

Move to a Segment of One

Next Best Action

Working together

Finding the Segment of One



Cristina Gil-Sevilla
Insight Unit Manager - RNIB



Rob Green
Senior Development Manager - RNIB

Working together

The Jeff Conundrum

- At RNIB, we wanted to think about donors differently.
- We want every donor to receive a great experience from us.
- We want them to actively choose to stay with us, particularly in a world of opt-in, and FPS.
- The aim is to give the same personalised experience we give 7-figure donors to those giving us £5.

Working together

The Jeff Conundrum

- Traditional Segmentation, RFV etc, works by starting with the campaign - *I'm going to send a cash appeal* - and then decides who the best donors are to receive it – *which donors (will) give to our cash appeals?*
- Running multiple appeals, selections are hierarchical rather than comparative. *We want to run conversion calls to RG and WL. RG is worth £100pa, WL is worth £60.* So we take the 50k best supporters and offer them a RG, and the next best 50k for WL, with the rest sent a usual cash appeal.
- We get the best RR to our highest value products & everybody's happy.

Working together

The Jeff Conundrum



Working together

The Jeff conundrum

- How can I identify what's right for all the Jeff's?
- Also what's right for RNIB - how can I know what the short, medium and long term income impact of each ask is for Jeff?
- In short, we were trying to get to the point that we are offering the right products, to the right donors, through the right channels, at the right time.

Working together

The brief

Please can you build a tool that tells me:

- For each donor on the base individually,
- which product(s) we should offer them,
- and in which order,
- and through which channels.

And,

- what offering each of these donors every possible combination of products and channels means for our short-, mid- and long term income.

Working together

Move to a Segment of One – The Next Best Action

THE SOLUTION

Working together

The Next Best Action Model

STEP

DESCRIPTION

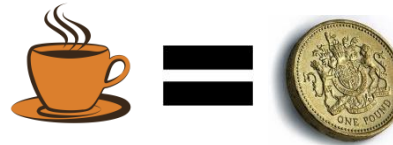
1

Propensity
Models

- Logistic regression models to identify the variables and their importance to predict likelihood to respond to our campaigns
- Normalisation of scores across models

Working together

Let's imagine the following situation



Working together



£1 = ISK150



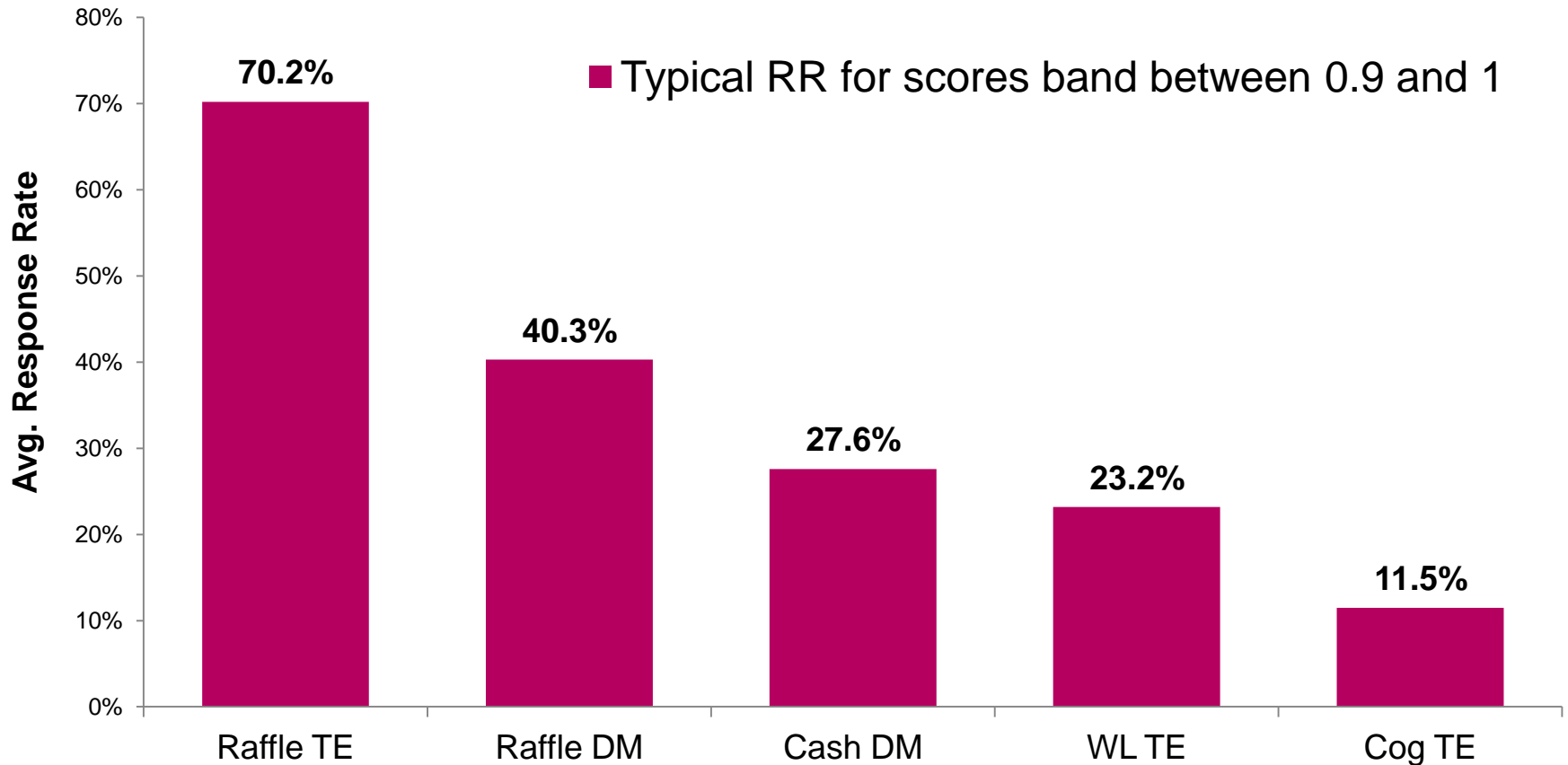
£1 = €1.1



The same pound will yield different results depending on the country we are in
Exchange Rates are a way to "normalise" money across countries


Working together

We use response rates to normalise scores



Working together

Score Band	Weekly Lottery (DD) Telephone	Committed Giving (DD) Telephone
	Response Rate	Response Rate
≥0.9	23.2%	11.5%
≥0.8<0.9	15.0%	9.5%
≥0.7<0.8	12.1%	7.2%

Jeff 



What's the best campaign for Jeff?

Working together

The Next Best Action Model

STEP #	DESCRIPTION
1	Propensity Models <ul style="list-style-type: none">• Logistic regression models to identify the variables and their importance to predict likelihood to respond to our campaigns• Normalisation of scores across models
2	Feasibility Filters <ul style="list-style-type: none">Standard restrictionsCurrent product mixProduct restrictionsChannel restrictions

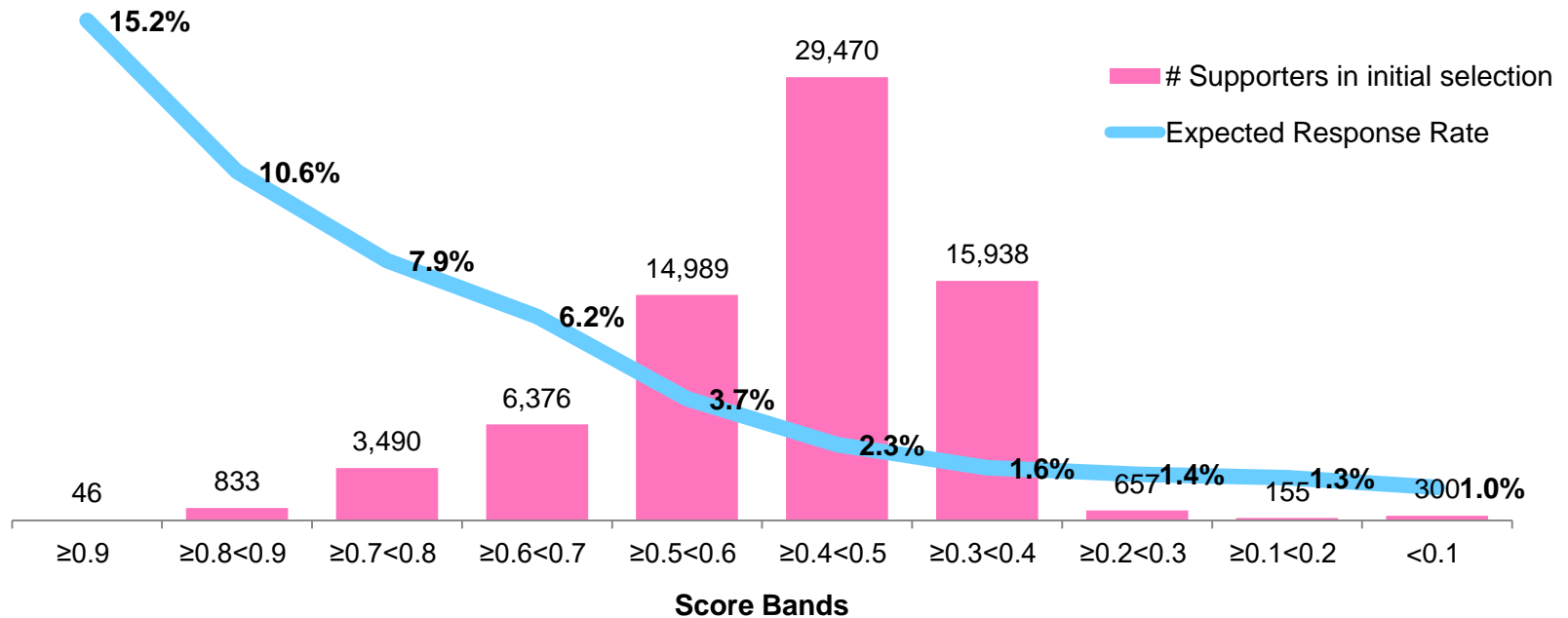
Working together

The Next Best Action Model

STEP #	DESCRIPTION
1 Propensity Models	<ul style="list-style-type: none">• Logistic regression models to identify the variables and their importance to predict likelihood to respond to our campaigns• Normalisation of scores across models
2 Feasibility Filters	<div data-bbox="494 511 813 675">Standard restrictions</div> <div data-bbox="842 511 1161 675">Current product mix</div> <div data-bbox="1190 511 1508 675">Product restrictions</div> <div data-bbox="1537 511 1862 675">Channel restrictions</div>
3 Campaign Scenario Planning	<p>We have calculated the typical response rates we can expect per product and channel and score band. We have also calculated which is the minimum response rate that will enable a positive ROI for each campaign.</p>

Working together

Scenario Planning for a certain campaign



Scenario	# Supporters for selection	Expected Response Rate
Selection of Scores 1 to 0.7	4,369	8.5%
Selection of Scores 1 to 0.6	10,745	7.1%
Selection of Scores 1 to 0.5	25,734	5.1%
Selection of Scores 1 to 0.4	55,234	3.6%
Selection of Scores 1 to 0.3	71,142	3.1%

If minimum Response Rate to achieve positive ROI is 3.5%, our optimal scenarios would be the first 4

Last scenario would return a negative ROI

The Next Best Action Model

STEP #	DESCRIPTION
1 Propensity Models	<ul style="list-style-type: none">• Logistic regression models to identify the variables and their importance to predict likelihood to respond to our campaigns• Normalisation of scores across models
2 Feasibility Filters	<div data-bbox="494 511 813 675">Standard restrictions</div> <div data-bbox="842 511 1161 675">Current product mix</div> <div data-bbox="1190 511 1508 675">Product restrictions</div> <div data-bbox="1537 511 1862 675">Channel restrictions</div>
3 Campaign Scenario Planning	<p>We have calculated the typical response rates we can expect per product and channel and score band. We have also calculated which is the minimum response rate that will enable a positive ROI for each campaign.</p>
4 Business Planning	<p>We can assess our different selections according to the short, middle and long-term revenue they will generate for the organisation, facilitating strategic decision making</p>

Working together

Business Planning

	SCENARIOS		
	Short Term	Medium Term	Long Term
Cash DM	44K	40K	32K
Raffle Telephone	XXX	XXX	XXX
Raffle DM	XXX	XXX	XXX
Raffle Email	XXX	XXX	XXX
Cog Telephone	XXX	XXX	XXX
Cog Upgrade Telephone	XXX	XXX	XXX
Cog Reactivation Telephone	XXX	XXX	XXX
Weekly Lottery Telephone	127K	200K	207K
Weekly Lottery Upgrade Telephone	XXX	XXX	XXX
Weekly Lottery Reactivation Telephone	XXX	XXX	XXX
Total	800K	800K	800K

Working together

The Next Best Action Model

STEP #	DESCRIPTION
1 Propensity Models	<ul style="list-style-type: none"> Logistic regression models to identify the variables and their importance to predict likelihood to respond to our campaigns Normalisation of scores across models
2 Feasibility Filters	<div style="display: flex; justify-content: space-around;"> <div data-bbox="494 511 813 675">Standard restrictions</div> <div data-bbox="842 511 1161 675">Current product mix</div> <div data-bbox="1190 511 1508 675">Product restrictions</div> <div data-bbox="1537 511 1860 675">Channel restrictions</div> </div>
3 Campaign Scenario Planning	<p>We have calculated the typical response rates we can expect per product and channel and score band. We have also calculated which is the minimum response rate that will enable a positive ROI for each campaign.</p>
4 Business Planning	<p>We can assess our different selections according to the short, middle and long-term revenue they will generate for the organisation, facilitating strategic decision making</p>
5 Donor Management	<p>Finally the tool will provide the optimal journey for each one of our supporters. Some supporters will only be suitable for one-product journey, some of them will be suitable for a multiple-product journey</p>

Donor Management



NBA 1	NBA 2	NBA 3
Weekly Lottery Telephone	Raffle Telephone	

Working together

Donor Management



NBA 1	NBA 2	NBA 3
Raffle DM	Regular Giving Reactivation Telephone	Cash DM

Working together

Donor Management



NBA 1	NBA 2	NBA 3
Cash DM		

Working together

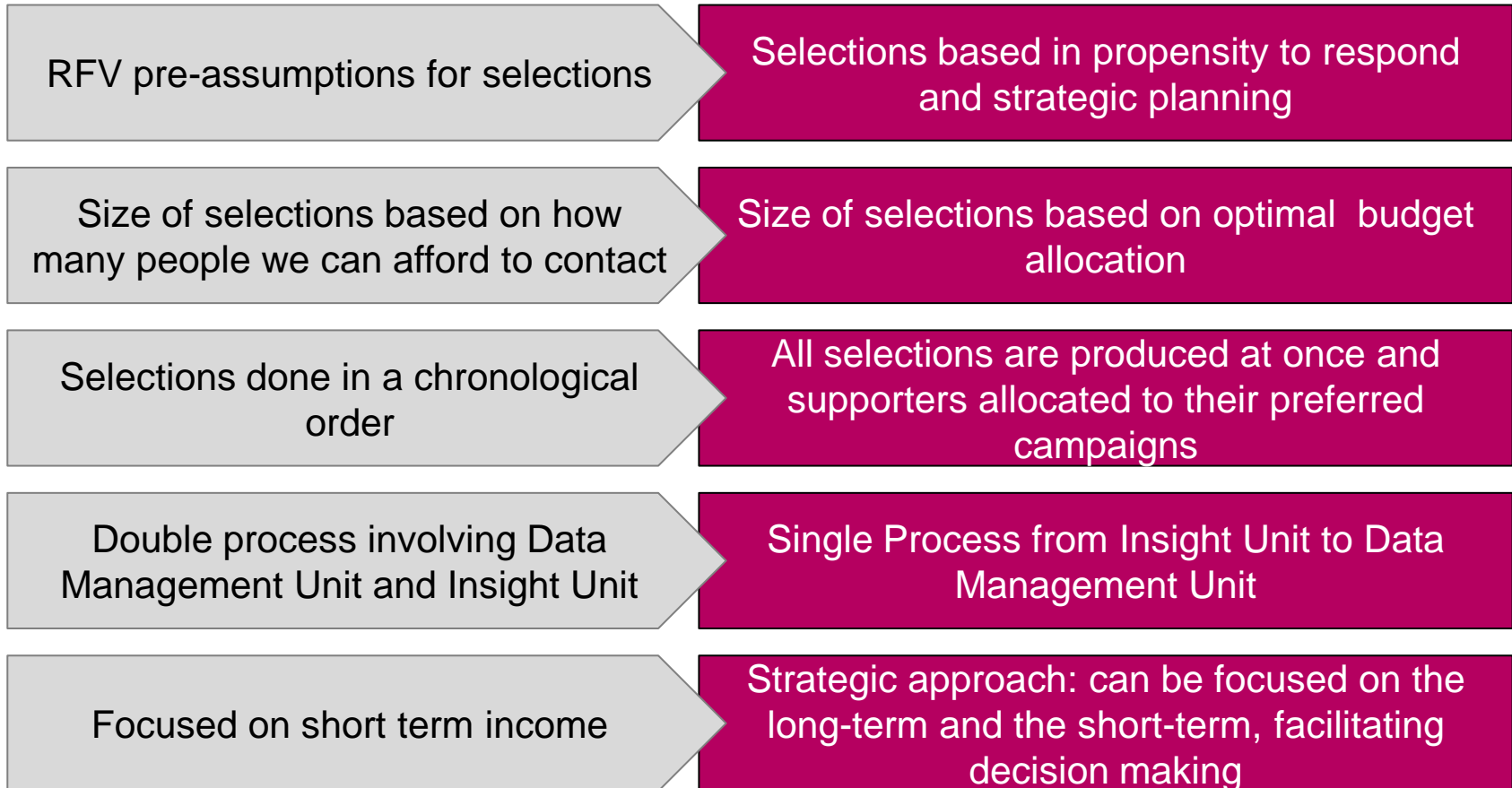
Move to a Segment of One – The Next Best Action

BENEFITS OF THIS NEW APPROACH

Working together

PREVIOUS APPROACH

NEW APPROACH



Working together

Move to a Segment of One – The Next Best Action

RESULTS

Working together

3 examples of how this model has helped

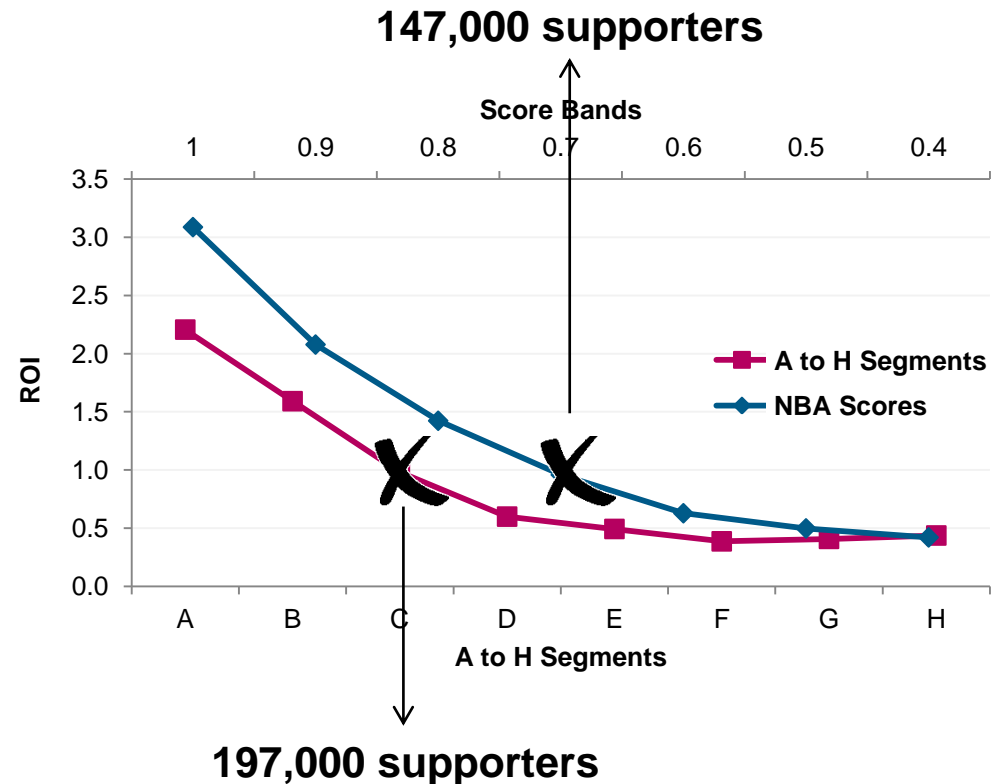
1. Could it be more reliable for selecting for campaigns than RFV segmentation - Raffle test
2. Could it identify donors we'd otherwise not contact, but who were willing to donate - Lapsed Weekly Lottery calling
3. Could it tell us where we are offering donors the wrong product - Cash test.

Working together

Can we get more reliable segments for campaigns selections than RFV segmentation?

RNIB NBA Score	Selected	Contact rate	Response rate	Predicted Response Rate
≥0.9	37,271	84%	70%	70%
≥0.8<0.9	47,112	78%	53%	49%
≥0.7<0.8	34,344	73%	39%	36%
≥0.6<0.7	28,529	66%	25%	24%
≥0.5<0.6	28,979	54%	16%	16%
≥0.4<0.5	32,143	49%	12%	12%
≥0.3<0.4	39,386	48%	10%	10%
Total	247,764	65%	38%	

RNIB A to H Segment	Selected	Contact rate	Response rate
A	121,041	81%	55%
B	2,971	75%	34%
C	13,344	69%	23%
D	6,244	63%	13%
E	13,822	57%	13%
F	20,594	46%	10%
G	3,902	35%	9%
H	65,481	46%	10%
Total	247,764	65%	38%



To achieve a positive ROI, the NBA would have saved circa £34,000 in calling and fulfilment costs compared to using A to H Segments

Working together

Could it identify donors we'd otherwise not contact, but who were willing to donate

Weekly Lottery test November 2015

- The tool identified, out of long lapsed and pledgers only, which supporters showed good propensity to respond to a Weekly Lottery Ask
- We called 6,200 of the supporters identified by the tool (scores between 0.5 to 1) during November 2015.
- The campaign was a success, obtaining a positive ROI and a response rate of 4%. We managed to reactivate 256 supporters who have generated more than £15,000 in less than 12 months.

Working together

Could it tell us when we are offering donors the wrong product?

Cash test September 2015

	Response Rate	Avg. Gift
Active 1 – last donated in the last 12 months	20%	£16
Active 2 – last donated between 13 and 24 months ago	4%	£17
Lapsing – last donated between 25 and 36 months ago	2%	£17
NBA Segment – Scores between 0.5 and 1	8%	£18

This additional segment of only 8,000 supporters generated an additional revenue for the campaign of £14,000, with an ROI of 3, outperforming by far Active 2

Working together

Move to a Segment of One - The Next Best Action

QUESTIONS?

Working together
