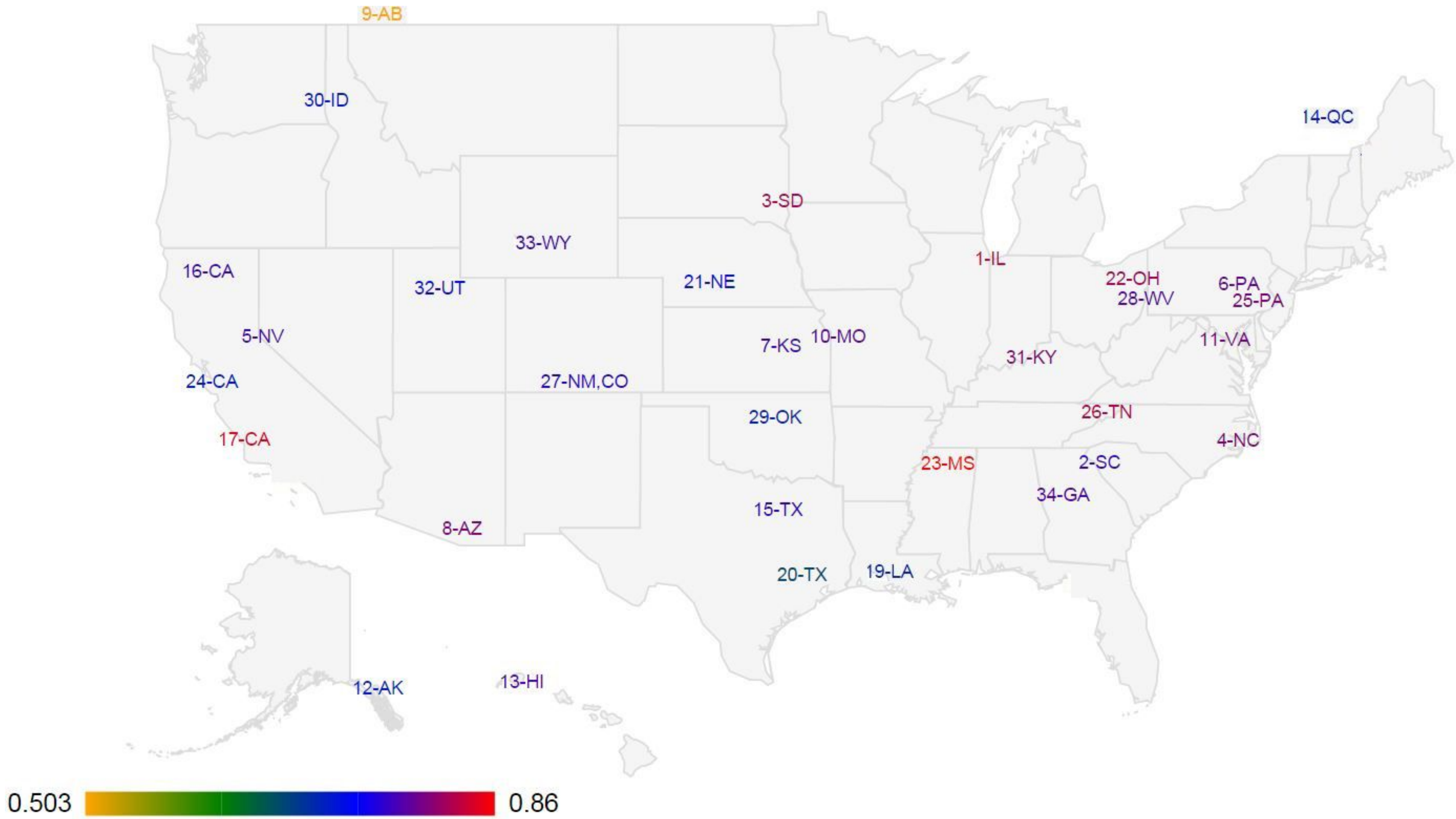


Promoter - {9,10}

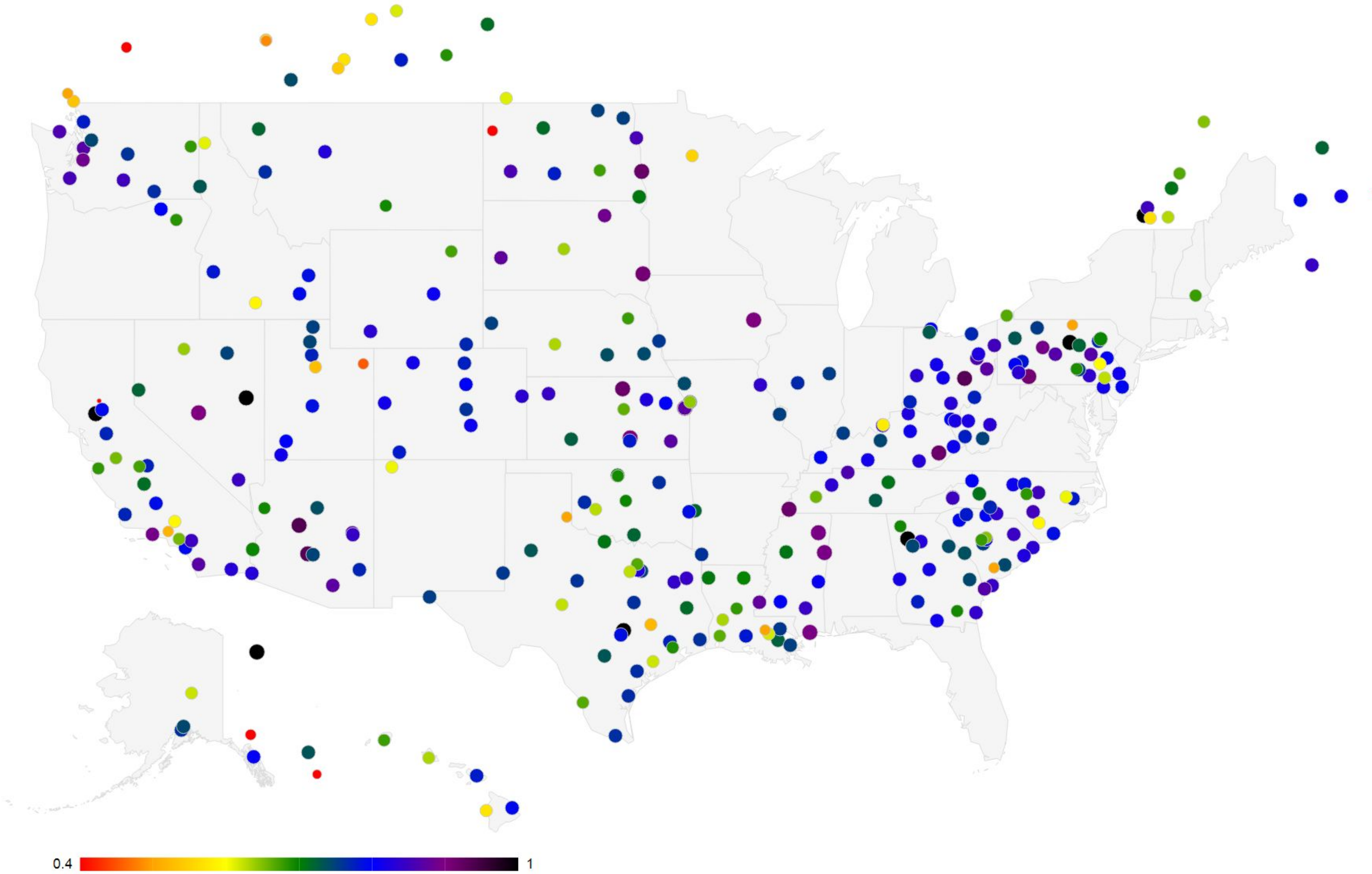
Passive – {8,7}

Detractor – {1,2,3…,6}

NPS rating for all clients



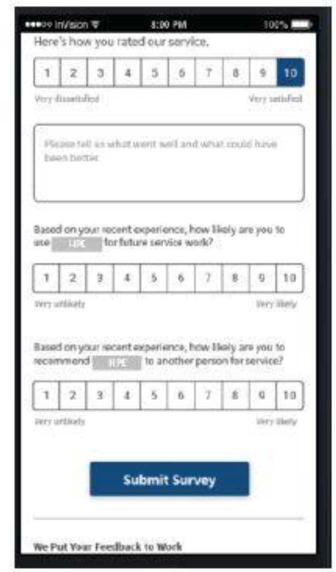
NPS rating for all shops



Structured and unstructured feedback

CLIRS ← Our System

- Score ratings - 0-10 scale, "star" ratings
- Unstructured: free-form text
  - thoughts
  - feelings
  - expectations



Initial Dataset – provided by Consulting Company

About 100,000 records representing answers to a questionnaire collected from over 35,000 randomly chosen customers in 2010 -2013.

Customers use services provided by 34 clients

Latest samplings:
about 300,000 records per year, 2010-2018

A questionnaire consists of:

Information about the customer
- Customer's name, location, phone number…

Information about the service
- Client's name, invoice amount, service type…

Information on customers' feeling about the service
- was the job completed correctly
- are you satisfied with the job
- likelihood to refer to friends
- …

Personal

Benchmarks

Decision Table built from customers survey

Customer	M/F	Phone	Bench1	Bench2	Bench3	Comments	Promoter Status
2011	M		3	9	5	text1	Promoter
2012	M		8	10	8	text2	Promoter
2013	F		8	5	8	text3	Detractor
2014	F		5	7	7	text4	Passive

New attributes can be derived

Text Mining & Sentiment Mining
can be used to build new attributes

Coming back to our customers feedback dataset

Rough Set REDUCTS have been used to identify features having the strongest impact on Promoter

Benchmark All Overall Satisfaction	35
Benchmark All Likelihood to be Repeat Customer	34
Benchmark All Dealer Communication	33
Benchmark Service Repair Completed Correctly	32
Benchmark Referral Behavior	31
Benchmark Service Final Invoice Matched Expectations	31
Benchmark Ease of Contact	30
Benchmark All Does Customer have Future Needs	28
Benchmark Service Tech Promised in Expected Timeframe	26
Benchmark Service Repair Completed When Promised	26
Benchmark Service Timeliness of Invoice	25
Benchmark Service Appointment Availability	24
Benchmark Service Tech Equipped to do Job	23
Benchmark All Contact Status of Future Needs	22
Benchmark Service Tech Arrived When Promised	21
Benchmark All Has Issue Been Resolved	19
Benchmark All Contact Status of Issue	17
Benchmark Service Technician Communication	6
Benchmark Service Contact Preference	3
Benchmark CB Call answered promptly	1
Benchmark Service Received Quote for Repair	1
Benchmark CB Auto attendant answered by correct department	1
Benchmark Service Call Answered Quickly	1
Benchmark All Marketing Permission	1

Randomly chosen customers are asked to complete Questionnaire. It has questions concerning personal data + 30 benchmarks

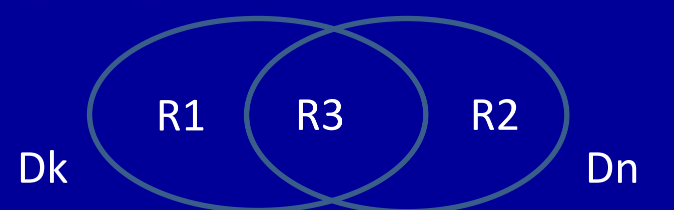
Semantic Similarity

$R_k = \{r_{k,i}: i \in I\}$ set of rules extracted from decision table D_k and $[c_{k,i}, s_{k,i}]$ denotes the confidence and support of rule r_i for all $i \in I_k$, $k=1,2$
With R_k, the number $K(R_k) = \Sigma\{ c_{k,i} \cdot s_{k,i} : i \in I_k\}$ is associated.

Assume that $R_k = \{r_{k,i}: i \in I\}$ is set of rules extracted from decision table D_k and $R_n = \{r_{n,j}: j \in J\}$ set of rules extracted from decision table D_n.
Also, assume that $R = [R_k - R_n] \cup [R_n - R_k] \cup [R_n \cap R_k]$,
$R1=[R_k - R_n] = \{r_{1,\, i1}: i1 \in I1\}$, $R2=[R_n - R_k] = \{r_{2,\, i2}: i2 \in I2\}$,
$R3=[R_n \cap R_k] = \{r_{3,\, i3}: i3 \in I3\}$.

The semantic distance $dist(D_k,D_n)$ between decision tables D_k and D_n, is defined as $\Sigma\{ c_{1,i1} \cdot s_{1,i1}: r_{1,\, i1} \in R1\} + \Sigma\{ c_{2,i2} \cdot s_{2,i2} : r_{2,\, i2} \in R2\} +$
$\Sigma\{ |c_{3,i1} - c_{3,i2}| \cdot | s_{3,i1} - s_{3,i2}| : r_{3,\, i3} \in R3\}$

Smaller the distance between tables, more similar they are.



RECOMMENDER SYSTEM CLIRS

based on semantic extension of a client dataset
created by adding datasets of other semantically similar clients

Classical Approach

Data

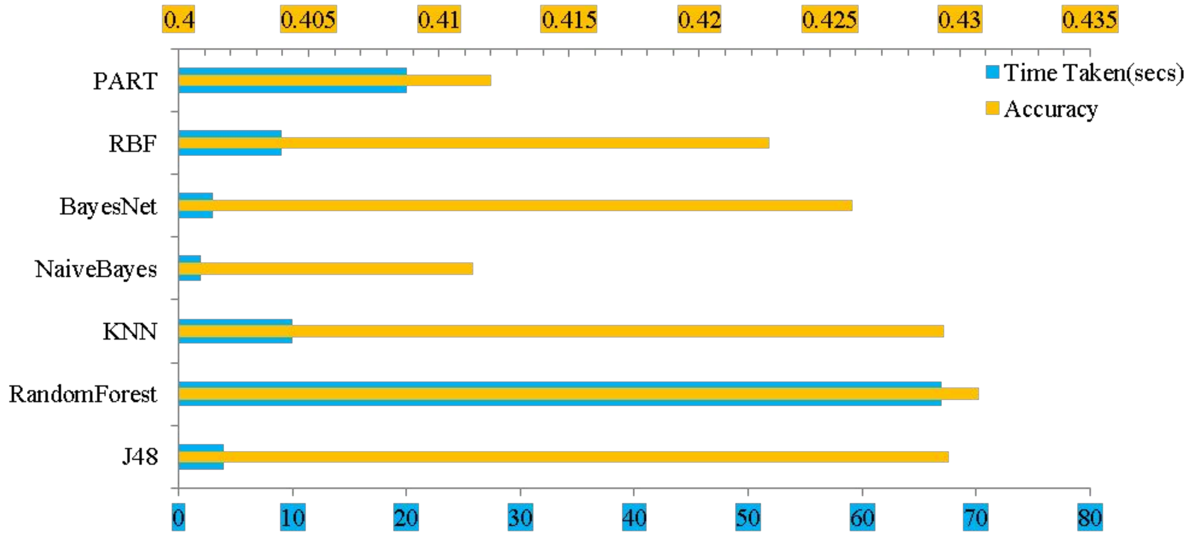
Data Preprocessing (including reduction of benchmarks)

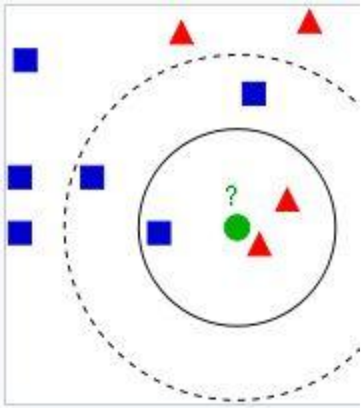
Knowledge Extraction
(Classical Tools - WEKA +
Our Software for Extracting Action Rules & Their Triggers)

Recommender Systems

Classification

Selection of Best Classification Algorithm





Example of k-NN classification.

	PART	RBF	BayesNet	NaiveBayes	KNN	RandomForest	J48 ★
Accuracy	2	3	4	1	5	7	6
Time Taken	2	4	6	7	3	1	5
Total score	4	7	10	8	8	8	11

Two Options

Initial Clients Datasets

1

Recommender Systems

local approach

2

global approach

Using Information about 34 Clients to Enlarge these Datasets

2

global approach

More Powerful Recommender Systems

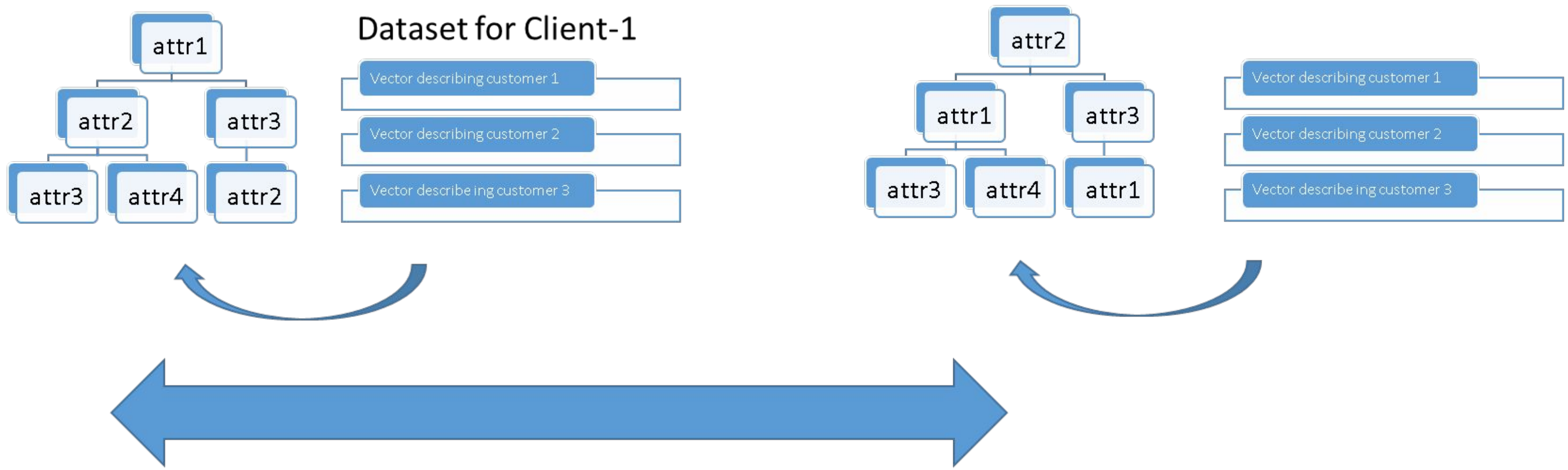
FIRST APPROACH for Dataset Enlargement

Semantic Distance between Clients

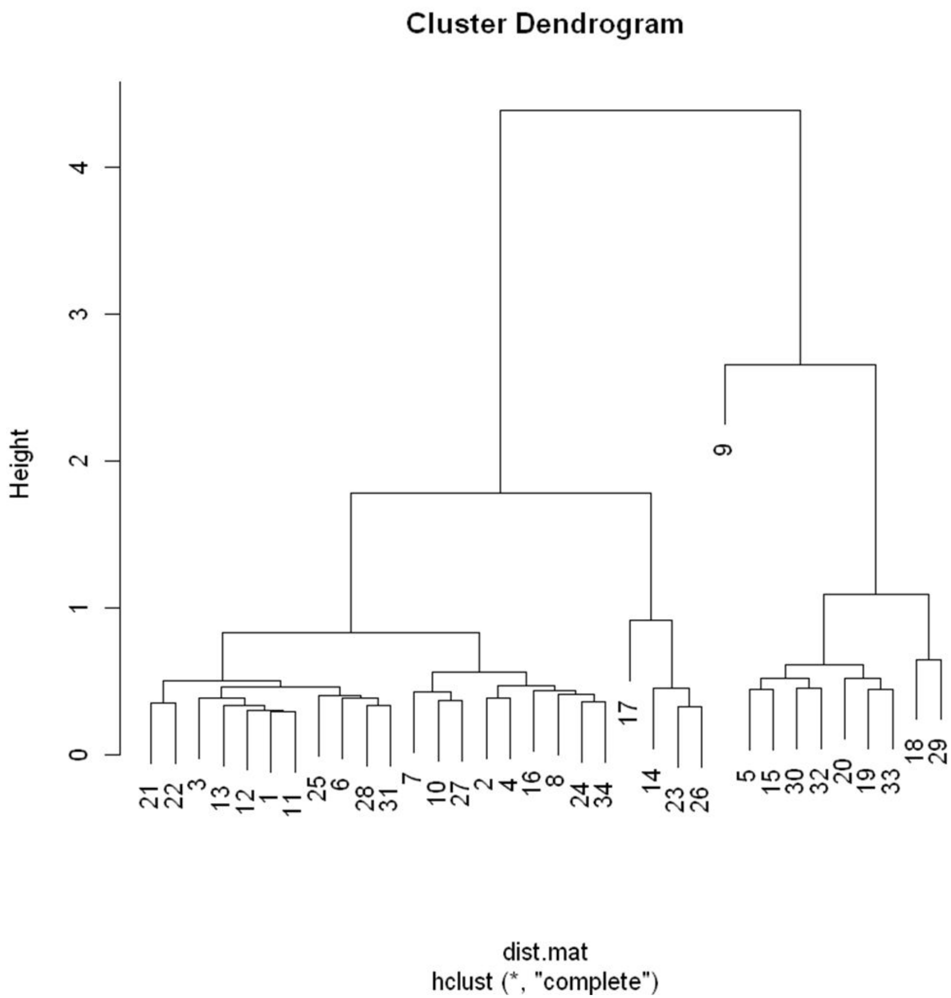
J48 classifier extracted from dataset D1 of Client-1

J48 classifier extracted from dataset D2 of Client-2

Dataset for Client-2



More similar these two classification trees, more close semantically the clients are



Semantic distance based dendrogram for Service

Recommender System Engine based on Semantic Similarity of Clients

Start with n1.
If NPS(n1) has to be improved, *"move to n3"*
If NPS(n2) > NPS(n1), then
Table3 := Table1 ∪ Table 2 is assigned to n3.
Classifier from Table3 is extracted and its
F-score is computed.

If F-score3 > F-score1,
then *"move to n5"*, otherwise STOP

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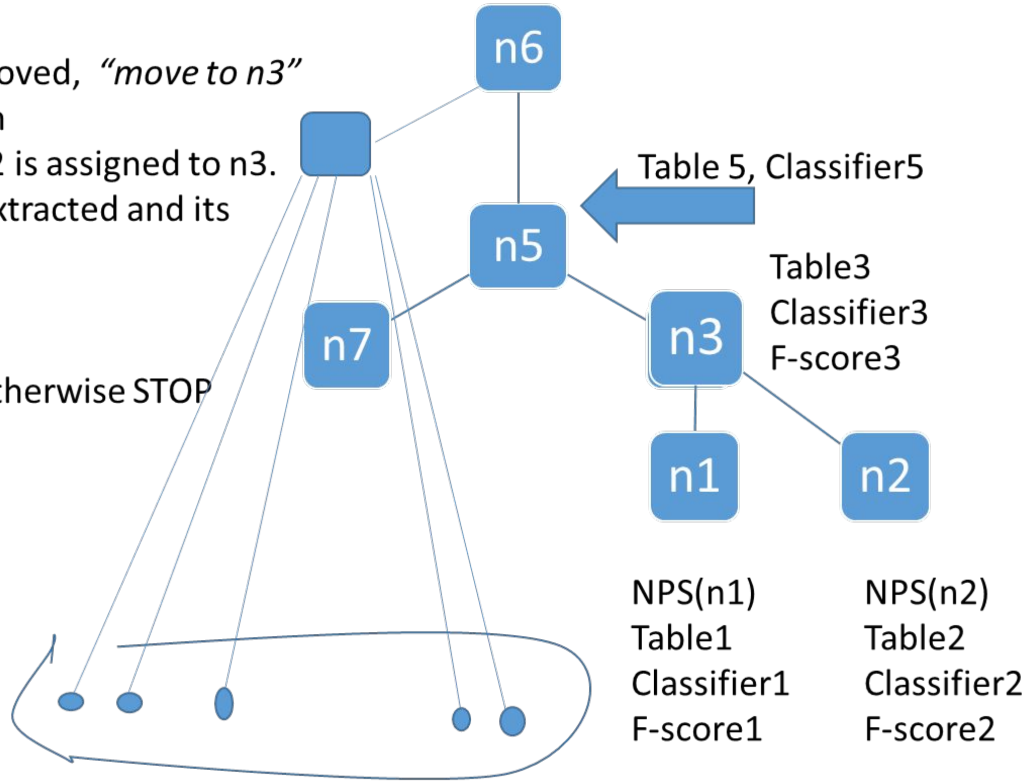


For each client (node) we need to identify the best ancestor to be used for action rules discovery

Extracting Meta-Actions

DATASET

Customer	Bench1	Bench2	Bench3	Comments	Prom_Stat
Cust1	high	med	high	C1, C2	Prom
Cust2	med	med	med	C2, C3	Pass
Cust3				C4, C3	

Benchmark Values ={low, medium, high}

Extracting Comments

C1
C2
C3
C4

C1 refers to Bench2
C3 refers to Bench1
C2,C4 refers to Bench3

Guided Folksonomy &
Sentiment Analysis

Meta-Actions

C2,C4 Knowledgeable Staff

C1,C3 Friendly Staff

Extracted Rules (example)

R1=[(Bench1=high)&(Bench2=med) ……………...... ⇒ (Prom_Stat = Prom)] sup(R1)={Cust1,..}; Let's say Confidence=90%
R2=[(Bench1=med)& ……………. (Bench3=med) ⇒ (Prom_Stat = Pass)] sup(R2)={Cust2,..}; Let's say Confidence=95%

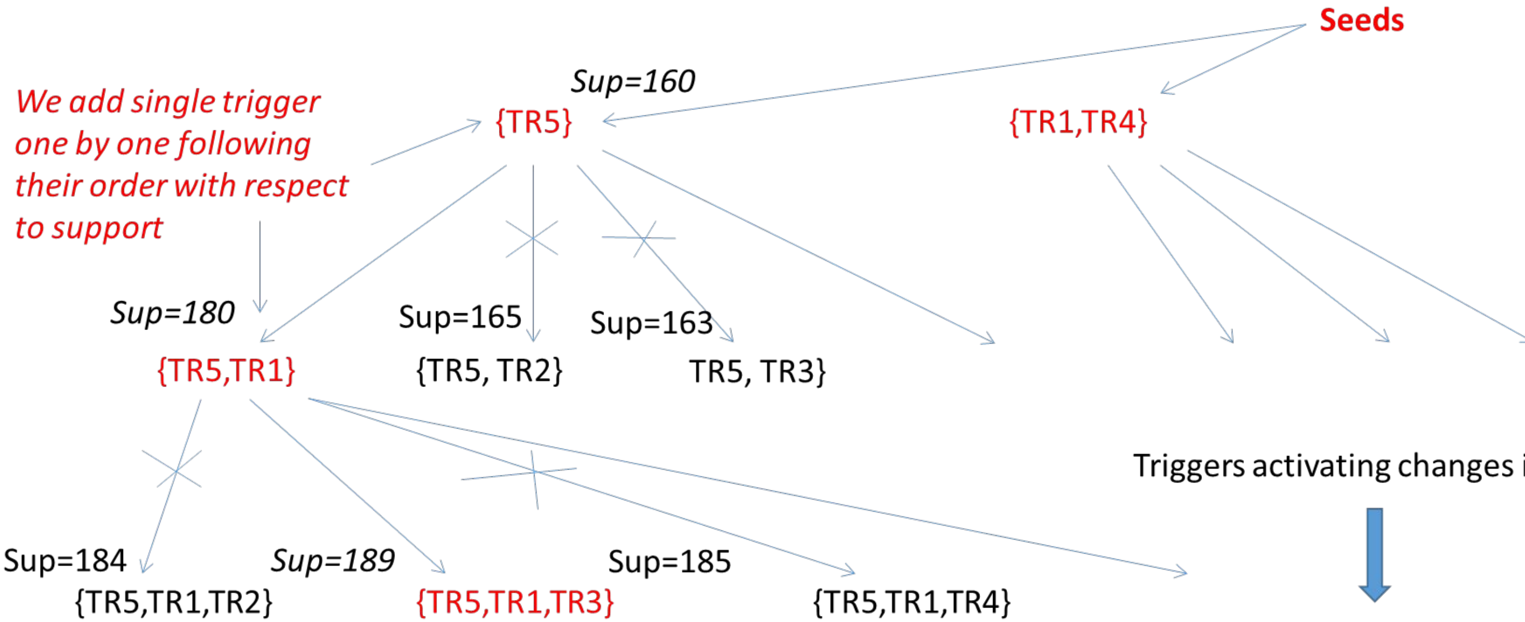
Action Rules

R= [(Bench1, med ->high)&(Bench2=med) ⇒ (Prom_Stat, Pass -> Prom)] Sup(R)={Cust2,..}; Confidence=90%*95%=85.5%.

Recommendation: Staff has to be more friendly (R will be activated)

How to construct optimal sets of meta-actions (triggers activating changes in customer NPS)

Threshold for adding triggers = 6



Triggers activating changes in customer NPS

1	2	3	4
TR5	{TR1,TR4}	{TR5,TR1,TR3}	
	{TR5,TR1}		

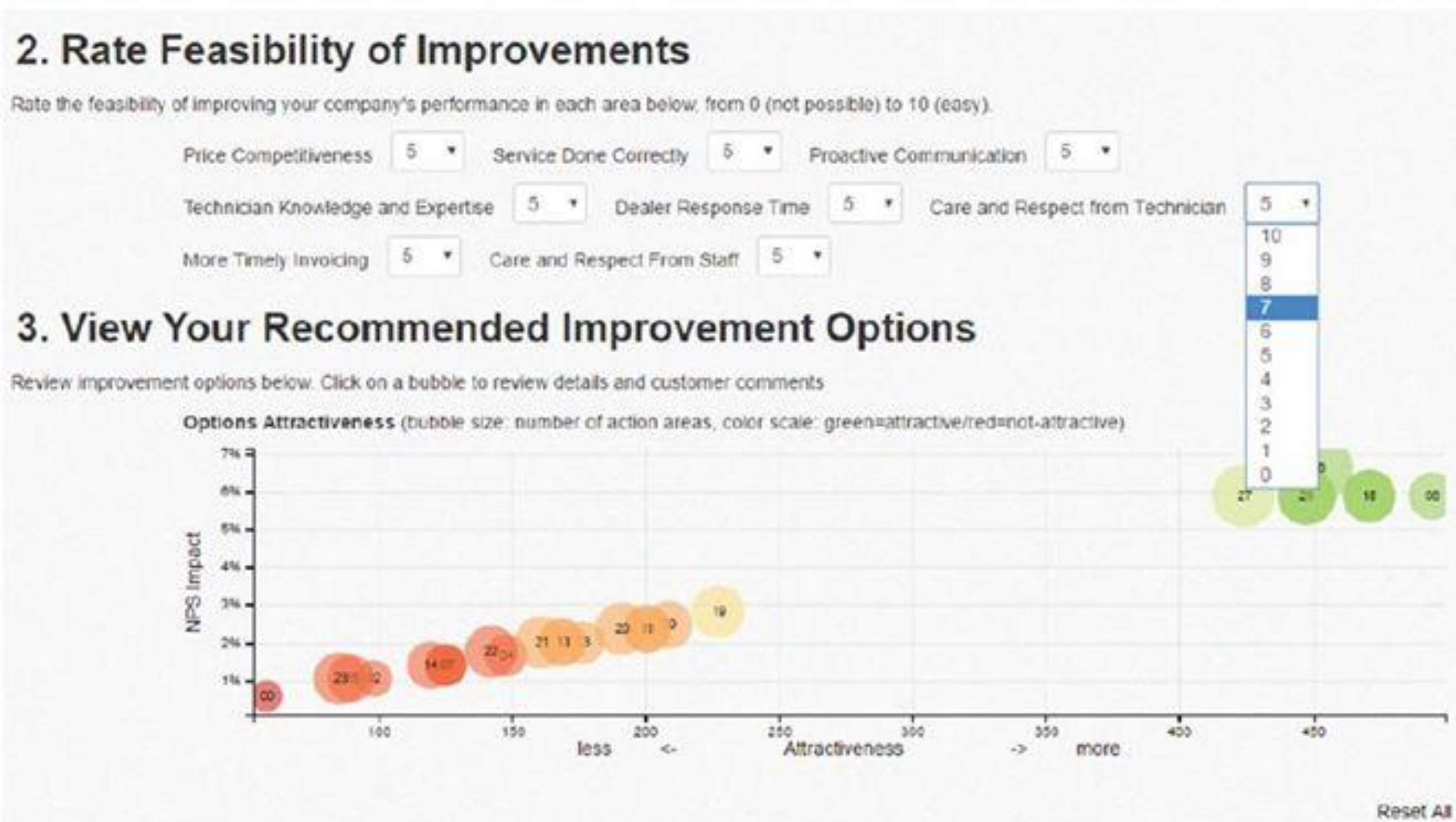
Search for the best sets of meta-actions for Client-2

idx	Meta-actions	effect
0	• ensure service done correctly	2.00
1	• ensure service done correctly • improve price competitiveness	7.62
2	• ensure service done correctly • properly set invoice expectations(slightly high)	5.0
3	• ensure service done correctly • sufficient staff	2.0
7	• ensure service done correctly • competitive price • improve price competitiveness	11.13
8	• ensure service done correctly • improve price competitiveness • sufficient staff	10.66
9	• ensure service done correctly • improve price competitiveness • properly set invoice expectations(slightly high)	9.99
10	• ensure service done correctly • improve price competitiveness • keep proactive communication	8.62

idx	Meta-actions	effect
22	• ensure service done correctly • competitive price • improve price competitiveness • sufficient staff	15.07
23	• ensure service done correctly • improve price competitiveness • properly set invoice expectations(slightly high) • sufficient staff	15.00
24	• ensure service done correctly • competitive price • improve price competitiveness • reasonable invoice	13.13
25	• ensure service done correctly • improve price competitiveness • reasonable invoice • sufficient staff	11.66
46	• ensure service done correctly • competitive price • improve price competitiveness • properly set invoice expectations(slightly high) • sufficient staff	19.41

User-Friendly Interface

NPS Impact Calculation and Improvement Options



Summary generation

Example: Set of Meta-Actions (with comments from customers)

Action Areas	Positive Comments	Negative Comments
08		
Proactive Communication	13685848 == Noel said that they communicated well to the customer. 13603456 == He stated good communication. 13686554 == He stated that they communicated well throughout the whole process. 12740469 == He stated they have good personal contact, they took time to explain everything and completed everything in a timely manner. 13976889 == He stated the communication between the 2 offices and his point of contact at carter. He stated the communication works well. 14811290 == Kenneth stated that the service manager stays in contact with him and provides good communication on status of repairs. 14922398 == John said contact is good. 14649902 == James said they have good communication and kept him informed. 12489864 == Peter said technician was easy to get along with and had good communication.	
Price Competitiveness	13602587 == He stated that they provided great service. The technician was on time, very knowledgeable and the pricing was good. 12262972 == He said they are very thorough, easy to work with, and the pricing is reasonable.	15098796 == Boog stated that they repaired the machine and got it going, but it is high priced. 15146035 == Hank stated while they are fast, and have good service, he feels the prices are too high.
Service Done Correctly	14969790 == Cole stated the job was done correctly the first time. 14027457 == He stated it was the way they handled the issue and got fixed in a timely manner. 12490730 == Joel stated the technician is efficient, came out right away and able to get right to the job and repair it correctly.	13741853 == Robert stated they made sure the problem got fixed quickly. 12994165 == Keith stated that the technician was very friendly.

Leaves

UNC CHARLOTTE

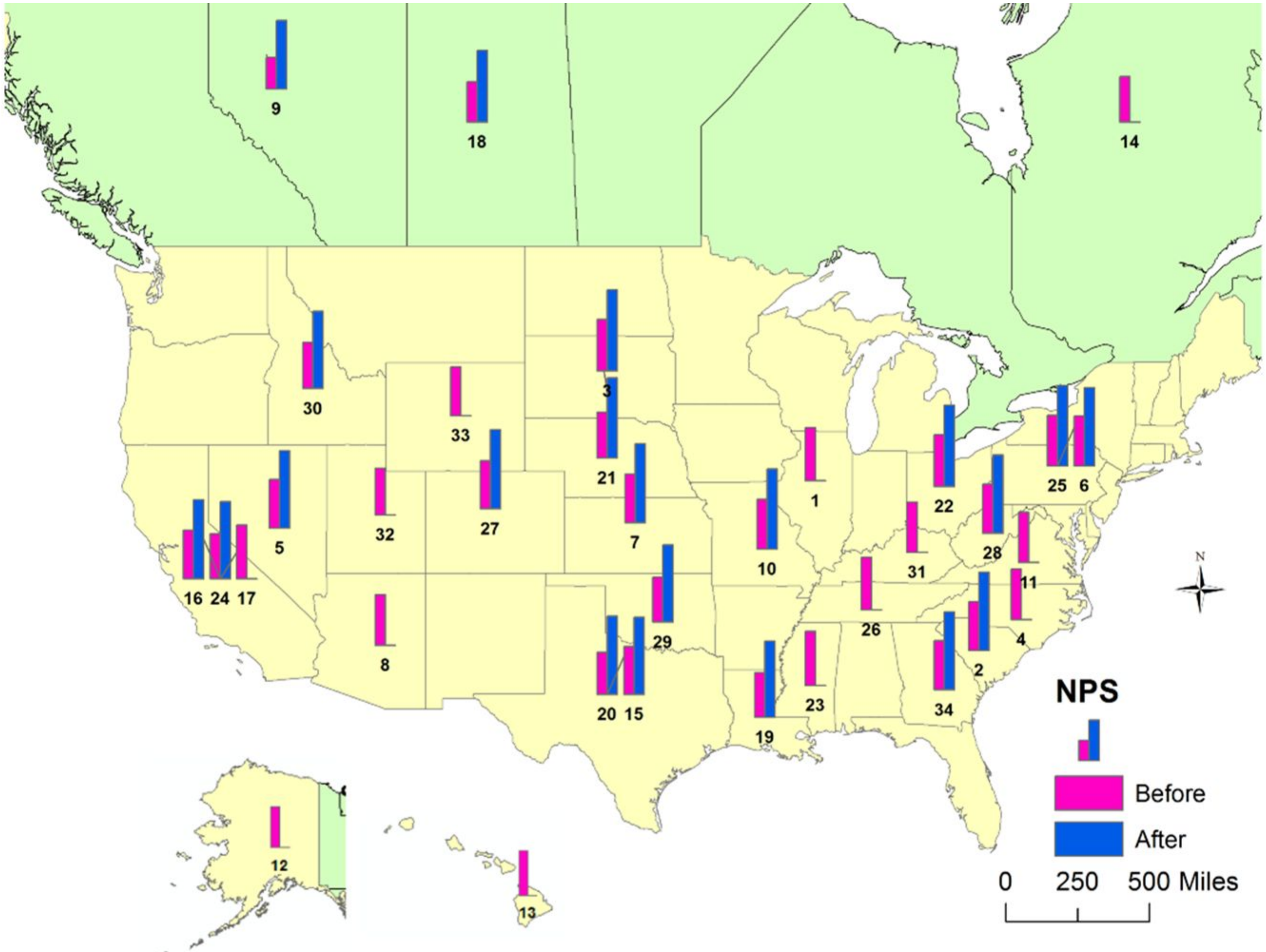
Buckets: Staff, Invoice, Price
(labels assigned to leaves constructed by folksonomy)

Examples of Comments with Sentiment Orientation

staff+++++,best manager=112
staff-----,bad experience because diagnosis=108
staff+++++,good technician=96
staff+++++,nice guy=87
staff+++++,excellent mechanic=85
staff+++++,great guy=83
staff+++++,excellent technician=79
staff+++++,good guy=74
staff+++++,wonderful dealer=71
staff+++++,good team=66
staff+++++,honest guy=60
staff+++++,pleased with manager=40
staff-----,not available technician=34
staff-----,wrong diagnosis=16
staff+++++,best mechanic=12
staff+++++,knowledgeable mechanic=6

invoice+++++,outstanding bill=141
invoice+++++,they billed properly=65
invoice+++++,fine invoice=61
invoice-----,refused pay bills=29
invoice+++++,happy with bill=12

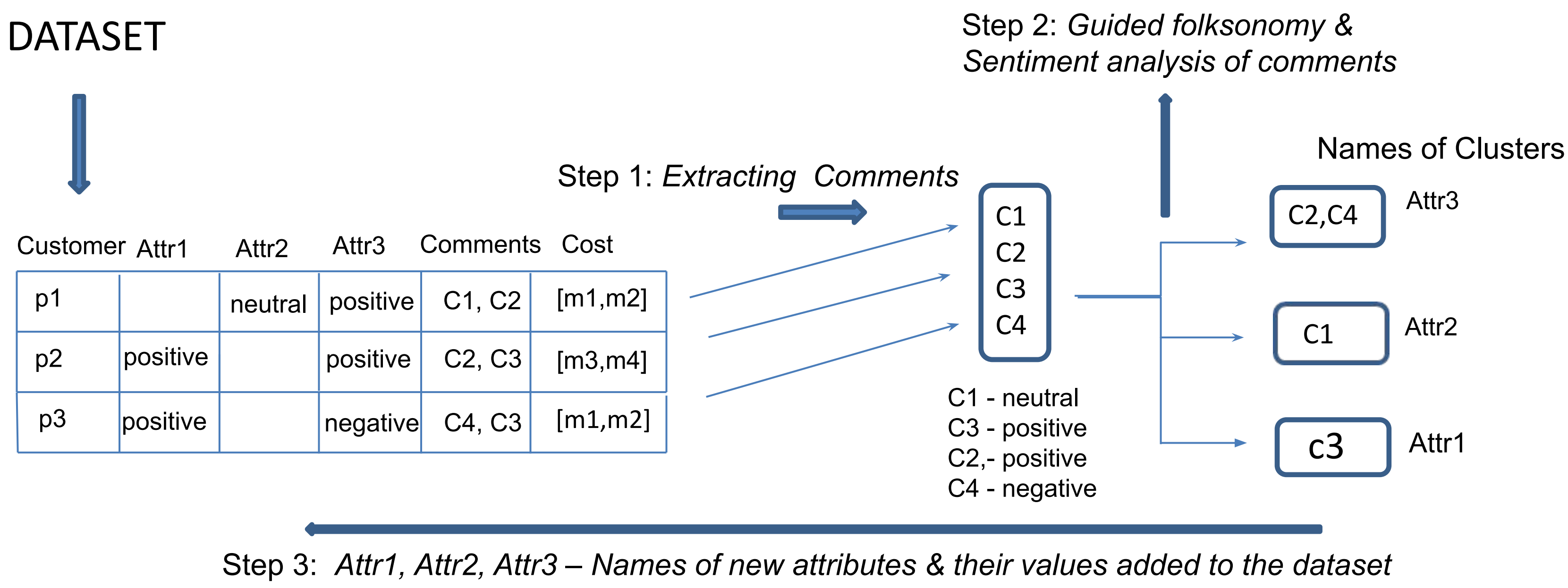
price-----,not fair pricing=108
price+++++,good price=108
price+++++,fair pricing=87
price-----,aggressive pricing=66
price-----,unreasonable charge fee=37
price-----,not satisfied with price=35
price+++++,better pricing=27
price-----,expensive amount charged=12
price+++++,the charged fairly=12



Columns in blue color show minimal expected improvement in NPS after following advice given by recommender system on clients level

Recommender System


Q
&
A


DATASET
Step 1: *Extracting Comments*
Step 2: *Guided folksonomy & Sentiment analysis of comments*
Names of Clusters
Customer
Attr1
Attr2
Attr3
Comments
Cost
p1
neutral
positive
C1, C2
[m1,m2]
p2
positive
positive
C2, C3
[m3,m4]
p3
positive
negative
C4, C3
[m1,m2]
C1
C2
C3
C4
C1 - neutral
C3 - positive
C2,- positive
C4 - negative
C2,C4
Attr3
C1
Attr2
c3
Attr1
Step 3: *Attr1, Attr2, Attr3 – Names of new attributes & their values added to the dataset*