BI Project: Bank Marketing

Group 1
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AGENDA

1
Data Description

2
Data Mining Model (1): Classification

3
Data Mining Model (2): Clustering

1

Data Description

1.1 Data Description
1.2 Background: Bank Telemarketing and Financial Crisis

1.1 Data Description

Data Description

Data Description		• The data is related with the **telemarketing campaign of a Portuguese retail bank** to sell a term deposit • Retail bank: a bank whose customer targets are individuals, SMEs rather than large corporations
Data Information	Time	• from May 2008 to November 2010
	# of records	• 41178
	# of attributes	• 22 including key attribute (ID) that we put in

1.1 Data Background

Source

archive.ics.uci.edu

UCI Machine Learning Repository
Center for Machine Learning and Intelligent Systems

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Bank Marketing Data Set

Download: Data Folder, Data Set Description

Abstract: The data is related with direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict if the client will subscribe a term deposit (variable y).

Data Set Characteristics:	Multivariate	**Number of Instances:**	45211	**Area:**	Business
Attribute Characteristics:	Real	**Number of Attributes:**	17	**Date Donated**	2012-02-14
Associated Tasks:	Classification	**Missing Values?**	N/A	**Number of Web Hits:**	379515

Source:

[Moro et al., 2014] S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, Elsevier, 62:22-31, June 2014

Data Set Information:

The data is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed.

There are four datasets:
1) bank-additional-full.csv with all examples (41188) and 20 inputs, ordered by date (from May 2008 to November 2010), very close to the data analyzed in [Moro et al., 2014]
2) bank-additional.csv with 10% of the examples (4119), randomly selected from 1), and 20 inputs.
3) bank-full.csv with all examples and 17 inputs, ordered by date (older version of this dataset with less inputs).
4) bank.csv with 10% of the examples and 17 inputs, randomly selected from 3 (older version of this dataset with less inputs).
The smallest datasets are provided to test more computationally demanding machine learning algorithms (e.g., SVM).

The classification goal is to predict if the client will subscribe (yes/no) a term deposit (variable y).

Attribute Information:

Input variables:
bank client data:
1 - age (numeric)
2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')
3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')

- UCI Machine Learning Repository: Bank Marketing Data Set

https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

1.1 Data Description

Attribute Information

Key Variable	Client ID
Output variable	Has the client subscribed a term deposit? (binary: 'yes','no')
Input Variables	1 Client Data; 2 Previous telemarketing data; 3 Social and economic context attributes

1.1 Data Description

Input Variables Break-down

1 Client Data

2 Previous telemarketing data

3 Social and economic context attribute

1. **age** (numeric)
2. **job** : type of job
   (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self employed','services','student','technician','unemployed','unknown)
3. **marital** : marital status (categorical: 'divorced','married','single','unknown')
4. **education** (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')
5. **default**: has credit in default? (categorical: 'no','yes','unknown')
6. **housing**: has housing loan? (categorical: 'no','yes','unknown')
7. **loan**: has personal loan? (categorical: 'no','yes','unknown')

1.1 Data Description

Input Variables Break-down

1 Client Data

2 Previous telemarketing data

3 Social and economic context attribute

1. **contact:** contact communication type (categorical: 'cellular','telephone')
2. **month:** last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
3. **day_of_week:** last contact day of the week (categorical: 'mon','tue','wed','thu','fri')
4. **duration:** last contact duration, in seconds (numeric)
5. **campaign:** number of contacts performed during this campaign and for this client (numeric)
6. **pdays:** number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
7. **previous:** number of contacts performed before this campaign and for this client (numeric)
8. **poutcome:** outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

1.1 Data Description

Input Variables Break-down

1 Client Data

2 Previous telemarketing data

3 Social and economic context attribute

1. **emp.var.rate:** employment variation rate - quarterly indicator (numeric)
2. **cons.price.idx:** consumer price index - monthly indicator (numeric)
3. **cons.conf.idx:** consumer confidence index - monthly indicator (numeric)
4. **euribor3m:** euribor 3 month rate - daily indicator (numeric)
5. **nr.employed:** number of employees - quarterly indicator (numeric)

1.1 Data Description

Excel Data

ID	age	job	marital	education	default	housing	loan	contact	month	day_of_we	duration	campaign	pdays	previous	poutcome	emp.var.ra	cons.price.	cons.conf.	euribor3m	nr.employ	y
1	56	housemai	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
2	57	services	married	high.schoo	unknown	no	no	telephone	may	mon	149	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
3	37	services	married	high.schoo	no	yes	no	telephone	may	mon	226	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
4	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	151	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
5	56	services	married	high.schoo	no	no	yes	telephone	may	mon	307	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
6	45	services	married	basic.9y	unknown	no	no	telephone	may	mon	198	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
7	59	admin.	married	profession	no	no	no	telephone	may	mon	139	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
8	41	blue-colla	married	unknown	unknown	no	no	telephone	may	mon	217	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
9	24	technician	single	profession	no	yes	no	telephone	may	mon	380	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
10	25	services	single	high.schoo	no	yes	no	telephone	may	mon	50	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
11	41	blue-colla	married	unknown	unknown	no	no	telephone	may	mon	55	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
12	25	services	single	high.schoo	no	yes	no	telephone	may	mon	222	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
13	29	blue-colla	single	high.schoo	no	no	yes	telephone	may	mon	137	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
14	57	housemai	divorced	basic.4y	no	yes	no	telephone	may	mon	293	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
15	35	blue-colla	married	basic.6y	no	yes	no	telephone	may	mon	146	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
16	54	retired	married	basic.9y	unknown	yes	yes	telephone	may	mon	174	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
17	35	blue-colla	married	basic.6y	no	yes	no	telephone	may	mon	312	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
18	46	blue-colla	married	basic.6y	unknown	yes	yes	telephone	may	mon	440	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
19	50	blue-colla	married	basic.9y	no	yes	yes	telephone	may	mon	353	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
20	39	managem	single	basic.9y	unknown	no	no	telephone	may	mon	195	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
21	30	unemploy	married	high.schoo	no	no	no	telephone	may	mon	38	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
22	55	blue-colla	married	basic.4y	unknown	yes	no	telephone	may	mon	262	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
23	55	retired	single	high.schoo	no	yes	no	telephone	may	mon	342	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
24	41	technician	single	high.schoo	no	yes	no	telephone	may	mon	181	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
25	37	admin.	married	high.schoo	no	yes	no	telephone	may	mon	172	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
26	35	technician	married	university.	no	no	yes	telephone	may	mon	99	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
27	59	technician	married	unknown	no	yes	no	telephone	may	mon	93	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
28	39	self-emplo	married	basic.9y	unknown	no	no	telephone	may	mon	233	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
29	54	technician	single	university.	unknown	no	no	telephone	may	mon	255	2	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
30	55	unknown	married	university.	unknown	unknown	unknown	telephone	may	mon	362	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
31	46	admin.	married	unknown	no	no	no	telephone	may	mon	348	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
32	59	technician	married	unknown	no	yes	no	telephone	may	mon	386	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
33	49	blue-colla	married	unknown	no	no	no	telephone	may	mon	73	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
34	54	managem	married	basic.4y	unknown	yes	no	telephone	may	mon	230	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no
35	54	blue-colla	divorced	basic.4y	no	no	no	telephone	may	mon	208	1	999	0	nonexister	1.1	93.994	-36.4	4.857	5191	no

Bank_Marketing

1.2 Background

What is Bank Telemarketing

The marketing of bank’s products or services by means of telephone calls, typically unsolicited, to potential customers.

Why Bank Telemarketing

After the 2008 Financial Crisis, banks try to attract more term deposits to recover its loss, so they use telemarketing as a way to reach out to potential customers.

1.2 Background

Portugal during the 2008 Financial Crisis

- Before the Crisis: Cumulating government debt + lasting high unemployment+ high public spending+ low productivity
- GDP of Portugal contracted by 2.7% in 2008–2009 largely due to shrinking domestic demand
- Unemployment rose to 9.47% in 2009
- Budget deficit increased from 2.8% of GDP in 2008 to 9.4% in 2009

(Source: Euro Challenge 2012)

Does this affect the banking choices made by Portuguese citizens?

2
Data Mining Model (1): Classification

2.1 Classification Problem
2.2 Building Mining Model
2.3 Result
2.4 Profit Chart
2.5 Implication

2.1 Classification Problem

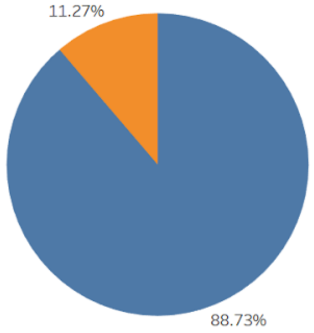
Classification Problem

“ Whether the customer will positively respond to the telemarketing campaign or not“

Minimum Acceptable Performance Indicator (Accuracy-focused)

1 Random Probability = 50%

2



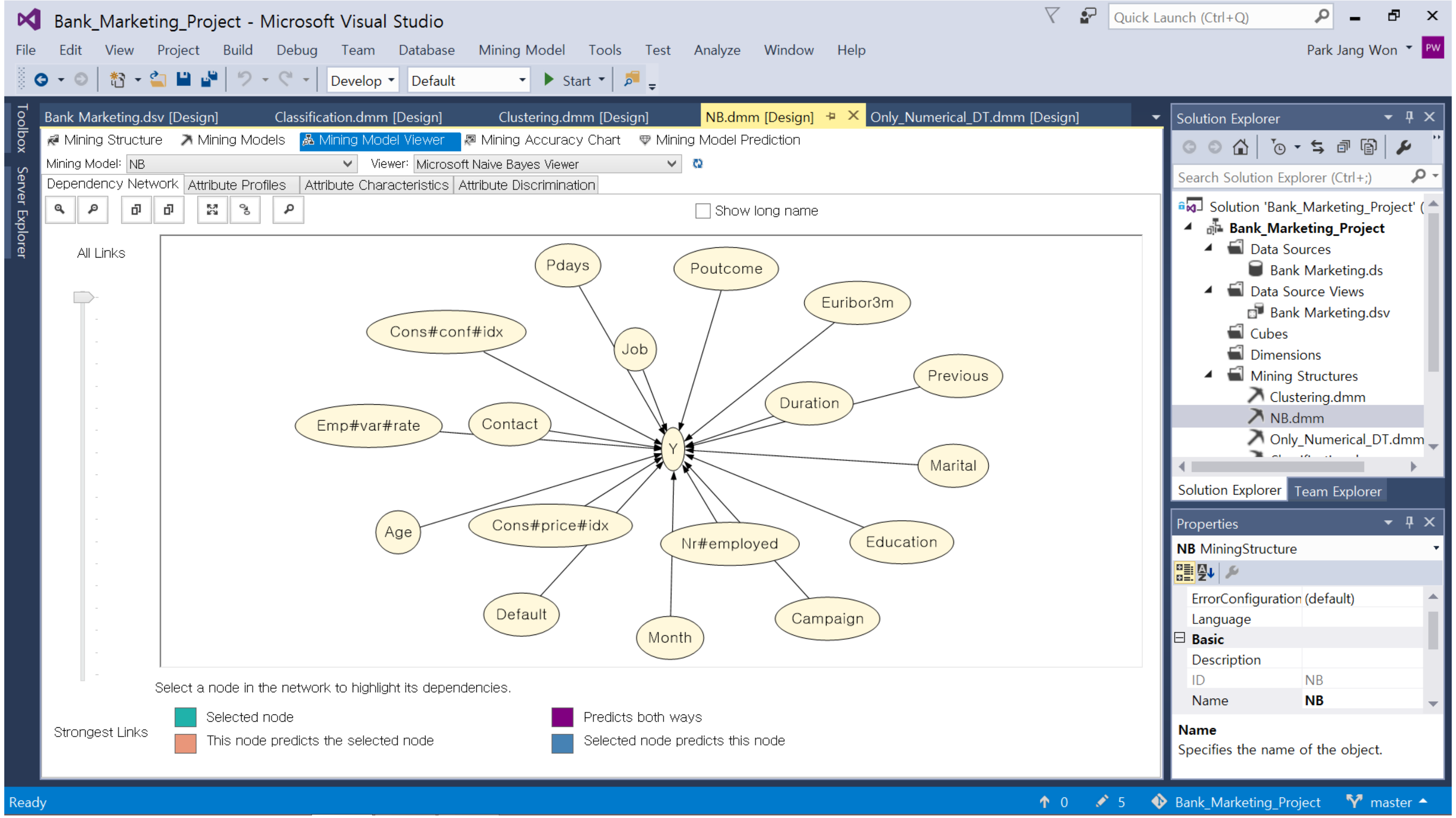
- Data Distribution: ‘yes’: 11.27% ‘no’: 88.73%
- Based on *Zero-R algorithm,*
  Prior Probability = 88.73%

MAX(50%, 88.73%) = 88.73%

Minimum acceptable performance indicator = 88.73%

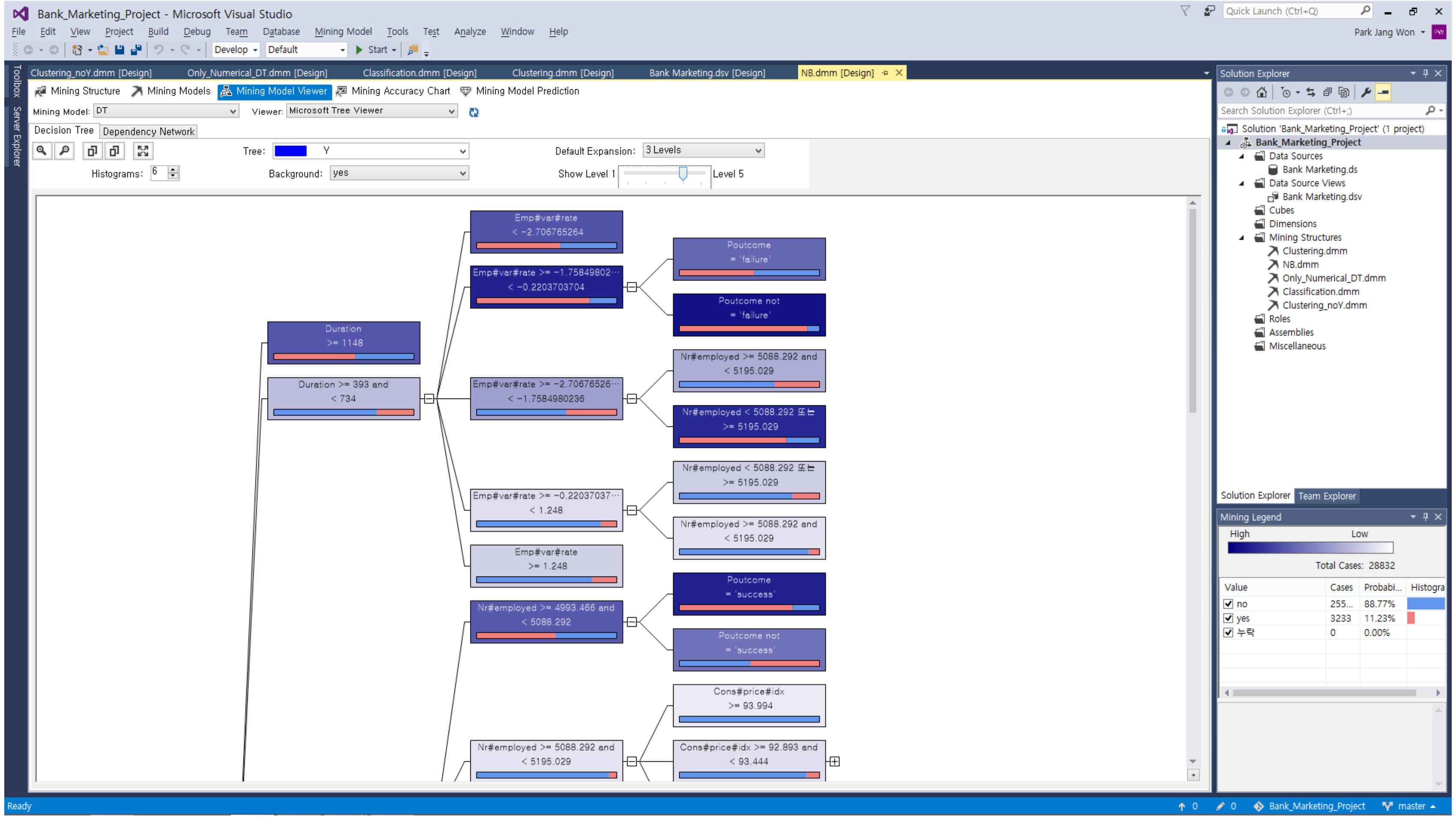
2.2 Building Mining Model

Using NB



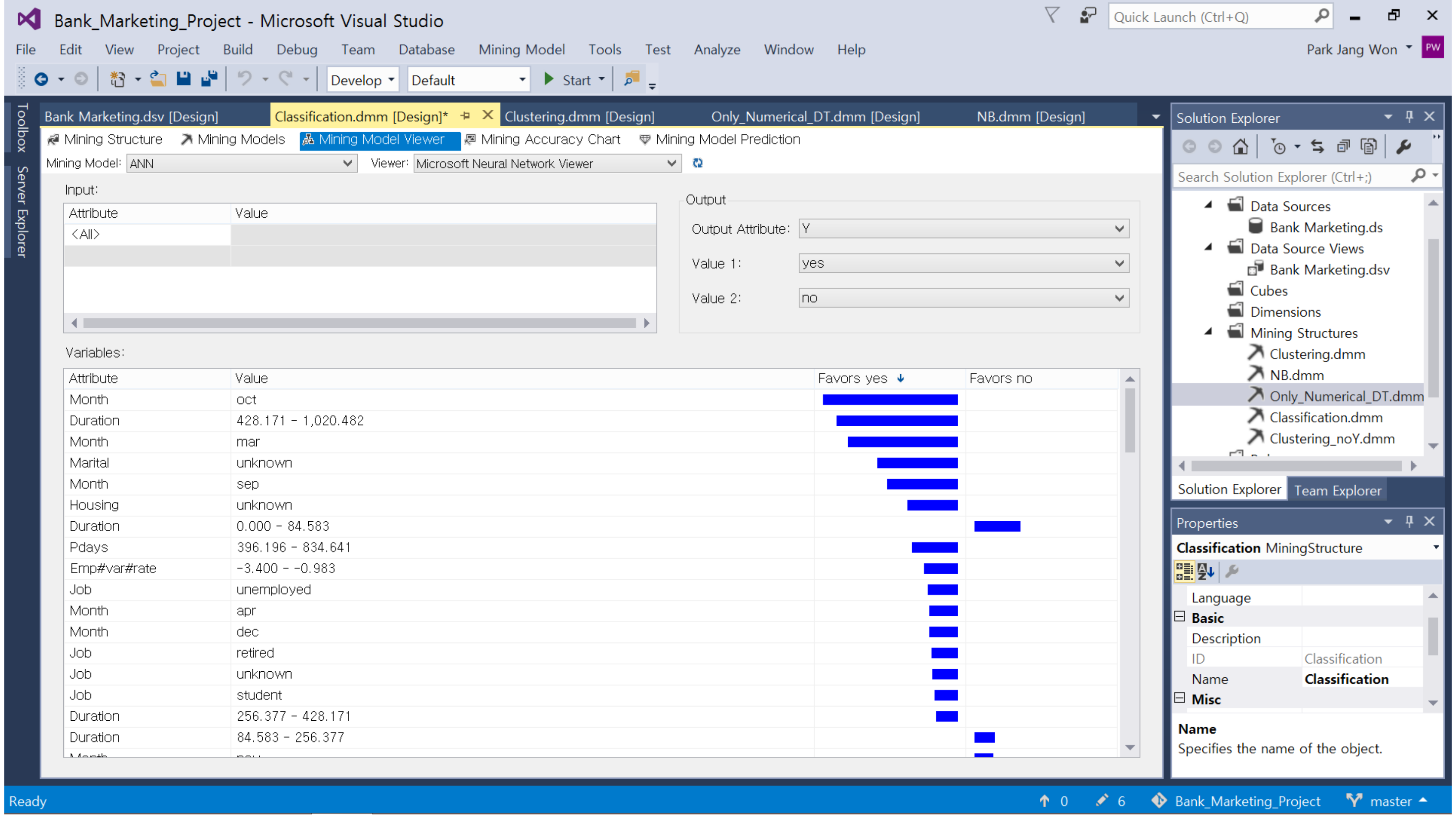
2.2 Building Mining Model

Using DT



2.2 Building Mining Model

Using ANN



2.3 Result

Classification Matrix (focused on Accuracy)

Counts for NB on Y:

Predicted	yes (Actual)	no (Actual)
yes	837	1092
no	570	9857

Counts for DT on Y:

Predicted	yes (Actual)	no (Actual)
yes	670	340
no	737	10609

Counts for NN on Y:

Predicted	yes (Actual)	no (Actual)
yes	823	871
no	584	10078

NB Accuracy = (837+9857) / (837+1092+570+9857)
= 86.55%

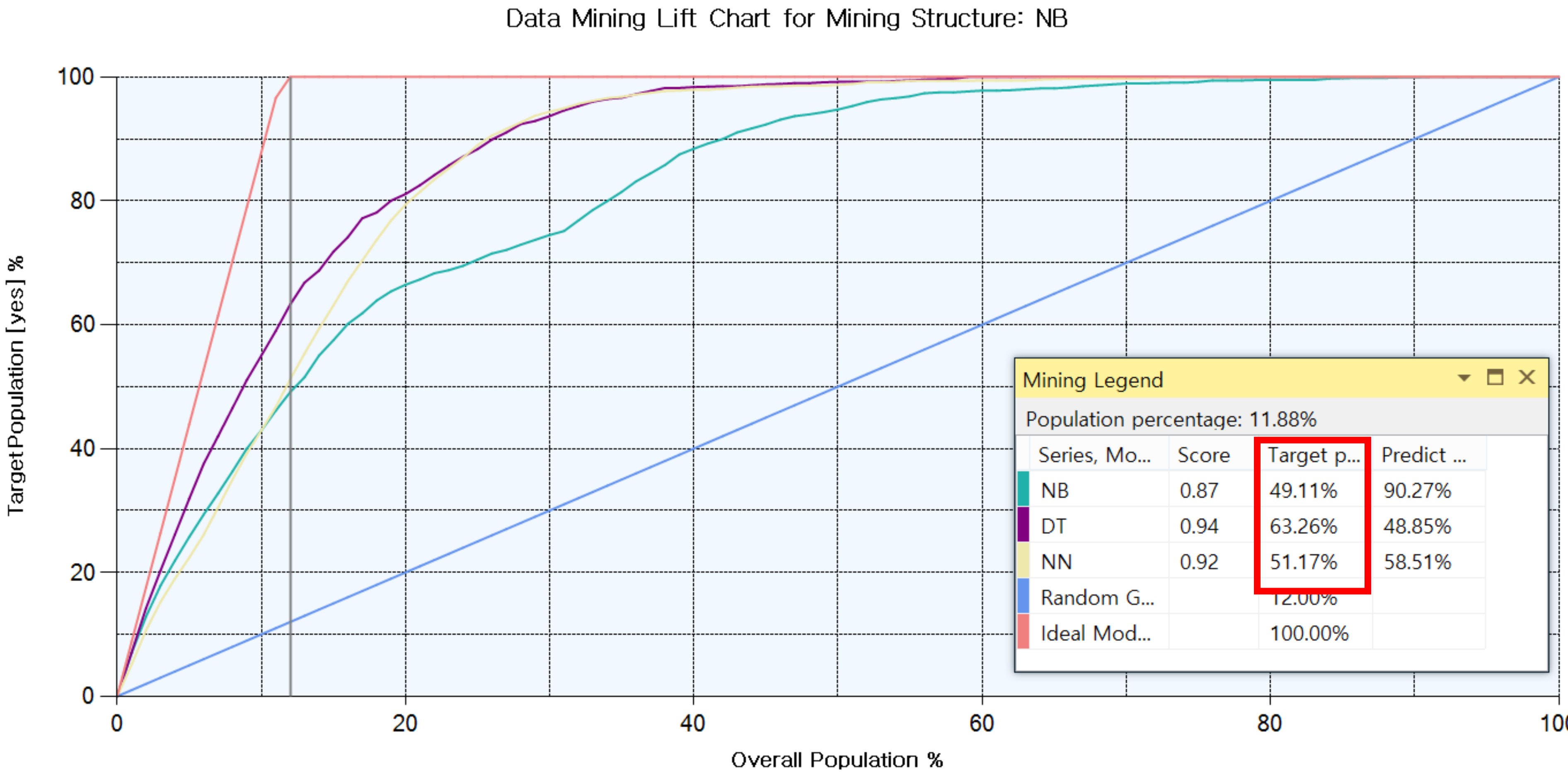
DT Accuracy = (670+10609) / (670+340+737+10609)
= 91.28%

ANN Accuracy = (823+10078) / (823+871+584+10078)
= 88.22%

Highest Accuracy : Decision Tree
Lowest Accuracy : Naïve Bayesian

2.3 Result

Lift Chart



2.3 Result

Q1. Is the difference 3% meaningful?

DT Accuracy = 91.28%
Accuracy based on Prior Probability = 88.73%

Difference = 91.28% - 88.73% ≒ 3%

“ Is this difference really meaningful?”

2.3 Result

Verification by Undersampling Technique

New Dataset with same proportion of “yes” and “no” => “ Undersampling”

- Yes : No = 50 : 50

- Keep the data with “yes”
- Randomly choose 4,640 data out of 36,548 data with “no”

2.3 Result

Conclusion

Counts for DT50to50 on Y:

Predicted	yes (Actual)	no (Actual)
yes	1304	304
no	80	1096

- Accuracy based on prior probabilities = 50%
- DT Accuracy = (1304+1096) / (1304+304+80+1096) = 86.21%
- 86.21% - 50% = <u>36.21 %</u>

Decision Tree is still a highly predictive and accurate tool in this data set

2.3 Result

Q2. Why is the Decision Tree better than Artificial Neural Network?

- ANN shows higher accuracy with continuous data
- In this data set, there are 10 categorical data attribute and 10 continuous data attribute

Verify through new dataset whose categorical data are excluded

2.3 Result

Verification by new data set

Counts for Only_Numerical_DT on Y:

Predicted	yes (Actual)	no (Actual)
yes	533	275
no	825	10723

Counts for Only_Numerical_ANN on Y:

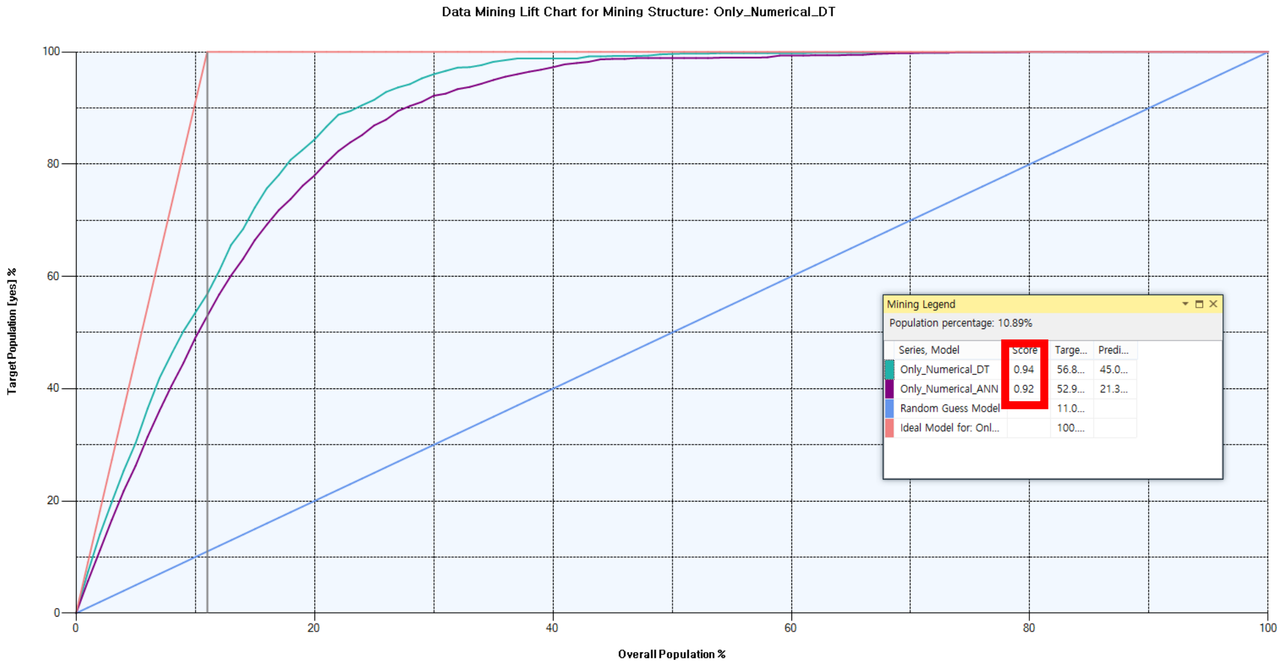
Predicted	yes (Actual)	no (Actual)
yes	283	190
no	1075	10808

	DT	ANN
Original Data Set	91.28%	88.22%
Only continuous	91.25%	89.76%
Difference	-0.03%	1.54%

Still, the Decision Tree is better than Artificial Neural Network…

2.3 Result

Conclusion



Still, DT is better than ANN
Why? Probable reasons:
- continuous data not dispersed enough
- Replacing them with 'Discretized' does not make big difference

2.4 Profit Chart

Basic Assumption

[Telemarketing Campaign]
- Duration: Telemarketing for 3 month
- Execution Method : Outsourcing the Telemarketing-specialized company

Population Assumption

Population	
Portugal Total Population	10,000,000
Above 25	73.1%
	7,310,000

Revenue Assumption

Revenue	
Avg GDP/person	$ 24,000.00
Avg household Saving Rate	4%
Avg saving amount/person	$ 960.00
Net Interest Margin	3%
	$ 28.80

2.4 Profit Chart

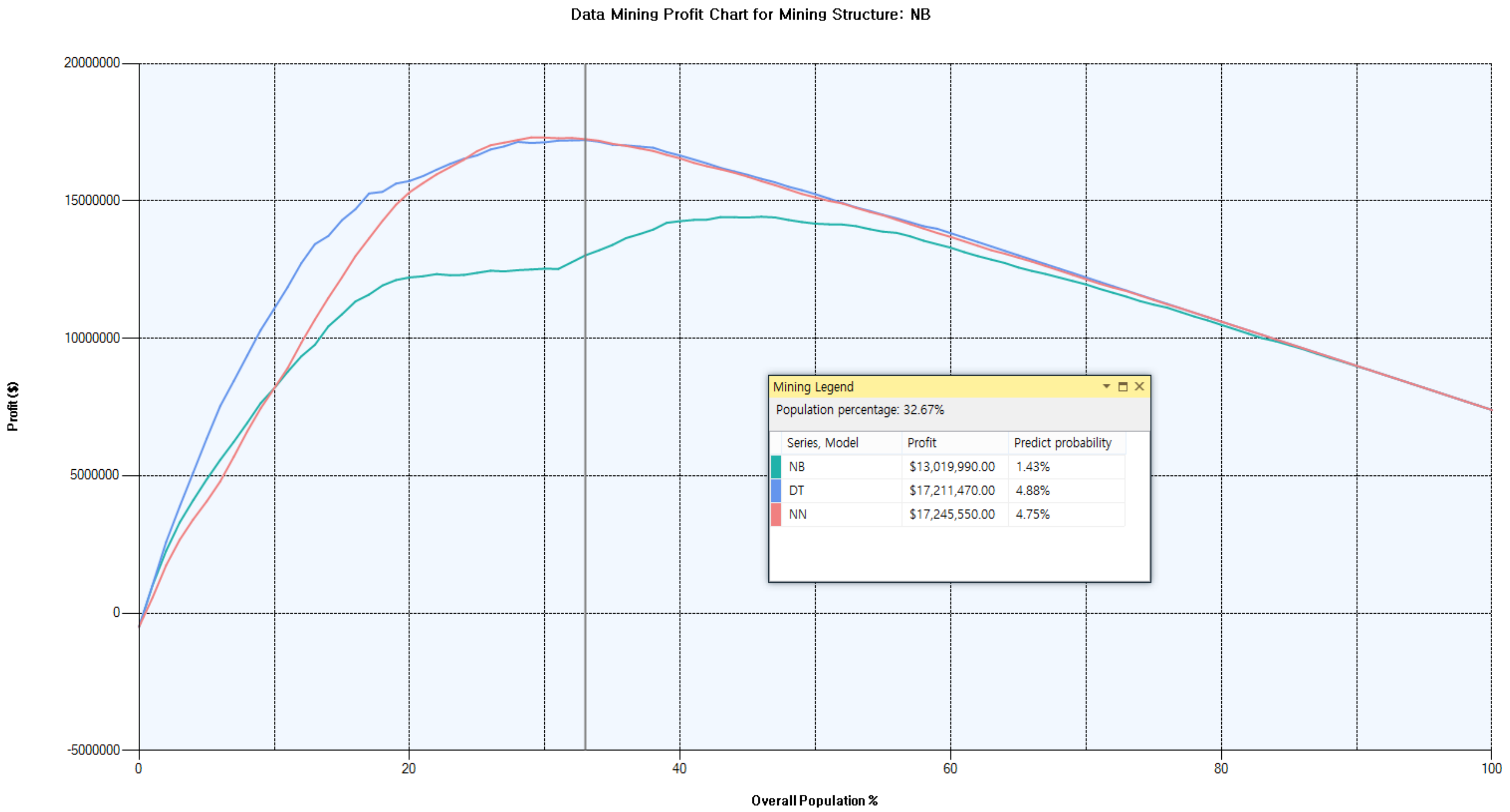
Fixed Cost Assumption

Fixed Cost	Price	Quantity	
Training Cost	$ 322.72	1	$ 322.72
Campaign Management(3 month total)	$ 64.54	3	$ 193.62
Marketing Gift(First-Come-First-Served)	$ 5.00	100,000	$ 500,000.00
			$ 500,516.34

Variable Cost Assumption

Variable Cost			
Avg Agent Cost/hour			$ 15.00
Avg Duration(min)/person			4
Avg Contact person/hour			15
Avg Agent Cost/person			$ 1.00
Avg Cost of Calls/person	$ 0.30	4	$ 1.20
			$ 2.20

2.4 Profit Chart



Should target 32.67% of the population

2.4 Implication

Which factor is the most influential?

1. Deposit tendency is substantially correlated with **Macro Factor**
   - When 1) Interest rate, 2) Number of employed is low and 3) variation of employment is -, it indicates economic depression and people tend to increase deposit
   - When interest rate is low, we usually think that people will decrease deposit but actually, in this data, people tend to increase deposit ← "psychological factor"

2. Deposit tendency is highly correlated with Previous **telemarketing data**
   - "Duration" was the most powerful factor when it comes to predict the outcome

3. Deposit tendency has lowest correlation with **Client Data**
   - Among client data, only default attribute was correlated
   - It indicates that marketing campaign afterwards do not have to consider much about client data and this fact can contribute to lower search cost

2.4 Implication

Other Findings

1 Months: October > March > December

- Since financial crisis arose around September (Bankruptcy of Lehman Brothers: 9/15/2008), it is likely that banks tried more to reach out customers right away
- We also hypothesized that since March and December is end of each quarter it is likely that “push sales” happened; since it is common practice in sales & marketing division to push sales at the end of quarter

Limitation

- Since the company has less control over macro economic factors and the duration of the call, even if they know the result, there is no room for dealing with it
- Therefore, needs for clustering arises → Find out characteristics of customer groups and utilize them for marketing

3

Data Mining Model (2): Clustering

3.1 Objective
3.2 Building Model
3.3 Result & Implication

3.1 Objective

Clustering Objective

Customer Segmentation

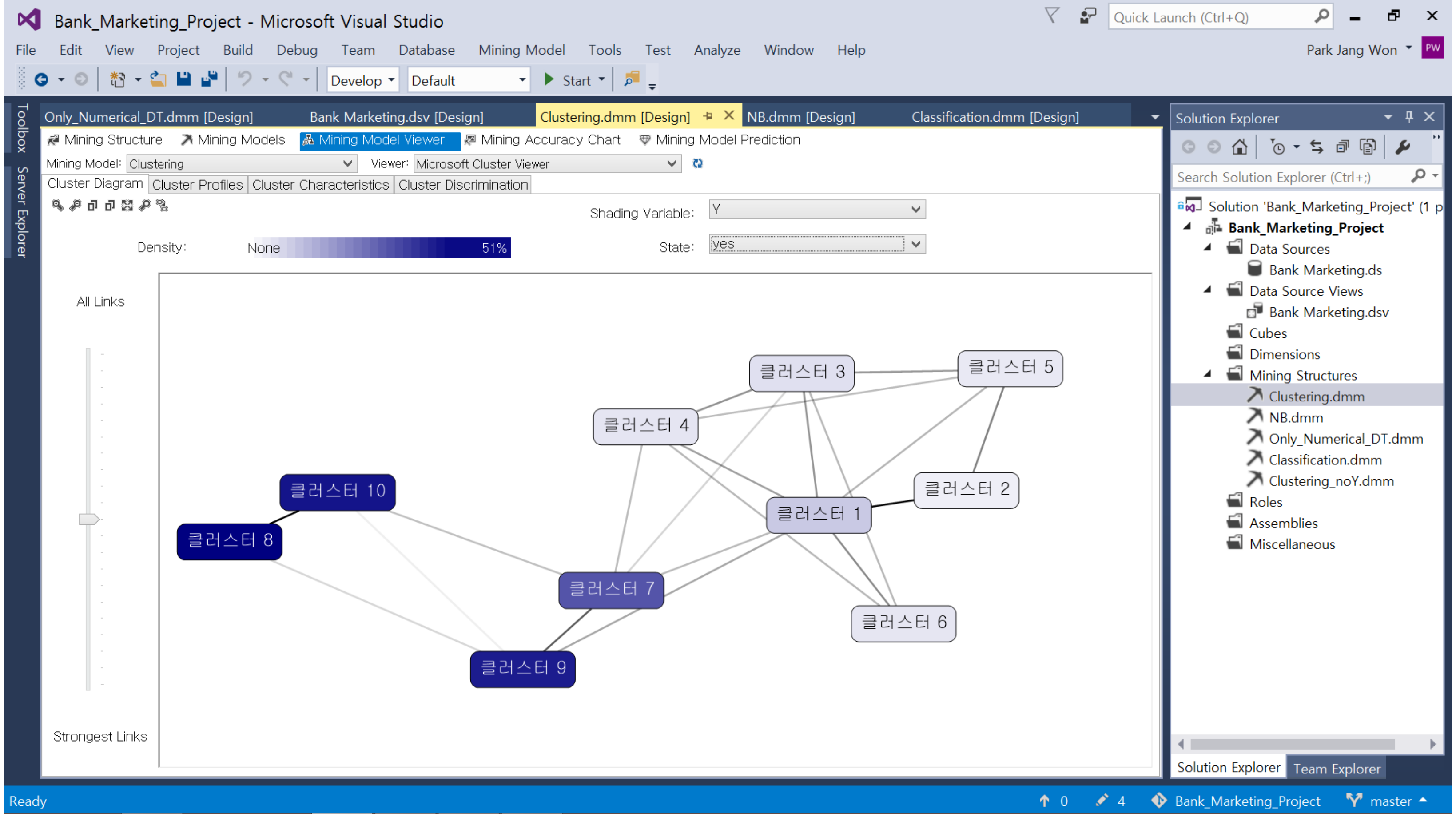
Identify

- Identify the most unique characteristics of the clusters with the highest Yes ratio

Target

- Design marketing strategies that concentrate on these targeted clusters

3.2 Building the Model

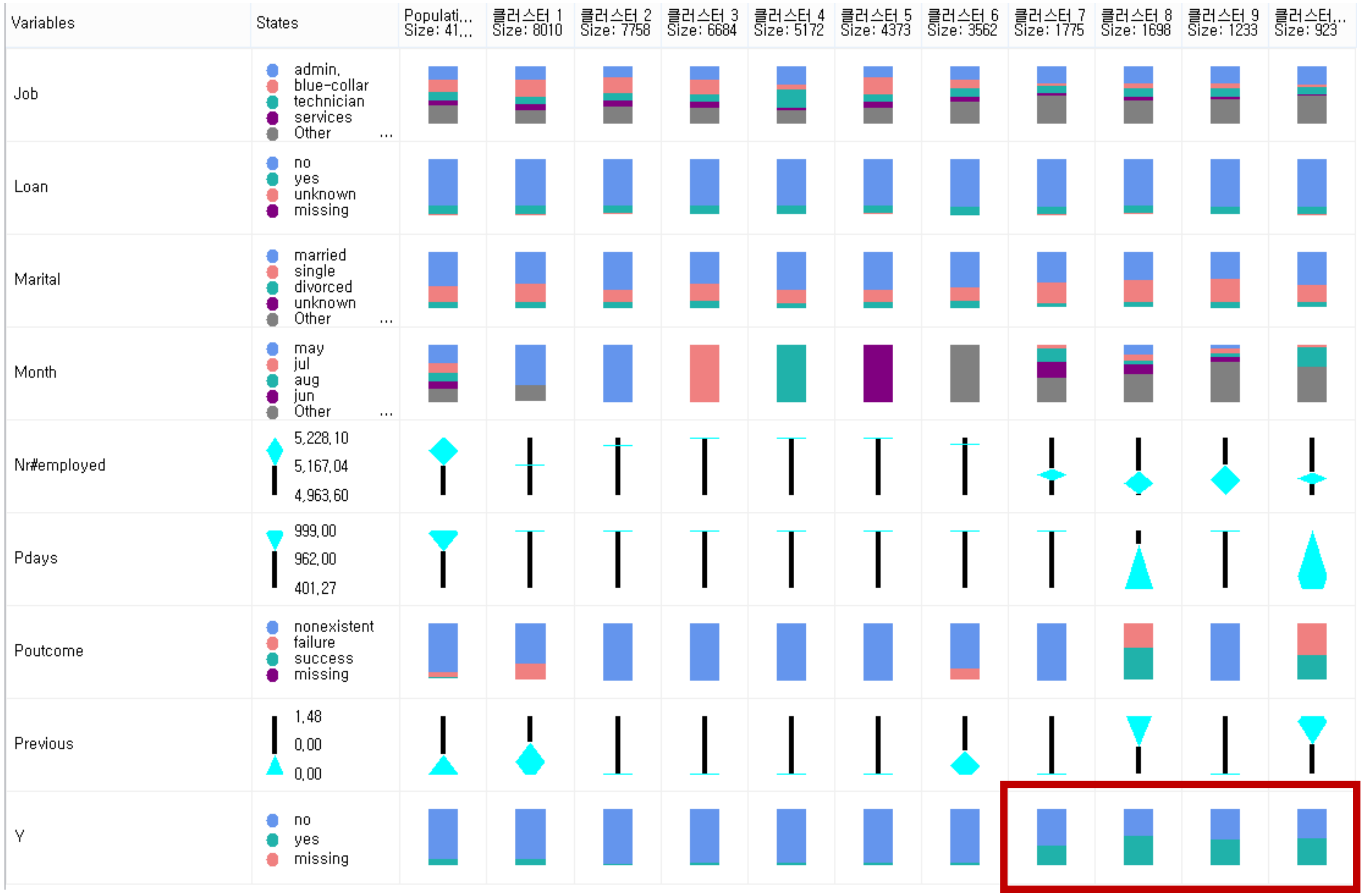


When we set the CLUSTER_COUNT parameter to 0, 10 clusters were formed.

3.3 Results & Implication

1

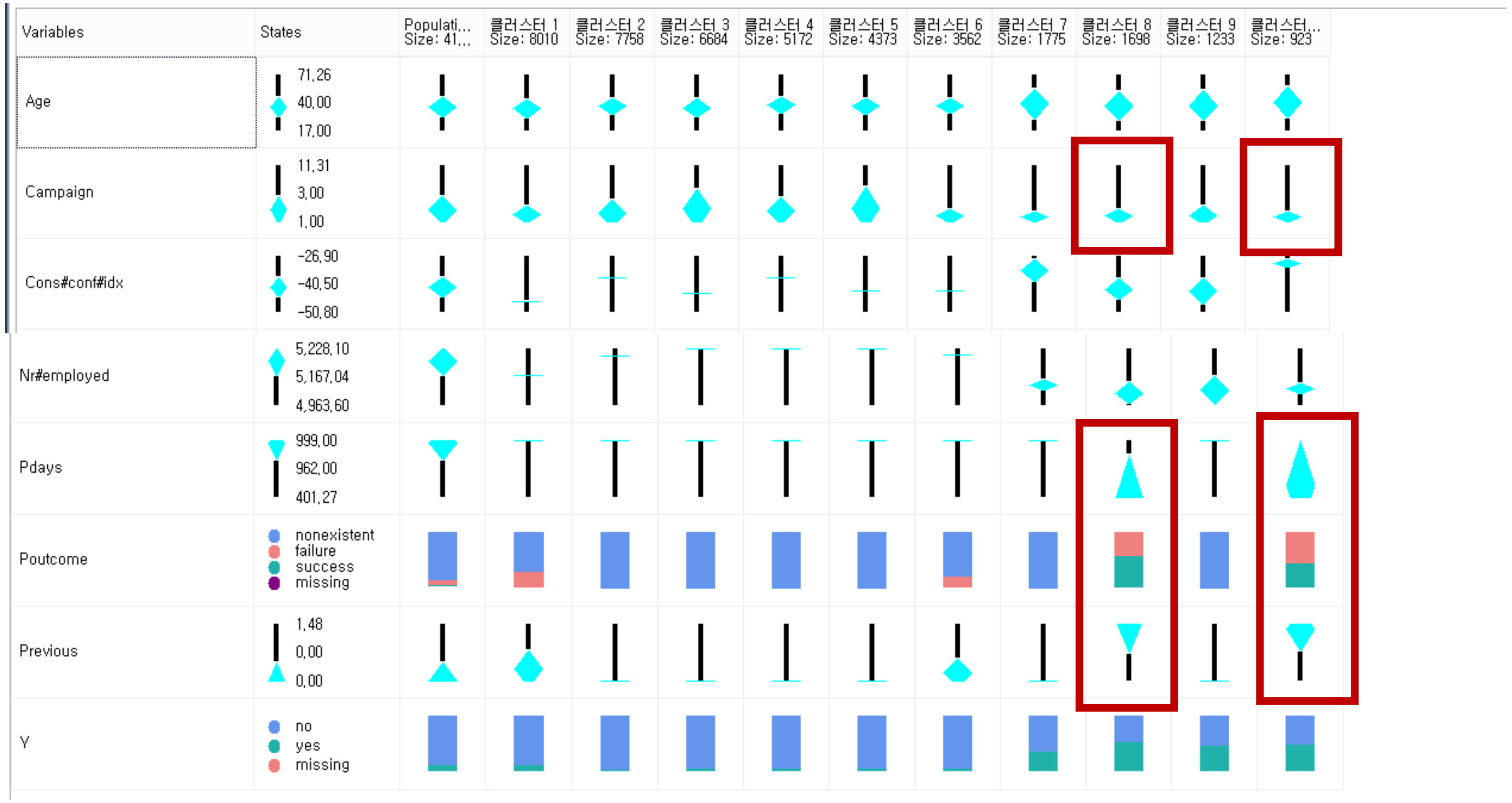
- Cluster 7, 8, 9, 10 has highest Yes ratio among the clusters, but there are still slight discrepancies among the clusters.



3.3 Results & Implication

1

- For further grouping based on similarities, can be paired as Cluster 7 & 9, and Cluster 8 & 10



Cluster 8 & 10 have higher values in attributes: campaign, pdays, previous, poutcome

3.3 Results & Implication

2

- Based only on the results of classification, we may fail to identify cluster-specific discrepancies → less efficient marketing

3

- From results of clustering, we can customize telemarketing strategy to attract more customers from Cluster 7,8,9,10
- Eg.: Contact customers in months that reflect higher Yes rate

After Project...

- Classification and Clustering are complementary
- Classification is used as a tool to study the factors in a broad view
- Clustering extracts the customer segments’ characteristic in a micro-perspective, helping to set practical action plans for the firm.

Thank you!

Appendix

1. Assumption for Profit Chart
2. Prediction
3. YouTube Link
4. Peer Evaluation Table

1. Assumption for Profit Chart

Charge	What is it?	Expected Cost
Hourly call rate	Primarily the cost of wages of the staff employed to make the calls.	£10-£30 per hour, per operative
Set up fee	These are the expenses involved in setting up your campaign, such as training staff to make calls for your particular product or service (during which time they are unavailable for other campaigns), writing a script and refining the sales pitch.	£250
Cost of calls	Will usually be rolled into the hourly call rate but there may be a surcharge for international calls.	Depends on location and targeting
Cost of data	If the telemarketing company needs to source the lists of names and numbers used in the campaign then you'll pay an extra fee for this.	Varies by project
Campaign Management	Admin and managerial fees for setting up and overseeing your campaign	£50 per month

Age structure:

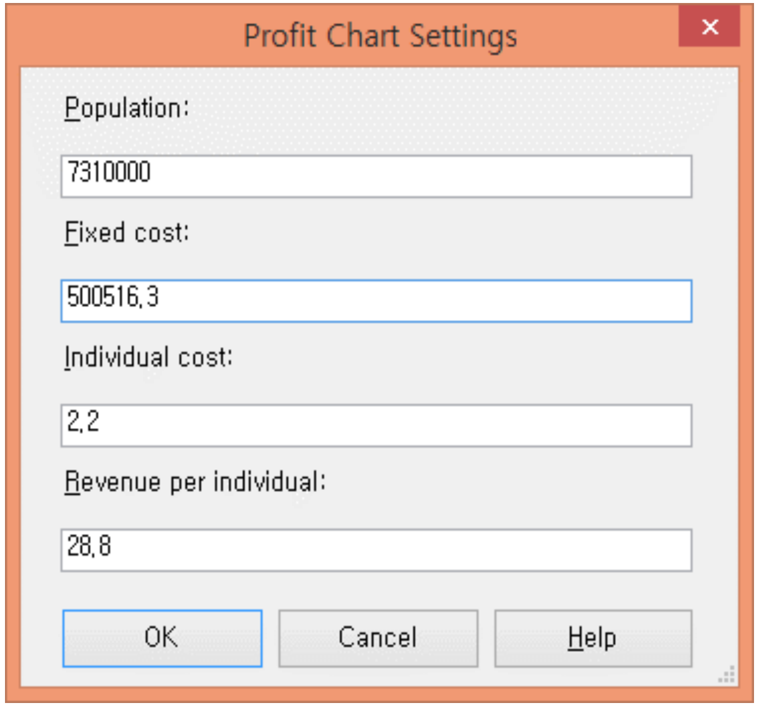
0-14 years: 15.5% (male 874,807/female 804,483)

15-24 years: 11.4% (male 655,234/female 579,669)

25-54 years: 41.88% (male 2,300,872/female 2,236,077)

55-64 years: 12.07% (male 610,886/female 697,287)

65 years and over: 19.15% (male 849,506/female 1,224,995) (2016 est.)

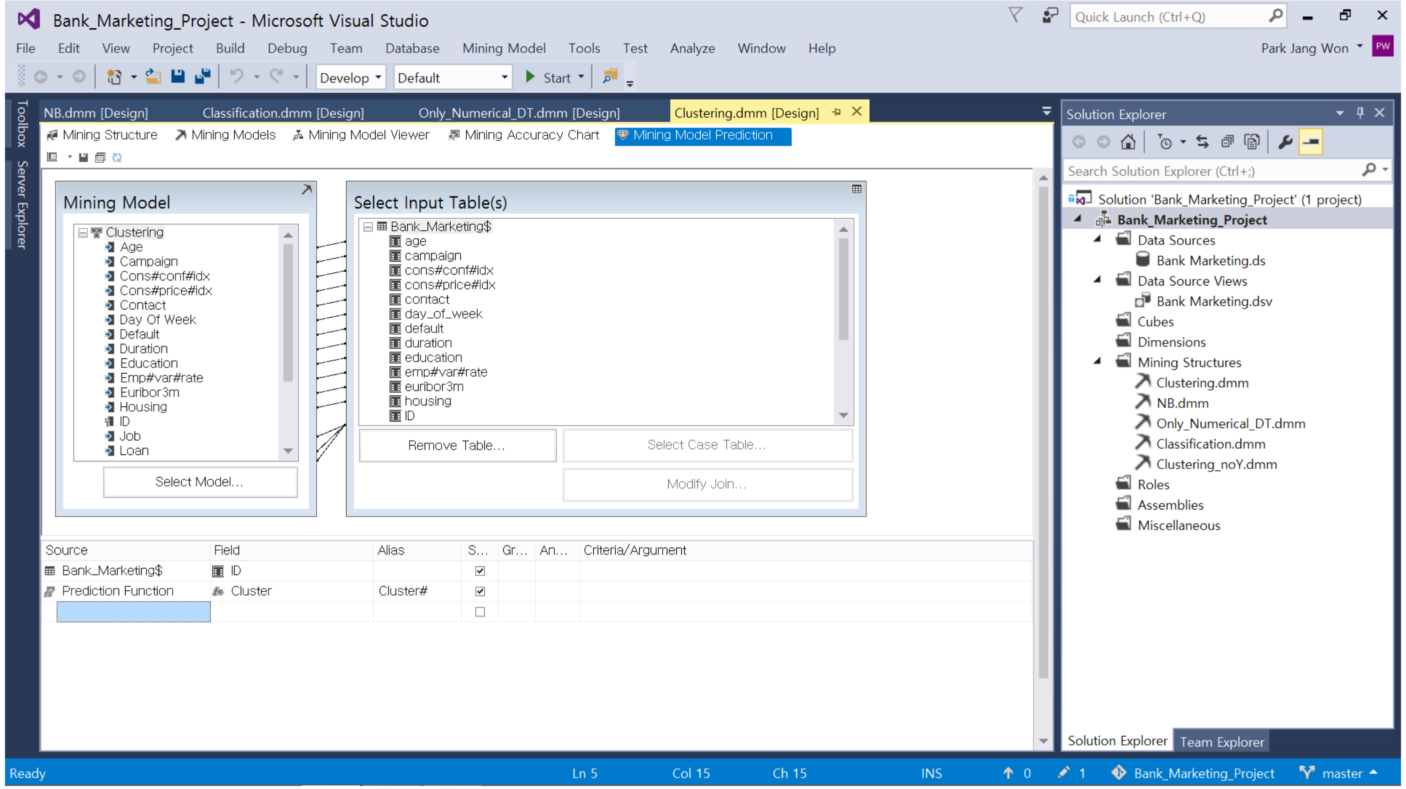


2. Mining Model Prediction

Predicting Which Cluster Customer Belongs to

1

Use Prediction Function with Cluster as Field

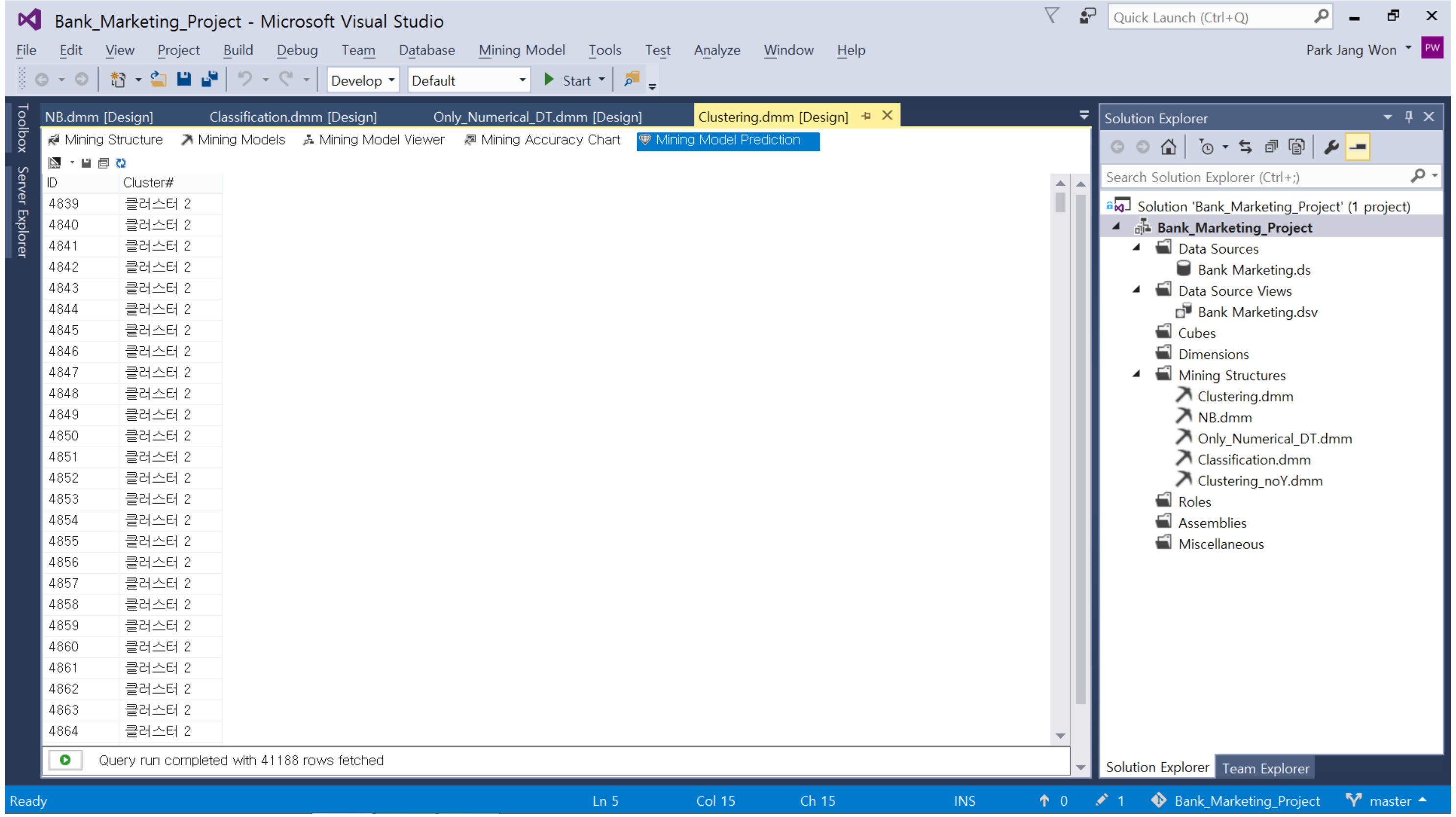


2. Mining Model Prediction

Predicting Which Cluster Customer Belongs to

2

Prediction Results in Query View

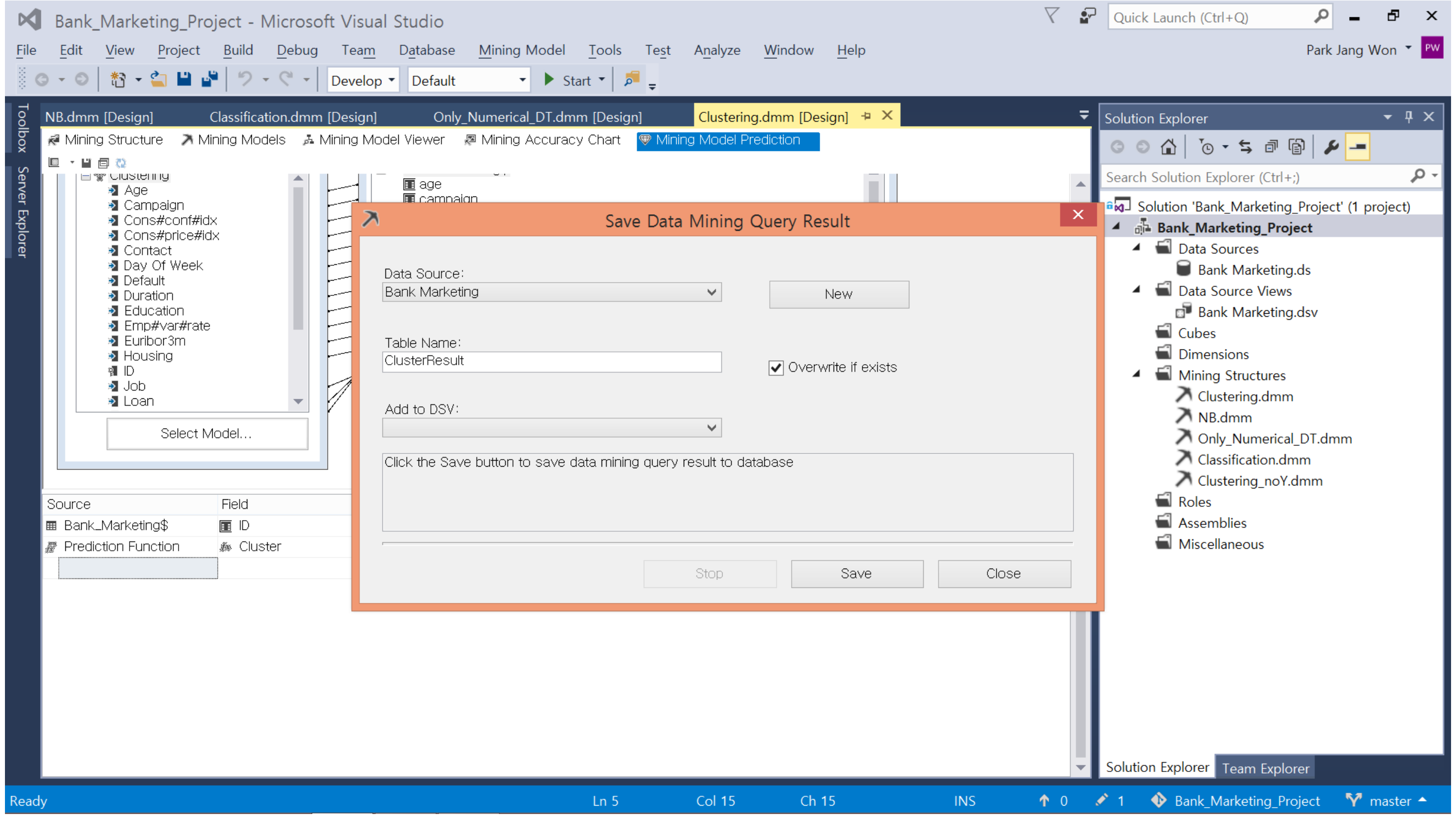


2. Mining Model Prediction

Predicting Which Cluster Customer Belongs to

3

Save results to SSMS

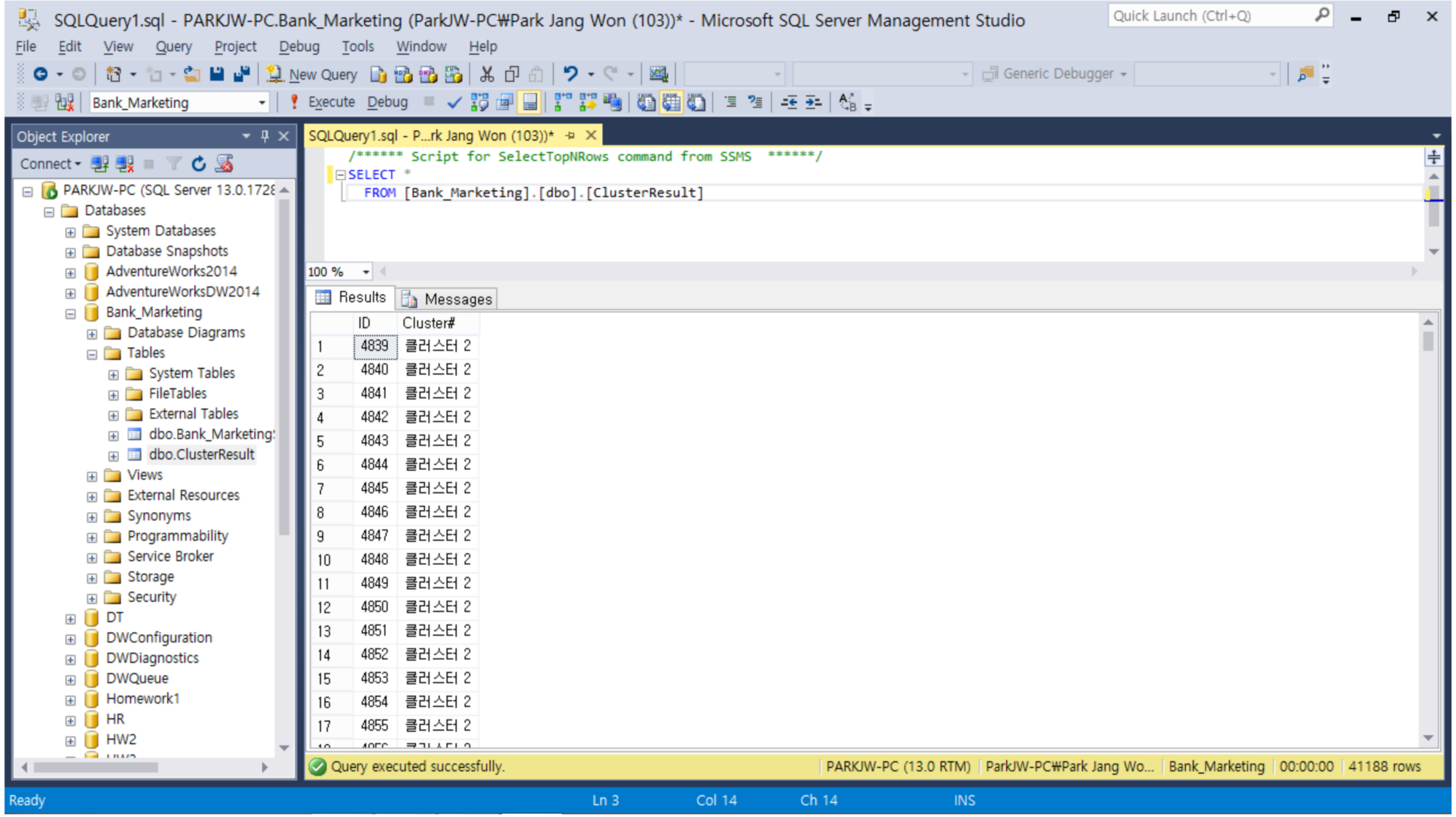


2. Mining Model Prediction

Predicting Which Cluster Customer Belongs to

4

Saved as Table ‘ClusterResult’ in SSMS

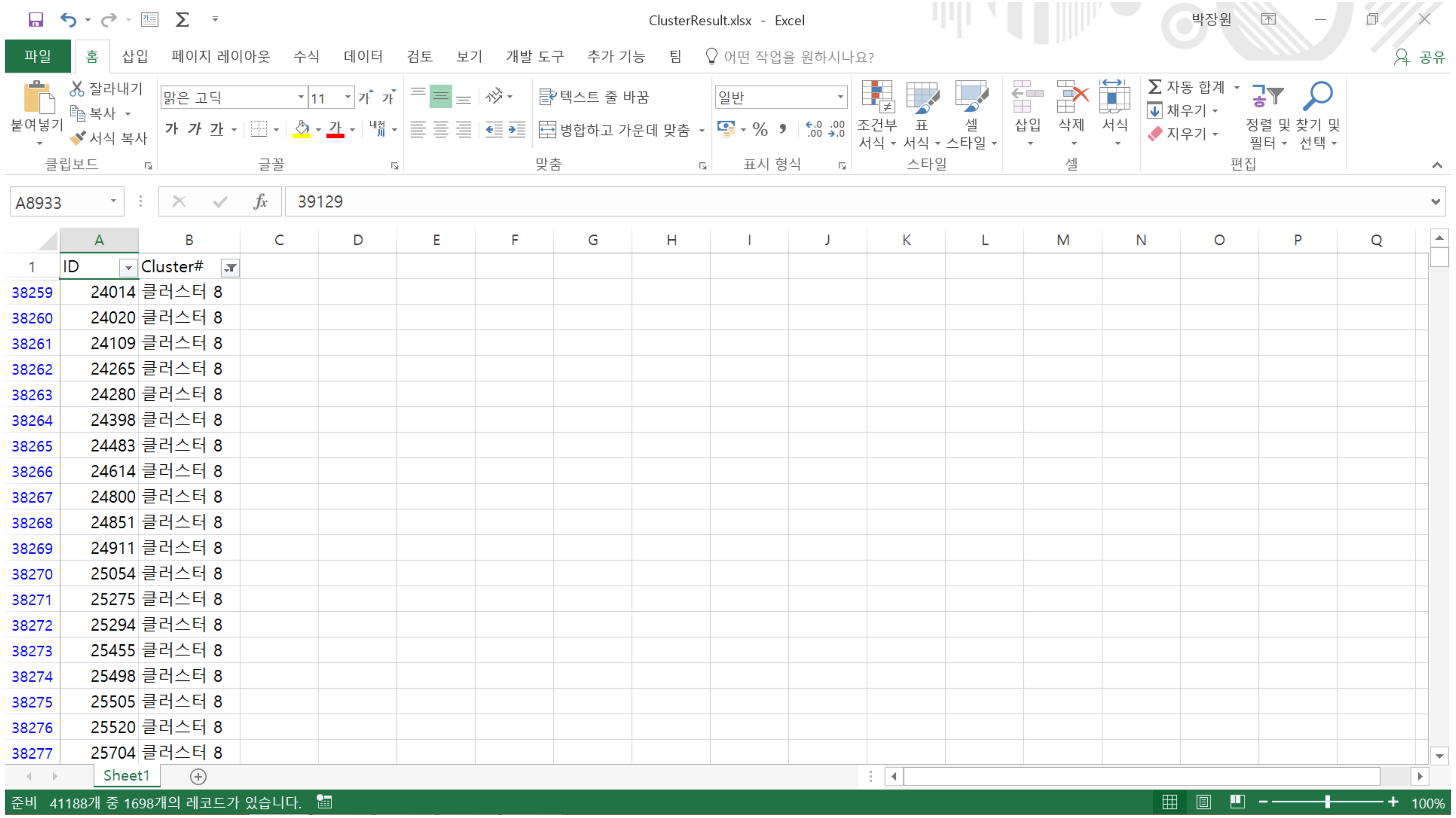


2. Mining Model Prediction

Predicting Which Cluster Customer Belongs to

5

Filter results in Microsoft Excel



3. YouTube Link

Click Here:

https://www.youtube.com/watch?v=-qhtImt6k08&feature=youtu.be

4. Peer Evaluation Table

Jeen Vern Liew	김용진	박장원
100%	100%	100%