CCI, UNC-Charlotte

User-friendly NPS-based recommender system for driving business revenue (CLIRS).

presented by

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Research sponsored by

Warsaw Univ. of Technology, 2018

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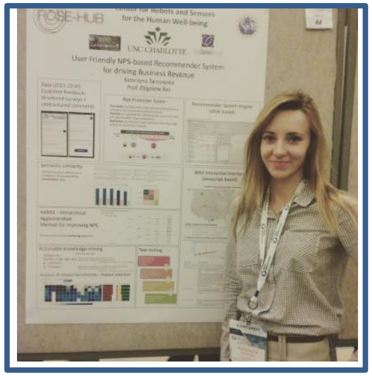

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115
49
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85
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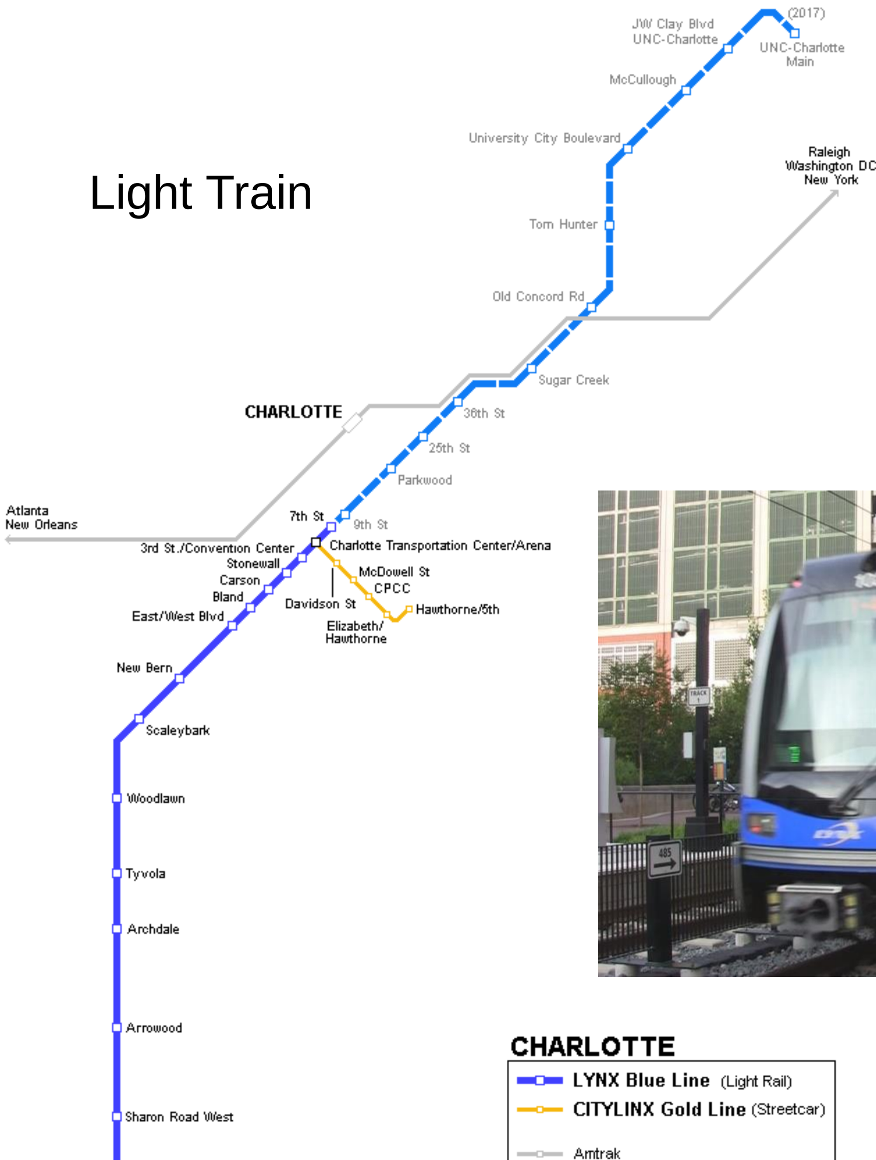
74
160

University of North Carolina at Charlotte

Light Train



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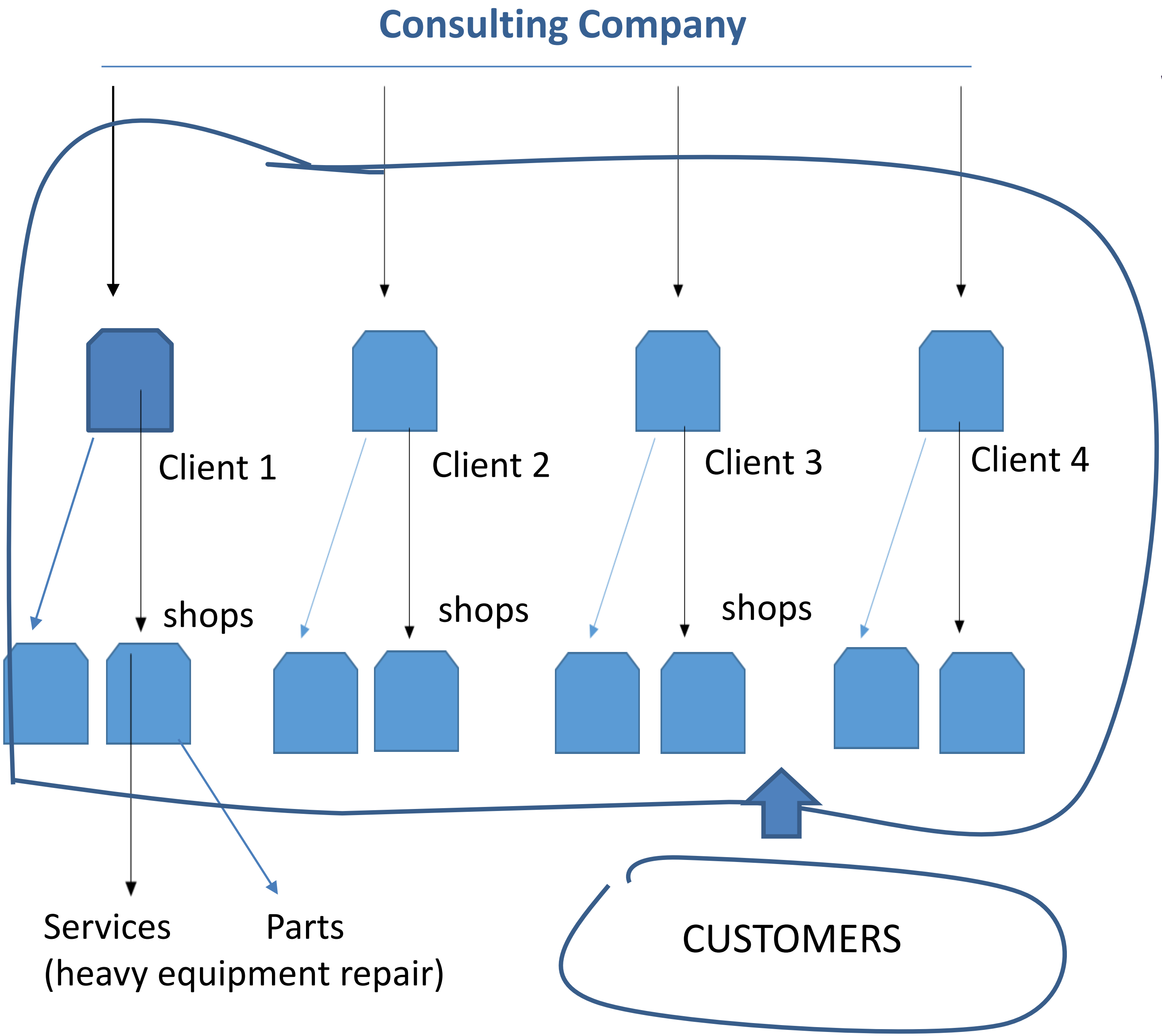
CLIRS -

Customer Loyalty Improvement Recommender System

Research sponsored by

Funding
(2013-current)



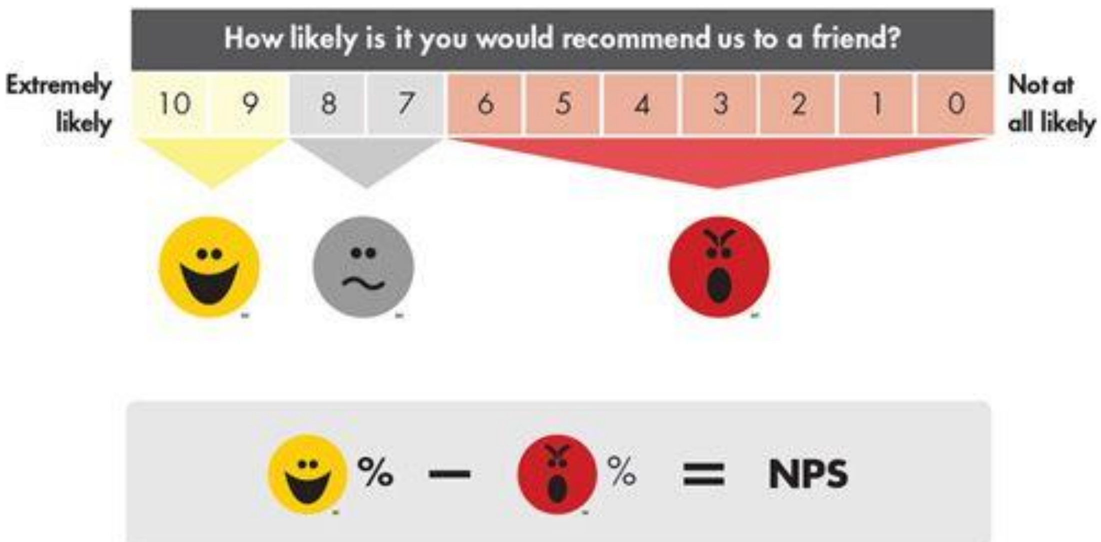
What we had to do

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

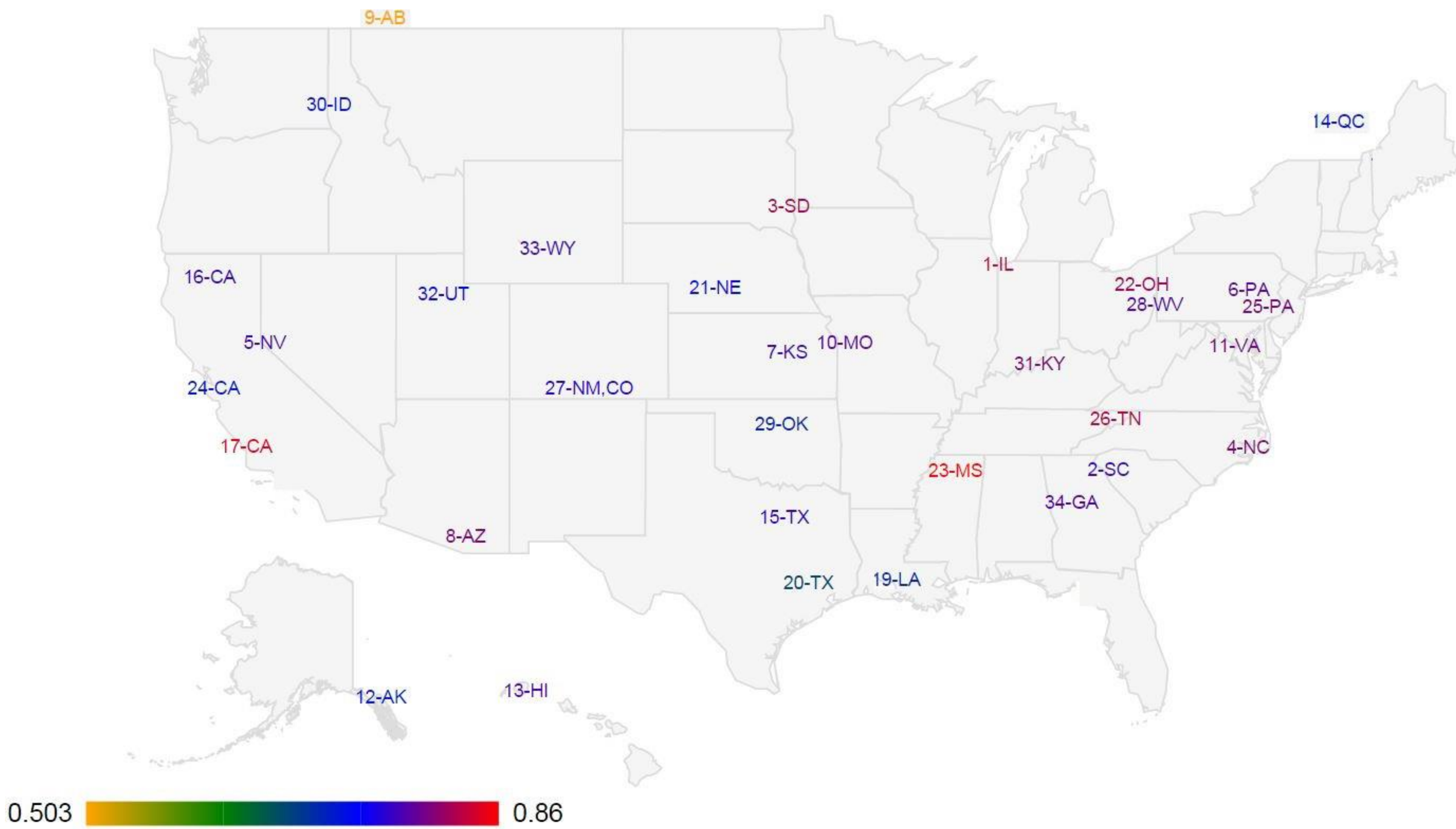


Promoter - {9,10}

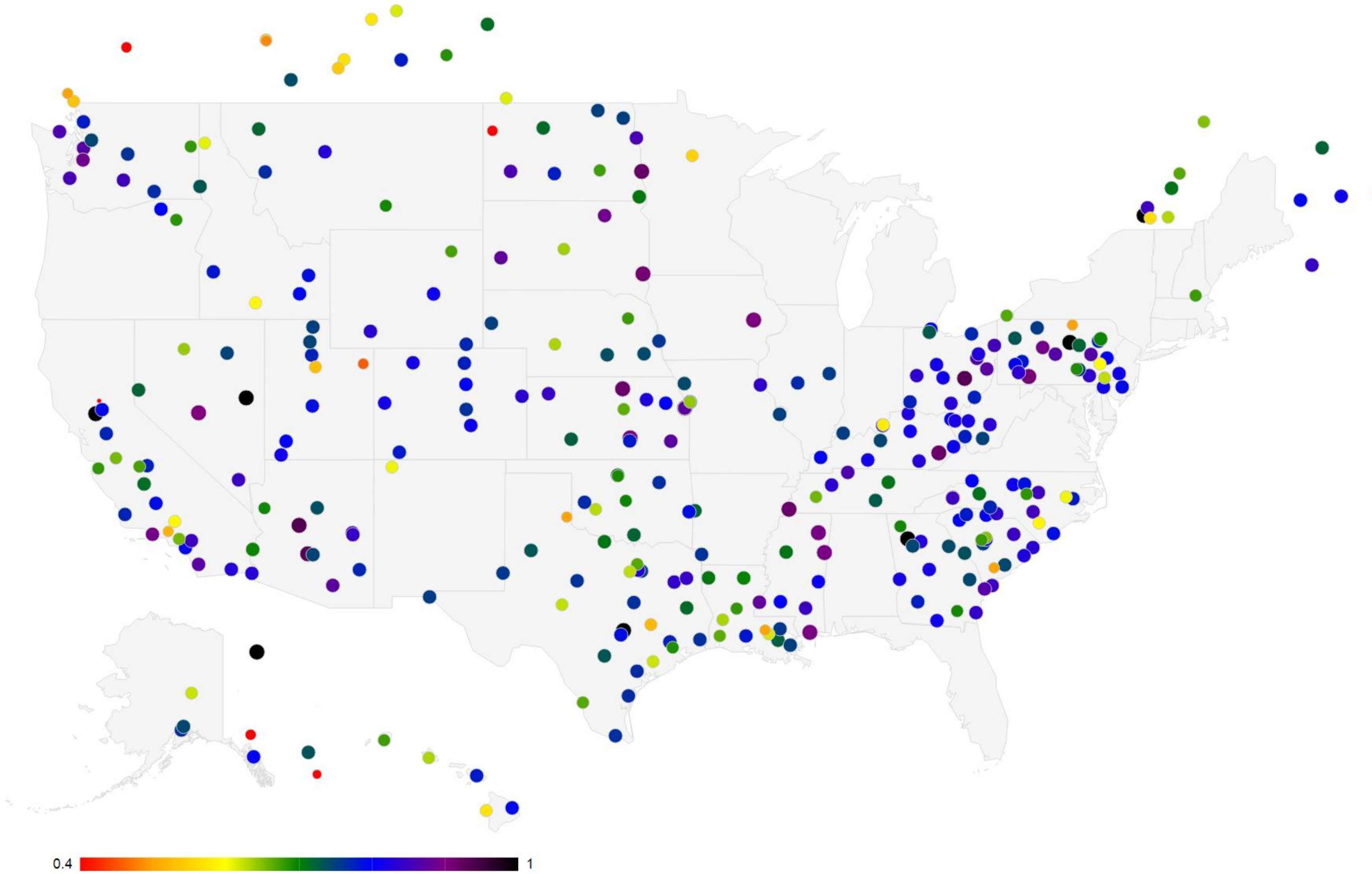
Passive – {8,7}

Detractor – {1,2,3…,6}

NPS rating for all clients



NPS rating for all shops

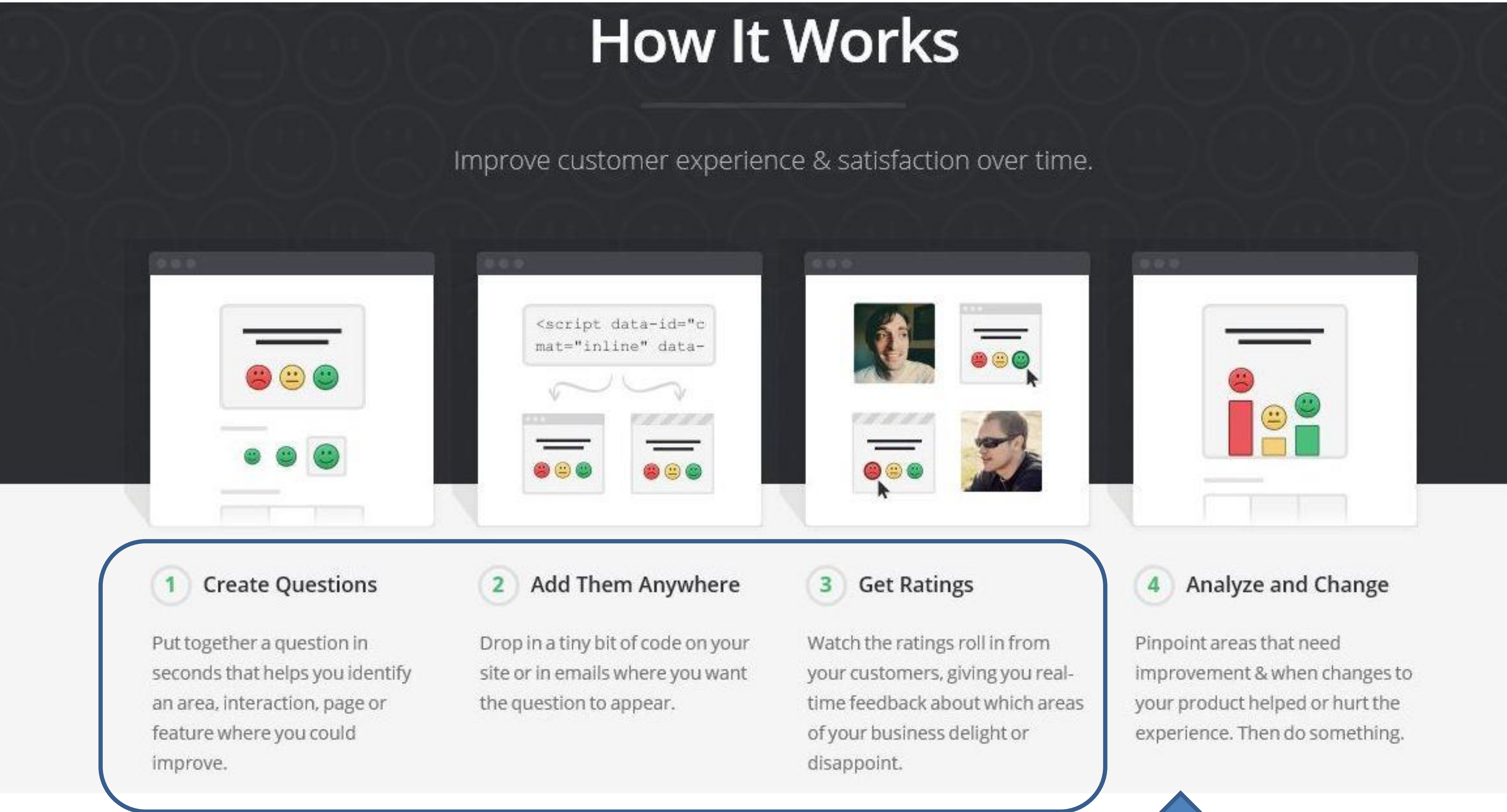


Customer Satisfaction Software Tools

- Survey design
- Feedback collection
- Score trend analysis over time
- Limited analytics and insight

CLIRS ← Our Software

Temper: https://www.temper.io/



[Temper]

Collecting Customers Data

Limited Analytics

Clarabridge CX Analytics [http://www.clarabridge.com/]

Key Features:

Deep Natural Language Processing (NLP) - Accurately analyze mountains of unstructured data to zero in on aspects of business that drive customers' dissatisfaction.

Linguistic categorization - Intelligently groups customer comments into topic buckets for smarter analysis.

Emotion detection - Decipher the emotional state of customers based on the tone of the feedback.

Context-sensitive sentiment analysis - Understands the intensity of feelings expressed by using deep Natural Language Processing, adjusting for industry and source-specific nuances.

Advanced discovery tools - Get to the core of customer issues using single click root cause analysis; unearth previously unknown topics using fully automated topic detection engine.

Speech analytics - Capture customer's voice, literally, by analyzing call recordings in the same platform as all your other data sources.

- *Does not discover actionable knowledge*
- *Data analytics does not provide any recommendations which guarantee NPS improvement*

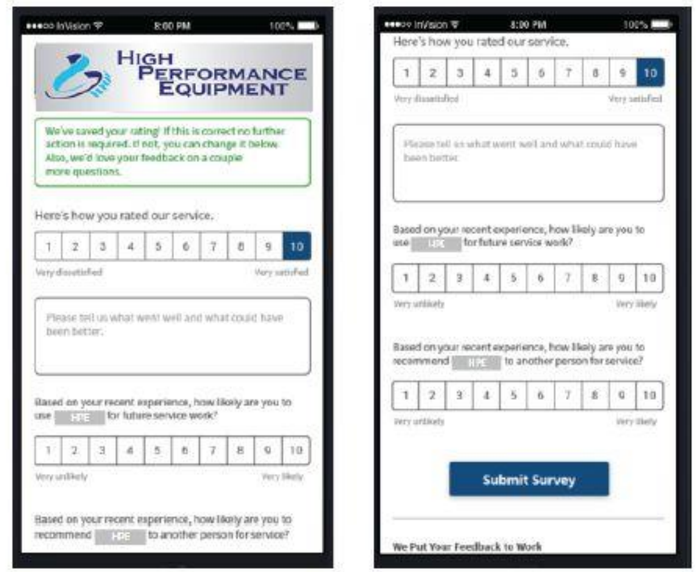
TATA Company: collects not only customers text data but also voice & video

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

Currently ~ sampling of 300,000 records per year 2010-2017

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

Sentiment analysis

- **Different levels of sentiment analysis:**
  - **Document level**
    - **general sentiment of all notes combined as a whole**
  - **Sentence level**
    - **Distinguishes between *subjective* and *objective* sentences**
  - **Entity and aspect level**
    - **What exactly people liked and did not like**

Sentiment analysis tools

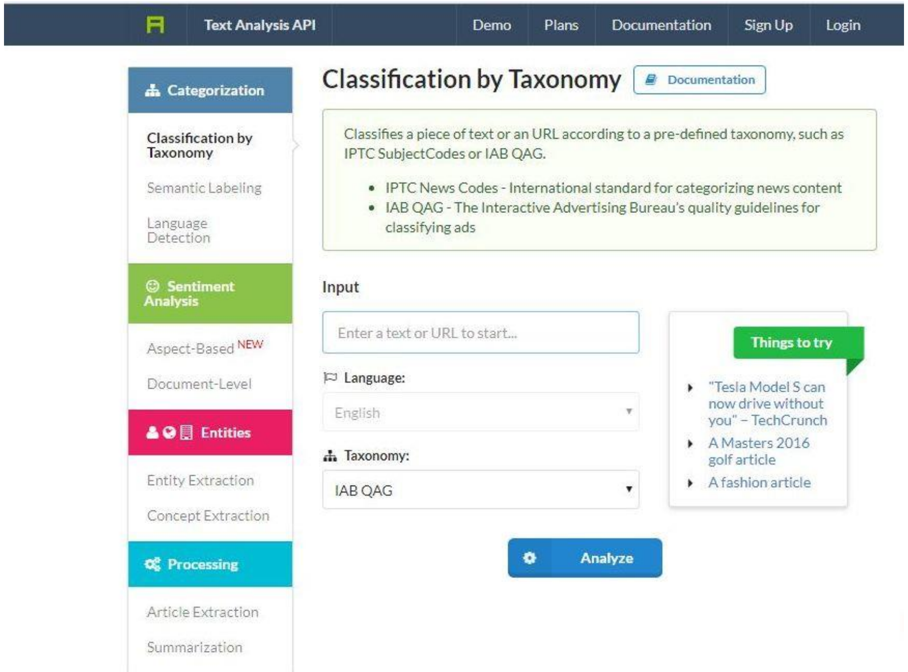
- **Python NLTK Text Classification demo**

- Demo uses classifiers trained on both **twitter sentiment** as well as **movie reviews**
- The results will be **more accurate on text that is similar to original training data**
- general sentiment analysis tools do not work very well

Sentiment analysis tools

[Rapid Miner demo (+ AYLIEN tool)]

[NLP Stanford Parser]

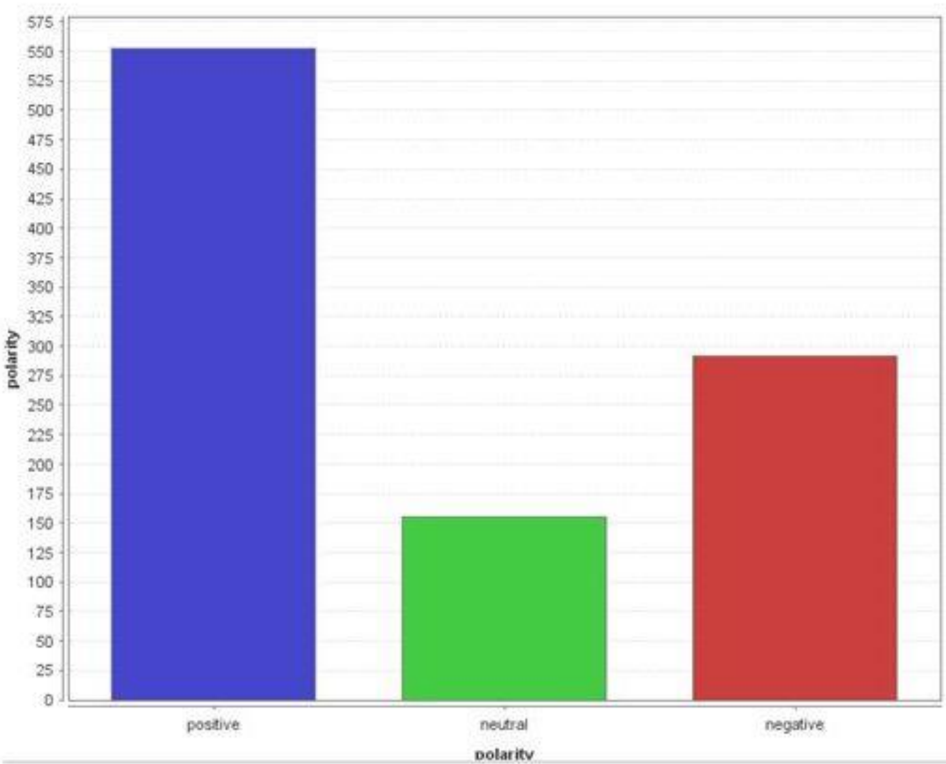


Conclusion: General sentiment analysis tools are not domain-specific

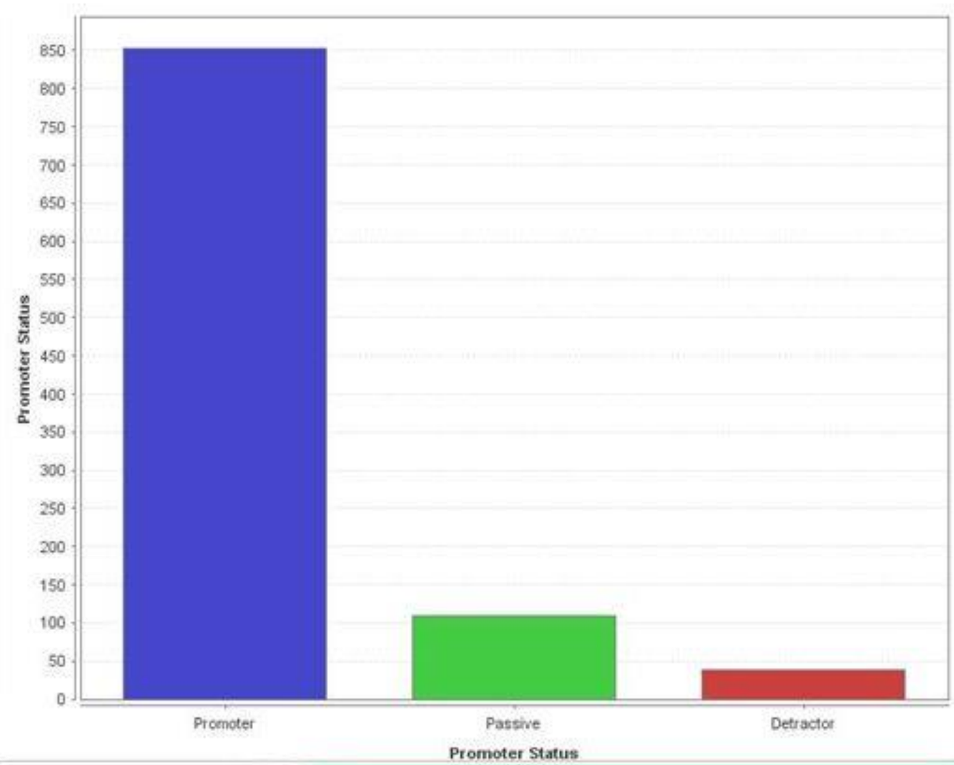
RapidMiner experiment

TheDanielsGroup Customer Datasets

Sentiment polarity indicated by program



Actual Promoter Score

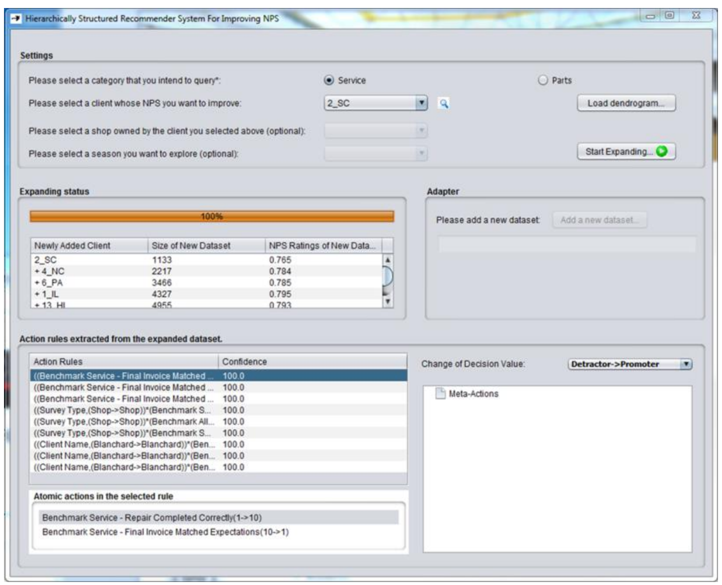


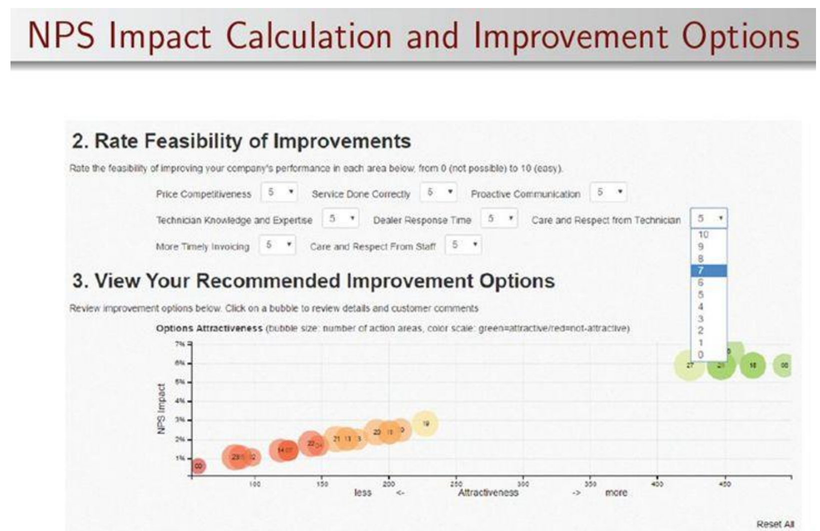
PLAN FOR TODAY's PRESENTATION

CLIRS - Customer Loyalty Improvement Recommender System

Definitions/Concepts needed to understand how CLIRS is built & works:

1) Reducts in Decision Systems
2) Action Rules and Meta-Actions
3) Decision Tables & Their Semantic Similarity





Decision System - Granules

	Bench1	Bench2	**Promoter Status**
x1	a1	b2	promoter
x2	a1	b1	passive
x3	a2	b3	passive
x4	a2	b3	promoter
x5	a3	b4	passive
x6	a1	b4	promoter
x7	a3	b4	passive

Promoter

Passive

Decision Granules:
{x1,x4,x6}, {x2,x4,x6}

Classification Granules:
Bench1: {x1,x2,x6}, {x3,x4}, {x5,x7}
Bench2: {x1},{x2},{x3,x4},{x5,x6,x7}
Smallest Granules:
{x1},{x2},{x3,x4},{x5,x7},{x6}

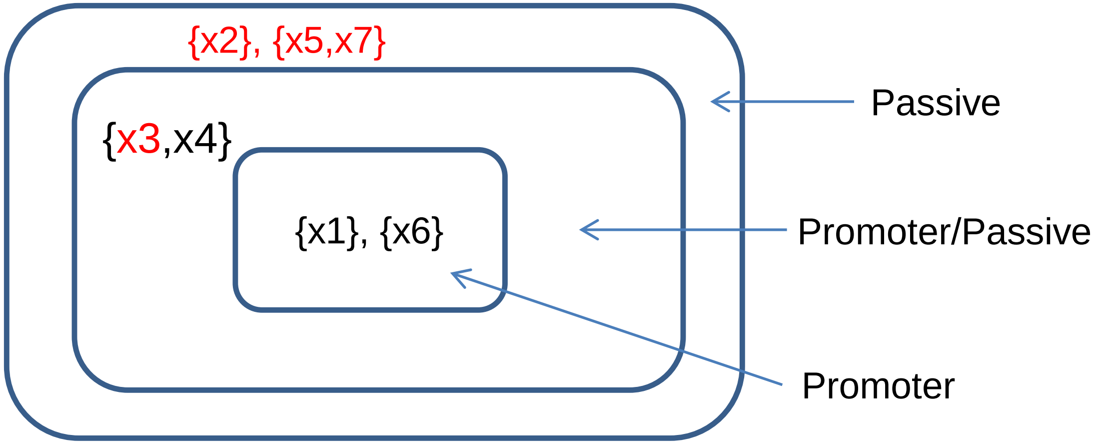


Figure 1

Informal Definition:
Reduct – smallest subset of classification attributes which **preserves** distribution of objects in Figure 1

?

Decision System & Reducts (Rough Sets)

U	*Headache*	*Muscle pain*	*Temp.*	*Flu*
U1	Yes	Yes	Normal	No
U2	Yes	Yes	High	Yes
U3	Yes	Yes	Very-high	Yes
U4	No	Yes	Normal	No
U5	No	No	High	No
U6	No	Yes	Very-high	Yes

We are looking for rules describing
Flu in terms of *Headache, Muscle Pain, Temp*.

Reduct1 **= {Muscle-pain,Temp.}**

U	*Muscle pain*	*Temp.*	*Flu*
U1,U4	Yes	Normal	No
U2	Yes	High	Yes
U3,U6	Yes	Very-high	Yes
U5	No	High	No

Reduct2 **= {Headache, Temp.}**

U	*Headache*	*Temp.*	*Flu*
U1	Yes	Norlmal	No
U2	Yes	High	Yes
U3	Yes	Very-high	Yes
U4	No	Normal	No
U5	No	High	No
U6	No	Very-high	Yes

ACTION RULES & META ACTIONS

Action Rules Miner:
Action4ft-Miner module in LISP Miner
http://lispminer.vse.cz/procedures/index.php?system=Ac4ftMiner
[developed by Jan Rauch (Univ. of Economics, Prague, Czech Republic]

Meta Action Miners: Only Domain Specific
(parts of domain specific software)

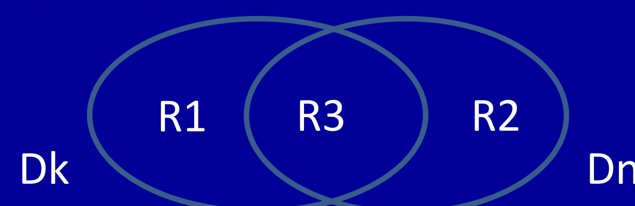
Triggers of Action Rules

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 $\Sigma\{ c_{1,i1} \cdot s_{1,i1}: r_{1, i1}\in R1\} + \Sigma\{ c_{2,i2} \cdot s_{2,i2} : r_{2, i2}\in R2\}+$
$\Sigma\{ |c_{3,i1} - c_{3,i2}| \cdot| s_{3,i1} - s_{3,i2}| : r_{3, i3}\in R3\}$



Coming back to our customers feedback dataset

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

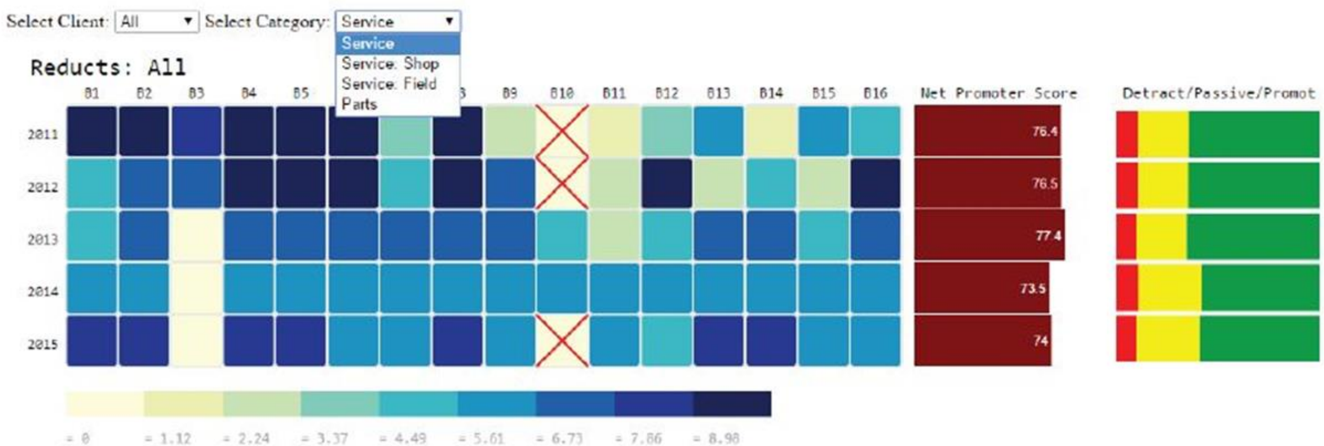
Benchmark All Overall Satisfaction	35
Benchmark All Likelihood to be Repeat Customer	34
Benchmark All Dealer Communication	33
Benchmark Service Repair Completed Correctly	32
Benchmark Referral Behavior	31
Benchmark Service Final Invoice Matched Expectations	31
Benchmark Ease of Contact	30
Benchmark All 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

To compute NPS we calculate average score of selected benchmarks for all customers. Knowing the number of promoters and detractors we know NPS.

Motivation

- Insight into the entire anatomy of feedback
- Discover hidden trends and patterns



Visualization for yearly trends in customers' sentiment analysis towards different aspects - benchmarks, for chosen client and survey type, and the impact on NPS

RECOMMENDER SYSTEM CLIRS

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

Classical Approach

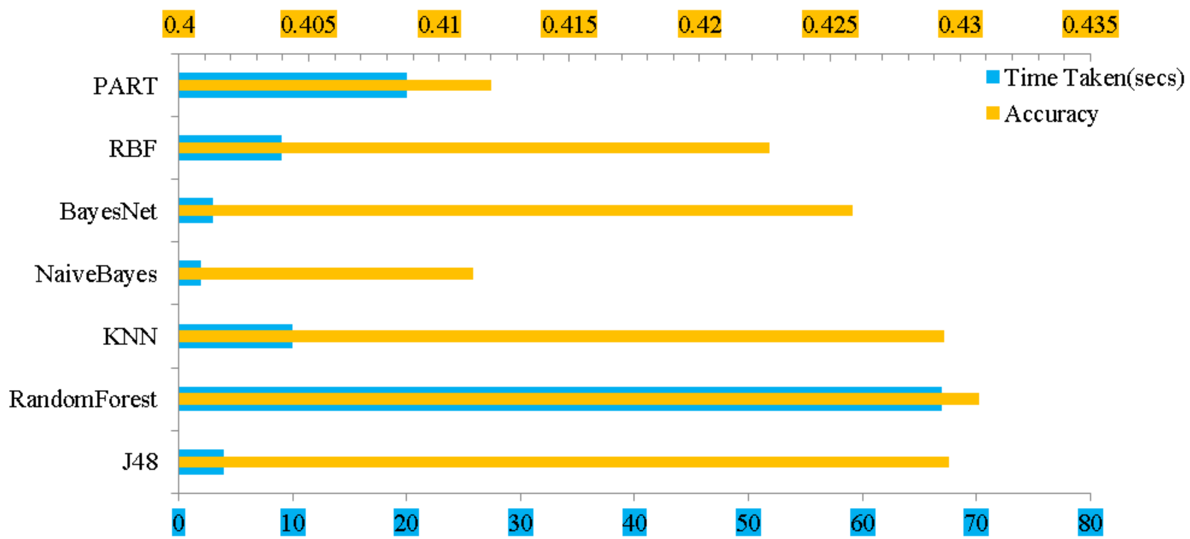
Data

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



	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

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Two Options

Initial Clients Datasets — 1 → Recommender Systems

local approach

2 ↓ global approach

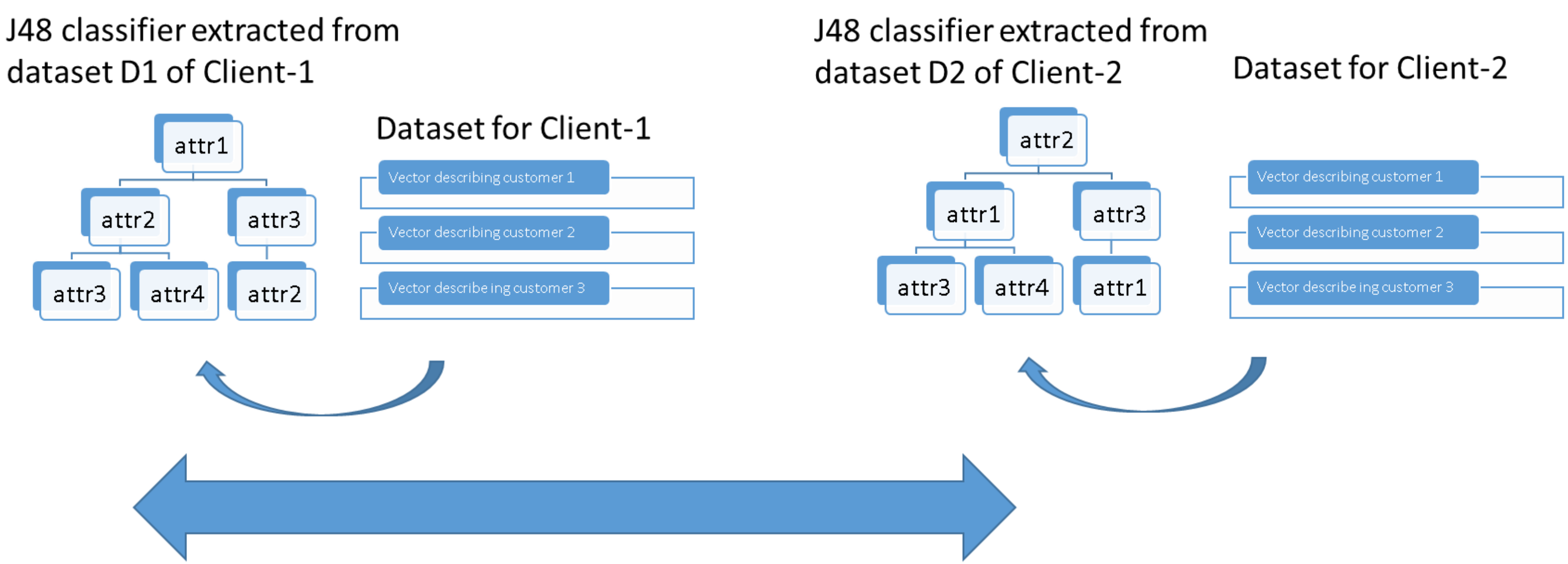
Using Information about 34 Clients to Enlarge these Datasets

2 ↓ global approach

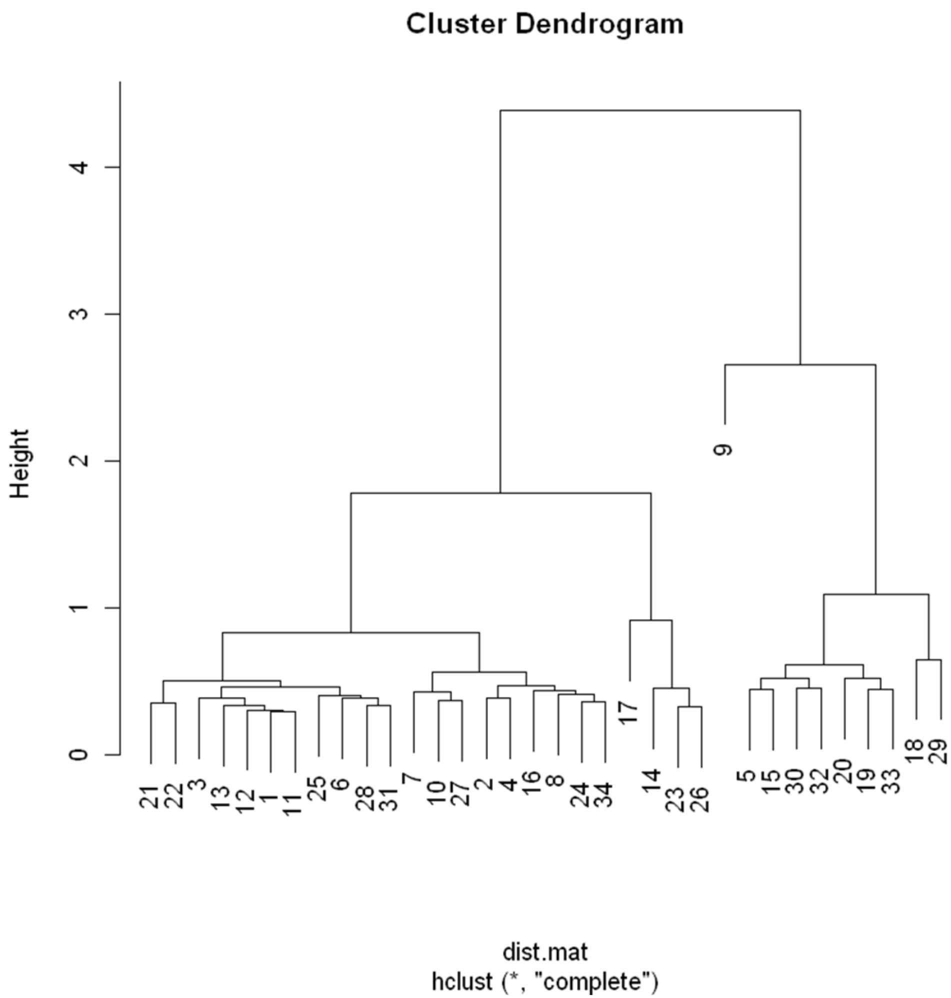
More Powerful Recommender Systems

FIRST APPROACH for Dataset Enlargement

Semantic Distance between Clients



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



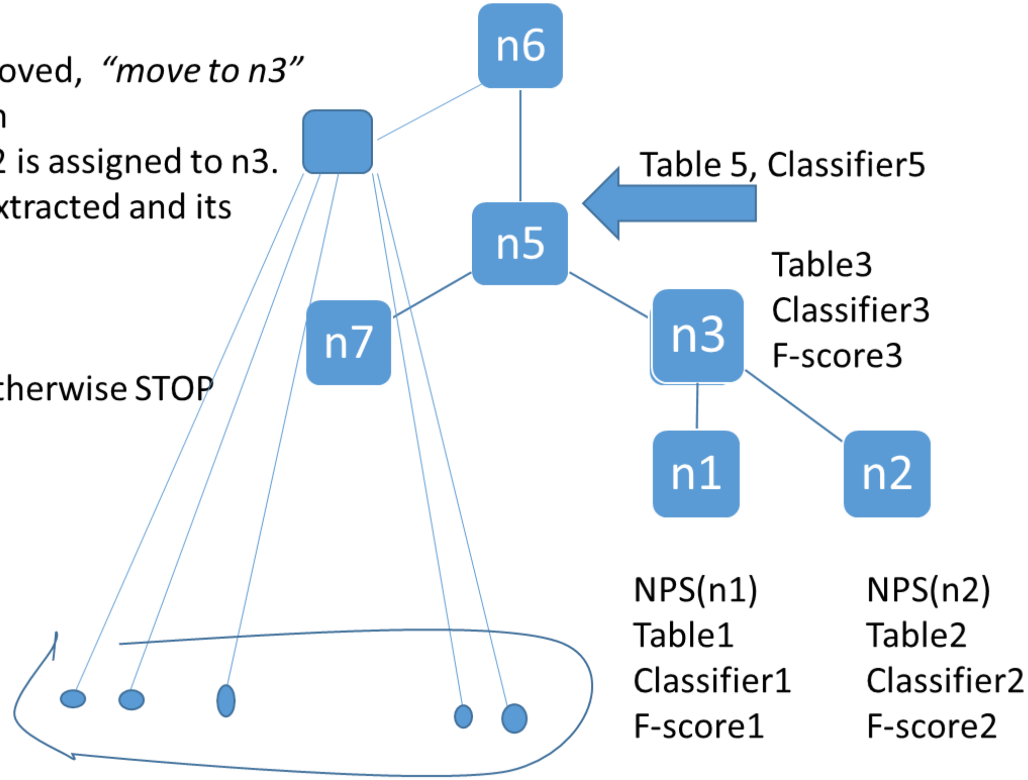
Semantic distance based dendrogram for Service

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

\



Now, from the enlarged Decision Table, we extract action rules

Examples of action rules:

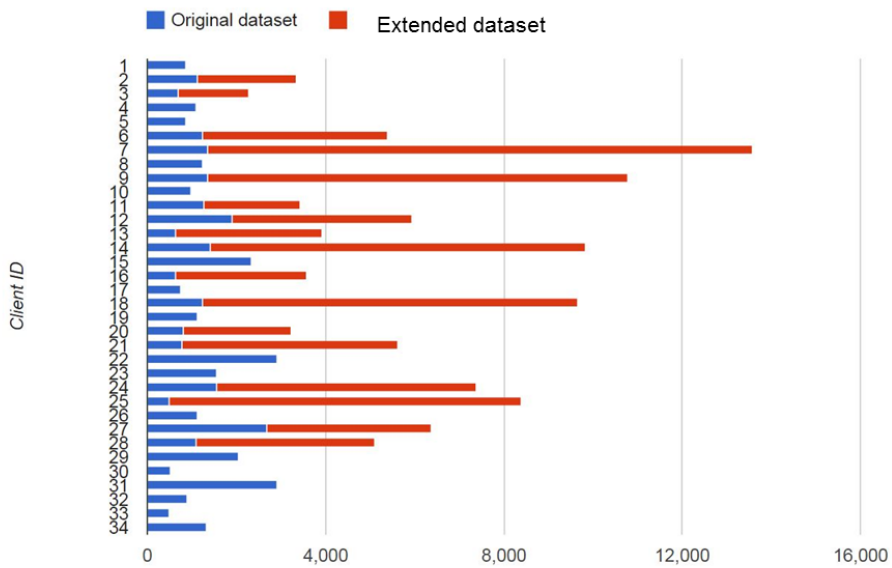
((Benchmark: All Overall Satisfaction, (1->10))*
(Benchmark: All Dealer Communication, (1->5)))
=>(Detractor->Promoter) sup= 5.0, conf= 100.0

((Benchmark: Service-Repair Completed When Promised, (8->3))*
(Benchmark: All Dealer Communication, (1->10)))
=>(Detractor->Promoter) sup= 5.0, conf= 100.0

NPS

Experiments with Semantic Dendrogram

- Performance of HAMIS on 34 clients with semantic similarity based dendrogram.



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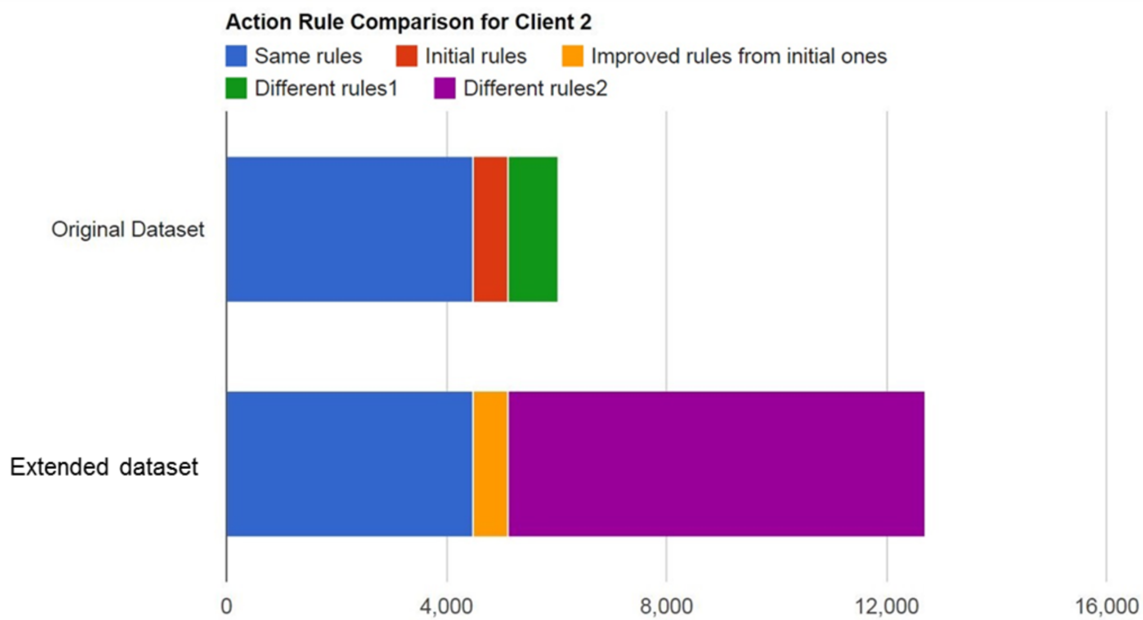
Comparison of sets of action rules extracted from dataset of Client 2 **before/after** HAMIS.



Expansion with Geographical Dist.

- Motivation:
  - Limitations of applying HAMIS with semantic similarity based dendrogram.
  - Merging with the most semantically similar clients may not be the only choice.

Take weighted combination of semantic & geographic distance

Now, when the dataset (decision system) is built,
we will start extracting action rules

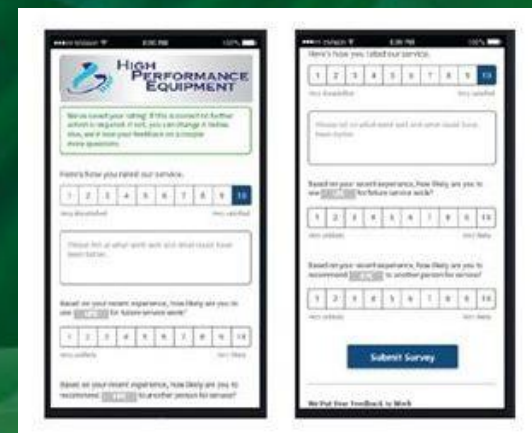
Action rule

Shows actions to undertake

IF Benchmark1 (3->6) AND Benchmark2 (7->9)

THEN Detractor -> Promoter

To make change happen



„Traditional" rules:

IF Benchmark1 =3 AND Benchmark2 =7

THEN Detractor

IF Benchmark1 =6 AND Benchmark2 =9

THEN Promoter

Show simply associations

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But…

Changes do not happen

On their own…

Meta actions:

- External, „higher-level” events that trigger changes in Benchmarks

Meta action1

Meta action2

IF Benchmark1 (3->6) AND Benchmark2 (7->9)

THEN Detractor -> Promoter

Meta action3

But…

Where to get

Meta actions from…

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Meta actions are mined from text:

Customer	Status	Q_1	Q_2	Q_n	Comments
Customer1	Detractor	3	7		He stated that he feels the prices are high. He also stated that getting them on the phone is not easy. He stated that when he calls, he needs parts right away and sometimes he gets transferred to different locations and Amarillo is closest to him.
Customer2	Promoter	6	9		She stated she never has problems and the parts are good quality. She stated she receives good customer service and good communication as they are prompt sending back emails.

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Mining detractor's sentiment:

Price competitiveness

- *„He stated that he feels the prices are high. He also stated that getting them on the phone is not easy. He stated that when he calls, he needs parts right away and sometimes he gets transferred to different locations and Amarillo is closest to him."*

Order Ease

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Mining promoter’s sentiment:

Parts quality

- „She stated she never has problems and the parts are good quality. She stated she receives good customer service and good communication as they are prompt sending back emails.”

Staff attitude

Communication quality

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1. Action rules:

- Are mined from large datasets with data mining algorithms
- Can be understood as patterns in the dataset
- Each rule is characterized by:
  - Support – how many customers can be changed
  - Confidence – probability of changing a customer

IF Benchmark1 (3->6) AND Benchmark2 (7->9)

THEN Detractor -> Promoter, sup=10, conf=90%

10 customers can be changed in this way with the probability of 90%

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2. Meta action mining:

Customer	Status	Q_1	Q_2	Q_n	Comments
Customer1	Detractor	3	7		*He stated that he feels the prices are high. He also stated that getting them on the phone is not easy. He stated that when he calls, he needs parts right away and sometimes he gets transferred to different locations and Amarillo is closest to him.*
Customer2	Promoter	6	9		*„She stated she never has problems and the parts are good quality. She stated she receives good customer service and good communication as they are prompt sending back emails."*

Price competitiveness

- *„He stated that he feels the prices are high. He also stated that getting them on the phone is not easy. He stated that when he calls, he needs parts right away and sometimes he gets transferred to different locations and Amarillo is closest to him. "*

Order Ease

Parts quality

- *„She stated she never has problems and the parts are good quality. She stated she receives good customer service and good communication as they are prompt sending back emails."*

Service quality

Communication quality

3. Triggering:

Pricing | Order Ease | Parts Quality | Staff attitude | Communication Quality

IF Benchmark1 (3->6) AND Benchmark2 (7->9)

THEN Detractor -> Promoter

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Extracting Meta-Actions

DATASET

Guided Folksonomy & Sentiment Analysis

Extracting Comments

Meta-Actions

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}

C1
C2
C3
C4

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

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%

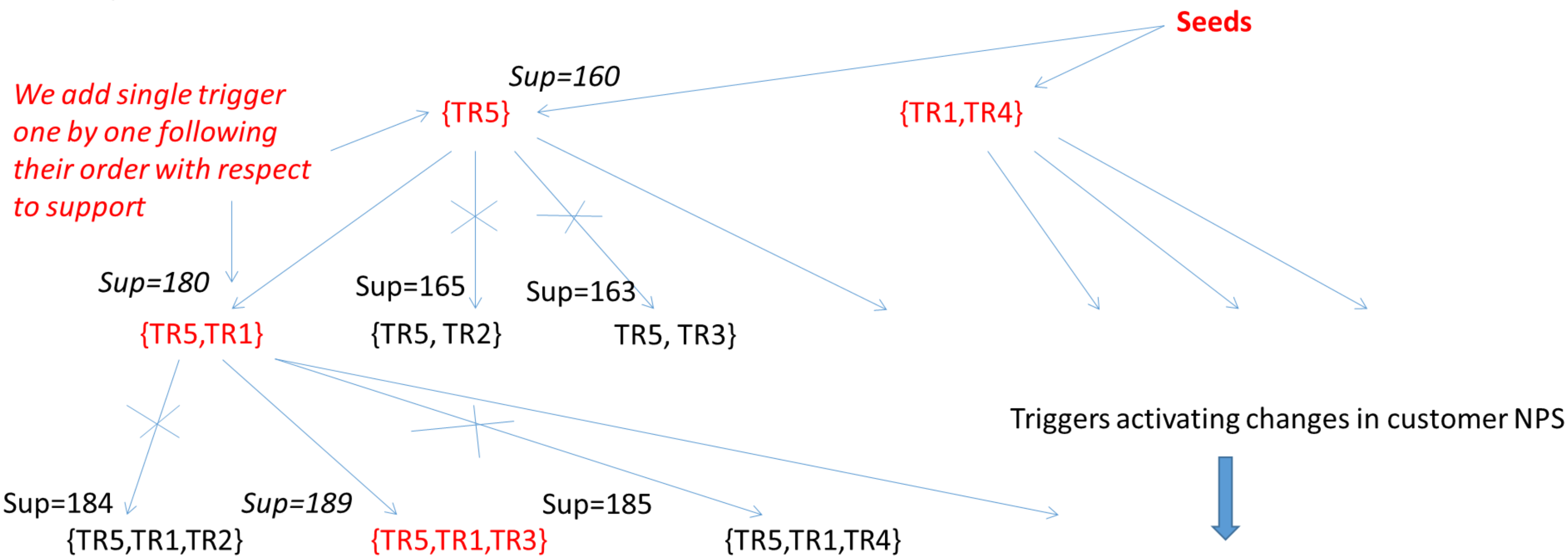
Action Rules

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



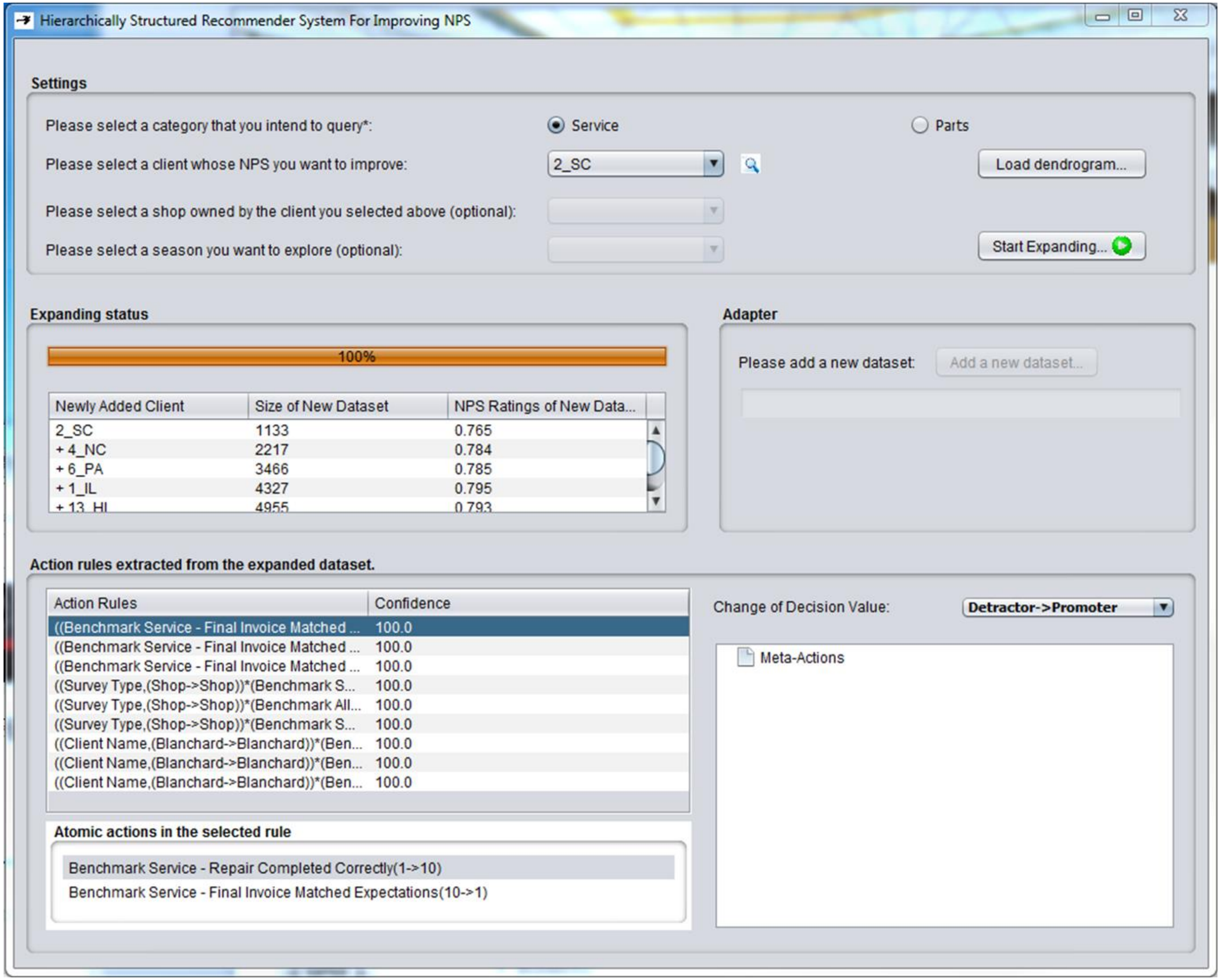
1	2	3	4
TR5	{TR1,TR4}	{TR5,TR1,TR3}	
	{TR5,TR1}		

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

Recommender System



User-Friendly Interface

NPS Impact Calculation and Improvement Options

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

Summary generation

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,

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Switching to comments-only method

1. Action rule mining from benchmarks table
2. Sentiment analysis / Meta Actions mining
3. Triggering / Creating meta-nodes
4. NPS Impact Calculation

1. Sentiment analysis (opinion table creation)
2. Action rule mining from opinion table
3. Creating meta-nodes
4. NPS Impact Calculation

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Making tables from comments

- Opinion analysis of comment :
- sentiment + feature
- ex : negative opinion of staff knowledge : (-1) + "Knowledgeable Staff"
- Goal :

	Bucket 1	Bucket 2	Bucket 3	Bucket 4	Bucket 5	Bucket 6	Bucket 7	...	Bucket21	Promoter Status
Customer 1	0	-2	1	2	0	0	1		-1	Promoter
Customer 2	2	2	2	0	0	1	-1		0	Passive
Customer 3	0	0	1	-1	1	0	1		1	Detractor
...	...	...	...	...	...	...	...		...	

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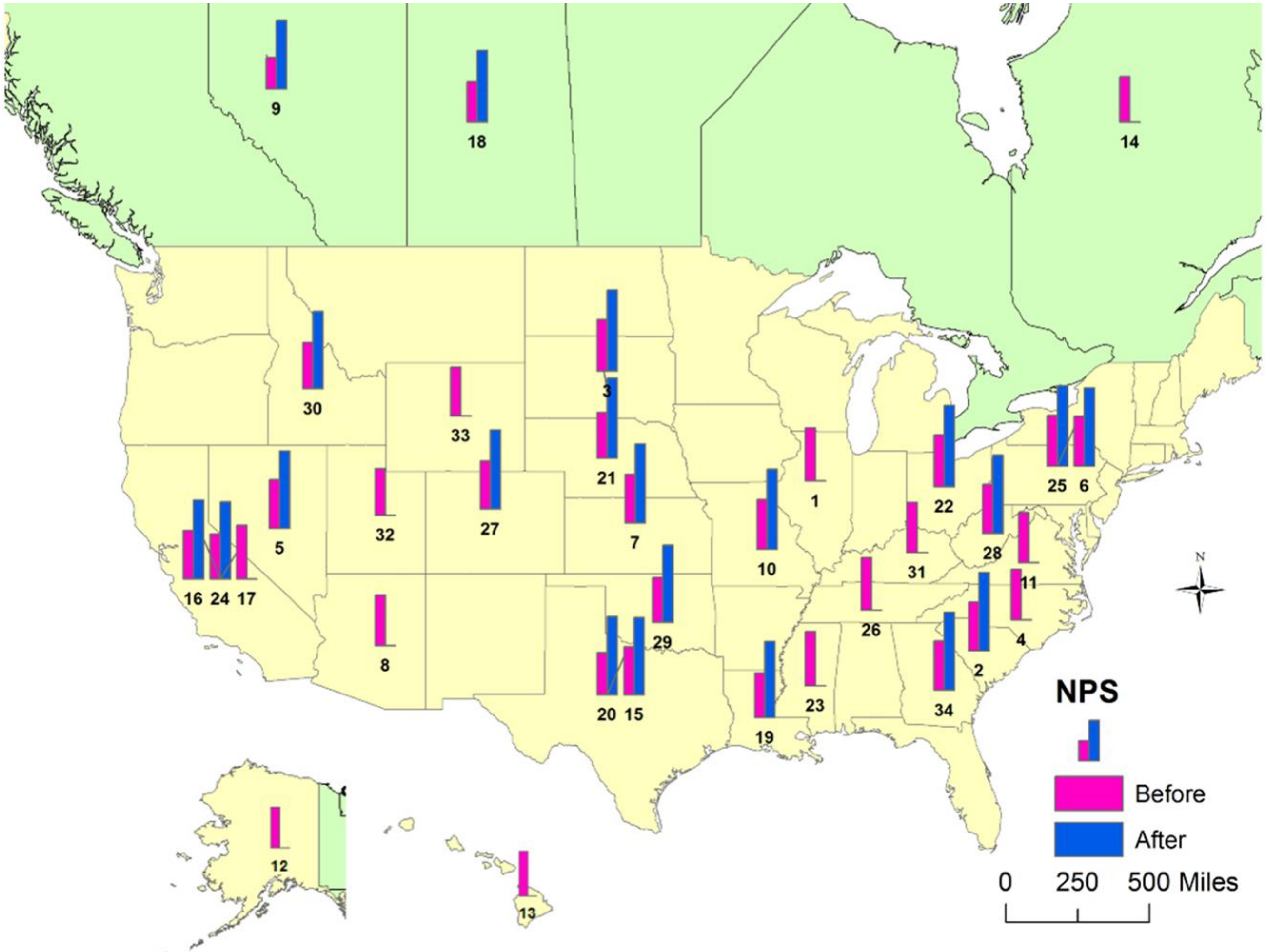
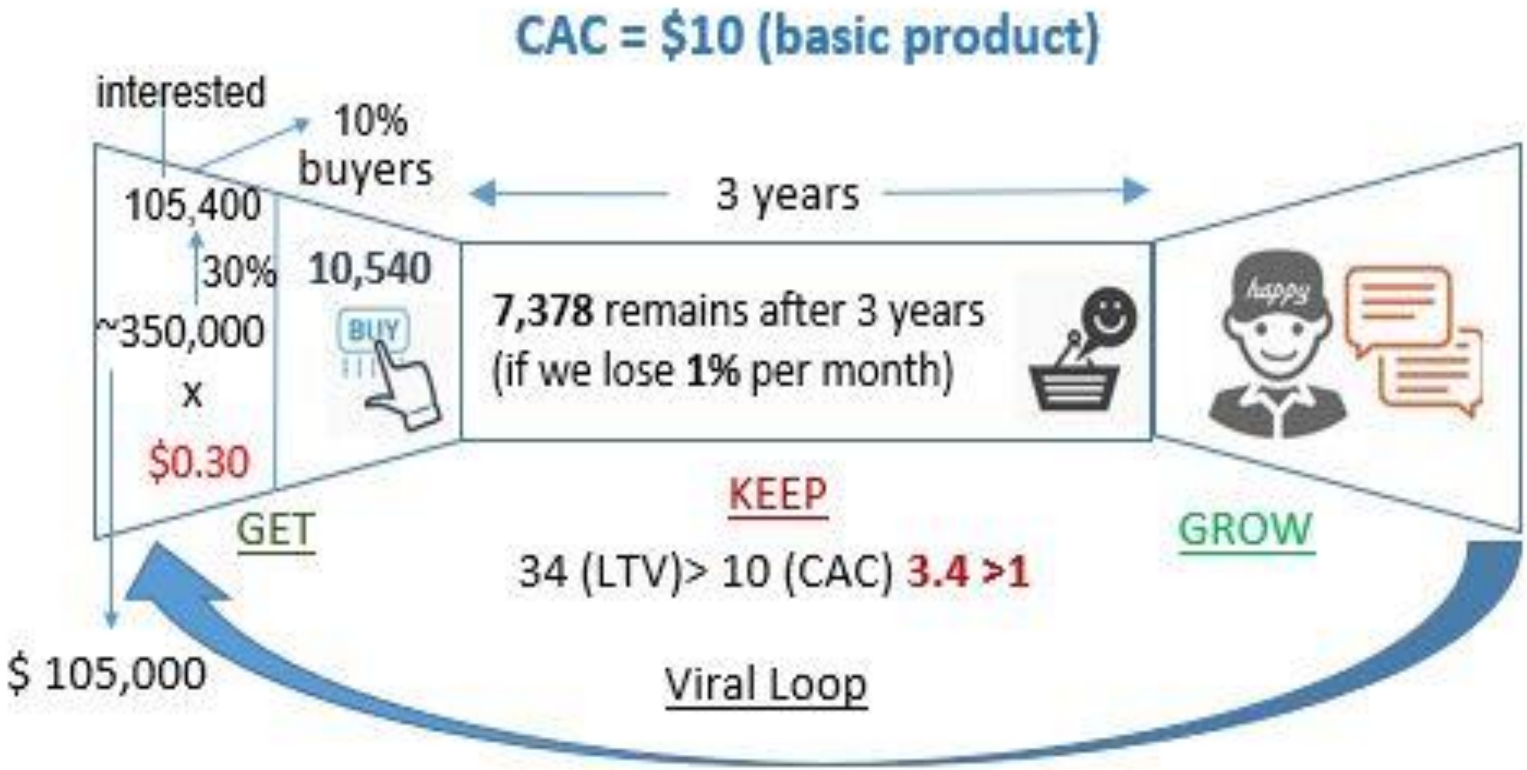


Columns in blue color show minimal expected improvement in NPS after following advice given by recommender system on clients level

[Recommender System]



GET KEEP and GR0W

Q
&
A