

4th Seminar on Data Science and Analytics

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Digital Behavior – A Hidden Treasure

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 - Health – Lead allocation and conversions
- Move towards using actuarial strengths in business-wide areas?

Need to understand Customer and Risk both

Are traditional risk based approaches enough?



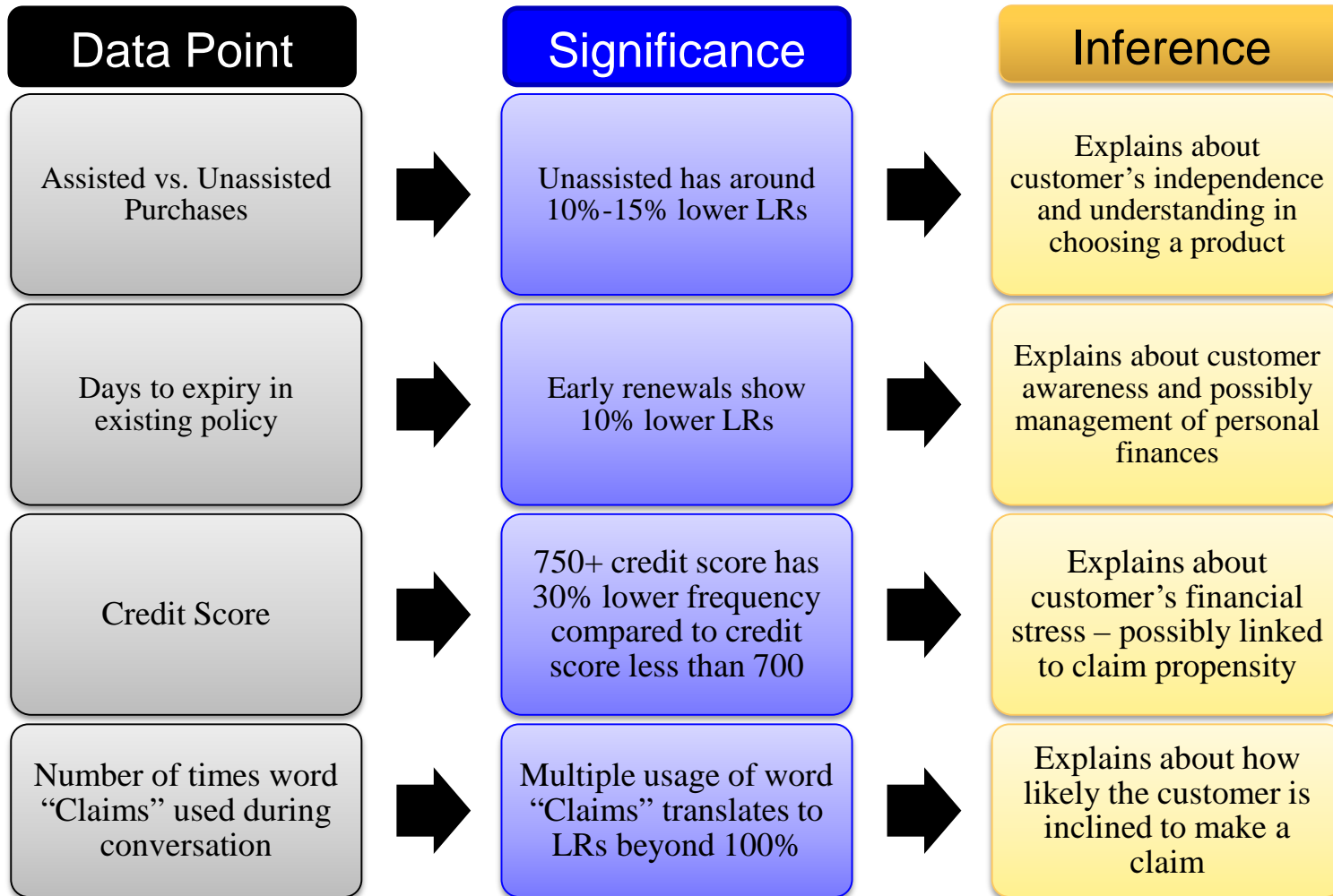
Traditional Approaches – Can we get answers to these?

- Individuals driving similar cars with same traffic and road conditions – Should they be charged same price?
- Price, Brand or Customization – What matters to a customer ?
- Know more about a customer – What should we know more ? Can we then Price better ?
- Which lead has a higher chance of becoming a customer?
-And we can continue to find endless questions

How Can actuaries bridge this gap and provide an enterprise wide solutions using data that can be derived to know more about a customer

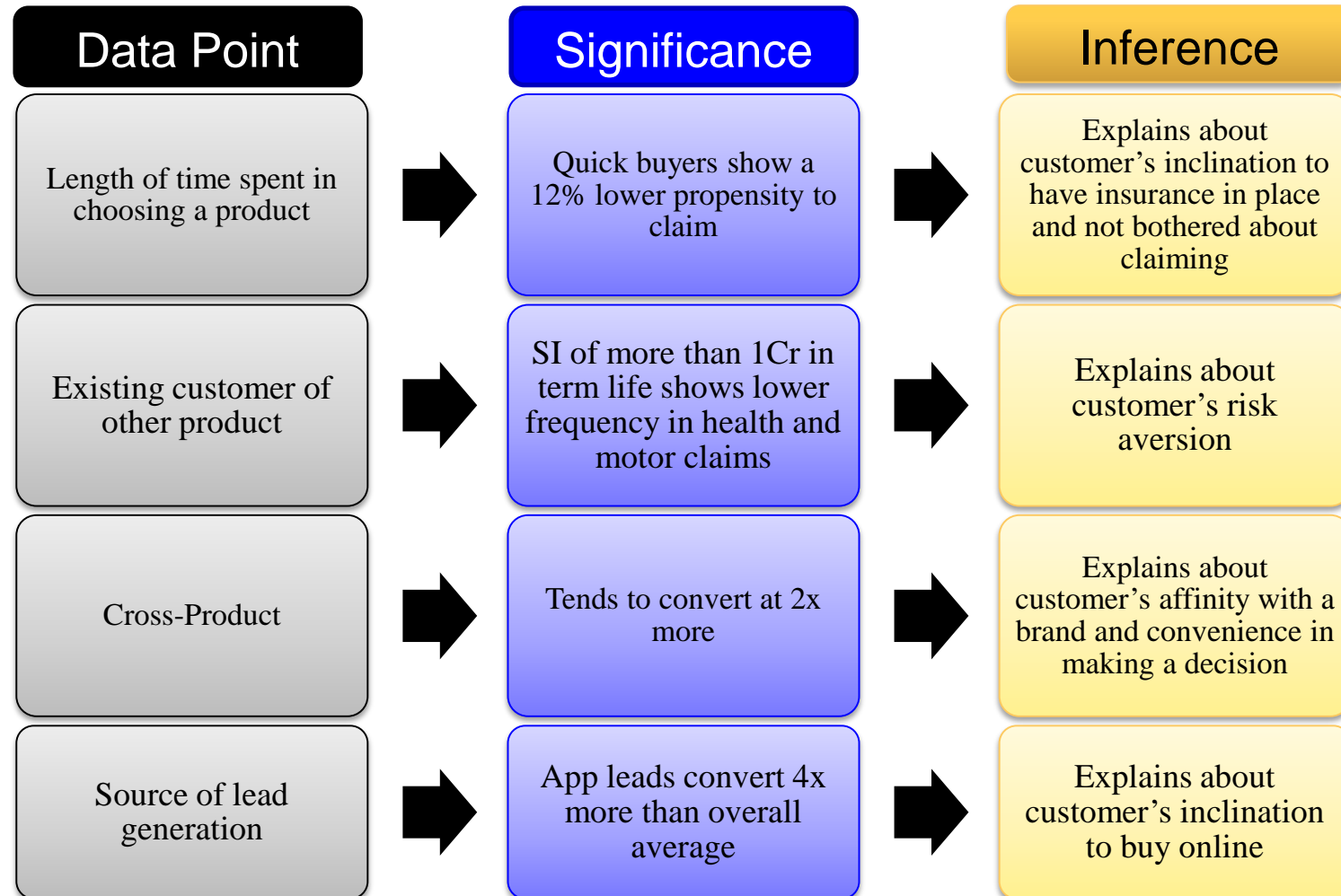
Digital Data/Behavior for Actuaries

What is digital data and what inference can be drawn



Digital Data/Behavior for Actuaries

What is digital data and what inference can be drawn – contd..



The list continues with more than 50 parameters studied

Techniques used to model Digital Data

Pvt. Cars – Increase in Unassisted Share



GLM Model created – Response Variable considered “Direct (Unassisted) Booking”

Propensity model built using a Binomial distribution function and Logit link function

Parameters Considered

- | | |
|---------------------------|-----------------------------------|
| 1. Lead Source | 12. SI in Term |
| 2. Selection in 5 minutes | 13. Prev. TW Booking(s) |
| 3. V. Make | 14. Prev. Motor Booking |
| 4. V. Model | 15. Prev. Insurer |
| 5. NCB | 16. Previous NCB |
| 6. V. Age | 17. Prev. Health Booking |
| 7. Fuel | 18. SI in Health |
| 8. Geography | 19. Prev. Travel Booking(s) |
| 9. Time to Expiry | 20. Prev. Investment Booking |
| 10. Time in journey | 21. Day and time of lead creation |
| 11. Prev. Term Booking | 22. Time spent on each page |

Model assigned a propensity score to each lead – higher the score, higher the time for which lead kept unassigned

Share of unassisted business increased from 35% (overall) to 48% (on pilot data)

Techniques used to model Digital Data

Pvt. Cars – Increase in Unassisted Share - Benefits



Cost savings to Policybazaar (PB) – Significant reduction in agent costs

Beneficial for Insurers – Direct correlation with lower LR's

Helpful to PB's Operations team – time of agents spent on leads that need assistance

Helpful to PB's Marketing team – Marketing spends channelized towards source (data segments) that creates more unassisted leads

Insights for PB's BD team – Give insights on price vs. brand value for each insurer

Overall value proposition to PB's shareholders – Helps in generating overall efficiencies in a low premium high transactions product

Techniques used to model Digital Data

Pvt. Cars – Understanding risk from Claims perspective

20% claims frequency imply 80% profitable business – Still UW losses

Insurers with high rate realization also showing LRs that are leaving no/little margins

Where can the problem be?

Are we ignoring data that is available and is a good proxy to understand risk better

Financial

Profession

Risk Coverage

Brand Affinity

Behavioral

Risk Profile

Referrals

Driving style

Kms. Driven

Debt/Mortgage

Lead Source

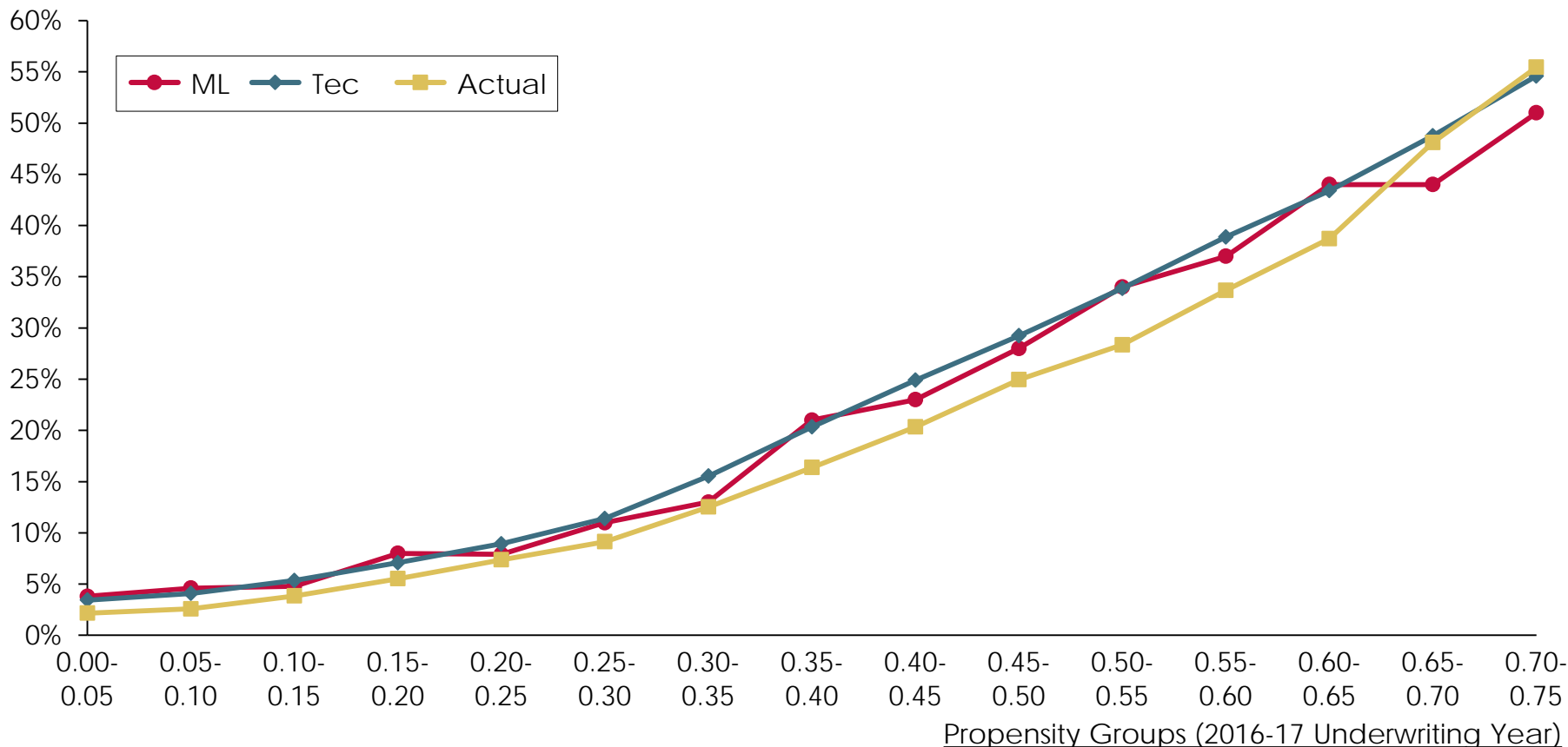
Techniques used to model Digital Data

Pvt. Cars – Use of AI – Frequency Outcome



Based on only Traditional Risk Parameters – in AI

Avg. Claim Propensity for Group (%)



AI on traditional parameters compared with tec. (traditional and digital) and actual data shows multiple discontinuities in AI curve

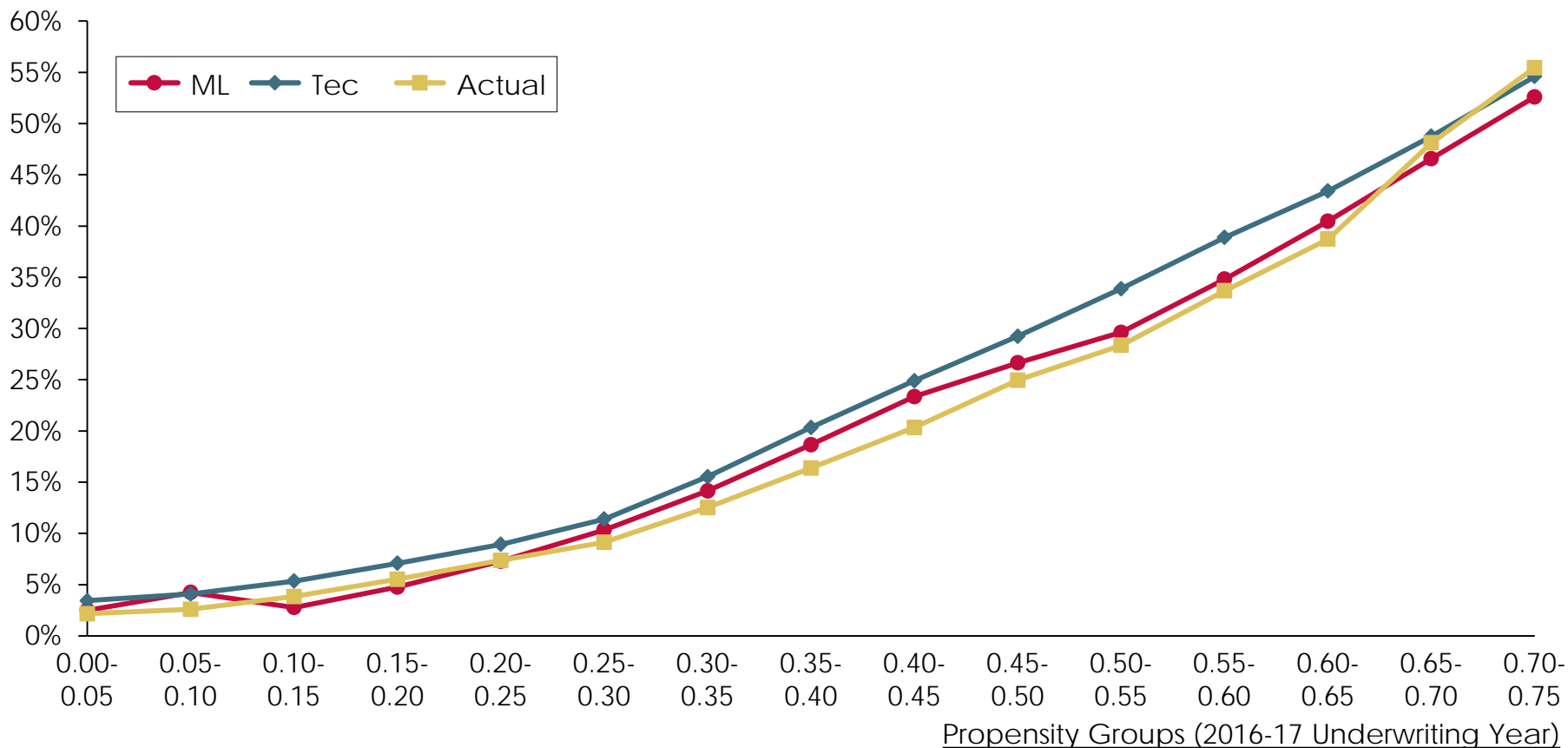
Techniques used to model Digital Data

Pvt. Cars – Use of AI – Frequency Outcome



Based on only Traditional + Digital Parameters – in AI

Avg. Claim Propensity for Group (%)



AI curve on traditional and digital parameters smoothens out and provides similar gradient as actual and technical curves on frequency

Techniques used to model Digital Data

Health Propensity – Increase in Conversions



GLM Model created – Response Variable considered “Is Booked”

Propensity Model

- Link Function : Logit
- Distribution: Binomial

Premium Model

- Link Function : Log
- Distribution: Gamma

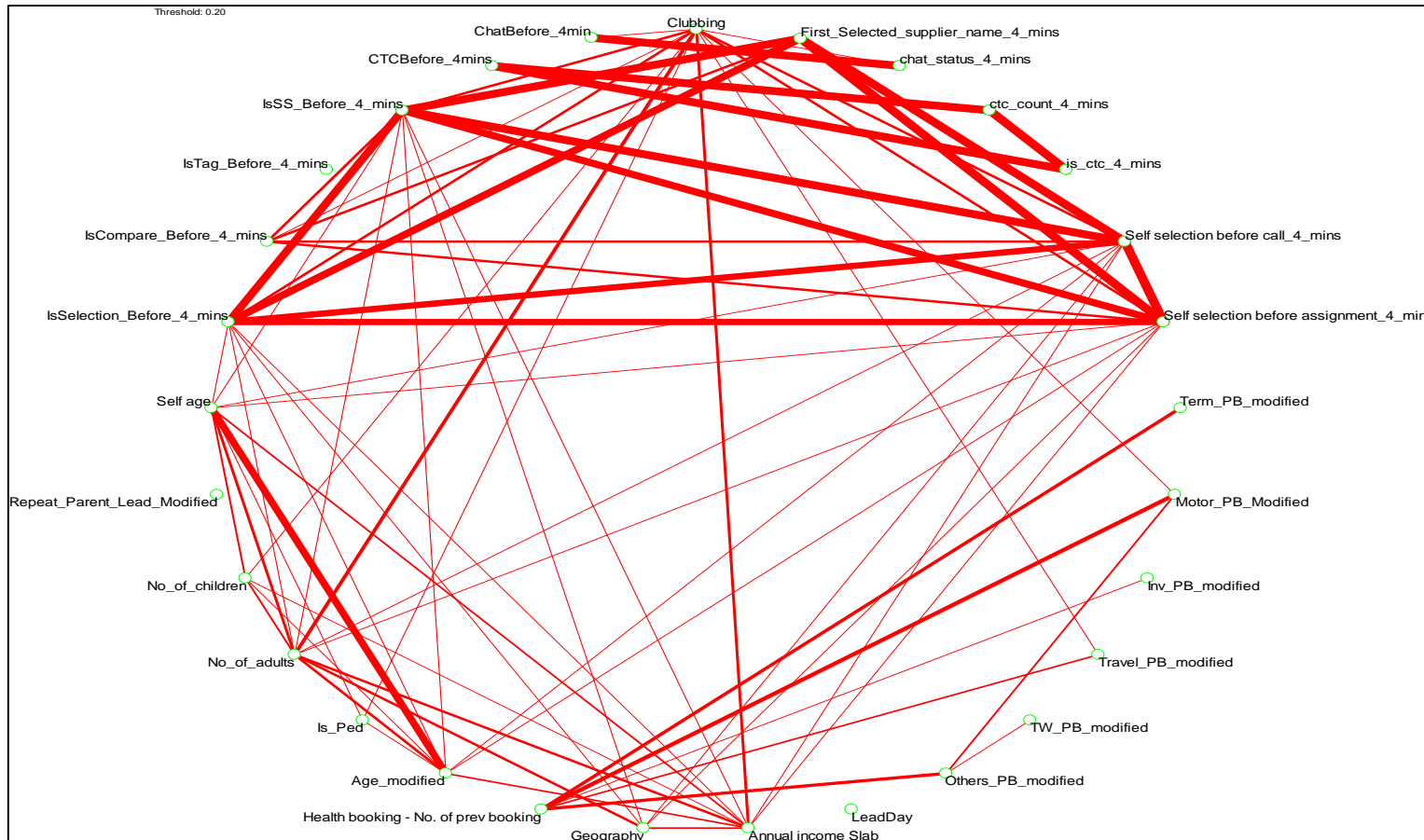
Parameters Considered

1. Lead Source
2. UTM Source
3. UTM Medium
4. Compare
5. Tag
6. Repeat Parent Lead
7. IS PED
8. No. of Children
9. No. of Adults
10. Self Age
11. Geography
12. No. of prev. health booking
13. Annual Income
14. Prev. Term Booking
15. Prev. Tw Booking
16. Prev. Motor Booking
17. Prev. Travel Booking
18. Prev. Investment Booking
19. Lead Time
20. First selected insurer
21. Self selection before call
22. Self selection before assignment
23. CTC count
24. Chat status
25. Gender
26. Lead Day
27. Selected Premium Range by user

Techniques used to model Digital Data

Health Propensity – Increase in Conversions

Correlation studied to check if any factors needed to be removed



Techniques used to model Digital Data

Health Propensity – Increase in Conversions



Parameters reduced to include mainly independent parameters

Propensity Model

- Link Function : Logit
- Distribution: Binomial

Premium Model

- Link Function : Log
- Distribution: Gamma

Parameters Considered

- | | |
|---------------------------------|--------------------------------------|
| 1. Lead Source | 15. Prev. Tw Booking |
| 2. UTM Source | 16. Prev. Motor Booking |
| 3. UTM Medium | 17. Prev. Travel Booking |
| 4. Compare | 18. Prev. Investment Booking |
| 5. Tag | 19. Lead Time |
| 6. Repeat Parent Lead | 20. First selected insurer |
| 7. IS PED | 21. Self selection before call |
| 8. No. of Children | 22. Self selection before assignment |
| 9. No. of Adults | 23. CTC count |
| 10. Self Age | 24. Chat status |
| 11. Geography | 25. Gender |
| 12. No. of prev. health booking | 26. Lead Day |
| 13. Annual Income | 27. Selected Premium Range by user |
| 14. Prev. Term Booking | |

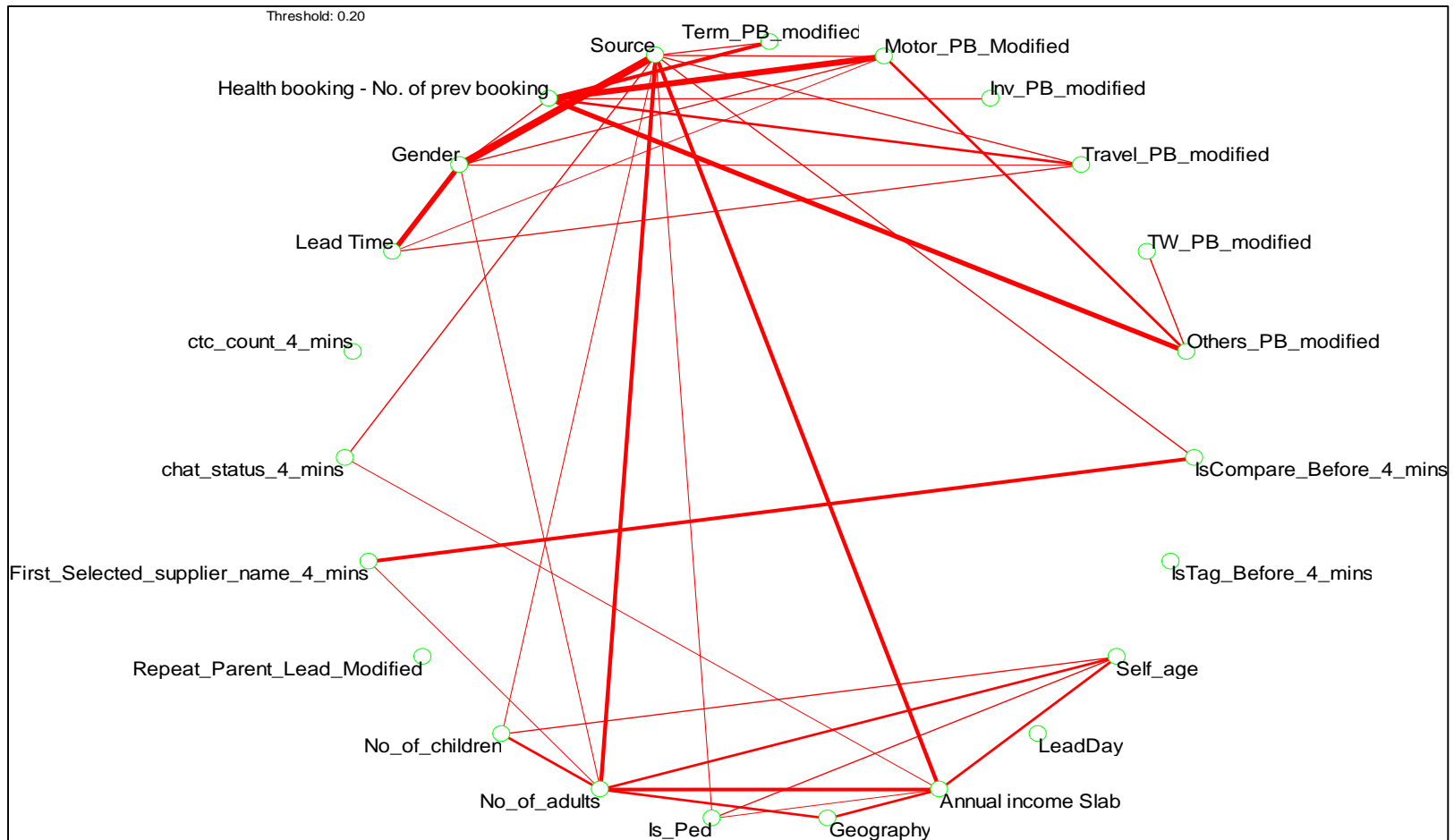
Parameters Used in final Model

- | | |
|-------------------------------|----------------------------|
| • Lead Source | • Booking |
| • UTM Source | • Prev. Tw Booking |
| • Compare | • Prev. Investment Booking |
| • Repeat Parent Lead | • Lead Time |
| • IS PED | • First selected insurer |
| • No. of Children | • Chat status |
| • Self Age | • Gender |
| • Geography | |
| • No. of prev. health booking | |
| • Annual Income | |
| • Prev. Term | |

Techniques used to model Digital Data

Health Propensity – Increase in Conversions

Revised Correlation Chart



Techniques used to model Digital Data

Health Propensity – Increase in Conversions



Multiple interactions created to capture the combined effect

Lead Grade	Propensity Level	Lead Share	Bookings Share	Strength of Actuarial Model
A1	0.7-0.8	5%	22%	2.3x
	0.6-0.7			
	0.5-0.6			
	0.4-0.5			
	0.3-0.4			
	0.2-0.3			
	0.1-0.2			
A2	0.095-0.1	9%	20%	1.7x
	0.09-0.095			
	0.085-0.09			
	0.08-0.085			
	0.075-0.08			
	0.07-0.075			
	0.065-0.07			
A3	0.055-0.06	26%	32%	1.2x
	0.05-0.055			
	0.045-0.05			
	0.04-0.045			
	0.035-0.04			
	0.03-0.035			
A4	0.025-0.03	35%	22%	0.8x
	0.02-0.025			
	0.015-0.02			
	0.01-0.015			
A5	0.005-0.01	25%	4%	0.4x
	0-0.005			

Techniques used to model Digital Data

Health Propensity – Increase in Conversions



14% leads converted into 42% of overall health business

Assignment of high converting leads when happening on pure segmentation basis was not giving desired efficiencies

A1 leads showed 2.3x higher conversion when compared with earlier segmentation based models

60% leads that were originally being given full effort actually fell into lowest range of conversion propensity – can be assigned to low ranked agents / use for training purposes

Health propensity model provided the best possible outcome for PB – Margins improvement, most optimal utilization of operations team, clear vision for marketing team for spends, more time now being spent in improving customer experience further and all these bringing increased ROI for shareholders

Actuarial strengths in business-wide areas

Are we ready to take our skills in non-traditional roles?



- Actuarial applications at PB showed all round efficiencies for BD, Operations, Marketing and Partners
- Internal efficiencies are gaining strength, we can step up to take the challenge further – helping partners differentiate between good and bad risk
- There is enough data that suggests that industry can move back towards pure technical pricing
- Actuaries – Underwriters, Data people, Data scientists.....
- Together we can demonstrate to stakeholders and regulator that the bank of data residing within our servers is a treasure

A treasure that is hidden but not yet hidden!!

Thank You



Institute of Actuaries of India