ESSEC BUSINESS SCHOOL

Strategic Marketing Analytics

Session 5
Predictive Modeling

Today's agenda

- Need-based segmentation
  - A quick refresher
- Choice-based segmentation
- Choice models, scoring, and score classes
- Practical applications
  - Target
  - Direct marketing fundraising
  - ESSEC Foundation
- Software overview
  - Predictive modeling

A quick refresher

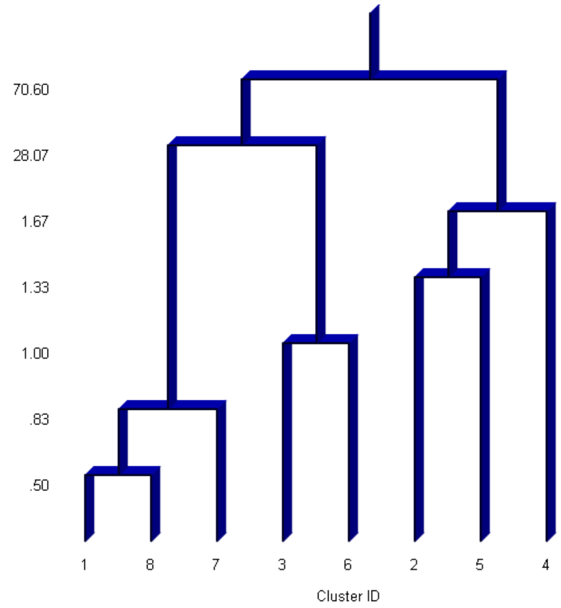
NEED-BASED SEGMENTATION

Reminder from last weeks

Need-based segmentation

How need-based segmentation works:

- Observe segmentation variables/bases (needs, profile, behavior)
- Group customers based on similarities
- Segments need to be
  - Manageable
  - Homogeneous
  - Distinct



- Once defined, describe and name segments

Illustration

Survey: Marketing Management

The results of this survey will be used to illustrate the choice-based segmentation concept next Monday.

* Required

When you graduate, will your first job be in marketing? *

1 2 3 4 5

Very unlikely ○ ○ ○ ○ ○ Very likely

When you graduate, will your first job be in finance, trading, banking? *

1 2 3 4 5

Very unlikely ○ ○ ○ ○ ○ Very likely

When you graduate, will your first job be in strategic consulting? *

1 2 3 4 5

Very unlikely ○ ○ ○ ○ ○ Very likely

Do you plan to launch a new company/a startup within the next five years? *

1 2 3 4 5

Very unlikely ○ ○ ○ ○ ○ Very likely

Would you say you have an analytical mind, you're good with numbers? *

1 2 3 4 5

Absolutely not ○ ○ ○ ○ ○ Absolutely

Do you enjoy marketing analytics, marketing research, quantitative methods applied to marketing? *

1 2 3 4 5

Absolutely not ○ ○ ○ ○ ○ Absolutely

Are you close to graduation? *

1 2 3 4 5

No, I just started ○ ○ ○ ○ ○ Yes, very close

So far, do you enjoy the Marketing Management course? *

You answer will remain anonymous

1 2 3 4 5

Not at all ○ ○ ○ ○ ○ Very much

Do you appreciate your professor/instructor (Marketing Management course)? *

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Not at all ○ ○ ○ ○ ○ Very much

Suppose a new elective course opened, named "Strategic Marketing Consulting". The entire course would be based on readings, a few lectures, and a big term project, where you would be asked to apply marketing engineering techniques (segmentation, targeting, positioning, pricing...) to solve real business problems (either one you have identified, or one submitted by a company). How likely would you take this course? *

1 2 3 4 5

I would never take this course ○ ○ ○ ○ ○ I would certainly take this course

How would you name this course? *

- ☐ Strategic Marketing Consulting
- ☐ Marketing Engineering
- ☐ Applied Marketing Analytics
- ☐ Other:

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How would you name this course?

FORGET ABOUT THIS PART FOR THE TIME BEING

- ☐ Strategic Marketing Consulting
- ☐ Marketing Engineering
- ☐ Applied Marketing Analytics
- ☐ Other:

Submit

Illustration

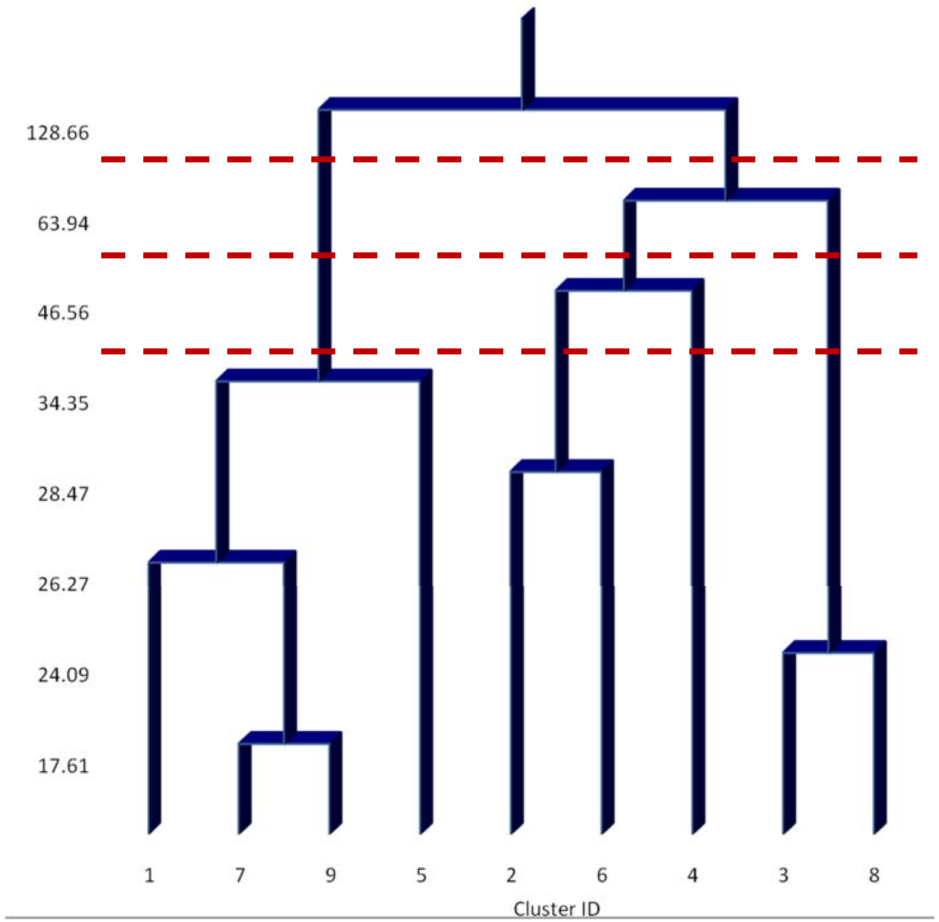
- Segmentation variables
  - When you graduate, will your first job be in **marketing**?
  - When you graduate, will your first job be in **finance**?
  - When you graduate, will your first job be in **strategic consulting**?
  - Do you plan to launch a **startup** within the next five years?
  - Would you say you have an **analytical mind**?
  - Do you enjoy **marketing analytics**?
  - Are you close to **graduation**?
  - So far, do you enjoy the Marketing Management **course**?
  - Do you appreciate your **instructor**?

- Discriminant variables
  - None

Dendogram

- Two segments?
  Three?
  Four?

- Let's run with four…



Segmentation results

Cluster Sizes

The following table lists the size of the population and of each segment, in both absolute and relative terms.

Size / Cluster	Overall	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Number of observations	44	20	11	9	4
Proportion	1	0.455	0.25	0.205	0.091

Segmentation Variables

Means of each segmentation variable for each segment.

Segmentation variable / Cluster	Overall	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Marketing	2.6	***4.1***	***1.2***	1.7	**1.5**
Finance	2.4	**1.4**	3.4	***4.1***	**1.3**
Strategic consulting	3.0	3.2	2.5	**3.9**	***1.3***
Entrepreneur	2.9	2.7	***4.5***	**1.9**	2.5
Analytical_Mind	3.8	3.9	4.2	3.6	***2.8***
Marketing_Analytics	3.3	3.6	3.3	3.4	***1.8***
Close_To_Graduation	3.5	3.4	4.1	**2.7**	3.8
Enjoy_MM	3.8	4.2	3.7	3.6	***2.5***
Enjoy_Instructor	4.3	4.4	***4.5***	***4.2***	**4.3**

Segment names and profiles

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- Segment 1
  - The "Marketeers"
  - 45%
- Segment 2
  - The "Entrepreneurs"
  - Close to graduation
- Segment 3
  - The "Dark Navy Suits"
  - No entrepreneurial spirit, youngest
- Segment 4
  - The "No-no-nothing"
  - 9% only

Strategy?

Suppose you were planning to open a new elective course named “Strategic Marketing Analytics”

- Which segment would you target?
- With what message/communication strategy?

The issue…

- Need-based segmentation is appropriate to understand similarities of profiles

- Not always appropriate to answer questions such as:
  - Will they buy my product or not?
  - What factors drive their choices?
  - Which brand will they pick (out of many)?

- Because similarities might not predict **choices** well

Another illustration

- Three segments in the high-end car market
  - Built on a sample of customers
  - Deep-needs analysis

SEGMENT 1
"Luxury/pleasure"
They want to indulge themselves with a luxurious and enjoyable toy.

SEGMENT 2
"Status"
To own an expensive car signals that they "made it", it's a status item.

SEGMENT 3
"Peace of mind"
They just want excellent quality and reliability, and outstanding service.

- Obviously, the segmentation is valuable
  - To understand customers' motivations
  - To tailor communication strategy/advertising to their motivations
  - Etc.

Illustration

- Three segments in the high-end car market
  - Built on a sample of customers
  - Deep-needs analysis

SEGMENT 1	SEGMENT 2	SEGMENT 3
"Luxury/pleasure"	"Status"	"Peace of mind"
They want to indulge themselves with a luxurious and enjoyable toy.	*To own an expensive car signals that they "made it", it's a status item.*	*They just want excellent quality and reliability, and outstanding service.*

But which segment is more likely to buy a Mercedes SLS?

CHOICE-BASED SEGMENTATION

Choice-based segmentation groups customers based on their response likelihood.

...Similarities only matter to the extent that they are predictive of customer choices.

Data needs

Need-based segmentation

Segmentation variables
(bases)

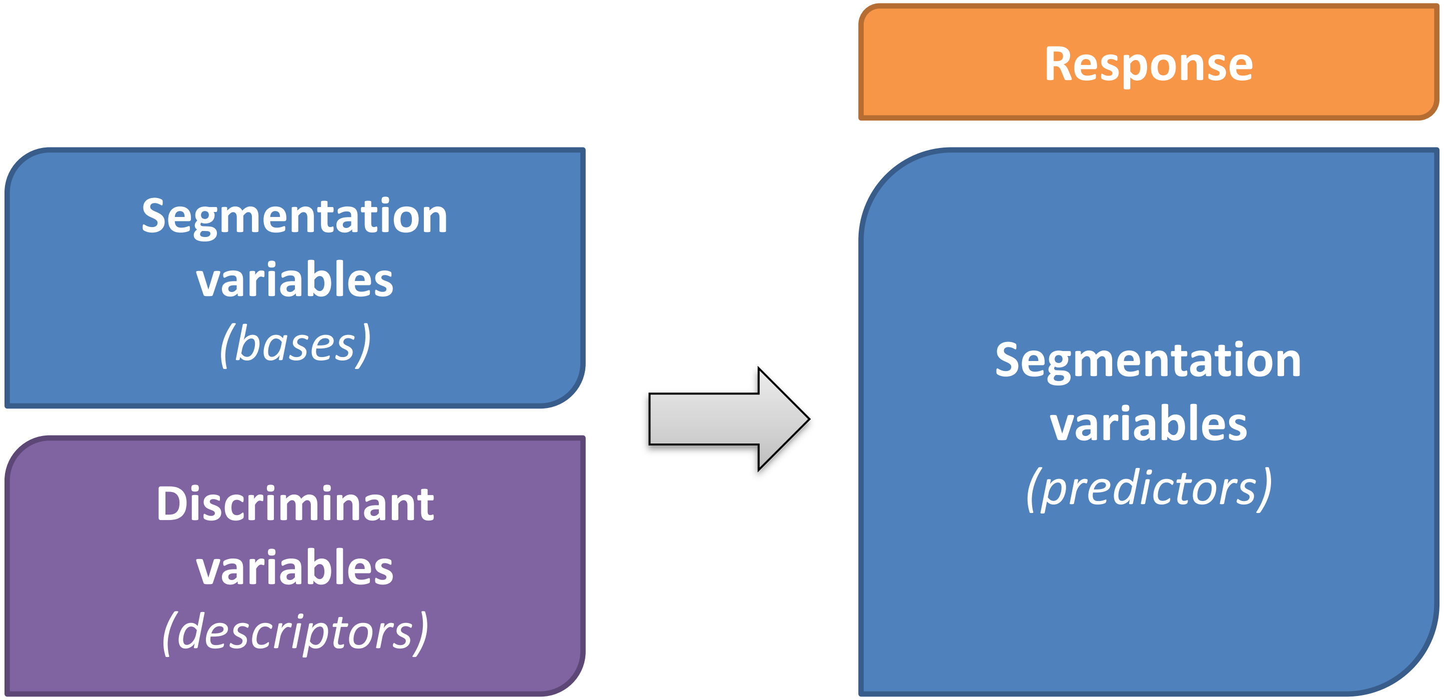
Discriminant variables
(descriptors)

- In need-based segmentation, we carefully divide data between segmentation and discriminant data, and build segments based on the former only…
- …Because we don't want to build segments on the base of irrelevant data
  - E.g., demographics, so what?

Data needs

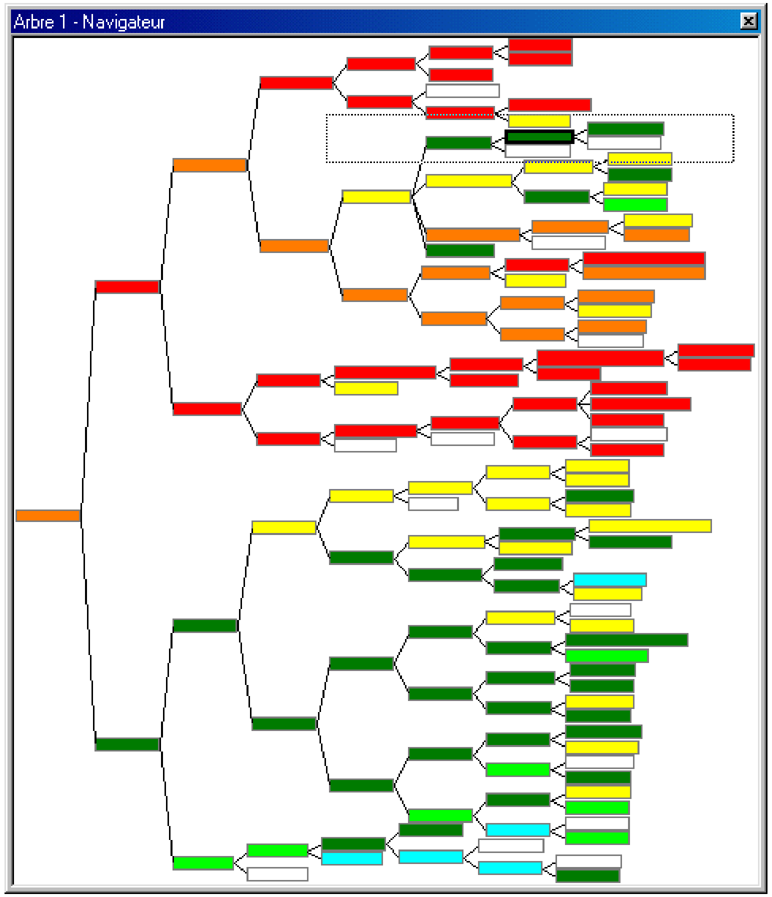
- In a typical choice-based segmentation, the *model* decides what's relevant, and everything becomes segmentation data (to predict likelihood of response)

Need-based segmentation **Choice-based segmentation**



CART

- **CART** (for classification and regression tree) is one of the most popular choice-based segmentation tools



CART in practice

1. Select the **predictors** (segmentation variables)
   - Past behavior
   - Demographics
   - …

2. Select the **response**, to be predicted/explained
   - Buy or not, Donate or not (0/1)
   - Brand choice (A, B, C)
   - Purchase amount ($X)

3. Group all the respondents/customers into one big **pool**
   - The “parent node”

CART in practice

4. For each available predictor, one by one, **split the population** (the parent node) into subgroups (the child nodes), and check to what extent the child nodes are
   - More homogeneous (within)
   - More distinct (between)

5. Keep the split that works best
   - Where “best” is usually measured by a statistical index, such as entropy, Gini index, RMSE, etc.

6. Repeat for each child node

7. Stop when some criteria are met
   - No further improvement,
   - Not enough data to keep going

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- ☐ Marketing Engineering
- ☐ Applied Marketing Analytics
- ☐ Other:

LET'S TRY TO PREDICT THESE RESPONSES

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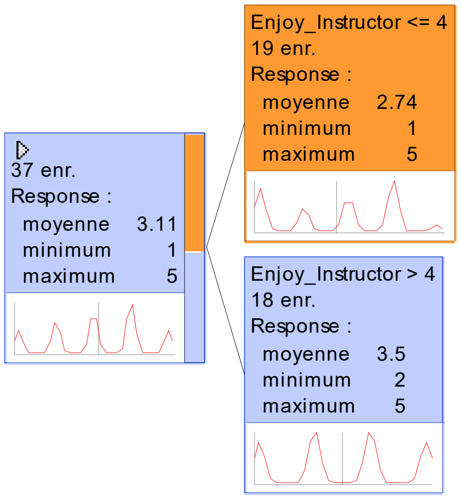
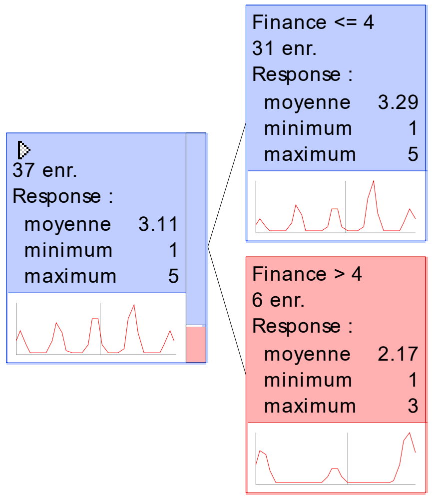
Illustration

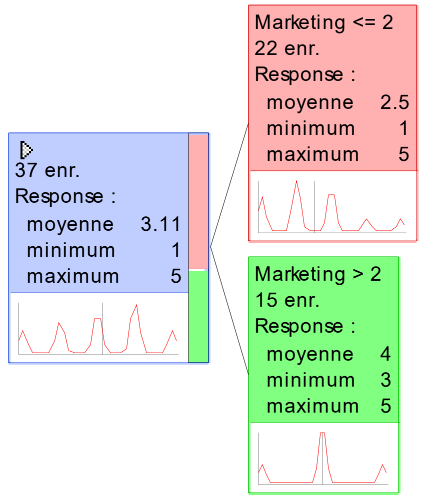
- Predictors:
  - Students' profiles (analytical mind, etc.)
  - Students' specialization (finance, etc.)
  - Current satisfaction (course, instructor)

- Response:
  - Likelihood to take an advanced elective course (1..5)

Testing all potential splits…







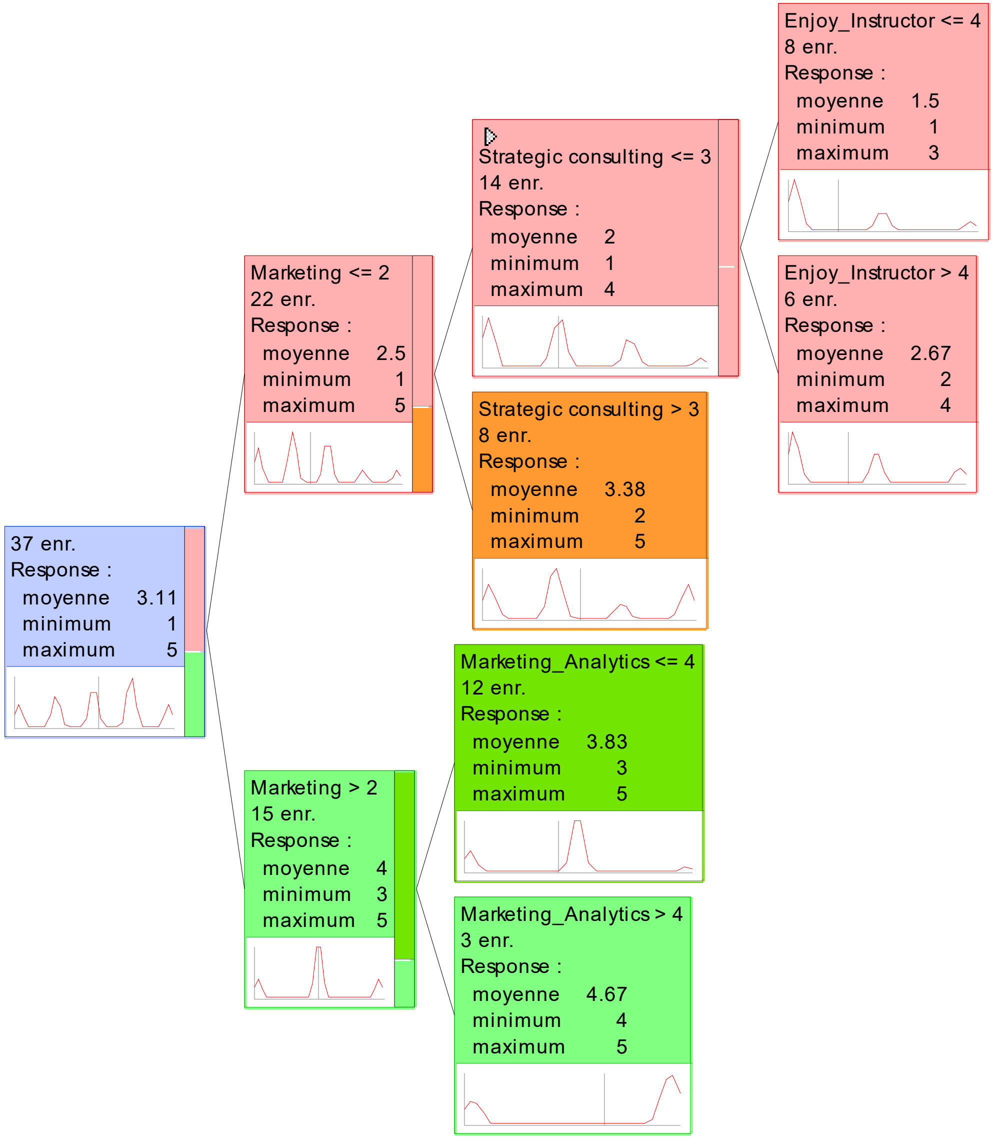
- Satisfaction with current instructor?
- Poor predictor

- Intend to specialize in finance?
- Slightly better

- Intend to specialize in marketing?
- **Excellent** predictor

And repeat the process for each leaf node

5 segments

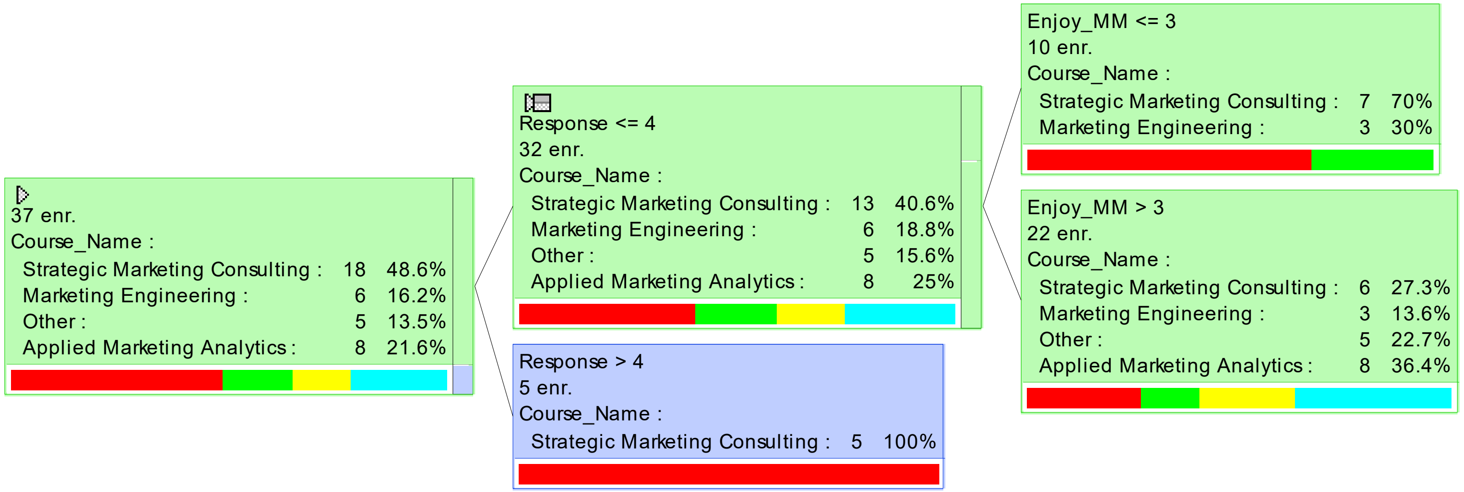


Use of CART

In CART, the predicted response can be…

- A binary decision
  - Buy / Do not buy
  - Donate / Do not donate
  - Register / Do not register
- An integer or a real number
  - Amount
  - Likelihood of…
- A choice out of a set
  - Brand A / B / C
  - Choice A / B / C

Example



- Replace “preferred course name” by “preferred brand”, and you’ll have a perfect marketing application of CART

Limitations of CART

- Each split reduces the size of the population left in the node
  - If you want to go deep, you need a lot of data!
  - Risk of overfitting the data
    (i.e., finding by chance a relationship that does not exist)

- The method only select a subset of predictors
  - Those that are not selected are the least important
  - But they still have predictive value
  - Yet, they are overlooked

- Within each node, response is still heterogeneous

CHOICE MODELS, SCORING, AND SCORE CLASSES

Choice model

> A **choice model** is a mathematical model that predicts the likelihood of an observed choice/response based on related characteristics data (or predictors)

Components of a choice model

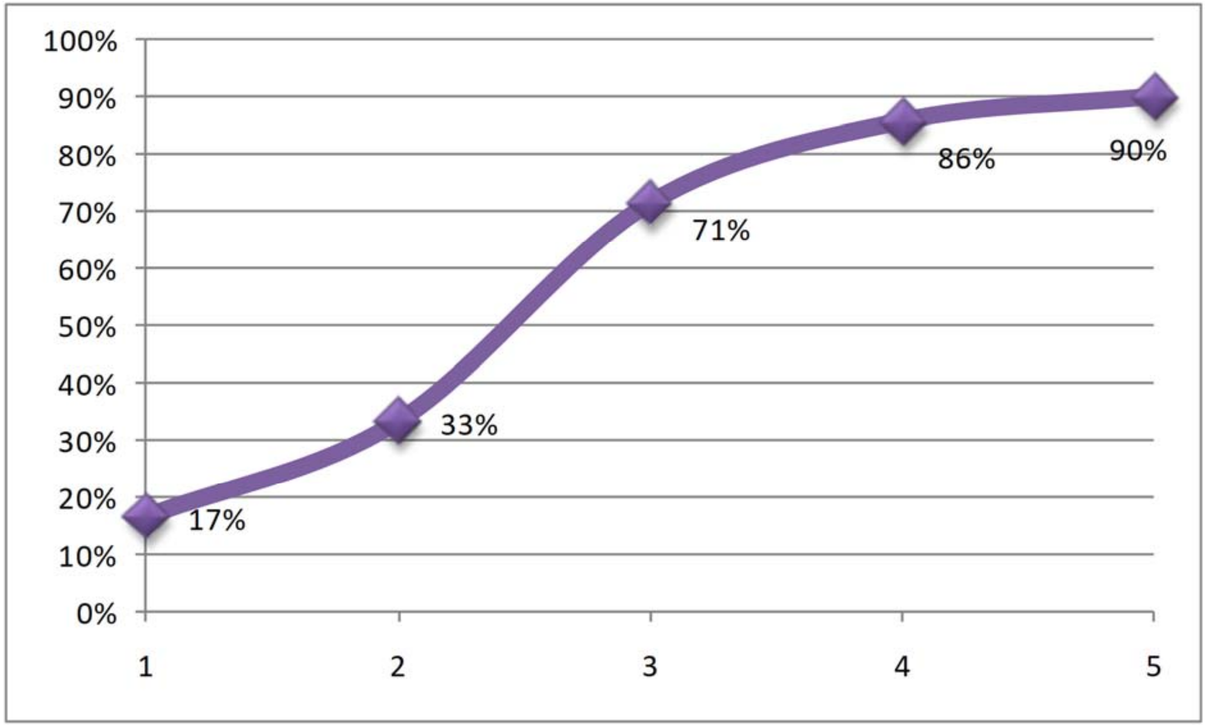
- Observed choice
  - Buy / not buy (e.g., direct marketers)
  - Brand bought (e.g., packaged goods)

- Predictors
  - Demographics
  - Attitudes, perceptions
  - Market conditions (price, promotion, etc.)
  - Past behavior, pattern of previous choices

- Link between the two
  - The model **predicts** customers' probabilities of purchase…
  - …And in the process, **reveals** importance weights of predictors (some might have little weight, hence being bad predictors)

Illustration

- Predictor "Interest in marketing" (scale 1-5)
- Response "Take this elective course" (0 or 1)



(*) For this illustration, we've assumed that an answer of 1 to 3 is equal to "no", and an answer of 4 or 5 is equal to "yes". The 86% figure here means that 86% of the respondents who answered "4" to the marketing question, answered either "4" or "5" to the target question.

The Logit model

$$response = \frac{1}{1 + e^{-\sum(weights \times characteristics)}}$$

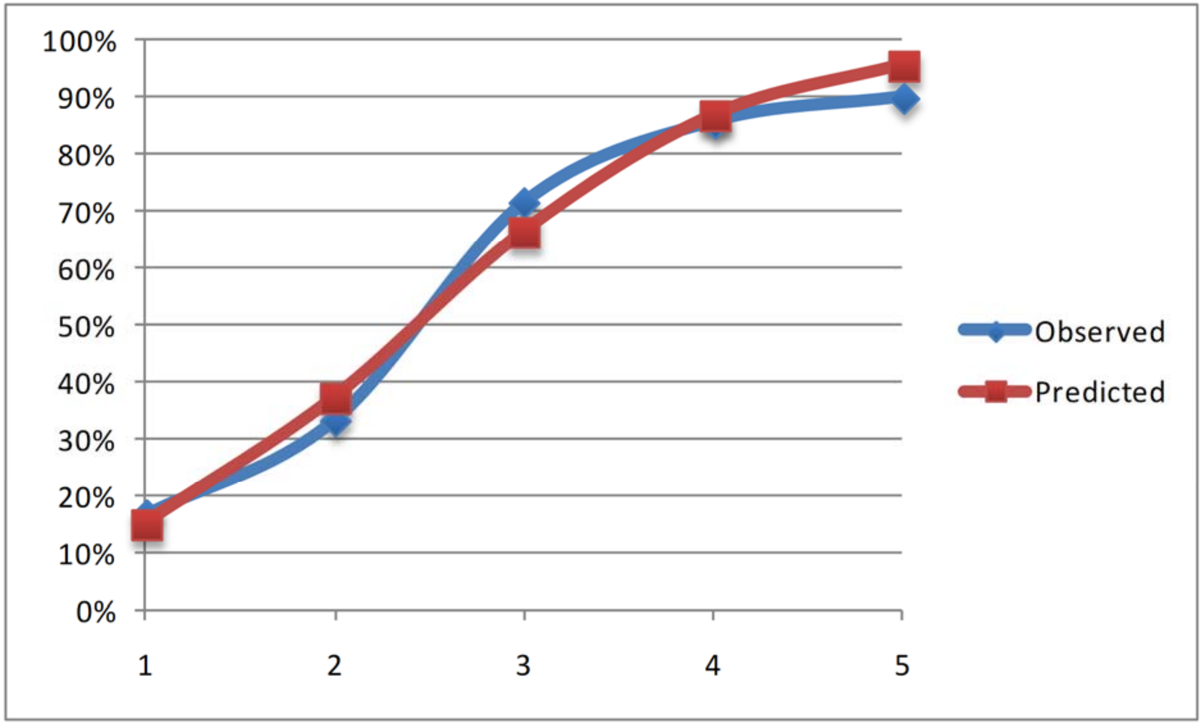
Observed
(0/1)

Inferred
to provide
best fit

Observed
(including an intercept)

The Logit model

$$Course = \frac{1}{1 + e^{-\left(-2.9 + \left(1.19 \times Marketing\right)\right)}}$$



This term is **positive** and significant

The higher the student's interest in marketing…

…the **more likely** he/she is going to take the elective course

Data

- 306 respondents
- 1 choice
- 9 predictors

Observations / Choice data	Choice (0/1)	Marketing	Finance	Strategic_Consulting	Entrepreneur	Analytical_Mind	Marketing_Analytics	Graduation	Enjoy_Course	Enjoy_Instructor
Enter id 1 here	1	5	1	2	4	5	5	5	5	5
Enter id 2 here	1	5	1	5	2	4	5	1	5	5
Enter id 3 here	0	1	4	1	5	4	4	5	4	4
Enter id 4 here	1	2	2	4	2	4	2	3	4	4
Enter id 5 here	0	1	5	2	4	5	3	4	4	5
Enter id 6 here	0	1	2	4	5	3	4	3	4	4
Enter id 7 here	1	3	2	5	3	4	3	5	4	4
Enter id 8 here	0	1	1	1	3	3	1	3	1	4
Enter id 9 here	0	1	4	4	2	4	3	4	4	5
Enter id 10 here	0	2	4	1	4	4	4	3	4	5
Enter id 11 here	0	1	5	3	2	4	3	1	2	2
Enter id 12 here	0	1	5	5	4	4	4	2	4	4
Enter id 13 here	0	1	4	3	3	3	2	4	4	5
Enter id 14 here	0	1	4	1	3	4	2	5	4	4
Enter id 15 here	0	1	3	2	1	3	4	3	3	5
Enter id 16 here	0	3	5	4	2	4	4	1	3	4
Enter id 17 here	0	1	1	3	5	4	4	5	4	4
Enter id 18 here	1	5	1	3	4	2	3	4	4	4
Enter id 19 here	0	2	5	4	2	5	4	2	5	5
Enter id 20 here	1	4	1	1	1	2	3	3	4	4
Enter id 21 here	1	3	4	4	2	2	3	4	4	5
Enter id 22 here	0	3	1	3	2	4	3	3	5	5
Enter id 23 here	0	2	1	1	2	4	2	4	2	4
Enter id 24 here	0	1	1	1	4	1	2	3	4	5
Enter id 25 here	1	2	4	5	5	5	3	5	4	5
Enter id 26 here	0	2	2	5	1	2	3	3	3	4
Enter id 27 here	0	4	1	4	3	4	4	3	4	5
Enter id 28 here	1	5	1	3	1	4	4	3	4	4
Enter id 29 here	0	1	5	1	5	5	3	4	2	3
Enter id 30 here	0	2	2	2	1	3	2	5	3	4
Enter id 31 here	1	3	1	3	1	4	4	4	3	3
Enter id 32 here	1	4	1	3	4	3	1	5	5	5
Enter id 33 here	1	1	1	1	5	5	4	4	2	5
Enter id 34 here	1	1	3	5	5	4	3	3	5	5
Enter id 35 here	1	5	1	4	2	5	3	5	4	5
Enter id 36 here	1	4	1	1	5	5	5	1	5	5
Enter id 37 here	1	3	2	2	5	5	2	5	4	4
Enter id 38 here	1	4	1	3	3	2	4	4	5	5
Enter id 39 here	1	4	1	4	4	4	2	3	4	4
Enter id 40 here	0	5	3	4	4	4	5	3	4	4
Enter id 41 here	1	4	2	3	1	4	5	3	3	4
Enter id 42 here	1	4	2	3	1	4	5	3	3	4
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Enter id 44 here	1	5	2	4	1	4	4	2	5	4
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Enter id 49 here	1	1	5	3	5	4	3	5	4	4
Enter id 50 here	1	2	4	4	2	5	5	1	3	4
Enter id 51 here	0	2	1	3	3	4	3	1	4	4

Results

Coefficient Estimates

Coefficient estimates of the Choice model. Coefficients in bold are statistically significant.

Variables / Coefficient estimates	Coefficient estimates	Standard deviation	t-statistic
Marketing	**1.19**	0.20	6.08
Finance	**-0.30**	0.13	-2.25
Strategic_Consulting	**0.41**	0.14	2.88
Entrepreneur	0.24	0.15	1.64
Analytical_Mind	**0.51**	0.22	2.35
Marketing_Analytics	-0.06	0.21	-0.29
Graduation	**0.40**	0.16	2.49
Enjoy_Course	-0.13	0.24	-0.53
Enjoy_Instructor	0.12	0.33	0.37
Const-1	-7.28	1.74	-4.17

- The most important drivers of choice are:
  - Interest in marketing
  - Analytical mind
  - Strategic consulting
  - Close to graduation
  - Interest in finance (-)

Provides a good fit?

Confusion Matrix on Estimation Sample

Comparison of observed choices and predicted choices (based on MNL analysis).

High values in the diagonal of the confusion matrix (in bold), compared to the non-diagonal values, indicate l

Analysis has been performed on the estimation dataset, and measures the goodness-of-fit of the model.

Observed / Predicted Choice	Response	Dummy
Response	**114**	18
Dummy	42	**132**

- 80% of respondents are well classified
  - 114 correct "yes" + 132 correct "no", over 306 observations
  - Very good !
- There are more "false positive" then "false negative"
  - 42 predicted as "yes", but indeed "no"
  - 18 predicted as "no", but indeed "yes"
  - Are we missing something?

Multinomial logit

- Not only used to predict a yes/no choice
- But also to predict a one-out-of-many choice
  - Brand, product, option…
  - Same logic, slightly more complicated formulation

$$p_{\text{Brand A}} = \frac{e^{-\sum(weights \times characteristics_{\text{Brand A}})}}{\sum\limits_{\text{All brands}} e^{-\sum(weights \times characteristics_{\text{All Brands}})}}$$

Applications of choice models

Targeting

1. **Calibrate** model coefficients on a sample of customers
   - Different customers (test)
   - Same customers, different period in time

2. **Apply** choice model to a larger list of customers
   - Predict likelihood of choice
   - Rank order, from least likely to most likely

3. **Target** customers based on predictions

Who to target?

Respondents / Choice probabilities	Response probability
Customer 15	0.993
Customer 26	0.976
Customer 20	0.964
Customer 19	0.947
Customer 12	0.944
Customer 8	0.943
Customer 7	0.934
Customer 24	0.917
Customer 27	0.901
Customer 17	0.893
Customer 5	0.837
Customer 18	0.816
Customer 16	0.804
Customer 21	0.801
Customer 22	0.801
Customer 28	0.778
Customer 11	0.698
Customer 2	0.675
Customer 1	0.442
Customer 13	0.374
Customer 3	0.362
Customer 14	0.335
Customer 10	0.283
Customer 6	0.259
Customer 30	0.229
Customer 29	0.214
Customer 9	0.132
Customer 25	0.128
Customer 23	0.123
Customer 4	0.035

- A list of 30 customers, with their respective likelihood of response
- Which ones to target?
- It depends on the **purpose** of the action

Goal #1: elicit a purchase

Respondents / Choice probabilities	Response probability
Customer 15	0.993
Customer 26	0.976
Customer 20	0.964
Customer 19	0.947
Customer 12	0.944
Customer 8	0.943
Customer 7	0.934
Customer 24	0.917
Customer 27	0.901
Customer 17	0.893
Customer 5	0.837
Customer 18	0.816
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Customer 6	0.259
Customer 30	0.229
Customer 29	0.214
Customer 9	0.132
Customer 25	0.128
Customer 23	0.123
Customer 4	0.035

If the goal is to:

- Send a catalogue to ask for an order
- Place a call to elicit a sale
- Send a direct mail to ask for donation
- …

Then the customers who are **most likely** to answer are the primary targets

MAXIMIZE PROFITABILITY

Goal #2: influence behavior

Respondents / Choice probabilities	Response probability
Customer 15	0.993
Customer 26	0.976
Customer 20	0.964
Customer 19	0.947
Customer 12	0.944
Customer 8	0.943
Customer 7	0.934
Customer 24	0.917
Customer 27	0.901
Customer 17	0.893
Customer 5	0.837
Customer 18	0.816
Customer 16	0.804
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Customer 14	0.335
Customer 10	0.283
Customer 6	0.259
Customer 30	0.229
Customer 29	0.214
Customer 9	0.132
Customer 25	0.128
Customer 23	0.123
Customer 4	0.035

If the goal is to:

- Send a coupon to ease trial/purchase
- Change, modify perceptions
- …

Then the customers who are **potential switchers** are the primary targets

MAXIMIZE MARKETING IMPACT

Why?

Respondents / Choice probabilities	Response probability
Customer 15	0.993
Customer 26	0.976
Customer 20	0.964
Customer 19	0.947
Customer 12	0.944
Customer 8	0.943
Customer 7	0.934
Customer 24	0.917
Customer 27	0.901
Customer 17	0.893
Customer 5	0.837
Customer 18	0.816
Customer 16	0.804
Customer 21	0.801
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Customer 1	0.442
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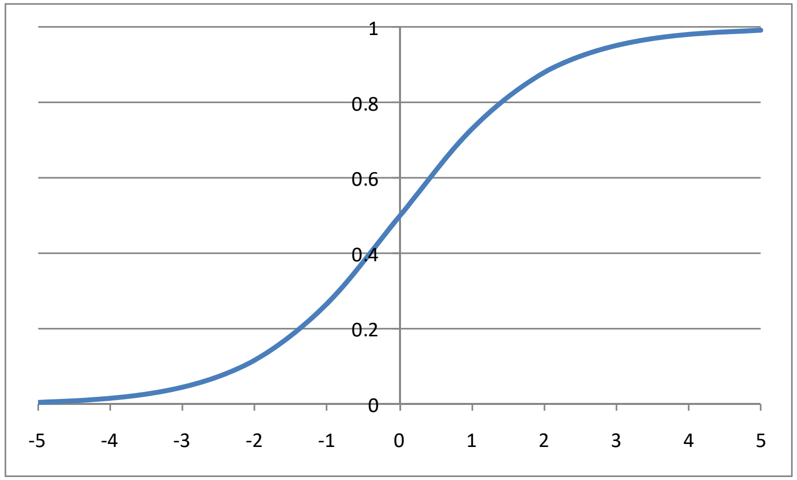
Customer 14	0.335
Customer 10	0.283
Customer 6	0.259
Customer 30	0.229
Customer 29	0.214
Customer 9	0.132
Customer 25	0.128
Customer 23	0.123
Customer 4	0.035

- These customers will be loyal anyway
- No need to send coupon
- No need to “convince” them
- They are already convinced

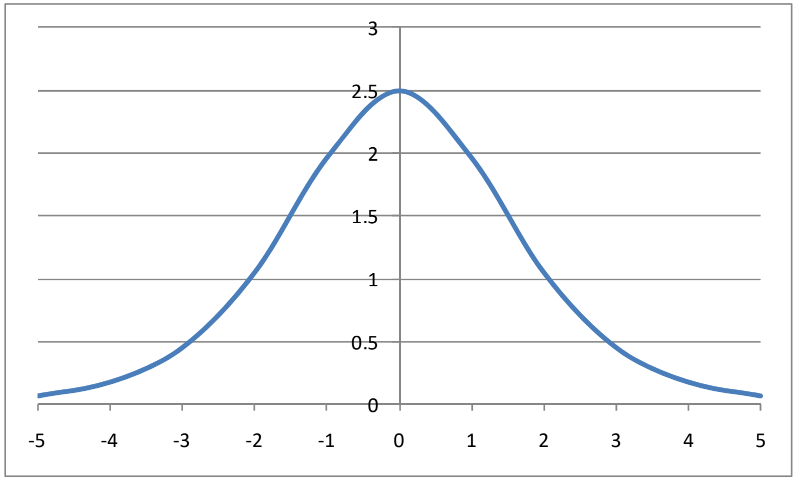
- These customers will never buy from you
- Don’t waste valuable time and resources

An important implication of the Logit model

- The first derivative of the Logit function gives us the marginal impact of a change in a variable (e.g., marketing actions)
- When probability of choices is near 50%, impact of marketing actions is maximized



LOGIT FUNCTION



LOGIT'S FIRST DERIVATIVE

A **score** is a characterization of a customer's most likely behavior or potential.

In the most simple case, a score is simply the result of a **choice model** (e.g., likelihood of purchase). In more complex cases, a score can be the result of a **combination** of choice and predictive models.

Example of score

Fundraising context:

- Likelihood of donation (choice model)
- Predicted donation amount in case of donation (e.g., regression analysis)
- Score = combination of both (expected donation amount)

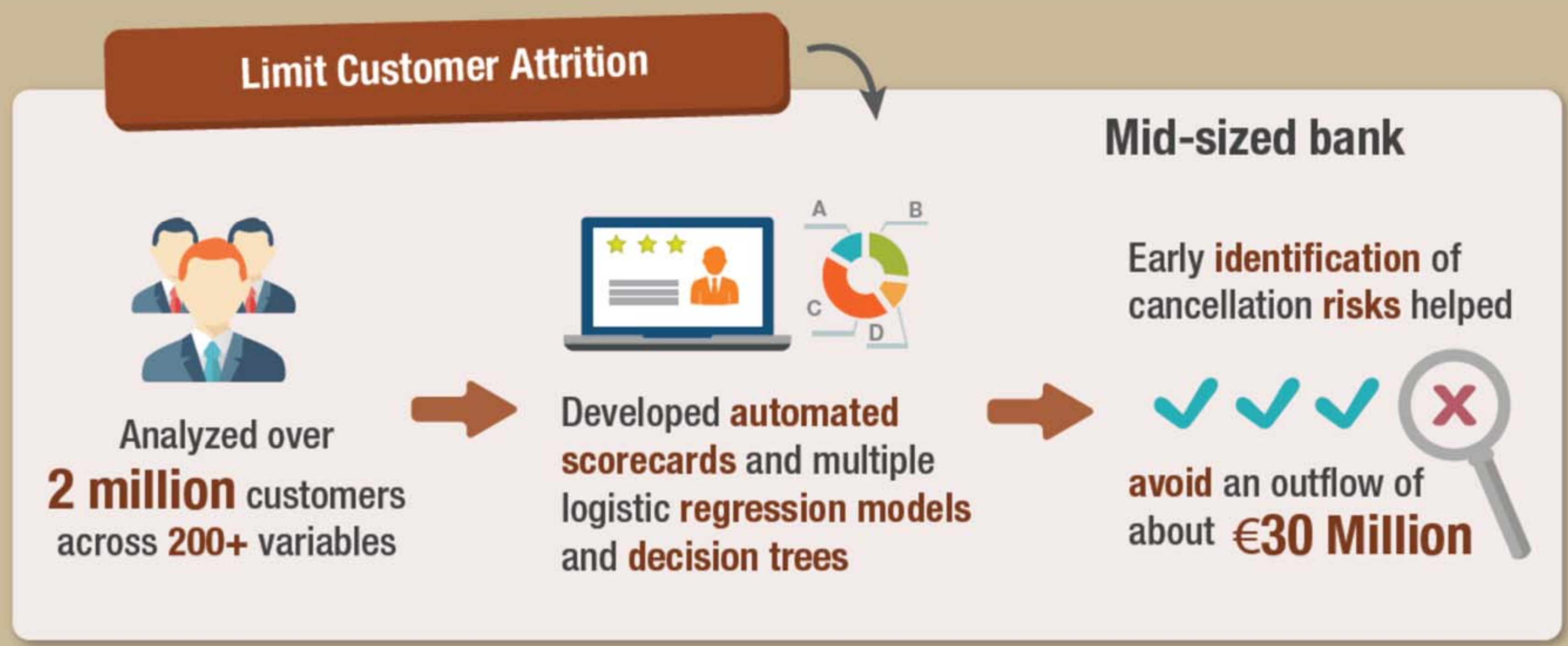
Two donors can have similar scores with different underlying behavior (*)

	Likelihood of donation	Predicted donation amount	Score
Donor 1	34%	€ 153	€ 52.7
Donor 2	48%	€ 61	€ 29.0
Donor 3	38%	€ 36	€ 13.8
Donor 4	7%	€ 185	€ 13.7
Donor 5	71%	€ 19	€ 13.5
Donor 6	33%	€ 34	€ 11.2
Donor 7	26%	€ 42	€ 11.0
Donor 8	5%	€ 58	€ 2.8
Donor 9	5%	€ 52	€ 2.6
Donor 10	3%	€ 83	€ 2.2
Donor 11	2%	€ 67	€ 1.6
Donor 12	2%	€ 68	€ 1.6
Donor 13	2%	€ 60	€ 1.4
Donor 14	1%	€ 124	€ 1.4
Donor 15	5%	€ 24	€ 1.3
Donor 16	3%	€ 45	€ 1.2
Donor 17	1%	€ 130	€ 1.0
Donor 18	1%	€ 73	€ 0.6
Donor 19	1%	€ 20	€ 0.3
Donor 20	2%	€ 14	€ 0.2

"

A **score class** is a grouping of customers whose scores fall within a given range.

Churn prediction



Source: Big Data Alchemy: How can Banks Maximize the Value of their Customer Data? Capgemini Consulting

Example of score classes

	Likelihood of donation	Predicted donation amount	Score
Donor 1	34%	€ 153	€ 52.7
Donor 2	48%	€ 61	€ 29.0
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Donor 20	2%	€ 14	€ 0.2

- Donors are grouped into 4 classes: A, B, C, D

TO SUMMARIZE…

Two approaches to segmentation

Need-based	Choice-based

Need-based

- Customers are grouped together based on their similarities in profiles
  - Needs
  - Wants
  - Lifestyles
  - Past behavior

> *Customers in segment "X" highly value prestige and peace of mind, are not highly price-sensitive, and many of them have been loyal customers for more than 3 years.*

Choice-based

- Customers are grouped together based on their (predicted) similarities in future behavior
  - Likelihood of donation, of purchase, of choice

> *80% of customers in segment "X" are expected to select our premium offering.*

Number of segments
In need-based segmentation

THE MARKET = ONE SEGMENT

Mass marketing

FEW SEGMENTS (3~6)

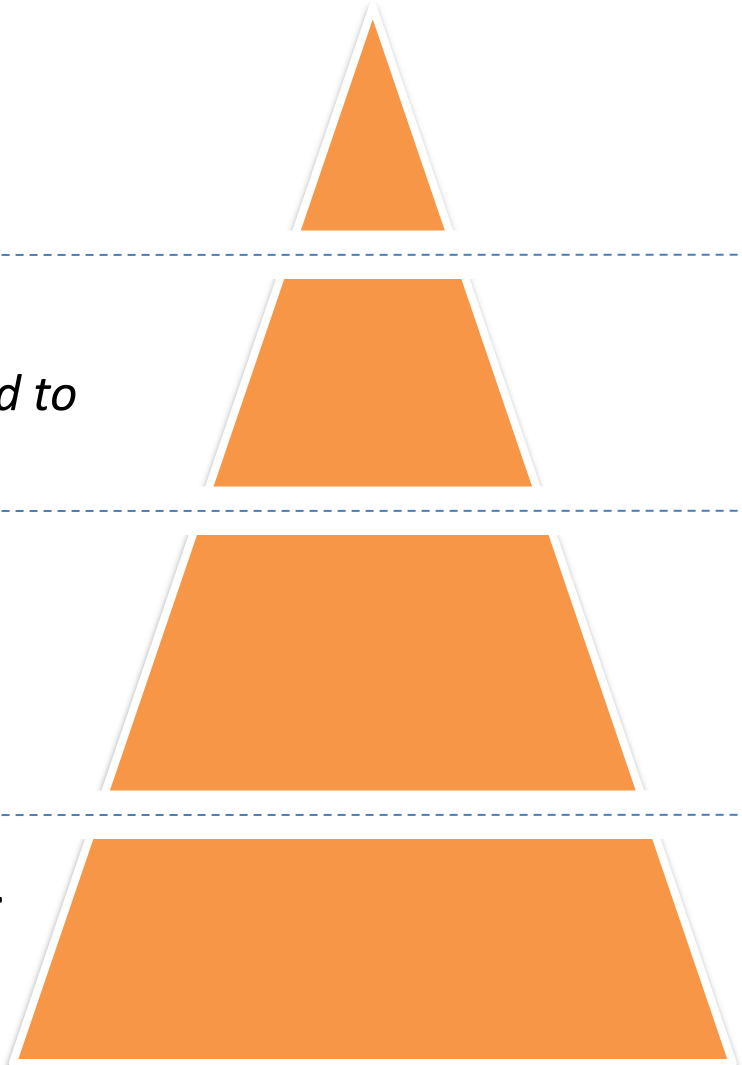
High-level view of the market, used to define company-wide strategy

MORE SEGMENTS (10~30)

More-detailed view of the market, to target specific groups, customize campaigns, optimize operations

ONE CUSTOMER = ONE SEGMENT

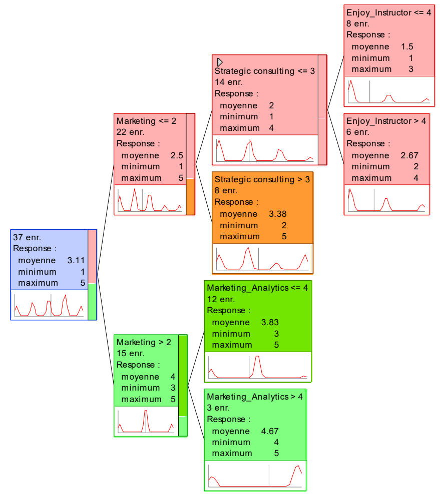
One-to-one marketing



Score classes vs. choice-based segmentation

Similarities:

- They group customers based on likelihood of choices
- They are simple to use (e.g., a few segments/classes)



Differences:

- Score classes are more complex…
  - They need regular updates of response models
  - They are more complete, more accurate, they use all data available
  - They are harder to "get" intuitively (who's in score class "A", and why?)

	Likelihood of donation	Predicted donation amount	Score
Donor 1	34%	€ 153	€ 52.7
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Donor 19	1%	€ 20	€ 0.3
Donor 20	2%	€ 14	€ 0.2

A
B
C
D

CLASSIC TRADE-OFF --- ACCURACY/PERFORMANCE vs. SIMPLICITY/USABILITY

Number of segments
In choice-based segmentation

THE MARKET = ONE SEGMENT

Average response of the market

MORE OR LESS COMPLEX
CHOICE_BASED SEGMENTATION

(3~30 segments)

CHOICE-BASED MODELS

Individual predictions and scores

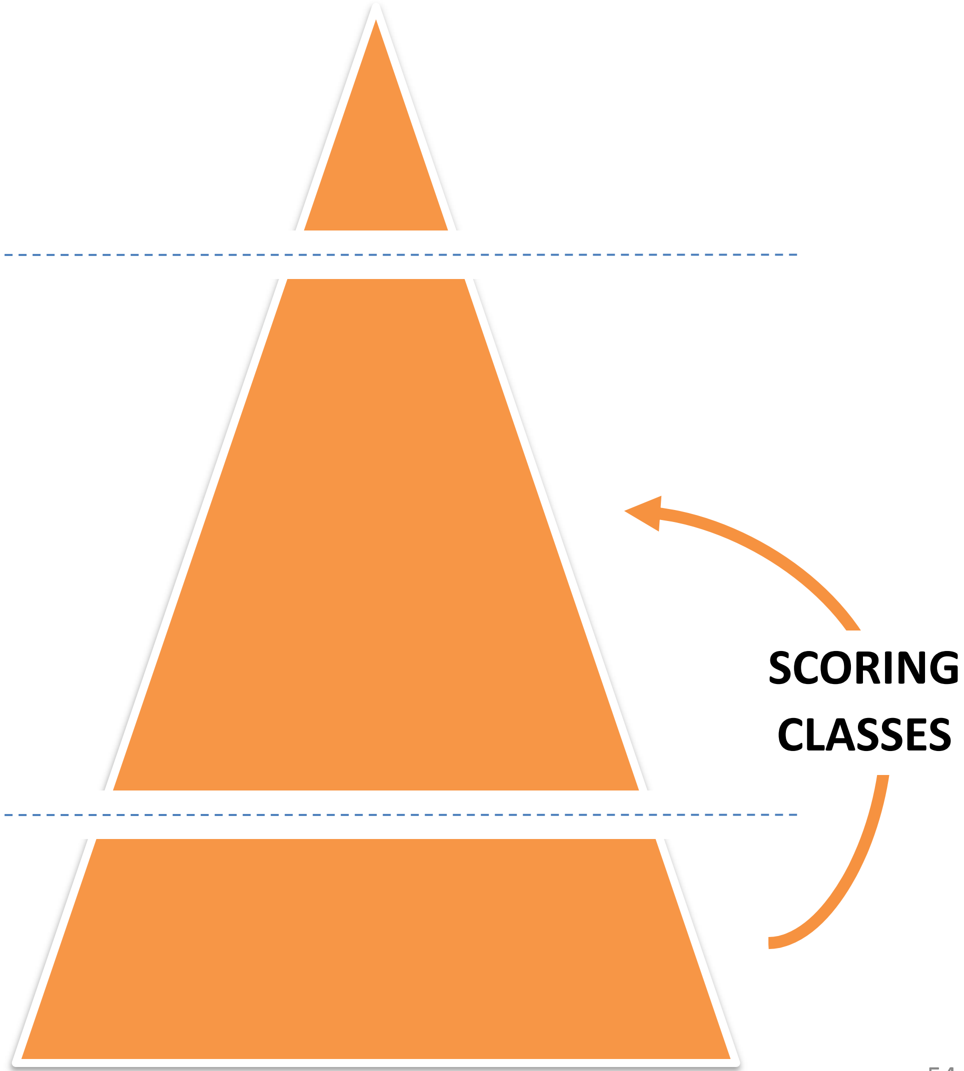


Illustration 1

TARGET

Forbes

TECH 2/16/2012 @ 11:02AM | 2,757,188 views

How Target Figured Out A Teen Girl Was Pregnant

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, for example, has figured out how to data-mine its way into your womb, to figure out whether you have a baby on the way long before you need to start buying diapers.

Target has got you in its aim

Charles Duhigg outlines in the New York Times how Target tries to hook parents-to-be at that crucial moment before they turn into rampant — and loyal — buyers of all things pastel, plastic, and miniature. He talked to Target statistician Andrew Pole — before Target freaked out and cut off all communications — about the clues to a customer's impending bundle of joy. Target assigns every customer a Guest ID number, tied to their credit card, name, or email address that becomes a bucket that stores a history of everything they've bought and any demographic information Target has collected from them or bought from other sources. Using that, Pole looked at historical buying data for all the ladies who had signed up for Target baby registries in the past. From the NYT:

Illustration 2

SCORING IN DIRECT MARKETING

Key figures

- A large charity sends a direct mail solicitation to its donors for its Christmas campaign

- A few key figures:

– Mails sent	301 500
– Donations	17 200
– Return rate	5.7%
– Total donations	992 000 €
– Average donation amount	57.7 €
– Mailing costs	182 500 €
– Net margins	809 500 €
– Return on investment	+ 443%
– Fundraising ratio *(e.g., needs 18 cents to collect 1€)*	18.4%

Scoring model

They used several choice models (scoring)

- Responses:
  - Likelihood of donation
  - Donation amount

- Predictors:
  - Recency
  - Frequency
  - Amount
  - Activity over the years
  - Demographics
  - …

Scoring model

- They built a score…

$$\text{Score} = \text{Likelihood of donation} \times \text{Donation amount}$$

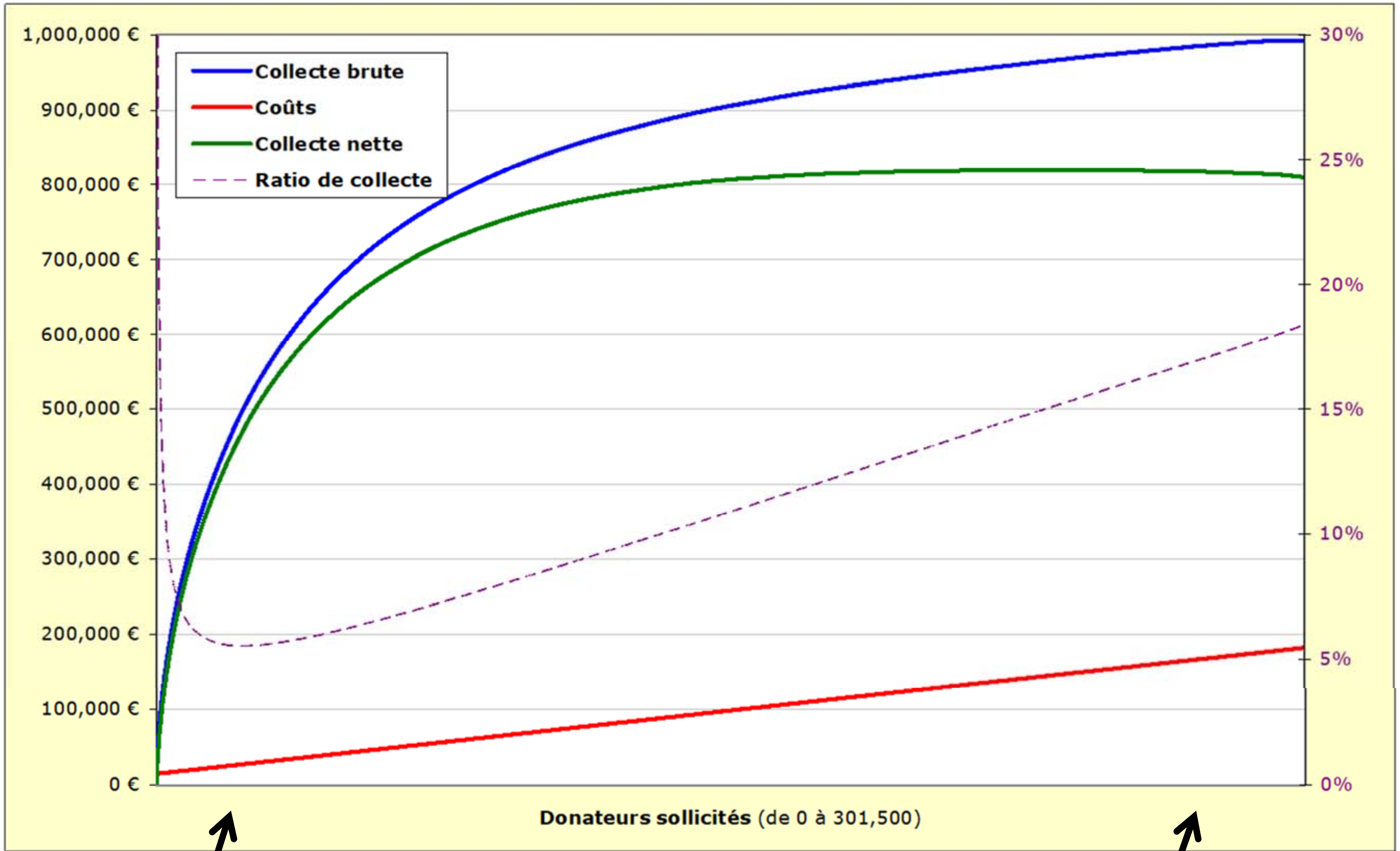
- And ranked all their donors by decreasing order

Managerial question

“What would have been the financial results, had we only solicited the top [X]% of our donors?

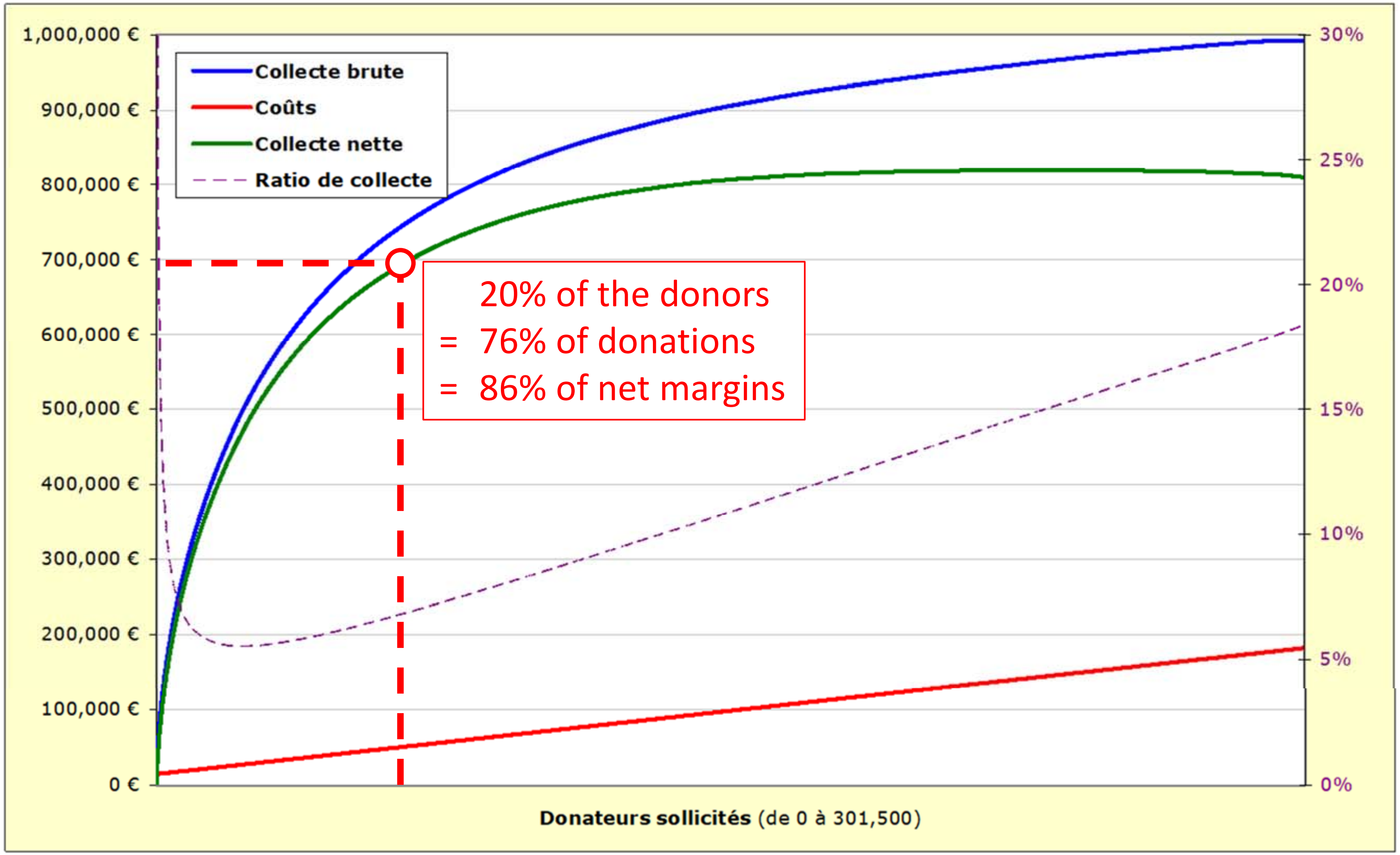
(e.g., the 10% of our donors who received the highest scores, the top-50%, etc.)

Financial results

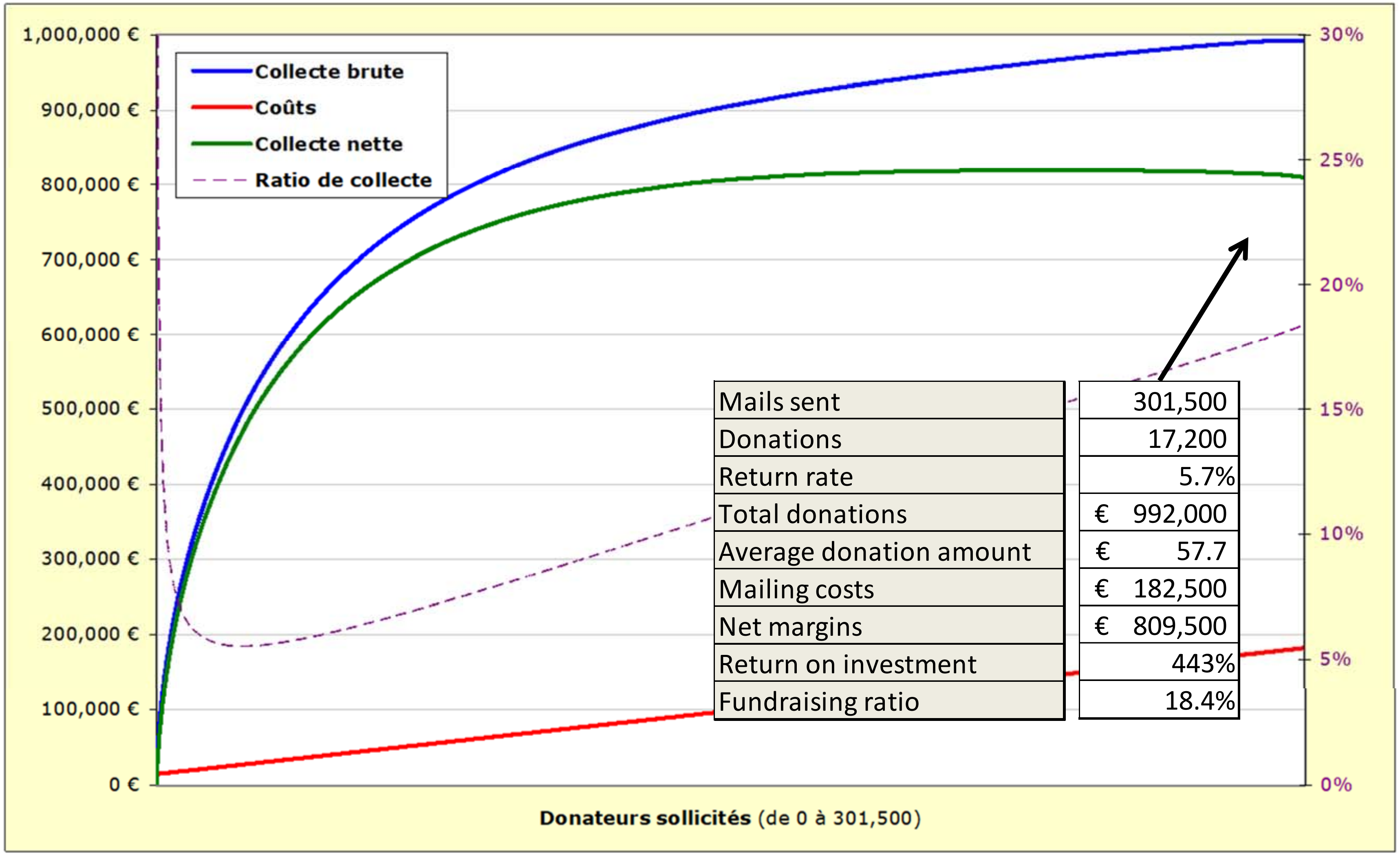


HIGHEST-SCORE DONORS **LOWEST-SCORE DONORS**

Financial results

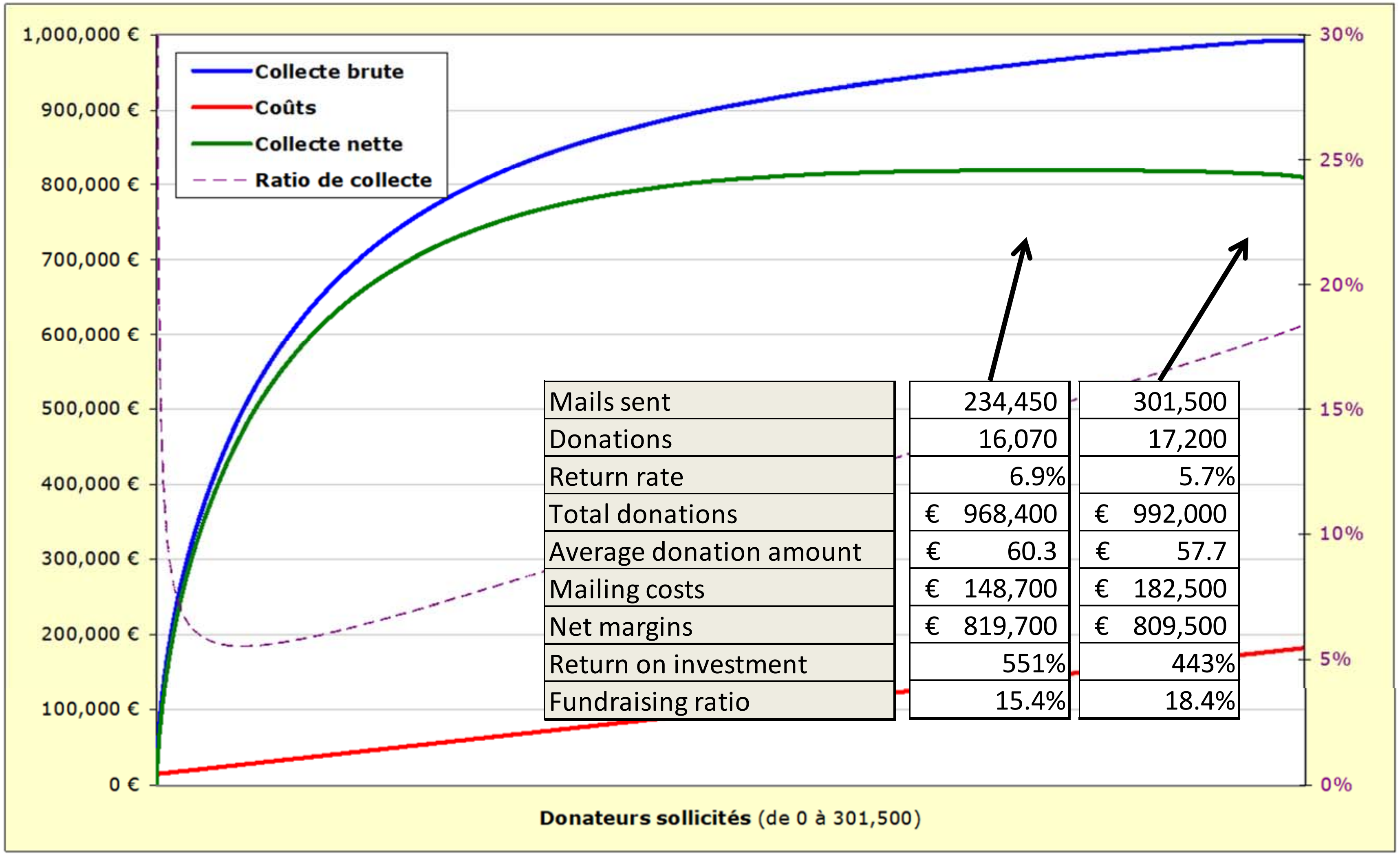


Financial results



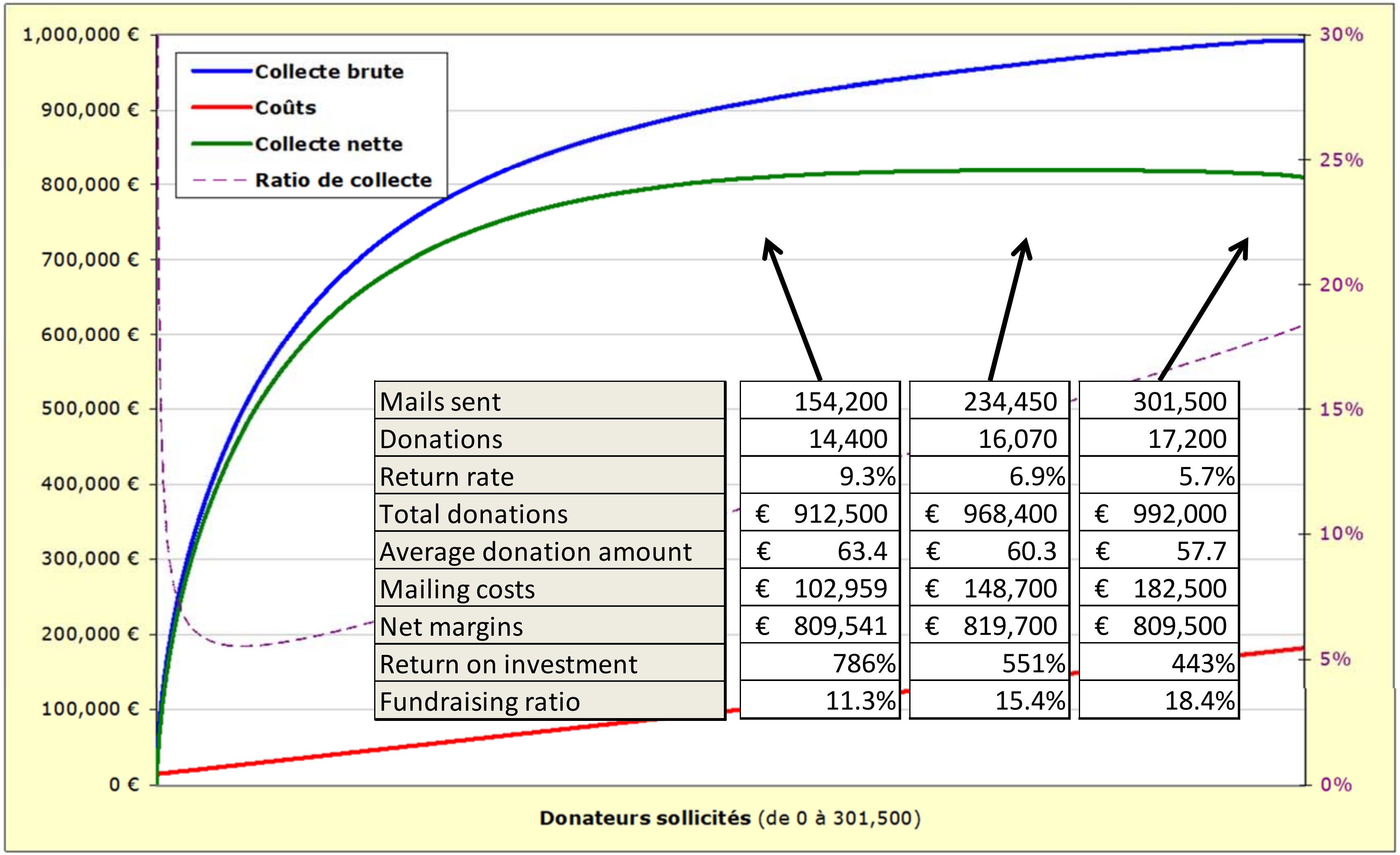
Mails sent	301,500
Donations	17,200
Return rate	5.7%
Total donations	€ 992,000
Average donation amount	€ 57.7
Mailing costs	€ 182,500
Net margins	€ 809,500
Return on investment	443%
Fundraising ratio	18.4%

Financial results



Mails sent	234,450	301,500
Donations	16,070	17,200
Return rate	6.9%	5.7%
Total donations	€ 968,400	€ 992,000
Average donation amount	€ 60.3	€ 57.7
Mailing costs	€ 148,700	€ 182,500
Net margins	€ 819,700	€ 809,500
Return on investment	551%	443%
Fundraising ratio	15.4%	18.4%

Financial results



Mails sent	154,200	234,450	301,500
Donations	14,400	16,070	17,200
Return rate	9.3%	6.9%	5.7%
Total donations	€ 912,500	€ 968,400	€ 992,000
Average donation amount	€ 63.4	€ 60.3	€ 57.7
Mailing costs	€ 102,959	€ 148,700	€ 182,500
Net margins	€ 809,541	€ 819,700	€ 809,500
Return on investment	786%	551%	443%
Fundraising ratio	11.3%	15.4%	18.4%

To conclude

Depending on the managerial objectives, this charity could:

- Collect more with less
  - + 10,000 €
  - Improve fundraising ratio from 18.4% to 15.4%
- Dramatically improve financial performance
  - Same net margins
  - Improve fundraising ratio from 18.4% to 11.3%
  - Improve ROI almost twofold
  - Save 80 000 € in costs

Illustration 3

ESSEC FOUNDATION

Predictive modeling

SOFTWARE OVERVIEW

ESSEC BUSINESS SCHOOL

That's all folks!