GAS Event June 2018

Programme

12.30pm – 1.00pm	**Registration and Coffee**
1.00pm – 1.15pm	**Welcome and Introduction** *Shivash Bhagaloo, Chairperson, Gulf Actuarial Society*
1.15pm – 2.15pm	**Session 1 – GLM Pricing and Data Science Algorithms** ***Speaker:*** *Michael Casalinuovo, Consultant* *Addactis Worldwide*
2.15pm – 3.00pm	**Session 2 – IFRS 17 – The New Financial Reporting Standards for Insurance Companies** ***Speaker:*** *Abdul Moid Ahmed Khan, Senior Manager & Consulting Actuary* *SHMA Consulting*
3.00pm – 3.15pm	**Coffee Break**
3.15pm – 3.45pm	**Session 3 – Claims Fraud Assessment** ***Speaker:*** *Sam Khunaizi, Actuarial Analyst* *Lux Actuaries and Consultants*
3.45pm – 4.25pm	**Session 4 – Data Driven Decision Making – Using Analytics to Optimise Profits** ***Speaker:*** *Hatim Maskawala, Managing Director* *Badri Management Consultancy*
4.25pm – 5.00pm	**Session 5 – Professionalism** ***Speaker:*** *Syed Hassan Qadir, Actuarial Manager* *RAK Insurance*
5.00pm – 6.00pm	**Drinks and nibbles reception and networking**

CPD Hours: 2.5 hours
Sponsor: SHMA Consulting and Badri Management Consultancy

GLM Pricing and Data Science Algorithms

28/06/2018

About the speaker

- Michael CASALINUOVO
  - Actuary in ADDACTIS®
  - ADDACTIS® Pricing responsible
  - Non-life consultant

- ADDACTIS
  - Consulting and Software firm
  - Life/Non-Life
  - Modeling/Pricing /Reserving/Reporting

Summary

Introduction

- Pricing challenges in a continuously changing market
- Insurance companies need to be:
  - adequately compensated for the risk they take;
  - continue to be competitive;
  - avoid anti selection.
- Following all these developments, insurers will need to:
  - operate very rapidly in a continuously changing and competitive market;
  - price their products correctly and therefore use appropriate data, sophisticated and best practice pricing models;

Introduction

- Necessary information:
  - Policies:
    - Start date
    - End date
  - Claims:
    - Claim cost
    - Claim count

Introduction

- Model

⇒Risk Premium = Frequency * Average Cost

⇒Frequency=Claims_count/Exposure

⇒Average_Cost=Claim_amount/Claim_count

Introduction

- Model without segmentation

$\Rightarrow$ Risk Premium = E[Frequency] * E[Average Cost]

- Basic models
  - $Frequency = \frac{\sum_{i=1}^{n} N_i}{\sum_{i=1}^{n} e_i}$

    $where\ N_i\ is\ the\ number\ of\ claims\ and\ e_i\ the\ exposure$
  - $Average\ cost = \frac{\sum_{i=1}^{k} C_i}{N_{Tot}}$

=>Anti selection

- Objective: use explicative variables to create risk profiles

Regression Scope

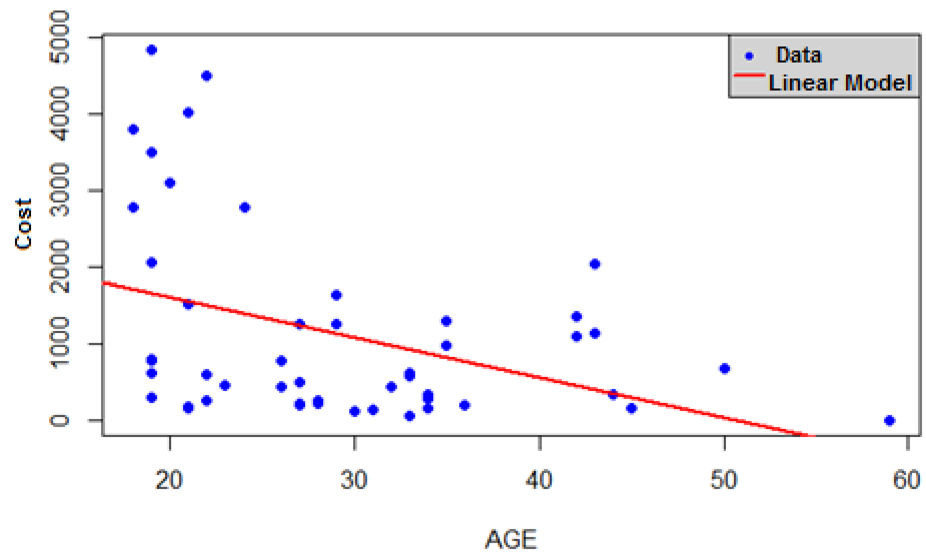
- Input data:
  - Explicative columns $\mathcal{X}$
  - Objective column $\mathcal{Y}$
  - $(x_1, y_1), \dots, (x_n, y_n)$

- Aim:
  - Learn a model : $h\colon\ \mathcal{X} \rightarrow\ \mathcal{Y}$
  - Prediction is noted $\hat{y}\ = h(x)$

Statistical Learning

Linear Models

- Model
  - $Y = \sum_{j=1}^{d} \alpha_j X_j + \epsilon$
  - $\epsilon \sim \mathcal{N}(0, \sigma^2)$



- Results
  - $\hat{\alpha} = (X^T X)^{-1} X^T Y$

Linear Models

- Advantages
  - Easy to implement
  - Interpretation

- Disadvantages
  - Gaussian hypothesis
  - Parametric method
  - Not possible to model complex phenomenons

Generalized Linear Models

- Model
  - $Y = g^{-1}(\beta_0 + \beta_1.X_1 + \cdots + \beta_n.X_n) + \epsilon$
  - Distribution does not need to be Gaussian but member of exponential family
  - Exemple:
    - $Bin(1, \mu)$
    - $Poisson(\mu)$
    - $Normal(\mu, \sigma^2)$
    - $Gamma(\mu, \alpha)$
    - $InverseGauss(\mu, \sigma^2)$

- Results:

  Maximise the fulllikelihood:

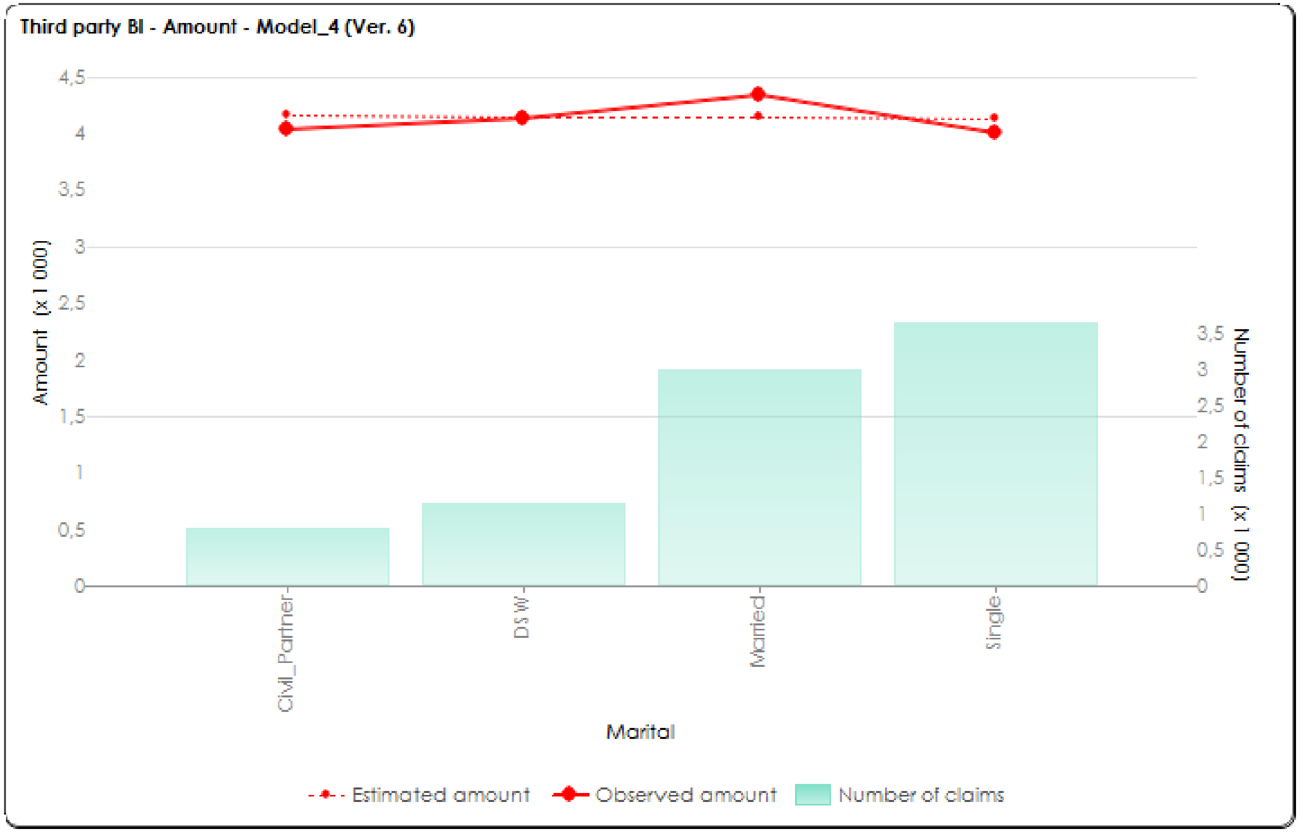
Generalized Linear Models

- Results- Multiplicative structure

Factor	Modality	Value	Standard error	Lower conf. limit	Upper conf. limit	Wald Chi-2	Pr > Chi-2	Multiplier	Nb. of claims
(constant)	(constant)	8,6724	0,0264	8,6207	8,7241	108 134,31	0,0000	5 839,3352	
Gender	F	-0,1499	0,0239	-0,1968	-0,1030	39,23	0,0000	0,8608	3 691
Gender	M	0,0000	0,0000	0,0000	0,0000	0,00	0,0000	1,0000	4 930
Fuel	Diesel	-0,0446	0,0238	-0,0911	0,0020	3,52	0,0607	0,9564	4 670
Fuel	Petrol	0,0000	0,0000	0,0000	0,0000	0,00	0,0000	1,0000	3 951
Age	[18 ; 28[	0,0000	0,0000	0,0000	0,0000	0,00	0,0000	1,0000	2 901
Age	[28 ; 35[	-0,1295	0,0349	-0,1979	-0,0611	13,76	0,0002	0,8785	1 504
Age	[35 ; 39[	-0,4097	0,0445	-0,4970	-0,3224	84,65	0,0000	0,6639	770
Age	[39 ; 45[	-0,4977	0,0405	-0,5770	-0,4184	151,18	0,0000	0,6079	987
Age	[45 ; 51[	-0,6431	0,0431	-0,7275	-0,5587	223,05	0,0000	0,5257	839
Age	[51 ; 59[	-0,6593	0,0443	-0,7462	-0,5724	221,26	0,0000	0,5172	779
Age	[59 ; ∞[	-0,5690	0,0430	-0,6534	-0,4847	174,95	0,0000	0,5661	841

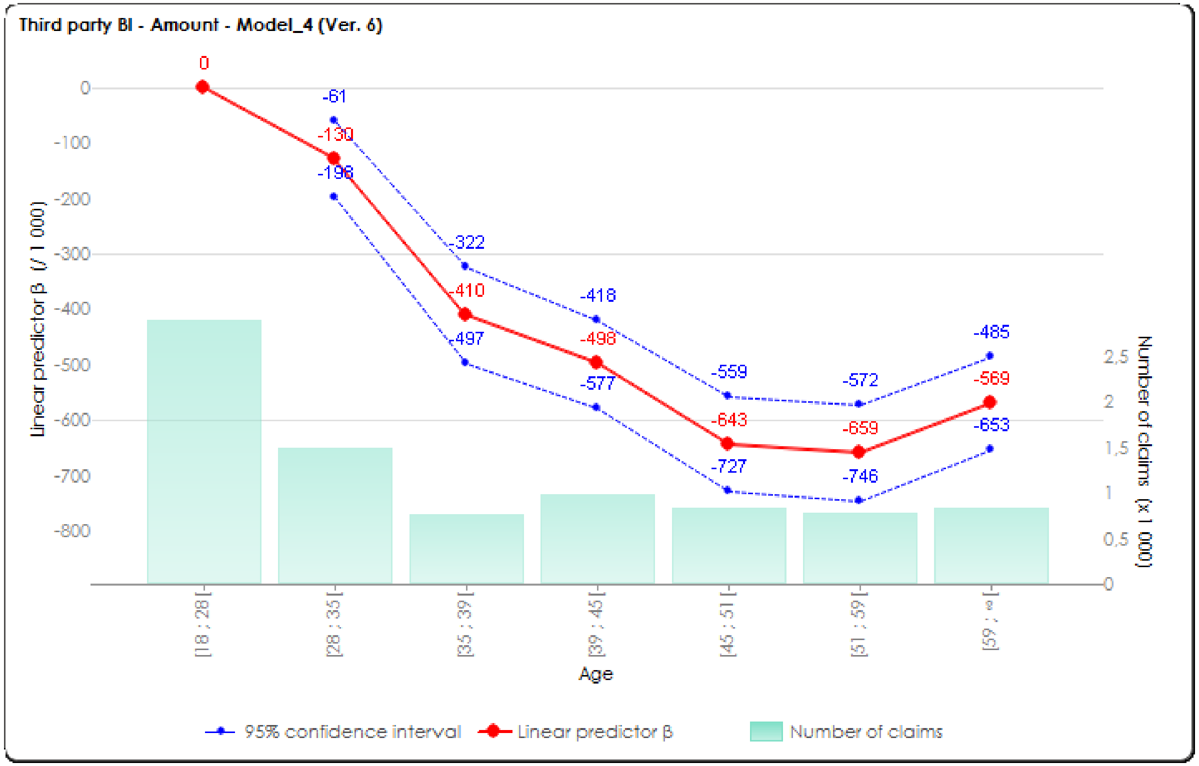
Generalized Linear Models

- Graphs estimated vs observed



Generalized Linear Models

- Graphs - Relativities and confidence intervals



Generalized Linear Models

- General Statistics

Model appreciation parameter	Value
Scale	0,8289
Scale standard error	0,0109
Deviance	12 288,6539
Scaled deviance	10 185,7114
Observations count (actually processed)	8 621
Degrees of freedom	8 612
AIC (smaller is better)	159 988,1453
AIC (corrected)	159 988,1709
BIC (smaller is better)	160 058,7649
(Log)Likelihood	-79 984,0727
Full (Log)Likelihood	-79 984,0727
Observed sum	35 664 002,9500
Estimated sum	35 662 528,5344

Generalized Linear Models

- Statistics- Variable significance

Criteria	Degrees of freedom	Chi-2	Pr > Chi-2
Age	6	486,8439	0,0000
Gender	1	13,1928	0,0003
Fuel	1	3,5707	0,0588
color	5	4,2855	0,5091

Generalized Linear Models

- Advantages
  - Easy to implement
  - Interpretation (Multiplicative structure)
  - Statistical tests (i.e. confidence interval, hypothesis tests,…)

- Disadvantages
  - Hypothesis on data
  - Parametric method
  - Not possible to model complex phenomenons

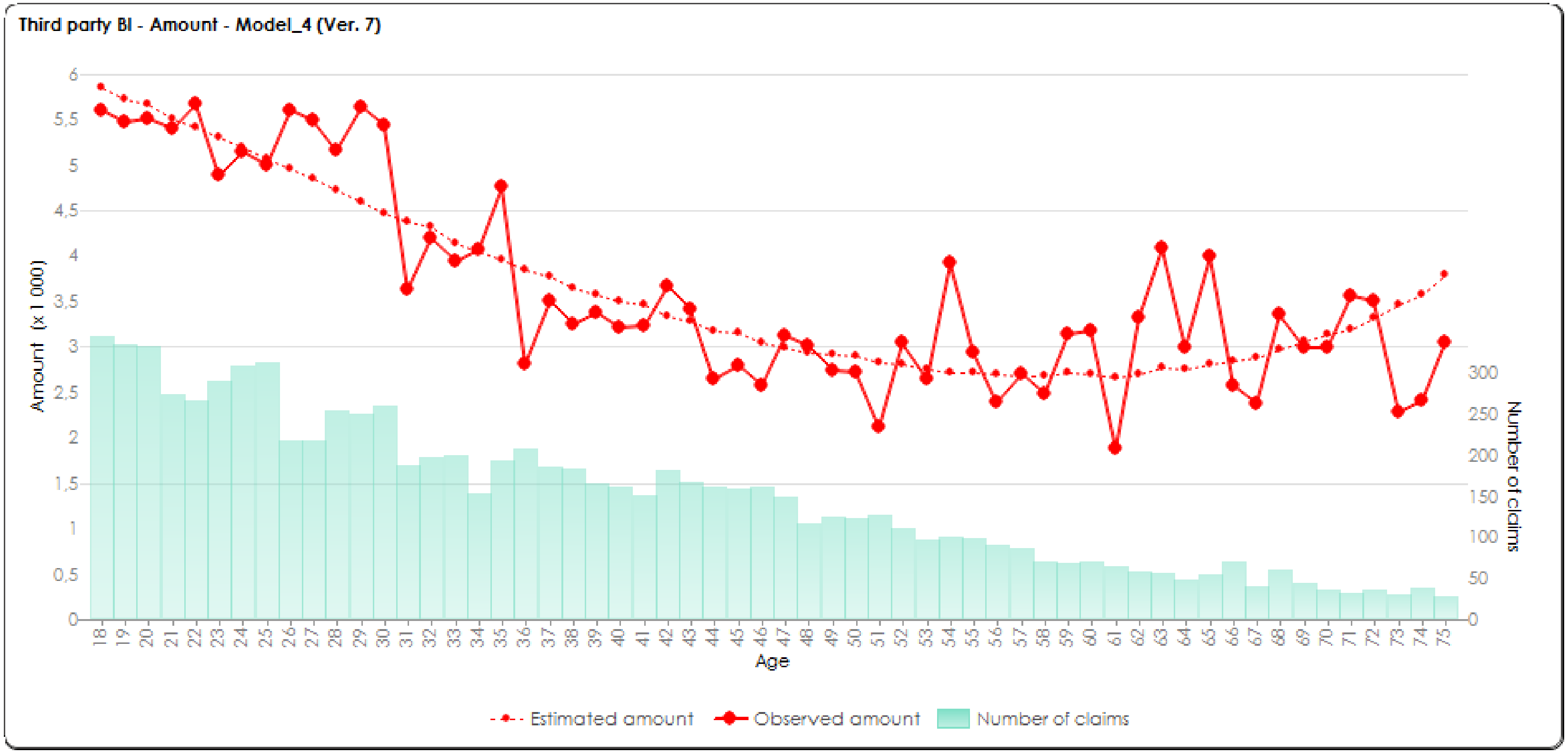
GLMs Improvements

- GAM
  - Model continuous variables
    - Semi-parametric approach
    - Polynomials
    - Splines

$$g(\mu_i) = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \sum_{j=k+1}^{p} f_j(x_{ij})$$

GLMs Improvements

- GAM
  - Model continuous variables



GLMs Improvements

- Penalization

Principle: Penalty constraint is added to the likelihood to maximize

- LASSO
  - $\lambda \sum_{p=1}^{n} |\beta_p|$
- Ridge
  - $\lambda \sum_{p=1}^{n} \beta_p^2$
- Elastic net
  - $\lambda \left[(1-\alpha) \sum_{p=1}^{n} |\beta_p| + \alpha \sum_{p=1}^{n} \beta_p^2\right]$

GLMs Improvements

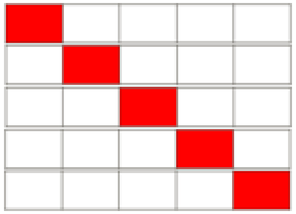
- Hold-Out validation
  - Principle:
    - Split initial base into 2 sets:
      - Training set
      - Testing set

    - Estimate the model with the training set
    - Validate the model on the testing set

    - Calculate "testing" statistics
      - MSE
      - $RMSE$
      - MAE
      - $MAPE$

GLMs Improvements

- Cross-validation
  - Principle:
    - Split the initial base into K sets.

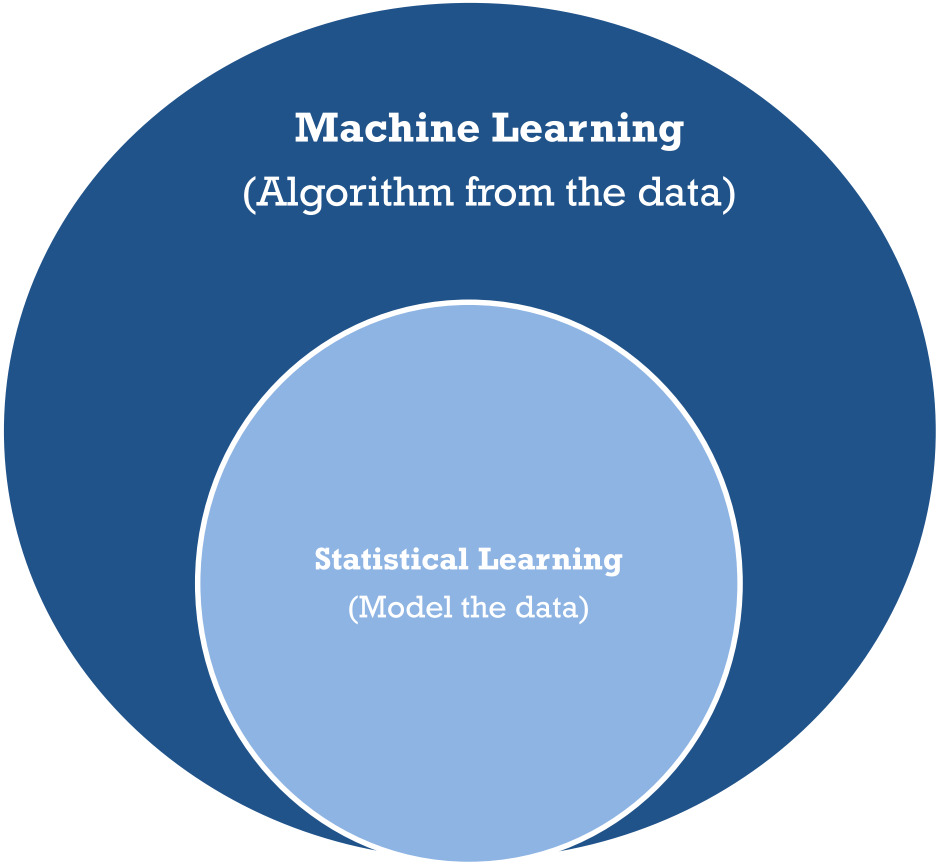


    - For i from 1 to K:
      - Use the Hold-out method with one set as the testing set and others as training set.
    - Take the average of estimations for each iteration.
    - Take the average of statistics for each iteration.

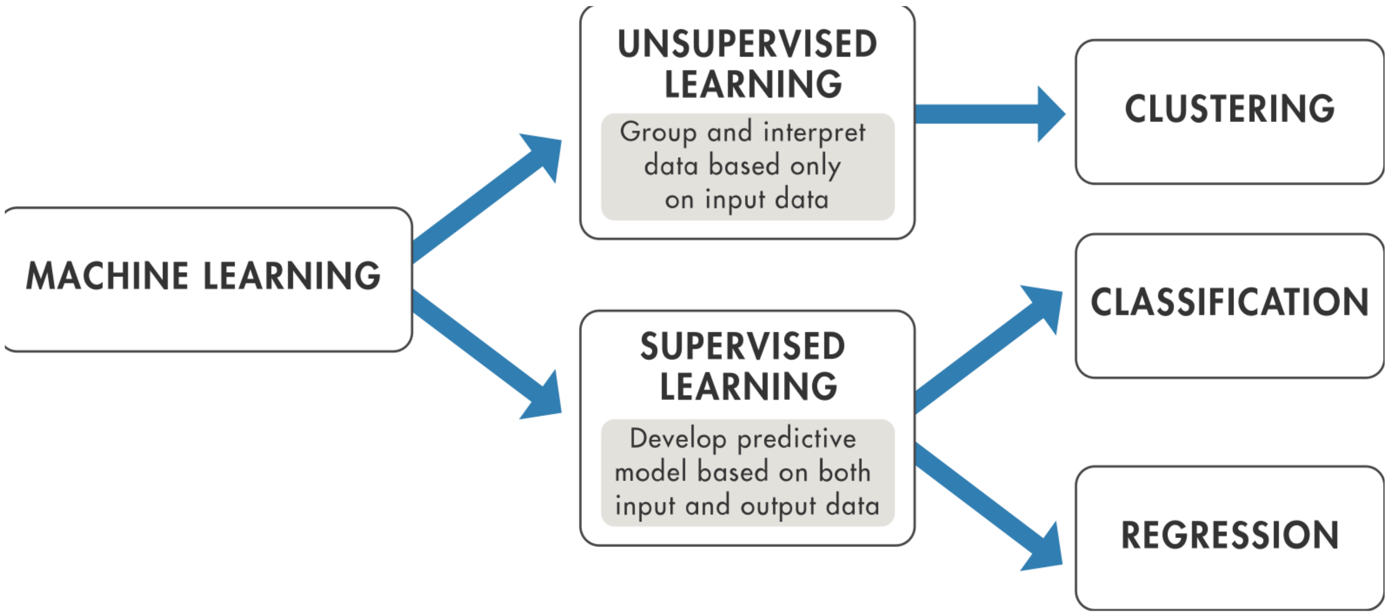
Machine Learning

Machine Learning- Introduction

- Technical framework



Machine Learning- Introduction

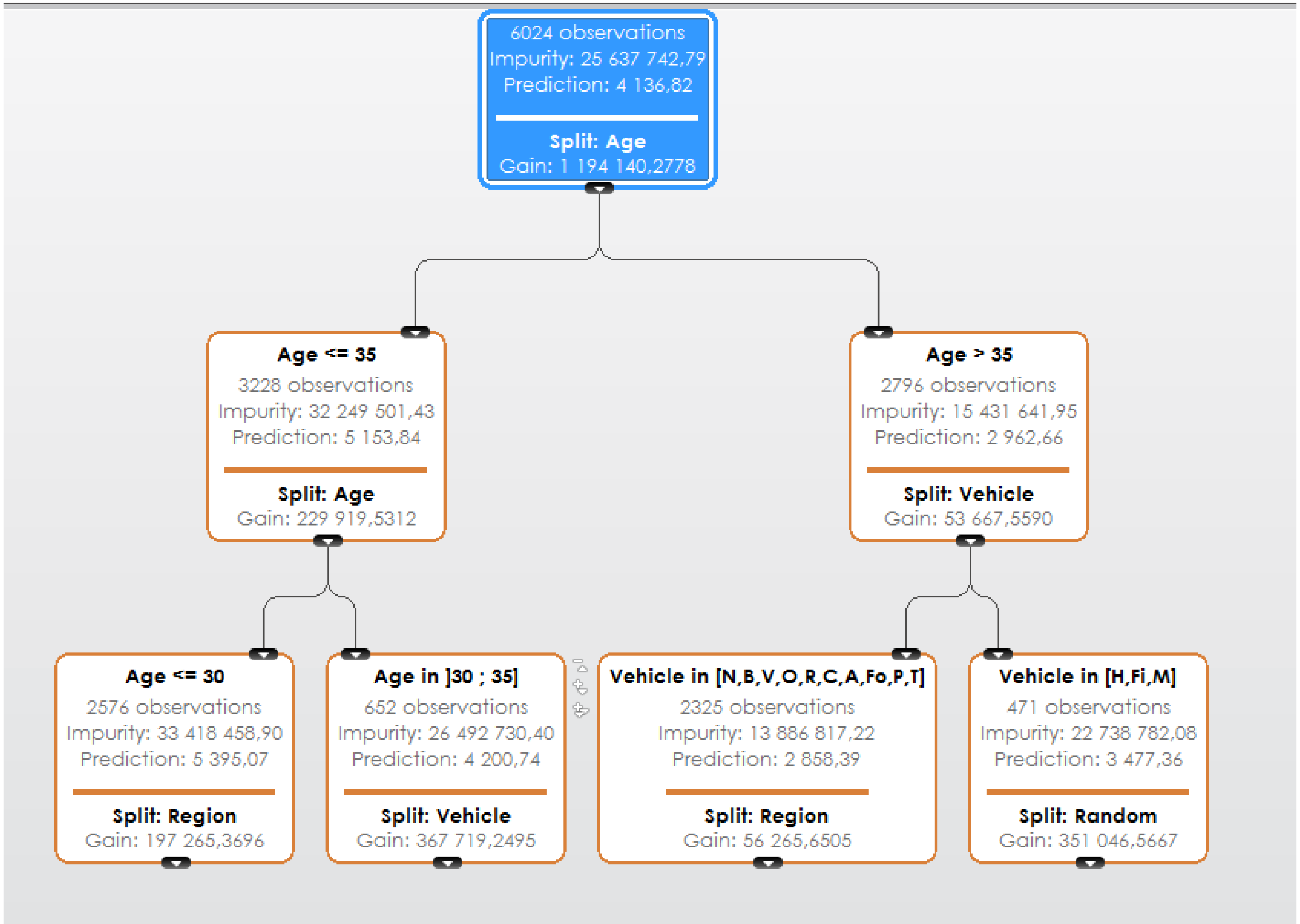


Regression by Tree

- Initialization
  - The initial base is split into 2 sets:
    - Training set
    - Validation set

- Principle: find the optimal segmentation of the predictor set in order to obtain the most homogeneous sets .
  The method is iterative. At each iteration, a set is split into 2 sets according to a variable condition.

Regression by Tree



Regression by Tree

- How to find the best split?
  - Define an homogeneous function.

    For Regression: Variance function

    $$H(N) = \frac{1}{n}\sum_{i\in N}(y_i - \bar{y})^2 \text{ where } \bar{y} = \frac{1}{n}\sum y_i$$

  - The gain of an operation which split a set N into two sets Nl and Nr is given by the formula.

    $$G(S) = \mathrm{H(N) - [H(Nl) + H(Nr)]}$$

  - The aim is to maximize this formula.

Regression by Tree

- Which splits are available?
  - For each explicative variable, all segmentations are listed:
    - For nominal variable with *m* modalities, there are $(2^{m-1}-1)$ possible segmentations
    - For ordinal variable with *m* modalities, there are (m-1) possible segmentations

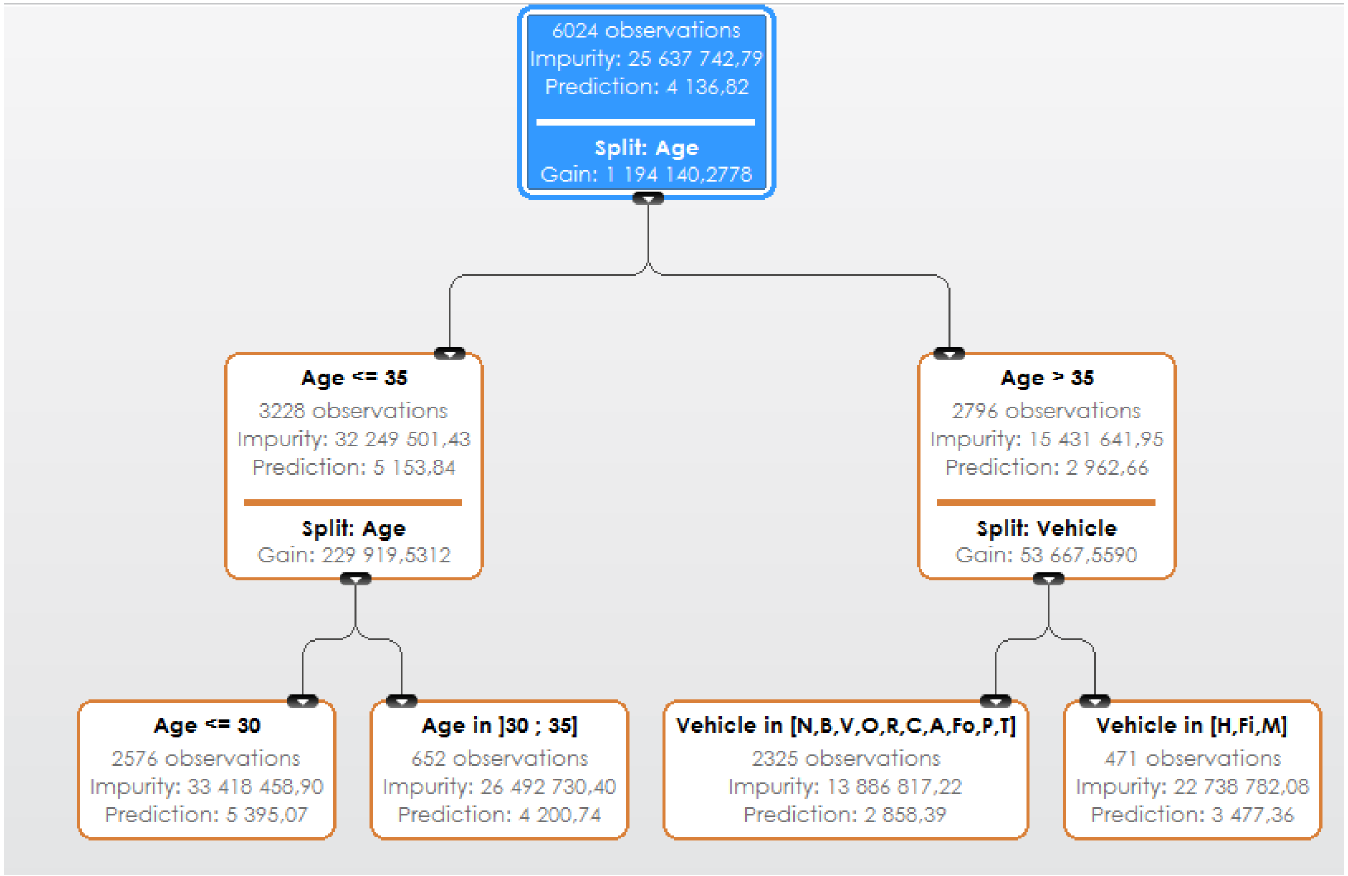
  - Among all the segmentations, the one with the highest gain function is chosen for splitting the set.

Regression by Tree

- When to stop the split?
  - No limitation=> algorithm splits until there are no more available segmentations.
  - User specifies a depth maximal for the tree.
  - User specifies a gain minimum for a split.
  - User specifies a size minimum for a set.

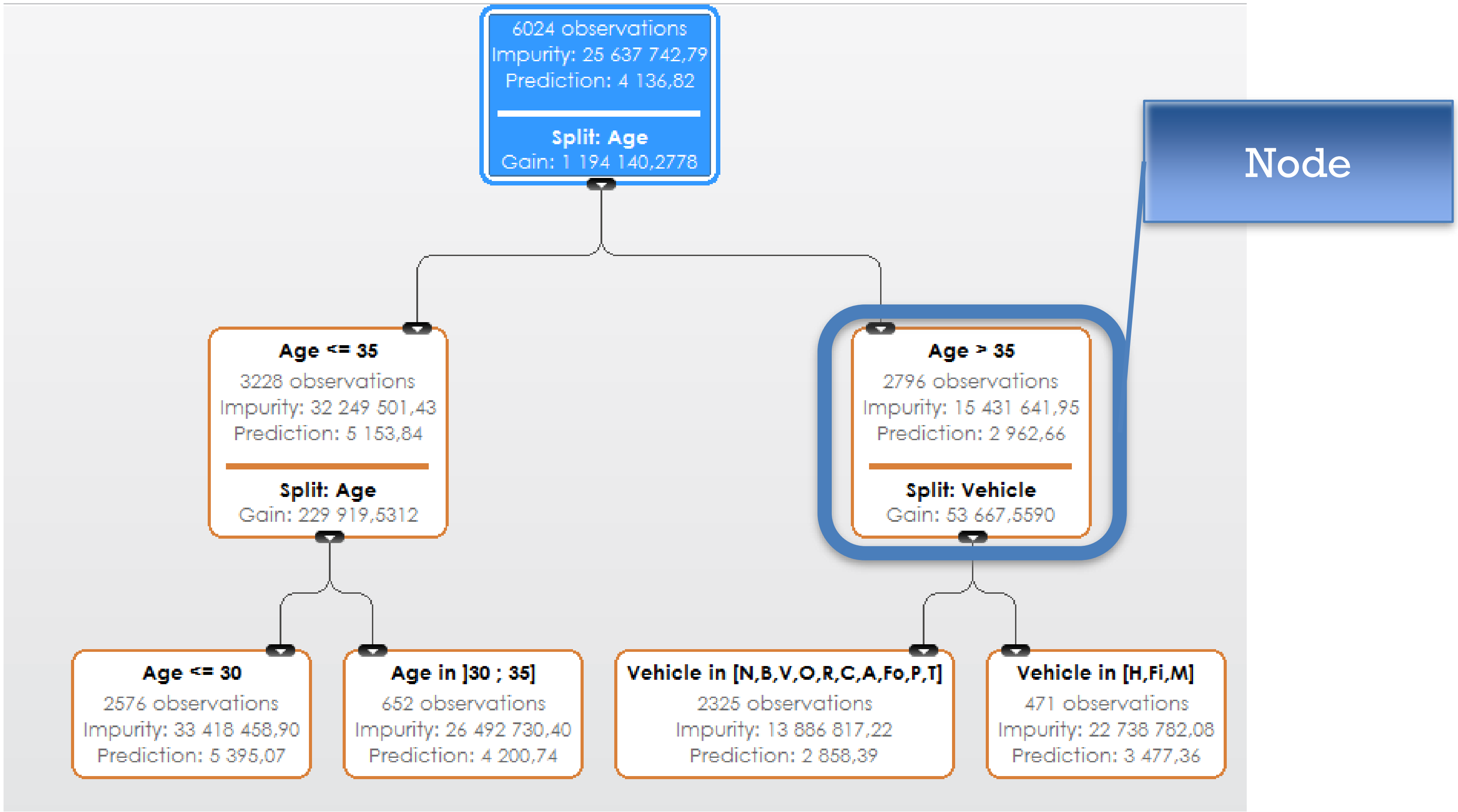
Regression by Tree

- Vocabulary



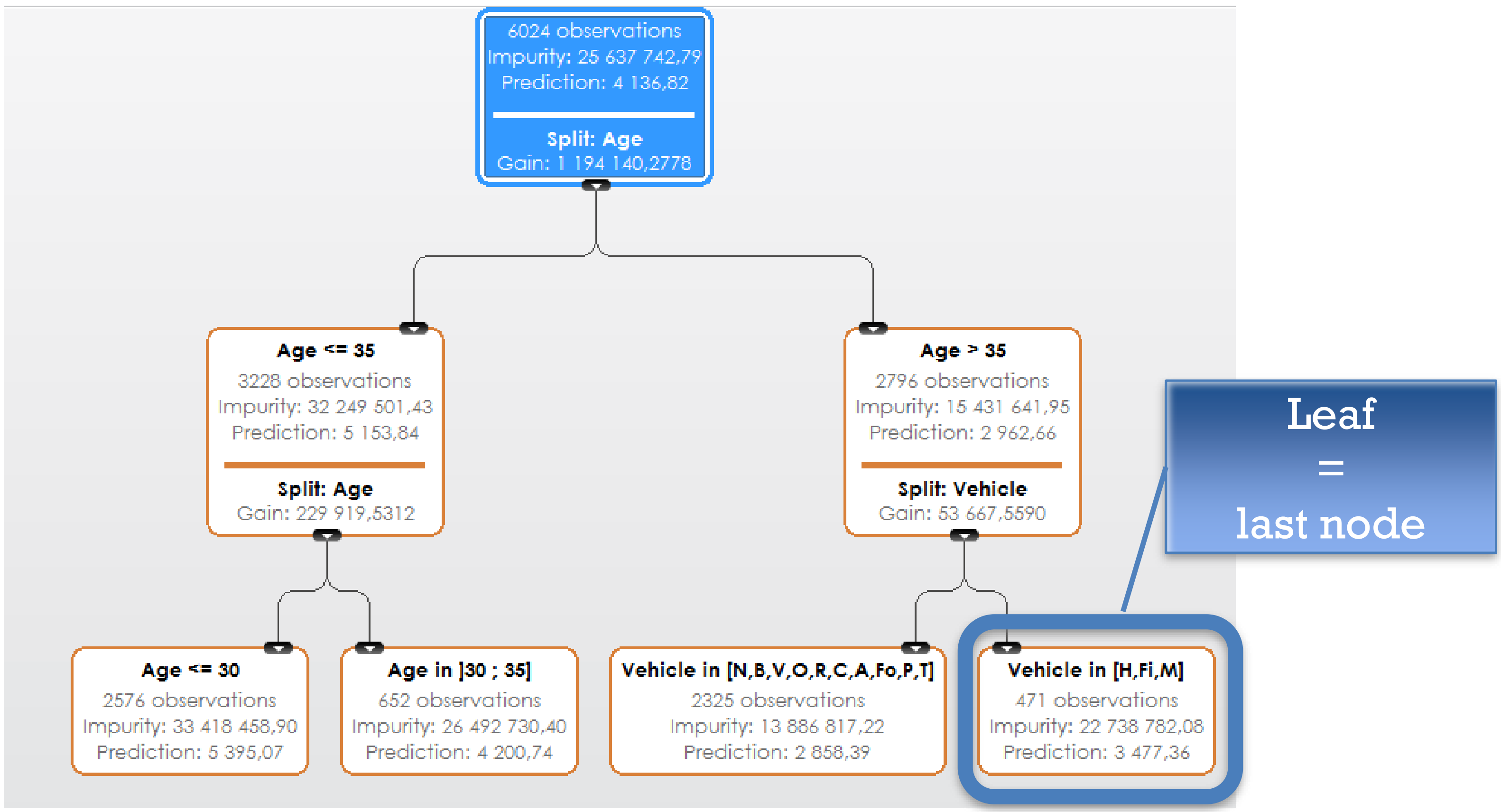
Regression by Tree

- Vocabulary



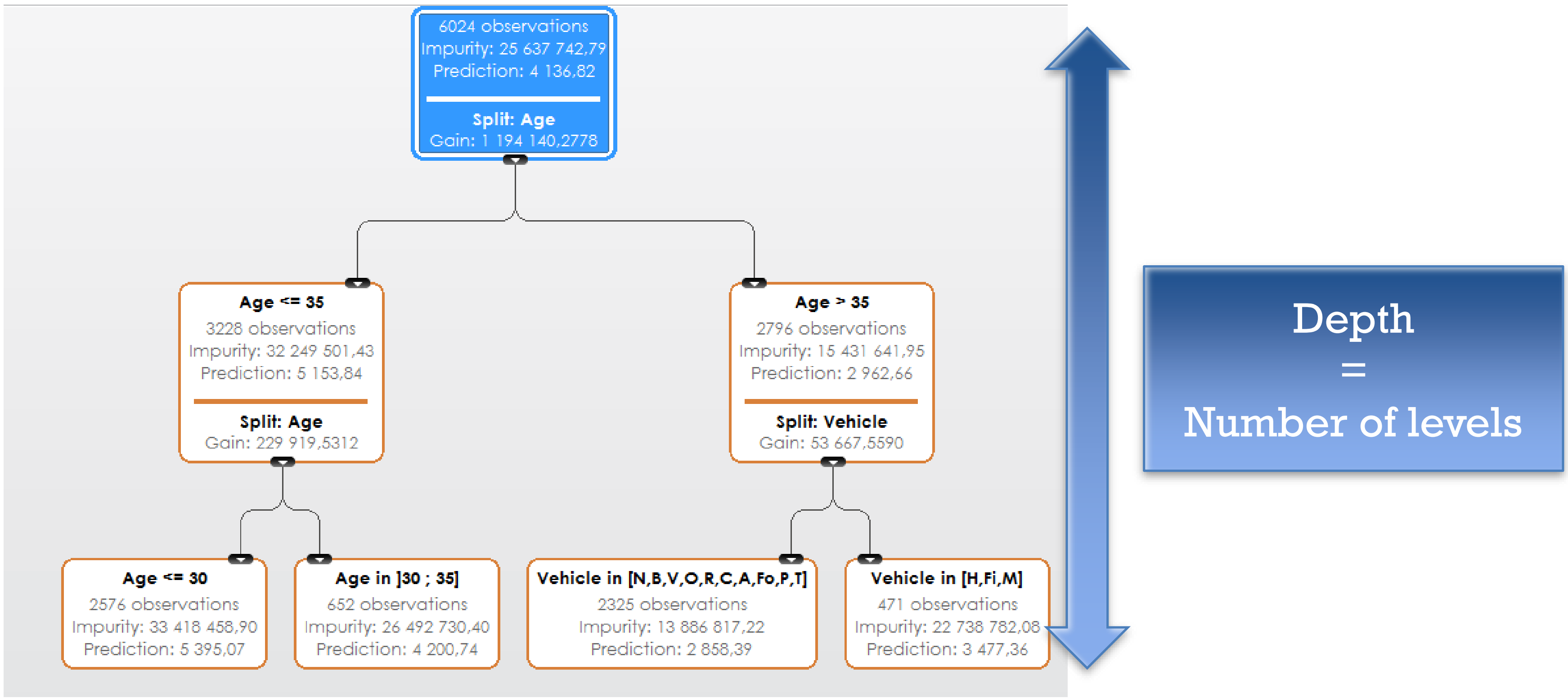
Regression by Tree

- Vocabulary



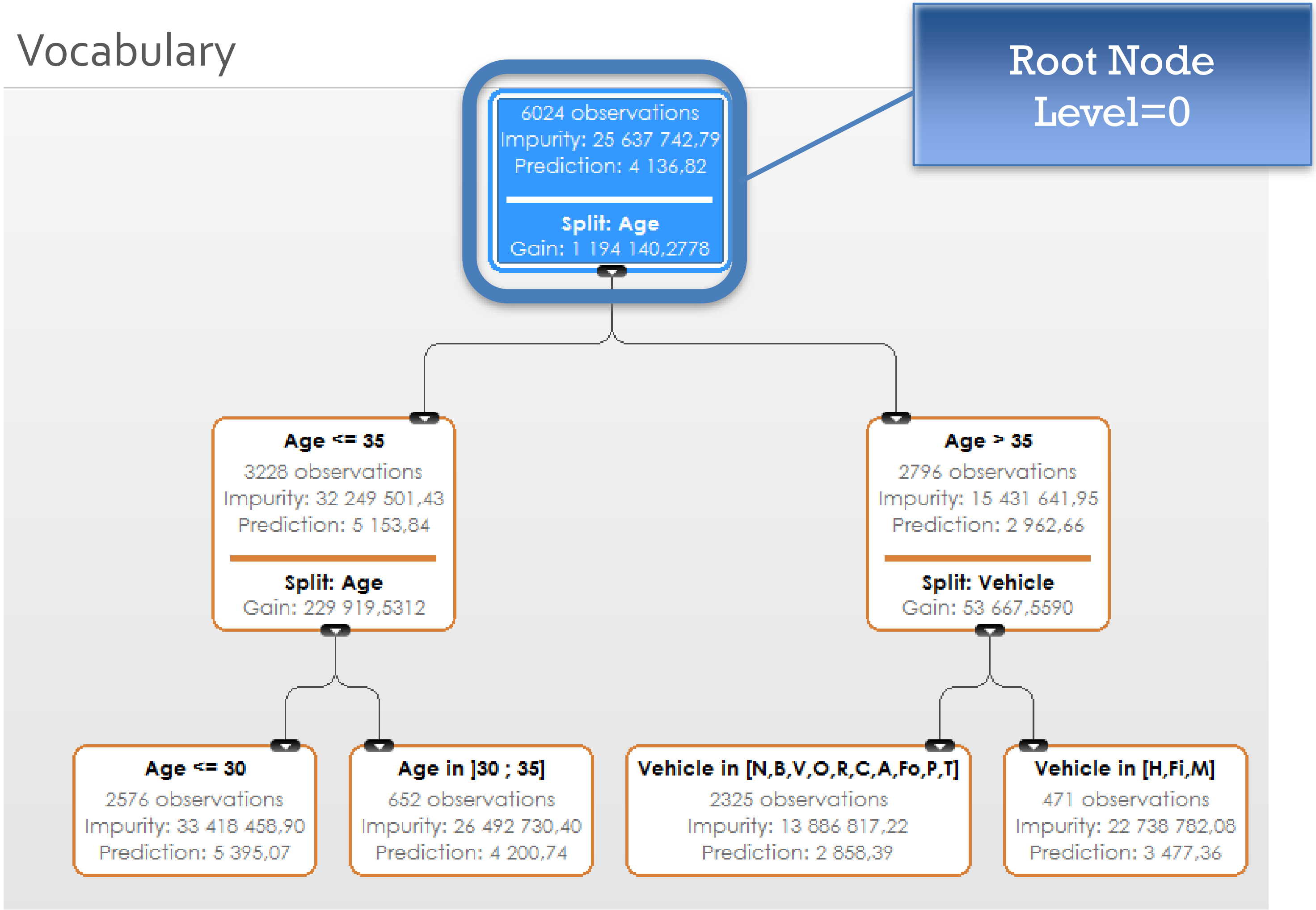
Regression by Tree

- Vocabulary



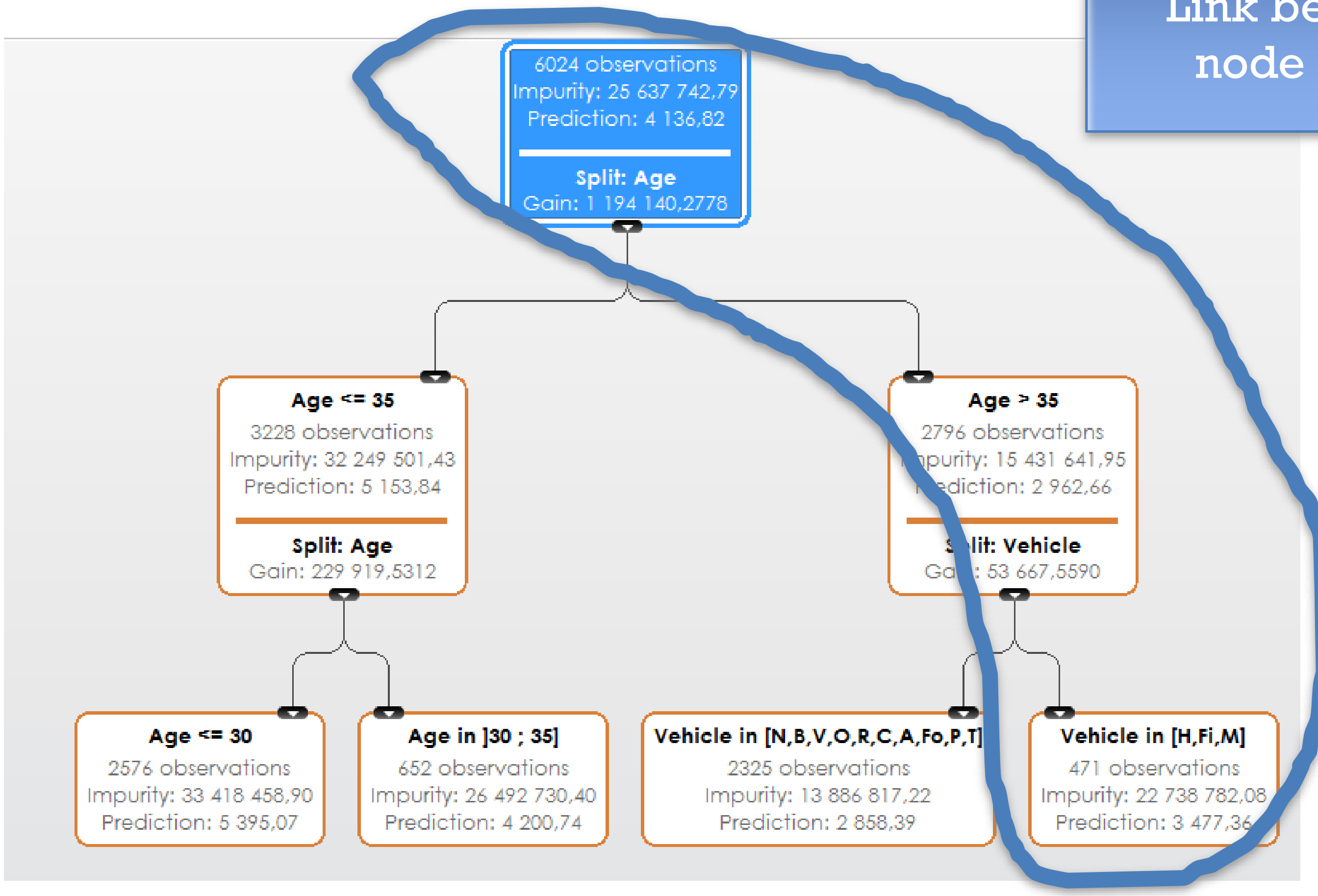
Regression by Tree

- Vocabulary



Regression by Tree

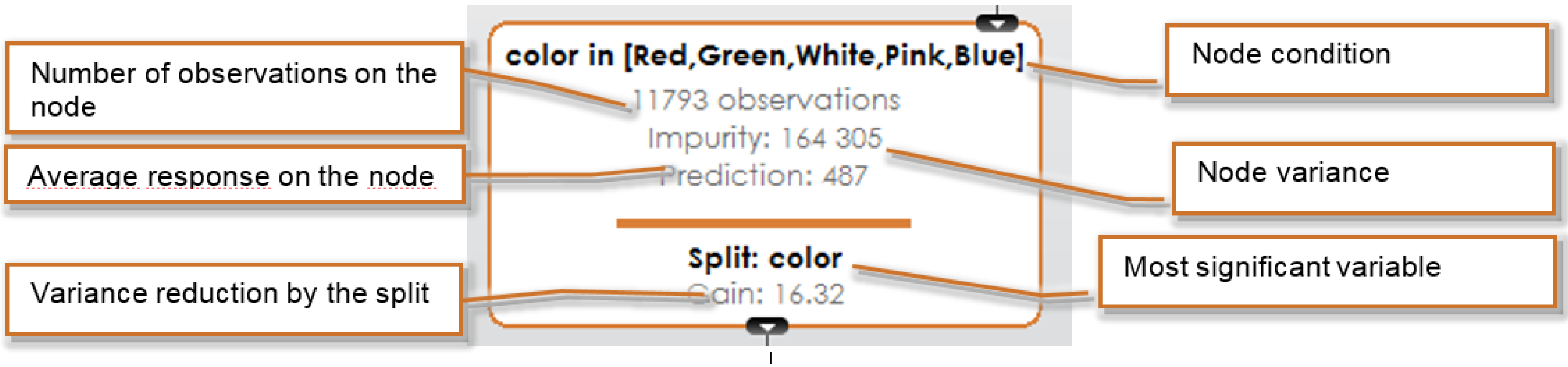
- Vocabulary



Branch
=
Link between root node and a leaf

Regression by Tree

- Vocabulary



Regression by Tree

- Results of the model
  - Each branch of the tree has an estimation
  - Estimation is calculated by taking the average of the target variable on the region.
  - To apply the model, prediction is the estimation of the branch corresponding to the observation.

Regression by Tree

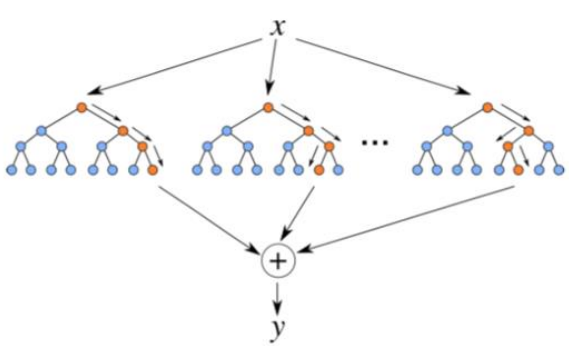
- Advantages
  - Not parametric
  - Interpretation
  - Complexity taken into account

- Disadvantages
  - Dependence on observed data

Bagging and Random Forest

- Bagging method
  - Principle: Run high number of trees by changing the source file each time.
  - How: at each iteration, a new set is created by sampling from the initial training set uniformly with replacement.
  - Prediction: average estimation of each iteration

$$y_k = \frac{1}{n}\sum_{i=1}^{n} y_k^i \ (where\ y_k^i is\ the\ estimation\ of\ the\ iteration\ i)$$



Bagging and Random Forest

- Random Forest method= Bagging + random selection of variables
  - Principle: Run high number of trees by changing the source file each time and selecting a limited number of variable.
  - How: at each iteration, a new set is created by sampling the initial training set uniformly and with replacement.
    Then during the algorithm, for each node, variables are randomly selected from the list of initial variables.
  - Prediction: average of estimations of each iteration.

$$y_k = \frac{1}{n}\sum_{i=1}^{n} y_k^i \ (where\ y_k^i is\ the\ estimation\ of\ the\ iteration\ i)$$

Bagging and Random Forest

- Random Forest method
  - How to define the number of variables used for each node?
    - If there are *p* variables, *p/3* is commonly used for regression.
    - Alternatively:
      - $\sqrt{p}$
      - $log_2(p)$
      - X% of p
    - If *p* variables are used => Bagging.

Bagging and Random Forest

- Random Forest
  - Advantages
    - Non-parametric
    - Robust
    - Reduce the variance
  - Disadvantages
    - Not easy to interpret

Boosting

- <u>Gradient Boosting</u>
  - Iterative method to reduce a loss function.

  - Principle:
    - Initialization: run a tree with small depth.
    - For each iteration: calculate the gradient of the loss function for the estimation and explain it by a tree.
      Sum it with the previous estimation.

    - **$\mu i(X) = \mu i\text{-}1(X) + E_i(X)$** where *µi* is the estimation at the step *i* and *E* the model of the loss function.

Boosting

- Gradient Boosting
  - Which loss function?
    - Squared error: $\sum_{i=1}^{n}(y_i - \widehat{\mu_i})^2$
    - Absolute error: $\sum_{i=1}^{n} |y_i - \widehat{\mu_i}|$
    - Huber α: if $|y_i - \widehat{\mu_i}| < \alpha$ then $(y_i - \widehat{\mu_i})^2$

      $$else\ \alpha|y_i - \widehat{\mu_i}| - \frac{\alpha^2}{2}$$

Boosting

- XGBoost= eXtrem Gradient Boosting
  - Improvements of the Gradient Boosting.
  - Differences:
    - Gradient= first order development of the loss function.
    - XGBoost uses second order development.

Boosting

- Gradient Boosting/ XGBoost
  - Advantages:
    - Accuracy
    - Flexibility
    - Complexity taken into account
  - Disadvantages
    - Not easy to interpret
    - High number of parameters

Machine learning models

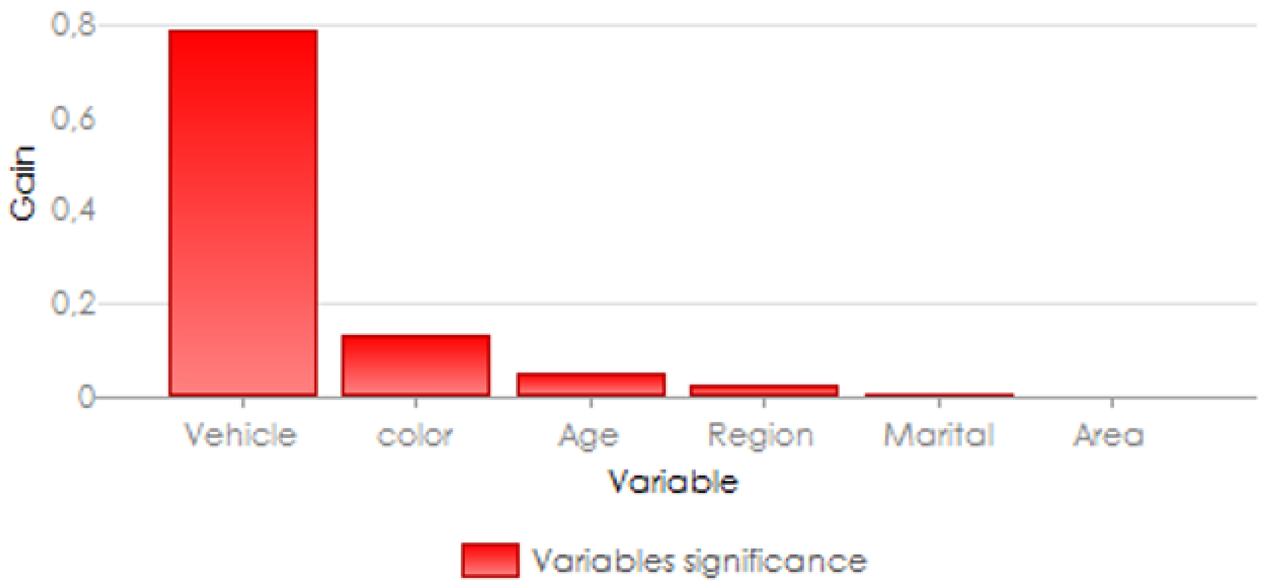
- Robustness
  - Models are estimated from the training set and then applied on the testing set.

  - 4 statistics are calculated:
    - $MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{\mu_i})^2$
    - $RMSE = \sqrt{MSE}$
    - $MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{\mu_i}|$
    - $MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \widehat{\mu_i}|}{y_i}$

Machine learning methods

- Variables Importance

  - Graph representing the contribution of each variable in the model.



Conclusion

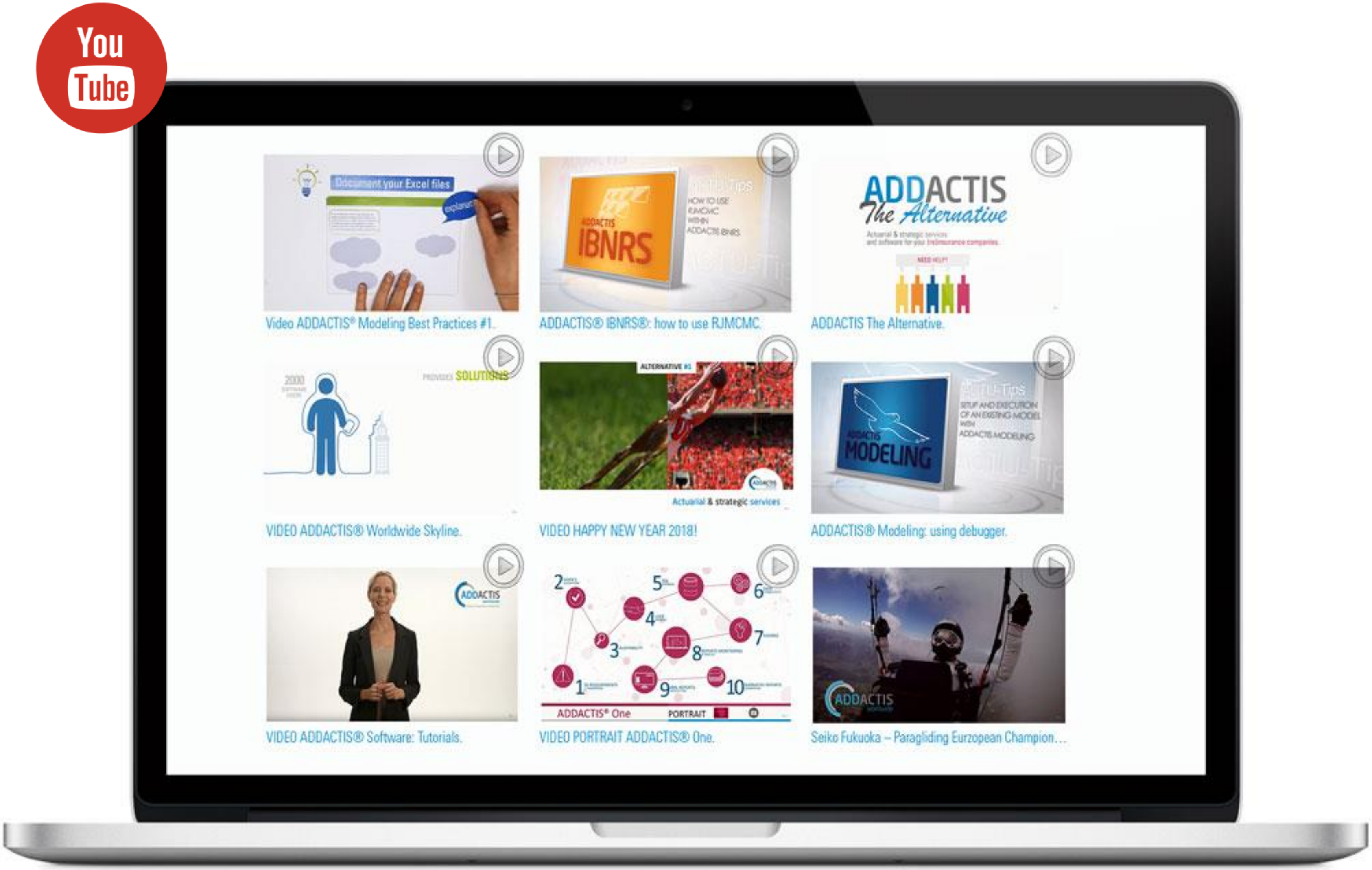
- Should Machine Learning algorithms replace GLMs??
  - No free lunch methods

    $\Rightarrow$ It depends of the segment and the indicator
  - No multiplicative structure

- What can we do?
  - Improve GLMs with machine learning models
  - Combine different kinds of models

Questions???

Videos support



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IFRS 17 – The New Financial Reporting Standards for Insurance Companies

Gulf Actuarial Society (GAS): Members' Event

Dusit Thani Hotel Dubai, UAE

Thursday 28th June 2018

Abdul Moid Ahmed Khan, ASA

Senior Manager & Consulting Actuary

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Agenda

- Overview & Transition Timelines
- Key Definitions
- Measurement Models
- Level of Aggregation
- Presentation of P&L and B/S
- Examples
- Transition

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Overview & Transition Timelines

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Big Picture: What is IFRS 17?

- **First "Insurance Accounting Standard":**
  - Accounting standard that took around 20 years in the making
  - IFRS17 supersedes existing IFRS-4 interim Standards for Insurance Contracts which was issued in 2004
  - Effective for financial periods beginning on or after January 1, 2021 (early adoption is however permitted).

- **Principles based:** Consistent, transparent and uniform reporting across countries

- **Touches all areas:** measurement, recognition, presentation and disclosure

- **Impact:** Significant impact on long-term contracts (life insurers) vs limited impact on short-term contracts (general insurers)

- New accounting Standards for insurance contracts – with significant actuarial involvement

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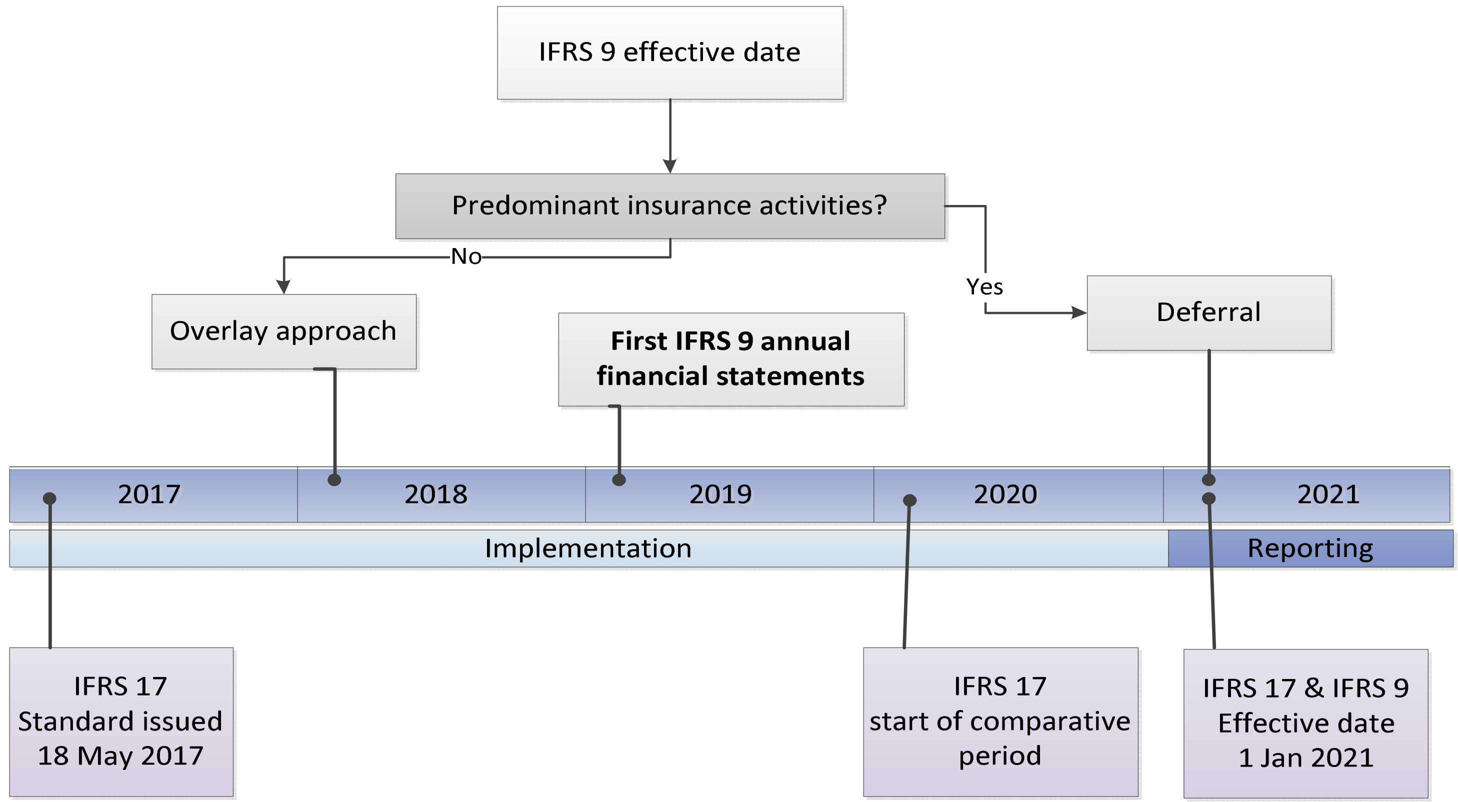
IFRS 17 Timelines



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IFRS 4 vs IFRS 17

Current Regime (IFRS 4)	IFRS 17
Mix of local statutory accountings across geographies	Consistent across geographies
Limited comparability between insurers and inconsistency with other industries	Increases transparency about profitability and will add comparability across the industries
Limited use for steering the business and understanding sources of profit	Greater insight into sources of profit within the business (e.g. underwriting, investment return)
Some key metrics based on IFRS (e.g., RoE and pay-out ratios) but significant use of secondary metrics	Introduction of New KPIs for IFRS 17
Locked-in assumptions (unless required)	Updated assumptions at each reporting period
Revenue includes Premiums	Deposit component is not included in revenue
Day 1 profit can be recognized	Exposure approach to recognition of profit and revenue – as insurance or investment services are provided. No "Day 1" profit

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How is a life insurance premium determined?

A life insurance premium typically consists of four key elements		Application when applying IFRS 17
1. Mortality and morbidity charge	Charges for the benefits	✓ Included
2. Expenses recovery	Cost incurred to issue and administer	✓ Included
3. Deposit	Repays to the policyholder regardless of insured event occurs	x Excluded
4. Profit for service and bearing risk	Amount expects to earn from providing services including a risk premium	✓ Included
✓ Included in insurance revenue when applying IFRS 17		
x Excluded in insurance revenue when applying IFRS 17		

Source: IASB – IFRS 17 Effect Analysis

Key Definitions

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Key Definitions

Non-financial risk

- Also referred as **insurance risk** such as death, injury, illness, disability, loss of property due to damage or theft, failure of a debtor to make a payment when it is due, etc.

Risk Adjustment for non-financial risk

- The compensation an entity requires for bearing the uncertainty about the amount and timing of the cash flows arising from non-financial risk (i.e. insurance risk).
- Part of total unearned profit
- Recognised in P&L as the Company is released from risk.

Portfolio of insurance contracts

- Insurance contracts subject to similar risks and managed together.

Contractual service margin

- Representing the unearned profit the entity will recognize as it provides services under the insurance contracts

Fulfilment cash flows

- An explicit, unbiased and probability-weighted estimate
- Expected value of the present value of the future cash outflows less the present value of the future cash inflows
- including a Risk Adjustment for non-financial risk

Measurement Models

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Measurement Models

General Model (GM) - Default

- Certain annuities
- Protection
- Long-duration non-life business
- Reinsurance written
- Whole life insurance

Variable Fee Approach (VFA)

- With-profit business
- Unit-Linked business

Premium Allocation Approach (PAA)

- Short-duration contract (mostly non-life insurance)
- Certain group contracts

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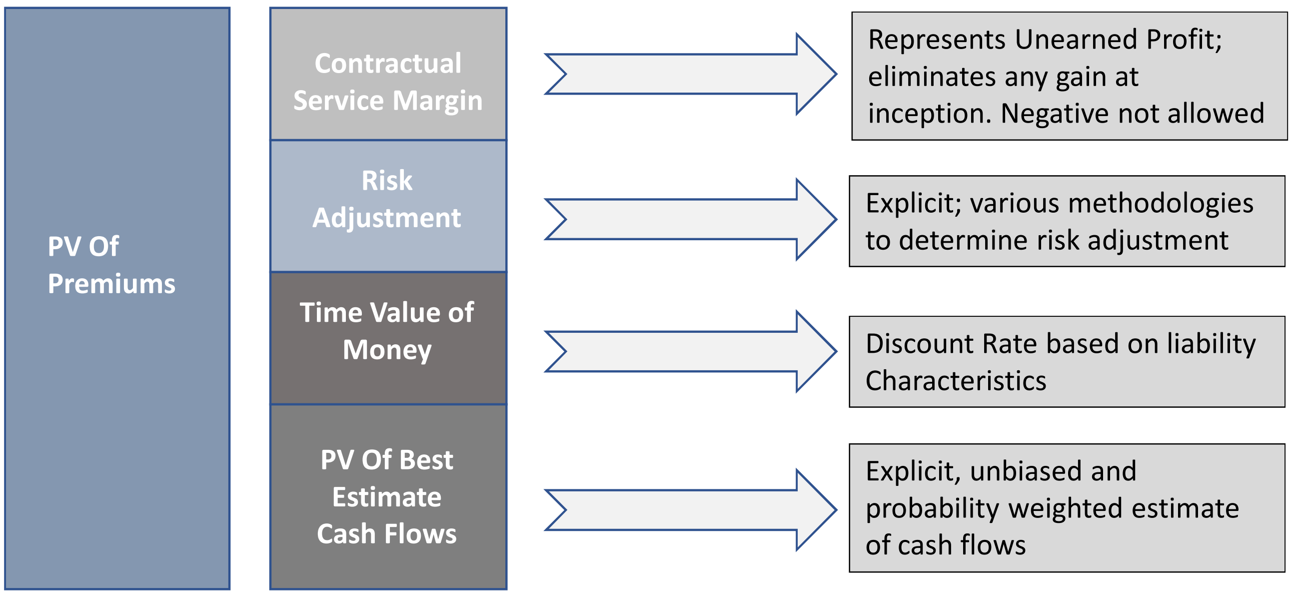
General Model (GM)



An entity expects significant variances in the FCF during the period before a claim is incurred, such contracts are not eligible to apply PAA and follow GM

Core requirements (Default)

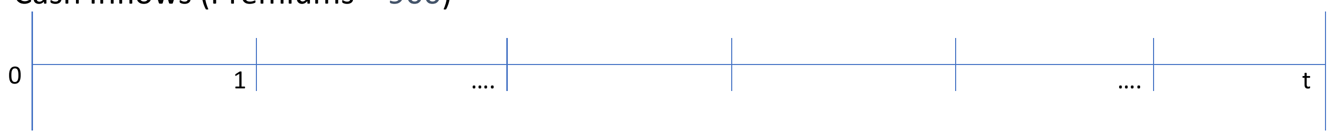
IFRS 17 asset or liability =

$$\underbrace{\text{PV of Future Cash Flows + Risk Adjustment}}_{\text{Fulfilment Cash Flows}} \text{ + Unearned Profit (CSM)}$$

CSM & IFRS Liability: at initial Recognition

Profitable Contract:

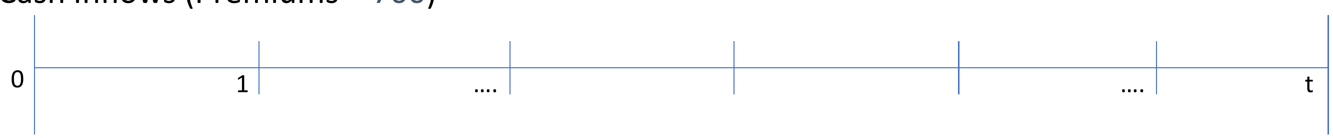
Cash Inflows (Premiums = 900)



Cash outflows (Benefits and Expenses = 635) + Risk Adjust. (120)	= 755
Contractual Service Margin OR Unearned Profit	= 145 (900 – 755)
IFRS Liability (at initial recognition)	= 0
IFRS Profit (at initial recognition)	= 0

Onerous (loss making) Contract:

Cash Inflows (Premiums = 700)



Cash outflows (Benefits and Expenses = 635) + Risk Adjust. (120)	= 755
Contractual Service Margin OR Unearned Profit	= 0 (negative not allowed 700-755)
IFRS Liability (at initial recognition)	= 55
IFRS Loss (at initial recognition)	= 55

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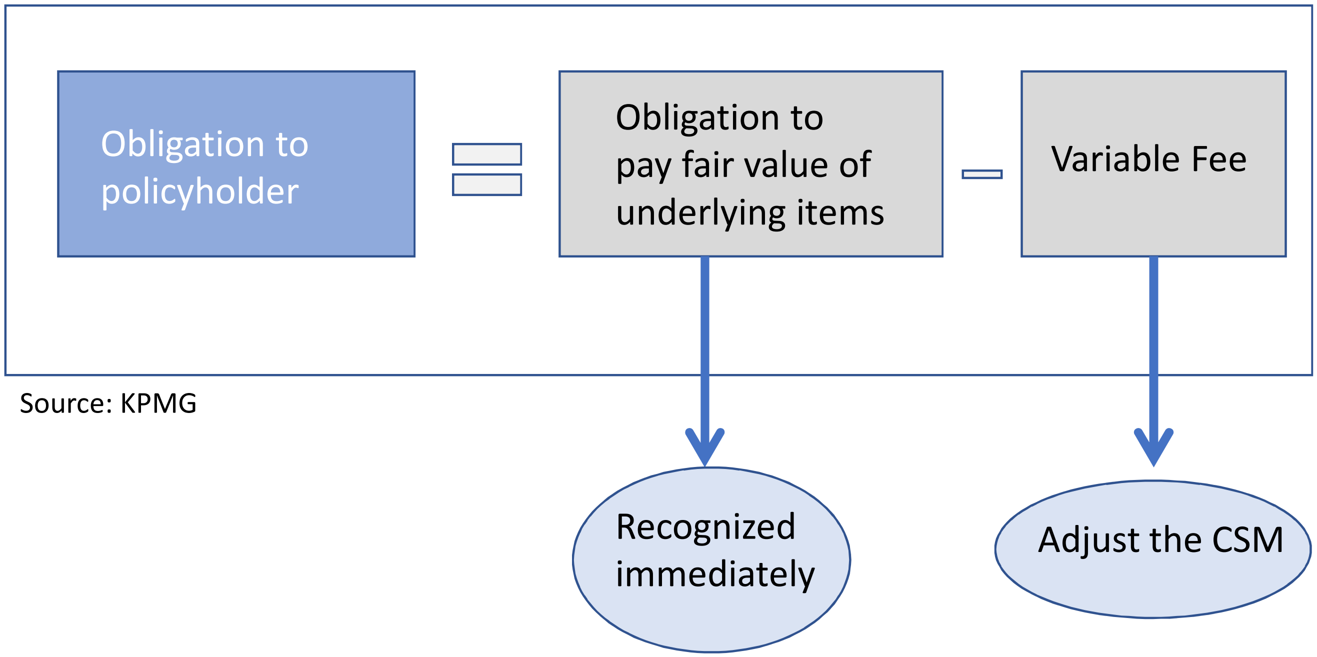
Variable Fee Approach

It follows the General Model with few modifications and it also reduces the volatility of net results. The approach considers the variable fee associated with direct participating contracts (such as Unit Linked or With Profits contracts)



Source: KPMG

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Variable Fee Approach vs General Model

	PV of Future Cash Flows	Risk Adjustment	Unearned Profit (CSM)
Initial Recognition	✓ No Difference	✓ No Difference	✓ No Difference
Subsequently	✓ No Difference	✓ No Difference	x Difference in how CSM is adjusted for changes in financial variables

Source: IASB

Premium Allocation Approach – Optional Simplified Approach

Liability for remaining coverage
(pre-claims coverage)

PV of Future Cash Flows	Risk Adjustment	Contractual Service Margin

Split in three blocks not required for:

- Contracts issued for a period of one year or less; OR
- Reasonable approximation of the General Model

Treatment of short term policies issued for more than 1 year is a concern and depends on variability of cash flows

+

Liability for incurred claims

PV of Future Cash Flows	Risk Adjustment	~~Contractual Service Margin~~

- As an example, Group Life continuation benefits may require to follow this approach
- Measurement under the general model but discounting of claims to be settled within 1 year not required

=

IFRS 17 Liability

Source: adopted from IASB

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Reinsurance Outwards (RI Contracts held)

- Para 82 of IFRS 17: an entity shall present income or expenses from reinsurance contracts held separately from the expenses or income from insurance contracts issued
- Therefore a same but independent exercise relating to reinsurance contracts needs to be conducted including determination of the margin resulting from effecting these contracts
- This means calculating the following for outward reinsurance :
    - best-estimate cashflows (discounted, if applicable)
    - Plus allowance for credit risk
    - Plus risk adjustment (reflecting the risk ceded)

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Level of Aggregation

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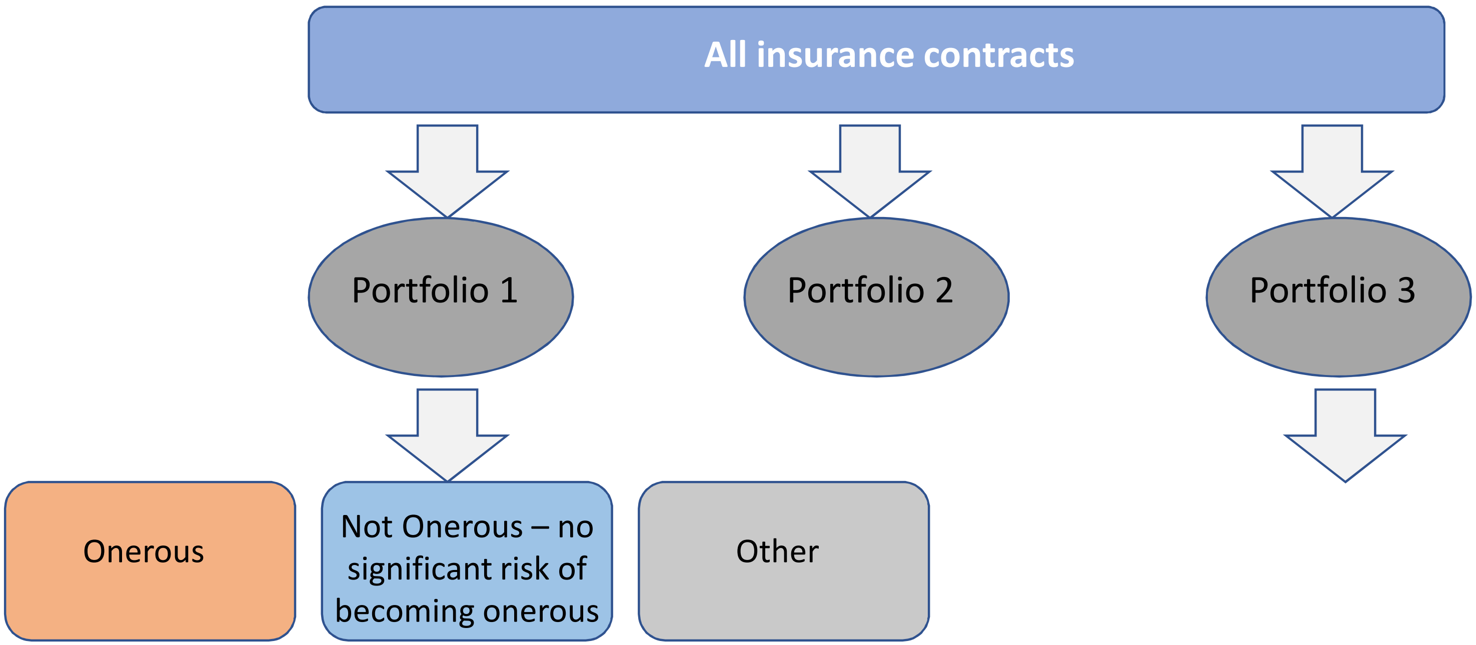
Level of Aggregation – IFRS 17 Requirements



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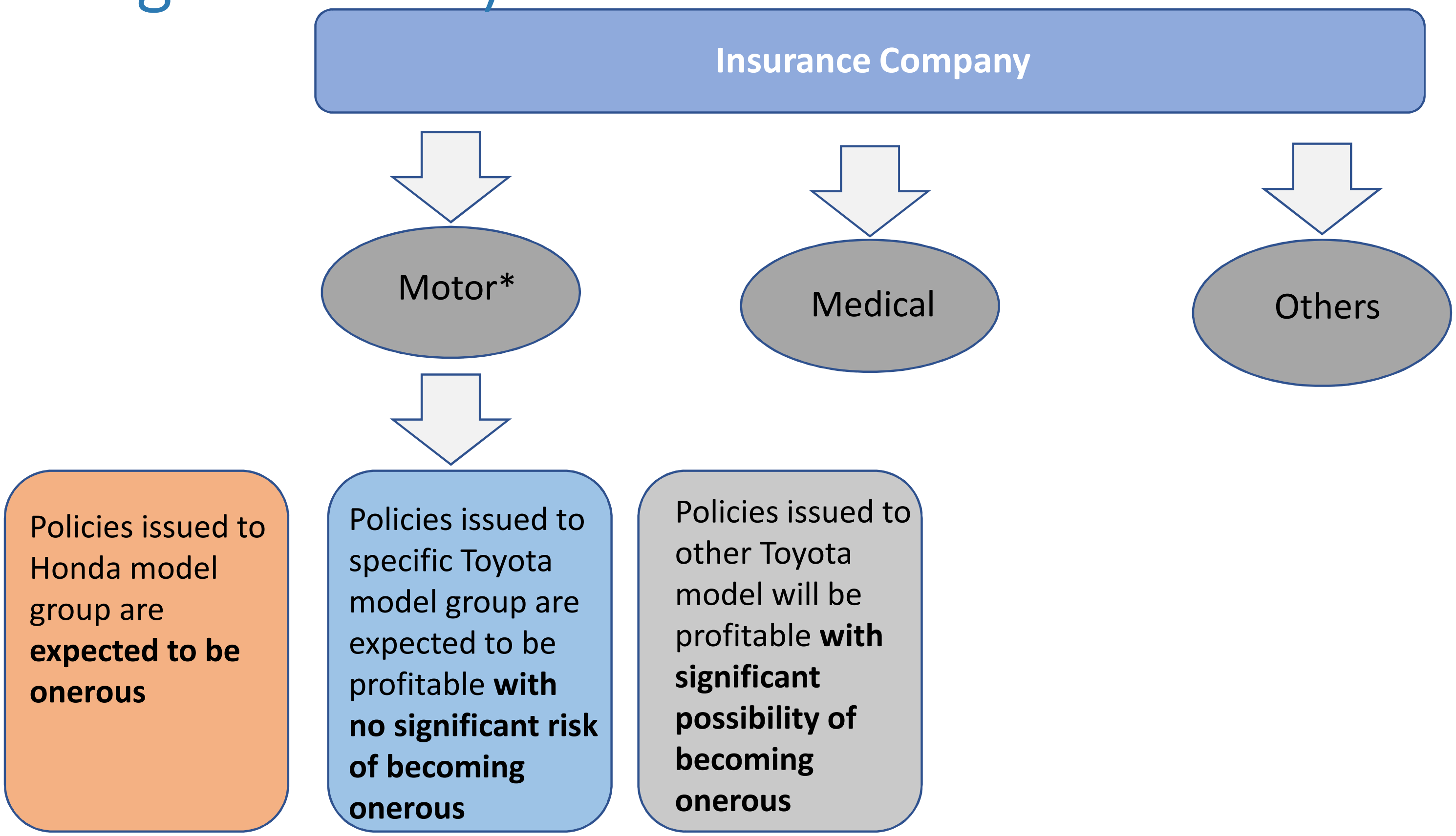
Level of aggregation (Motor Example at inception on a prob. weighted basis)



* Grouping of portfolio is also subject to local regulatory requirements

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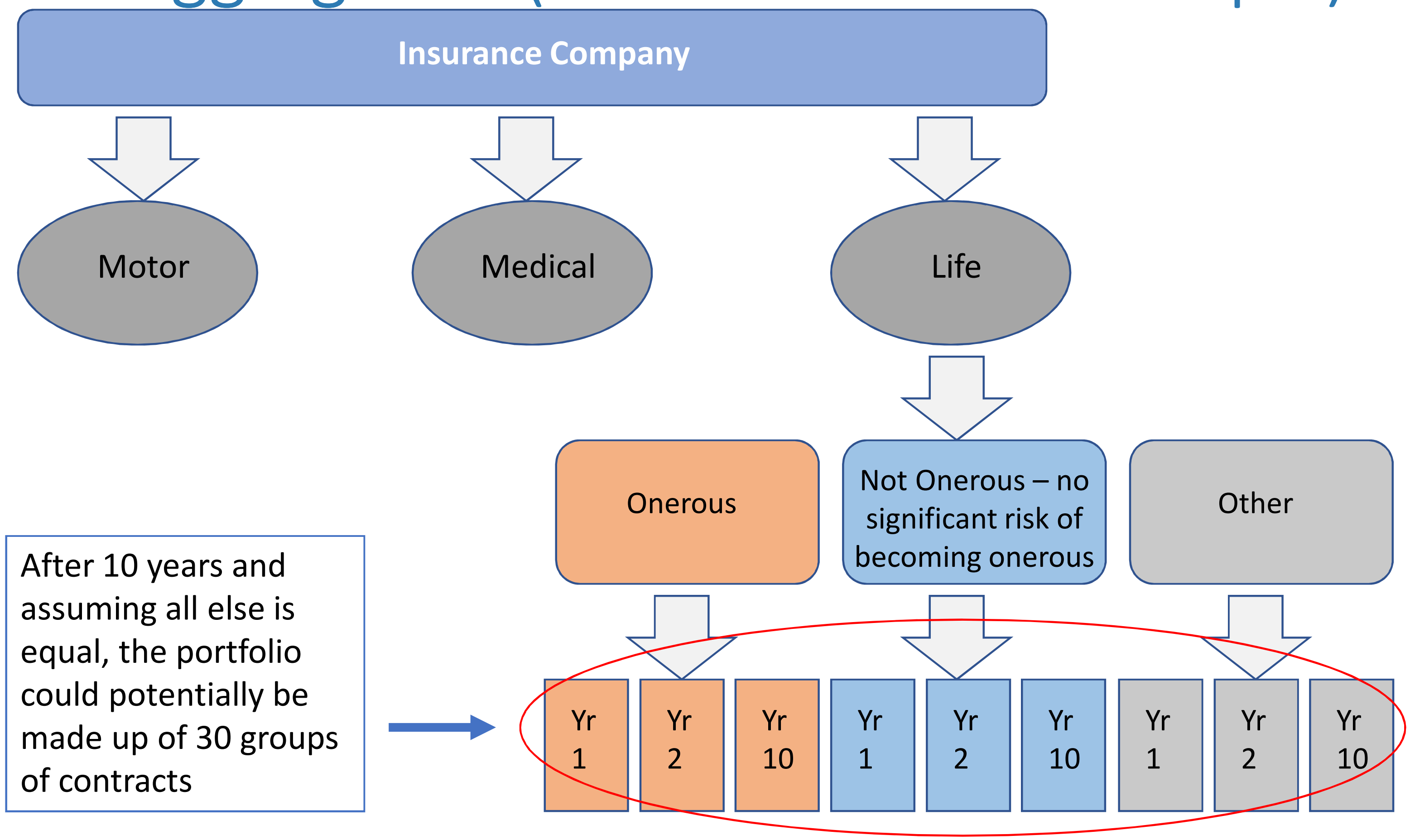
Level of aggregation (Term Assurance Example)



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Presentation of P&L and B&S

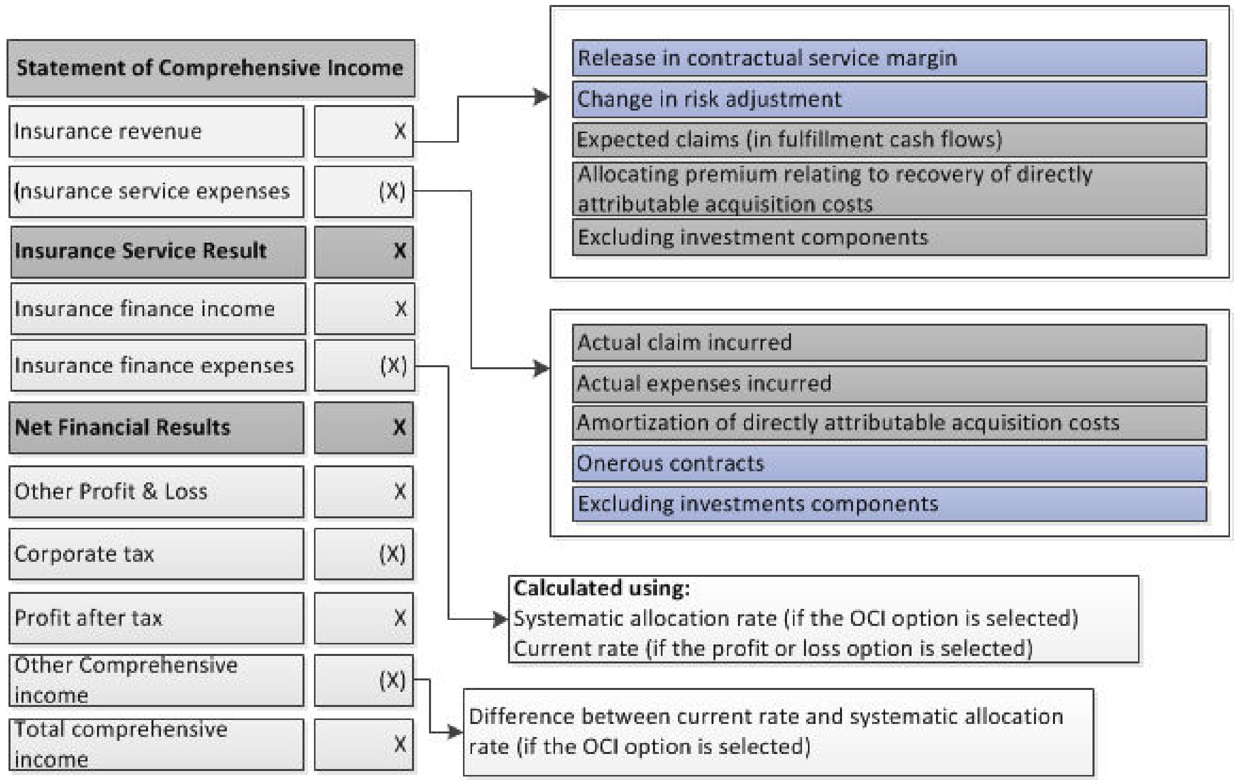
Changes to Profit & Loss Presentation

IFRS 4*	IFRS 17
Premiums	Insurance Revenue
Investment Income	Incurred claims and expenses
Incurred claims and expenses	Insurance service result
Change in Insurance contract liabilities	Investment Income – Return on financial assets (IFRS 9)
Profit or Loss	Insurance Finance Expense (effect of time value of money and financial risk e.g. discount rate – optional)
(*) Common presentation in the statement of comprehensive income in applying IFRS 4.	Net Financial Result
	Profit or Loss
	Discount rate changes on insurance liability (optional)
	Total comprehensive income

Source: IFOA

Statement of Comprehensive Income	
Insurance revenue	X
Insurance service expenses	(X)
Insurance Service Result	**X**
Insurance finance income	X
Insurance finance expenses	(X)
Net Financial Results	**X**
Other Profit & Loss	X
Corporate tax	(X)
Profit after tax	X
Other Comprehensive income	(X)
Total comprehensive income	X

Presentation



- Investment Components are excluded from insurance revenue and service expenses
- Entities can choose to present the effect of changes in discount rates and other financial risks in P&L and OCI to reduce volatility

Source: EY

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Changes to Balance Sheet Presentation

IFRS 4	IFRS 17	Key Change
Assets		• Contracts that are assets are separately presented from those that are liabilities • Simplified presentation consistent with the economics
Reinsurer Share of OS Claims	Reinsurance Contract Assets	
Reinsurer Share of UPR (i.e. prepayments)	Insurance contract assets	
Deferred Acquisition Costs		
Premiums Receivable		
Liabilities		
Outstanding claims incl. IBNR	Insurance contract liabilities	
Unearned Premiums	Reinsurance contract liabilities	
Claims payable		

Source: IASB

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Examples

Example 1: Term Life

Particulars	Value
Sum Assured	1,000,000
Single Premium	8,000
Benefit Term	3 years
Discount Rate	10%

- For simplicity:
  - Risk adjustment and expenses have not been assumed

Term Life – Contractual Service Margin

IFRS 17				
Year	0	1	2	3
PV Expected Future Cash Inflows	(8,000)	-	-	-
PV Expected Future Cash Outflows	6,138	4,752	2,727	-
PV Expected Future Net Cash Flows	**(1,862)**	**4,752**	**2,727**	**-**
Risk Adjustment	-	-	-	-
Fulfillment Cash Flows	**(1,862)**	**4,752**	**2,727**	**-**
Contractual Service Margin:				
Opening Balance	-	1,862	1,365	751
New Contracts	1,862	-	-	-
Interest Accretion	-	186	137	75
Recognized in P&L	-	(683)	(751)	(826)
Closing Balance	**1,862**	**1,365**	**751**	**-**

CSM times discount rate

It is the time value of money on CSM

Expected profits at initial recognition

Unearned profits recognized in P&L as revenue

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Term Life – Profit & Loss

IFRS 4				
Year	1	2	3	Total
Premium Income	8,000	-	-	**8,000**
Investment Income	850	650	400	**1,900**
Total Income	**8,850**	**650**	**400**	**9,900**
Claims Incurred	(1,500)	(2,000)	(2,500)	**(6,000)**
Change in Future Year Liabilities	(4,752)	2,025	2,727	**-**
Profit / (Loss)	**2,598**	**675**	**627**	**3,900**

IFRS 17				
Year	1	2	3	Total
Release in CSM	683	751	826	**2,260**
Expected Claims	2,000	2,500	3,000	**7,500**
Insurance Service Revenue	**2,683**	**3,251**	**3,826**	**9,760**
Insurance Service Expense	**(1,500)**	**(2,000)**	**(2,500)**	**(6,000)**
Insurance Service Result	**1,183**	**1,251**	**1,326**	**3,760**
Insurance Finance Income	850	650	400	**1,900**
Insurance Finance Expenses	(800)	(612)	(348)	**(1,760)**
Net Financial Result	**50**	**38**	**52**	**140**
Profit / (Loss)	**1,233**	**1,289**	**1,378**	**3,900**

Claims expected based on the assumptions as at beginning of the period

Time value of money

Analogous to expected investment income

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Term Life – Insurance Contract Liability

IFRS 4				
Year	0 (BOY)	1 (EOY)	2 (EOY)	3 (EOY)
PV Future Cash Flows	-	4,752	2,727	-
Liability for Future Years	**-**	**4,752**	**2,727**	**-**
Claim Reserves	-	-	500	500
Insurance Contract Liability	**-**	**4,752**	**3,227**	**500**

IFRS 17				
Year	0 (BOY)	1 (EOY)	2 (EOY)	3 (EOY)
PV Expected Future Cash Flows	(1,862)	4,752	2,727	-
Risk Adjustment	-	-	-	-
Fulfillment Cash Flows	**(1,862)**	**4,752**	**2,727**	**-**
Contractual Service Margin	1,862	1,365	751	-
Liability for Future Years	**-**	**6,117**	**3,478**	**-**
Claim Reserves	-	-	500	500
Insurance Contract Liability	**-**	**6,117**	**3,978**	**500**

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Example 2 – General Insurance product

Particulars	Value
Coverage Period	2 Year
Total Premium	Rs. 500 Paid at start of coverage
Total Claims	Rs. 500 Paid at end of Year 3 Incurred Uniformly over the first two years (i.e. a claim is expected at the end of each year)
Discount Rate	3.00% p.a. (assumed not to be changed)
Investment Return	5.00% p.a. of Invested Premiums
Accounting Model	Premium Allocation Approach (PAA)

- For Simplicity Risk Adjustment and Expenses have been ignored
- This example does not assume any changes in the discount rate. If there were changes in the discount rate, the insurer could choose to present the changes in the investment activity that are related to the effect of changes in the discount rate in Other Comprehensive Income (OCI).
- This entire example has been adopted from IFOA

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Example 2 – Profit and Loss

IFRS 4				
Year	1	2	3	Total
Earned Premiums	250	250	-	500
Investment Income	25	26	28	79
Total Income	**275**	**276**	**28**	**579**
Claims Paid	-	-	(500)	(500)
Change in Claims Reserves	(250)	(250)	500	-
Incurred Claims	**(250)**	**(250)**	**-**	**(500)**
Profit / (Loss)	**25**	**26**	**28**	**79**

IFRS 17				
Year	1	2	3	Total
Insurance Service Revenue	258	265	-	523
Insurance Service Expense	(236)	(243)	-	(478)
Insurance Service Result	**22**	**23**	**-**	**44**
Insurance Finance Income	25	26	28	79
Insurance Finance Expense	(15)	(15)	(15)	(44)
Net Financial Result	**10**	**11**	**13**	**34**
Profit / (Loss)	**32**	**34**	**13**	**79**

IFRS 17 – Assets under PAA			
Year	1	2	3
Opening Balance	500	525	551
Interest Accretion (5%)	25	26	28
Closing Balance	**525**	**551**	**579**

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Example 2 – Liability for Remaining Coverage & Incurred Claims

IFRS 17 – Liability for Remaining Coverage			
Year	**1**	**2**	**3**
Opening Balance	500	258	-
Interest Accretion	15	8	-
Amount Recognized in P&L	(258)	(265)	-
Closing Balance	**258**	**-**	**-**

IFRS 17 – Liability for Incurred Claims			
Year	**1**	**2**	**3**
Opening Balance	-	236	485
Interest Accretion	-	7	15
Claims Incurred	236	243	-
Closing Balance	**236**	**485**	**500**

Insurance Service Revenue

Insurance Finance Expense

Insurance Service Expense

Transition

Transition – Approaches

Full Retrospective Approach

Identify, recognize and measure each group of insurance as if IFRS 17 had always applied

If it is **impractical** to apply Full Retrospective Approach, the following two can be adopted:

Modified Retrospective Approach

Achieve the closest outcome to retrospective application possible using reasonable and supportable information available without undue cost or effort

Fair Value Approach

Determine the CSM or loss component for remaining coverage as the difference between fair value of a group of insurance contacts and the fulfillment cash flows

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Applying IFRS 17 – effects on reported equity

Factors that are expected to impact on the reported equity	Impact on Equity
Acquisition costs are currently expensed as incurred	⇧
Insurance Contracts are currently measured using historical interest rates that are lower than market rates	⇧
Risk margins currently used are higher than the risk adjustment used to apply IFRS 17	⇧
Profits are currently recognized at contract inception (not apply to general insurers)	⇩
Aggregation of onerous contracts and profitable contracts is currently permitted	⇩
Discount rates are currently based on assets backing insurance contract liabilities	⇩
Insurance Contracts are currently measured using historical interest rates that are higher than market rates	⇩
Risk margins currently used are lower than the risk adjustment used to apply IFRS 17	⇩

Source: IASB – IFRS 17 Effect Analysis

⇧ = Increase ⇩ = decrease

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Recap: IFRS 17

It will change your financial statements as follows	Impact on Life insurers	Impact on General insurers
Value of insurance liabilities: new calculations	High	Moderate to High
No "Day 1" profit: released to P&L over the life of the contract	High	Moderate
Revenue recognized reduces liability for remaining coverage attributable for services provided in the period	Moderate	Low
Presentation of P&L and balance sheet: look very different	High	Moderate
Payments to policyholders unrelated to insured event (return of 'deposits') are not revenue	Moderate	N/A
Grouping of results (aggregation): big impact on systems and processes	High	High
New disclosures: lots of additional information	High	Moderate
Lots of judgments to be made	High	Moderate

IFRS 17 – A Game Changer for Life Insurers?

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IFRS 17 Globally

Country	IFRS-17 Planning
Canada	Full Convergence with IFRS
United States	Will not adopt IFRS 17
UK	UK listed companies are required to use EU-adopted IFRSs in their consolidated accounts. Choice between UK GAAP or EU-adopted IFRS for individual companies
EU	Full convergence with IFRS Endorsement of IFRS 17 started
Vietnam	Vietnam plans to adopt IFRS from 2020 for listed companies. The remaining entities will adopt IFRS by 2025. Possible alignment of local GAAP to IFRS in 2018.
Malaysia	Full adoption to MFRS 17 Carrying out QIS
Singapore	Move to full IFRS in 2018
South Africa	Full convergence with IFRS
Thailand	IFRS 17 will be endorsed in Thai FRS but with a 12 month delay on the effective date
Philippines	Philippine FRS are aligned with IFRS text and PFRS 17 is expected soon

Source: Actuarial Society of Hong Kong

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IFRS 17 Globally

Country	IFRS-17 Planning
Peoples Republic of China	Chinese Accounting Standards for Business Enterprises (CAS) are substantially converged with IFRS, except for certain modifications which reflect China's unique circumstances and environment
South Korea	Formed special task force, requested high level impact assessment to be submitted to regulator
Japan	Eligible companies are permitted to voluntarily apply IFRS. A Technical Committee has been set up to deliberate the ASBJ's views on IFRS 17
Taiwan	Delayed adoption
Hong Kong	Full convergence with IFRS
Pakistan	Working Group has been set-up to evaluate the IFRS 17 adoption feasibility and approaches
Australia	To decide later next month if Australia will adopt IFRS 17

Source: Actuarial Society of Hong Kong

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Possible Impact on IA Regulations?

- IA's Financial and Technical Regulations for Insurance and Takaful Companies have just been fully implemented, however, changes may be required after adopting IFRS 17

Technical Provisions	Solvency Margin	Data & Records Maintained by Companies	Accounting Policies and Reporting Forms
• Current assumptions • Fulfilment cashflows • Explicit risk adjustment	• Solvency regime might have to be reviewed • Underwriting risk is determined using technical provisions • Might need to be revisit the basis for underwriting risk	• Requirement regarding aggregation • Recording and tracking CSM and risk adjustment	• Need to be aligned with IFRS 17 • Reporting forms may also need to be changed

Any Questions

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Disclaimer

- *The information contained in this presentation has been extracted from IFRS 17 Insurance Contracts Standards, issued in May 2017*
- *In this presentation, presenter has expressed his views, opinions and conclusions on the impact of IFRS-17 for insurers, unless stated otherwise*
- *Examples have also been provided based on the presenter's view*
- *The purpose of this presentation is solely to give an overview, idea and brief the requirements of IFRS-17 Insurance Standards for Insurers only however implementation requires significant judgement which may have different views*

Claims Fraud Assessment

Gulf Actuarial Society

Sam Khunaizi, Actuarial Analyst

28 June 2018

Agenda

1. Insurance Fraud Definition
2. Interesting Statistics
3. Fraud Detection Implementation
4. Auto Fraud Internal Investigation
5. Med. Fraud Internal Investigation
6. A Model for Fraud Detection
7. Questions

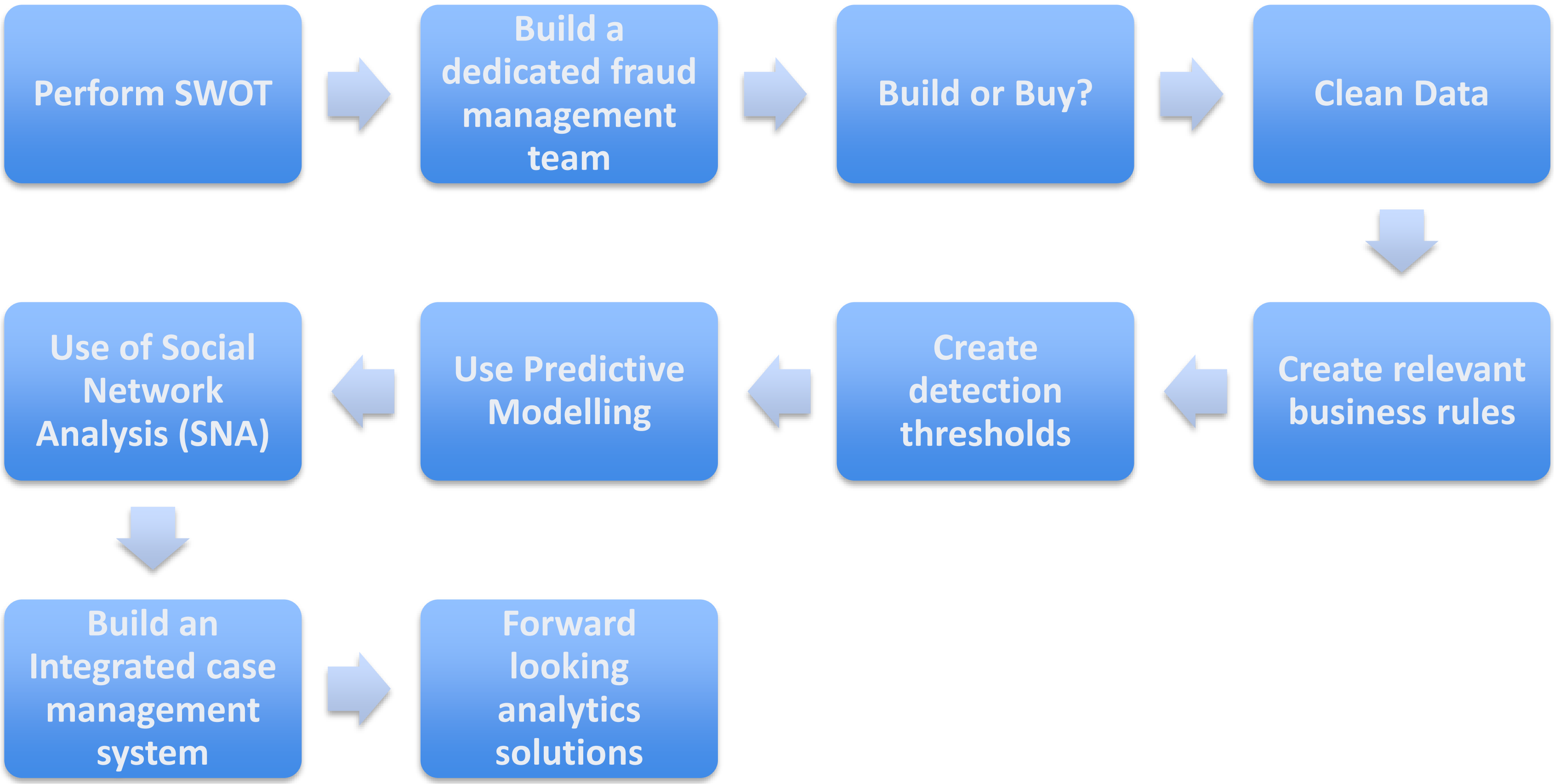
Insurance (Claims) Fraud Definition

- When someone provides false information to an insurance company in order to gain something of value that he or she would not have received if the truth had been told, they've committed insurance fraud.[1]
- A deliberate act committed against an insurer or an insurance broker with the view to obtaining a financial benefit.
- Claims Fraud can be also less deliberate (waste/abuse).[1]

Interesting Statistics

- It is estimated that around 10% of insurance claims in the Middle East are fraudulent and only 20% of those claims are detected.[2]
- Around 54% of insurers believe that fraud stands as the number one threat. [3]

A 10-Step Approach to Implement Analytics for Fraud Detection



[4]

Internal Investigation of Auto Fraud - 1

General Indicators

- **A Claim History with previous thefts**
- **Gap in Cover**
- **Vehicle is stolen from a mall or a large parking lot**
- **Insured delays filing police report**
- **Insured's age**
- **Urban vs. non-urban location**
- **Same family name for insured and other party**
- **The Area and Time the accident has occurred**
- **The Accident happens within 3 months of policy inception**

[5]

Internal Investigation of Auto Fraud - 2

Vehicle Indicators

- **Vehicle Value is inflated**
- **Vehicle Specification is not GCC**
- **Recovered with total loss damage only**
- **Recovered condition does not match condition on report of loss**

[5]

Title/Ownership

- **Title holder and insured not the same**
- **Signs of Vehicle Registration sticker tampering**
- **Insured wishes to retain salvage on an obvious total**

[5]

Internal Investigation of Medical Fraud

GP Indicators

- Recommend unnecessary procedures and follow ups
- Altering Diagnosis to get the claim settled
- Submitting Partial Case details to get coverage and get claims settled
- Ordering unnecessary services and laboratory tests

Pharmacy

- False Invoicing (Copy Card and making false claims in regular basis)

Patient

- Patient accepts cash from Pharmacies

Insurance

- Underwriting Insurance Policies which cover less Medical services than necessary

[6]

A Model for Fraud Detection –Logistic Regression

- Logistic Regression:
  - Statistical method for analysing a dataset in which there are one or more independent variables that determine an outcome.[7]
  - The outcome is measured with a dichotomous variable.[7]

Logistic Regression

- Dependent Variables:
  - The Claim is Fraudulent – (1)
  - The Claim is not Fraudulent – (0)
- Independent Variable:
  - The number of years the an insured has been with the Company
  - Claims History of the Insured
  - Claims History of the Insured per year
  - New Business
  - The time between when the claim is filed and reported
  - Others listed above

[5]

Logistic Regression Formula

- General Form of the Model:
  - The Odds:

$$odds = \frac{P}{1-P}$$

  - The Derivation of the Logistic Regression Formula:

$$\ln\left(\frac{P}{1-P}\right) = a + bX$$

$$\frac{P}{1-P} = e^{a+bX}$$

$$P = \frac{e^{a+bX}}{1+e^{a+bX}}$$

[8]

Logistic Regression: Motor Example

- Suppose we solve for P and arrive at an equation with this form: [1]
  Logit (P/(1-P)) = -1.135 + 0.671(Claims per Years) + 1.601 (New Business)
- Let us consider that we have a policyholder who claimed that has
  - Average of 1 claim per year
  - A non-new policy (e.g. renewal policy)
- The probability that the claim is fraudulent is as follows:
  - Logit Y = -1.135 + 0.671(1) + 1.601(0) = -0.464
  - Y = exp(-0.464) = 0.63
  - P = 0.63 /1+0.63 = 39%
- Since the probability is less than 50%, this case may not warrant further investigation for fraud.

[5]

Questions

Sources

[1] What is Insurance Fraud: http://www.helpstopfraud.org/what-is-insurance-fraud/definition

[2] 10% of insurance claims in Mideast are fraudulent: https://www.emirates247.com/business/corporate/10-of-insurance-claims-in-mideast-are-fraudulent-2015-07-15-1.596998

[3] Insurance fraud detection and cost to the industry: http://www.atlas-mag.net/en/article/insurance-fraud-detection-and-cost-to-industry

[4] Using Analytics for insurance Fraud Detection: 3 Innovative methods and a 10-step approach to kick start your initiative - https://www.the-digital-insurer.com/wp-content/uploads/2013/12/53-insurance-fraud-detection.pdf

[5] An Analytical Approach to Detecting Insurance Fraud Using Logistics Regression, J. Holton Wilson, Central Michigan University - http://www.aabri.com/manuscripts/08103.pdf

[6] Should more be done to combat medical fraud in the UAE? - http://gulfbusiness.com/done-combat-medical-fraud-uae/

[7] Logistic Regression - https://www.medcalc.org/manual/logistic_regression.php

[8] Logistic Regression - http://faculty.cas.usf.edu/mbrannick/regression/Logistic.html

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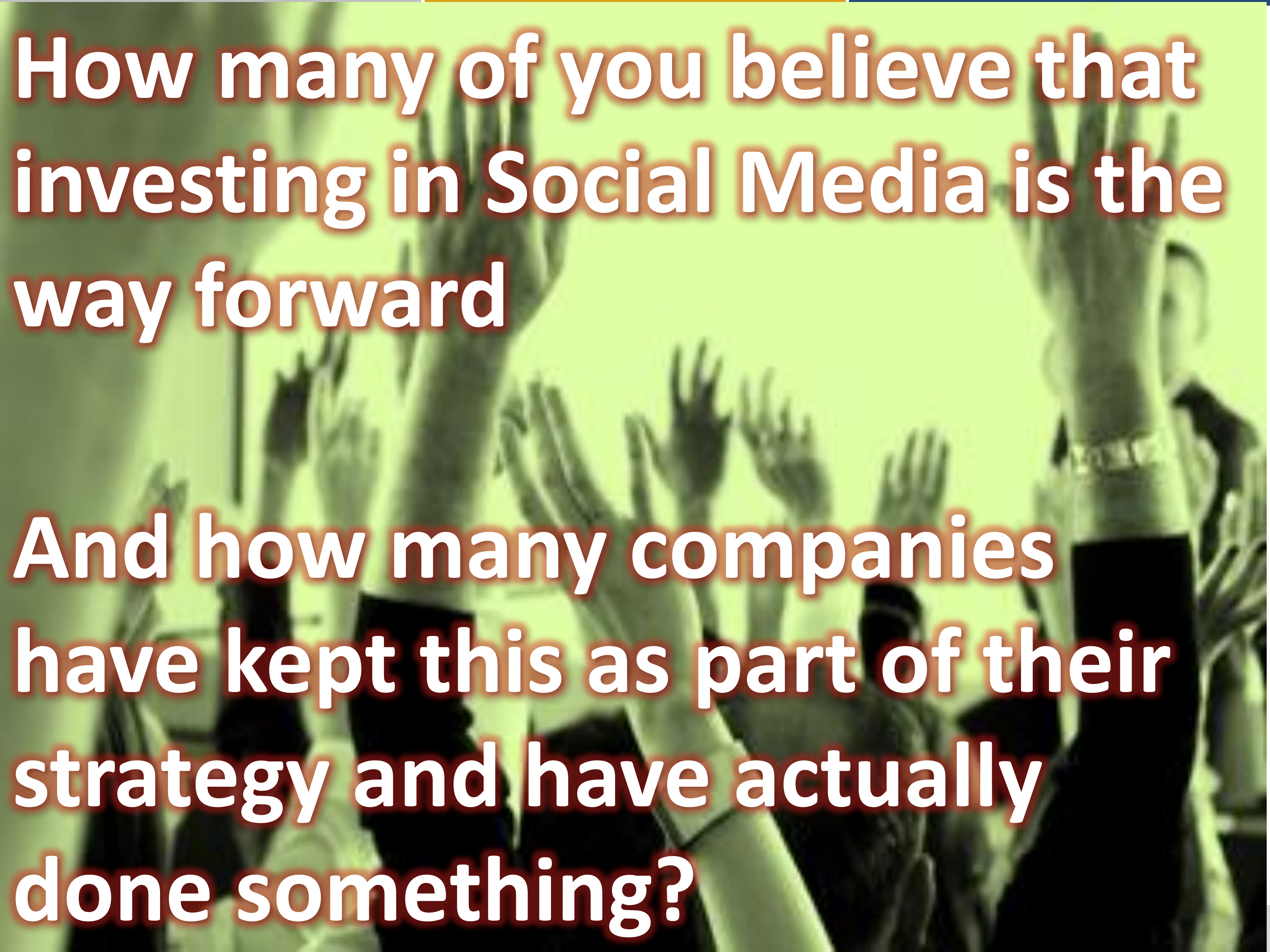
MANAGEMENT CONSULTANCY
ACTUARIES | RISK MANAGERS

Data Driven Decision Making

Hatim Maskawala

June 28, 2018


How many of you believe that investing in Social Media is the way forward

And how many companies have kept this as part of their strategy and have actually done something?

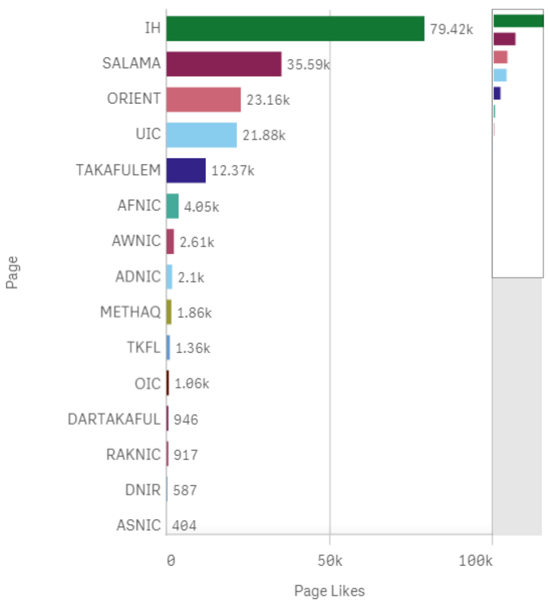
Facebook Analysis - Insurance

BADRI

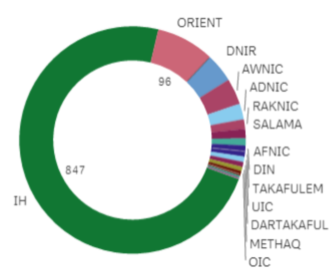
Facebook Fan Page Analysis for Insurance Companies in UAE

Last Post Share Date	Listed Insurance Companies	No. of Posts	Avg. Sentiment	No. of Positive Comments	No. of Neutral Comments	No. of Negative Comments
17-Oct-2017	29	950	0.05	35	588	7

Likes by Company



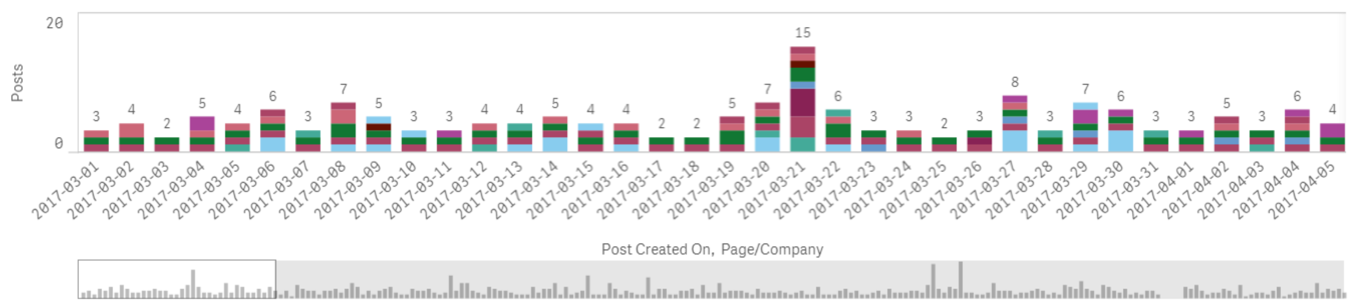
Talking About Counts by Company



Sentiment Analysis by Company

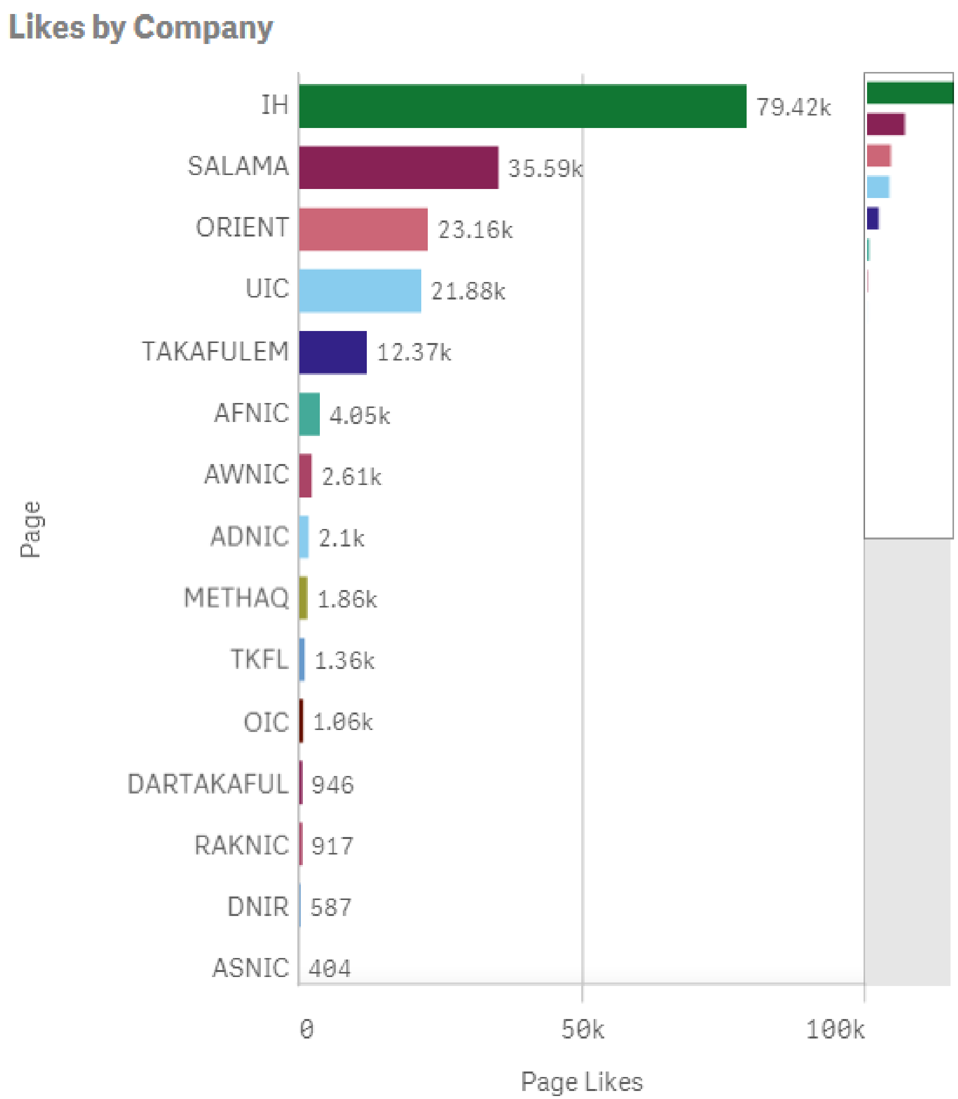
Company/...	Positive Comments	Neutral Comments	Negative Comments
Totals	**35**	**588**	**7**
IH	28	319	2
AWNIC	4	14	1
ADNIC	1	22	0
AFNIC	1	1	0
ASNIC	1	1	0
DARTAKAFUL	0	2	4

Date Wise Posts by Company



Data as of 17th of October 2017

Facebook Analysis - Insurance



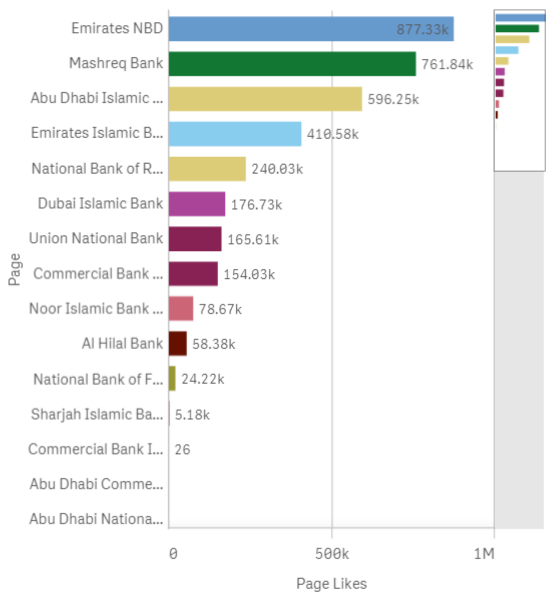
Data as of 17th of October 2017

Facebook Analysis - Banks

Facebook Fan Page Analysis for Banks in UAE

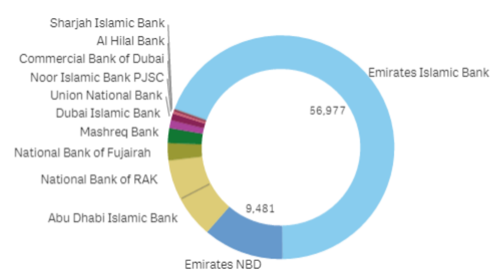
Last Post Share Date	No. of Banks	No. of Posts	Avg. Sentiment	No. of Positive Comments	No. of Neutral Comments	No. of Negative Comments
17-Oct-2017	19	4.05k	0.00	273	38.51k	43

Likes by Banks



Data as of 17th of October 2017

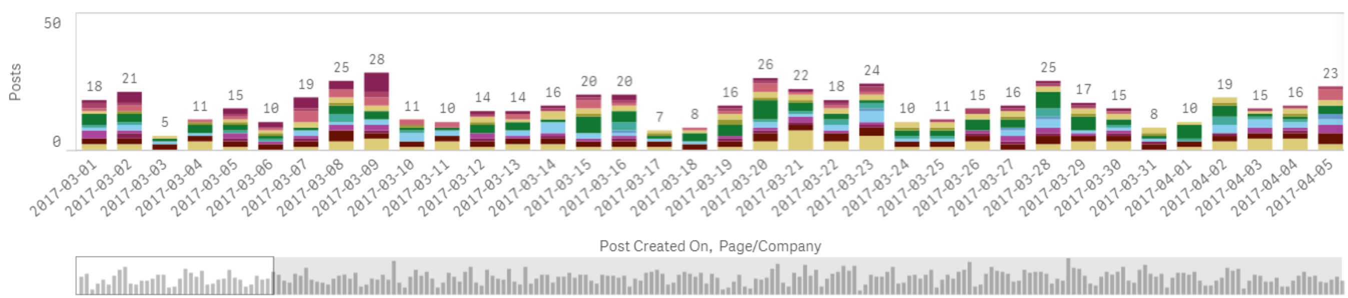
Talking About Counts by Banks



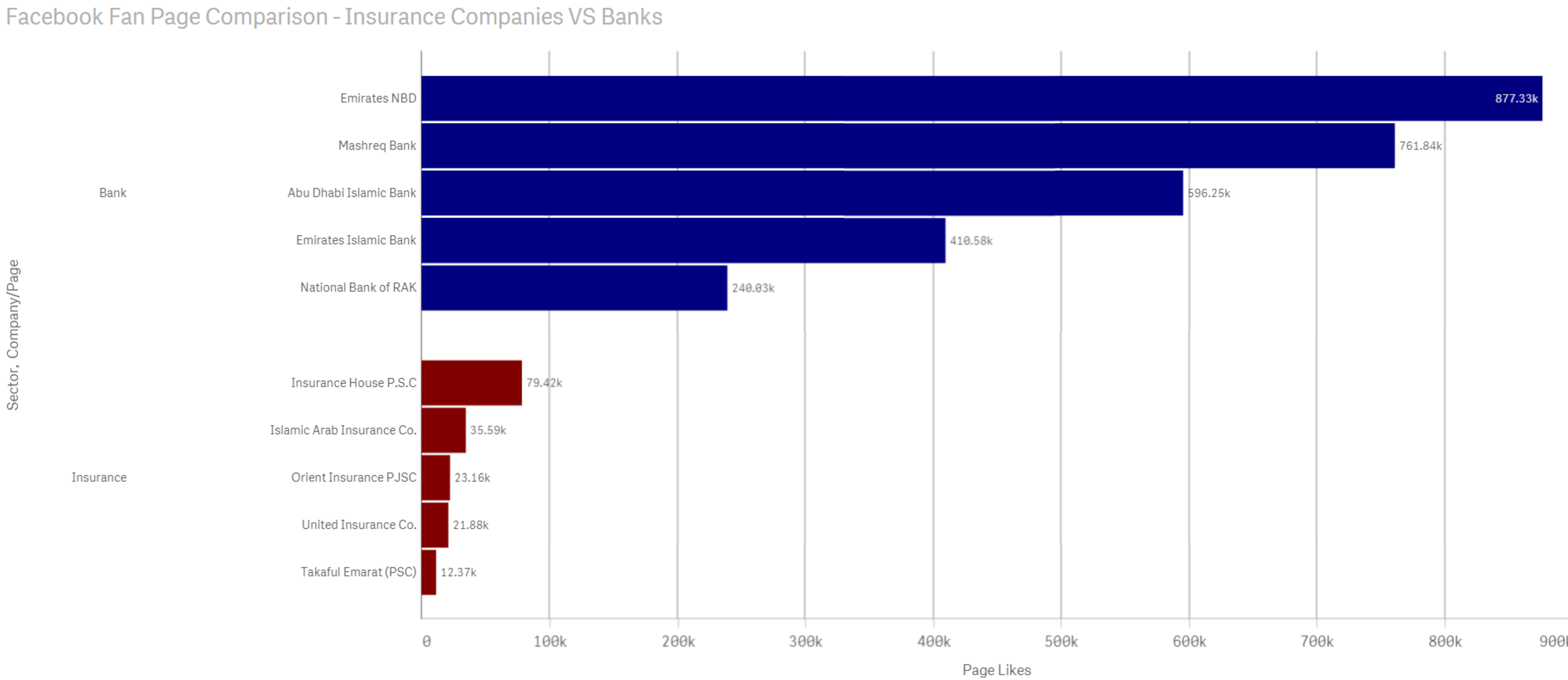
Sentiment Analysis by Banks

Company/Page	Positive Comments	Neutral Comments	Negative Comments
Totals	**273**	**38509**	**43**
Emirates Islamic Bank	273	20398	43
Mashreq Bank	0	4231	0
Union National Bank	0	4218	0
Abu Dhabi Islamic Bank	0	2826	0
National Bank of RAK	0	2480	0
Emirates NBD	0	2056	0

Date Wise Posts by Banks



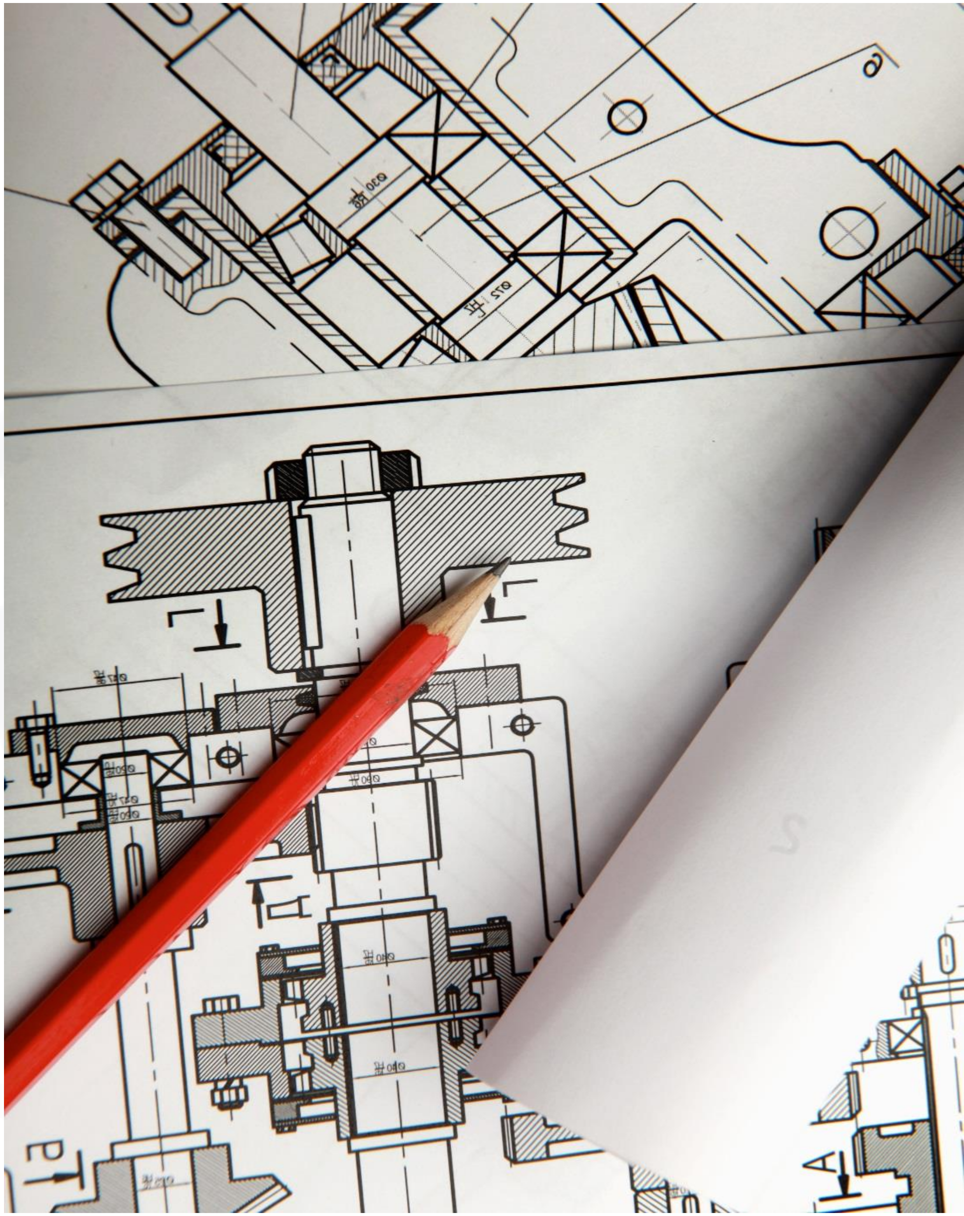
Insurance vs Banks



Data as of 17th of October 2017

Underlying Forces

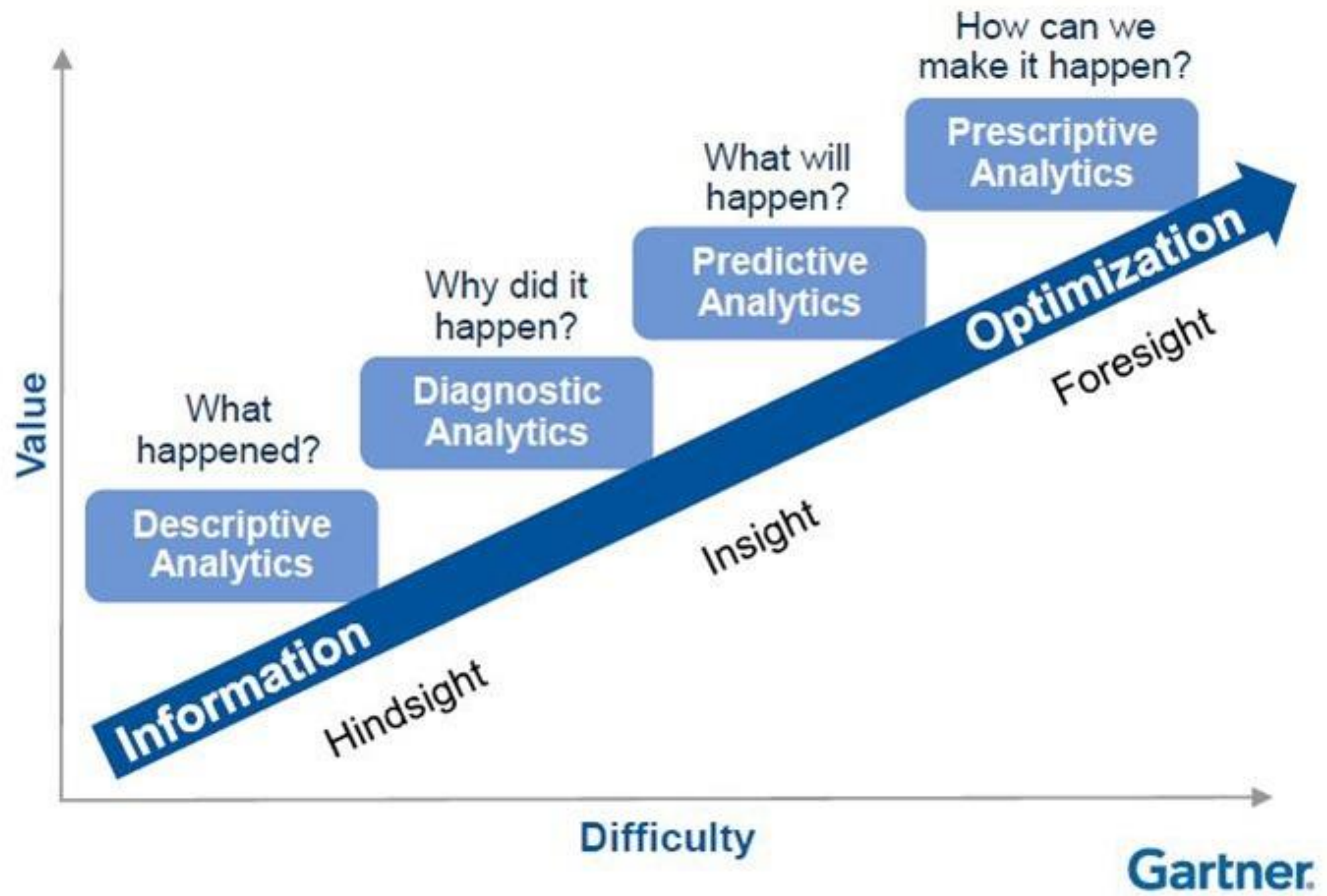
- An explosion of data and contents
- Reliance on external data
- An explosion in computing power
- The rise of information activism
- Self service BI



Challenges

- No single view of customer
- Ineffective customer segmentation
- Multiple distribution channels
- High volumes of fraud, wastage and abuse
- Most insurers in MENA rely on policy admin systems for analytics
- Underwriting vs Financial/Accident years
- Data is segregated across systems
- Manual data / excel files
- Many calculations are in excel
- Need for Customization Requests

Analytics Maturity

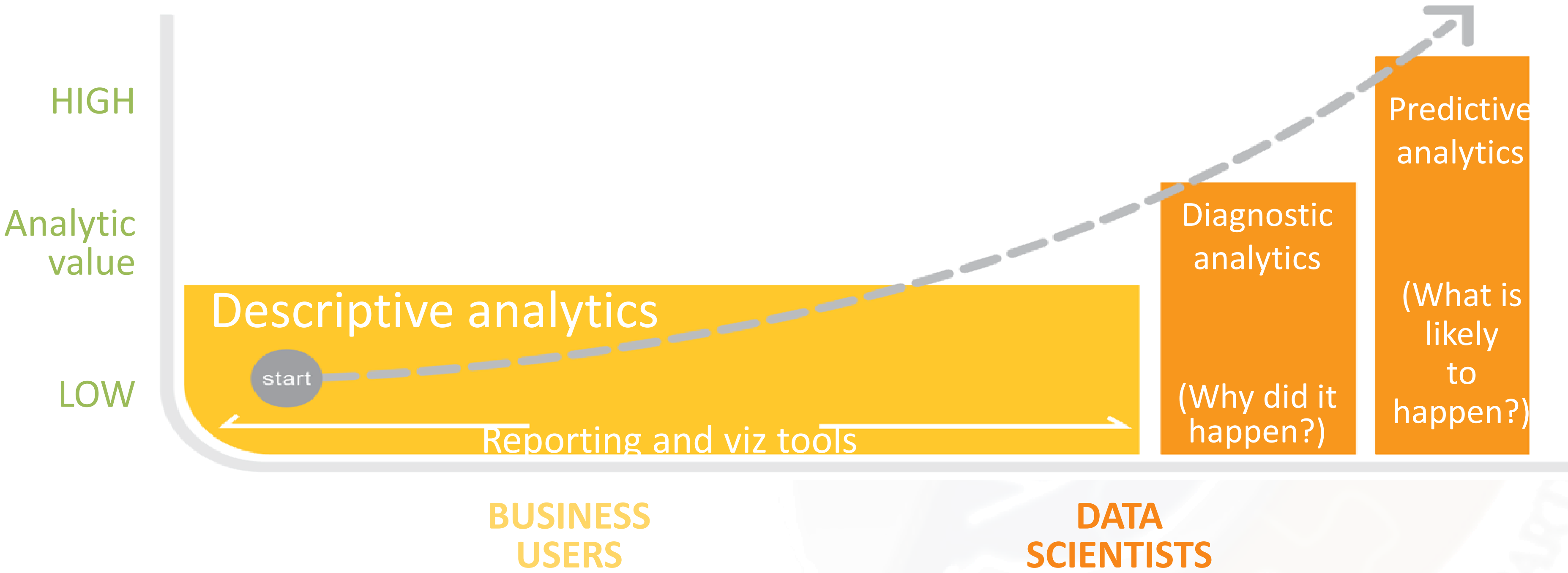


Descriptive Analytics


Predictive
Analytics

Diagnostic Analytics

Maximizing analytic value



Need to combine all in one tool

Difference Between Flat Reports and BI

- Flat reports give too much information about what happened.
- Used for transaction
- BI tells WHY it is happening
- Allows you to interact with the data
- Answers your next question

Difference Between Flat Reports and BI

Criteria	Operational Reports	Business Intelligence
Business Function	Tactical	Analytical
Users	Staff	Executive Management, Analysts, LOB Heads
Data Sources	Core system Only	Any including core e.g. TPA Data
Mode of Operation	Query then Analyze	Analyze then query (on the go)
Type	Static	Dynamic
KPI Measurement	No	Yes
Real Time	Yes	Near Real Time
Analysis Across Subject Areas	No	Yes e.g. Combined Ratio (as it has expenses, etc)

DAR Concept

Dashboard

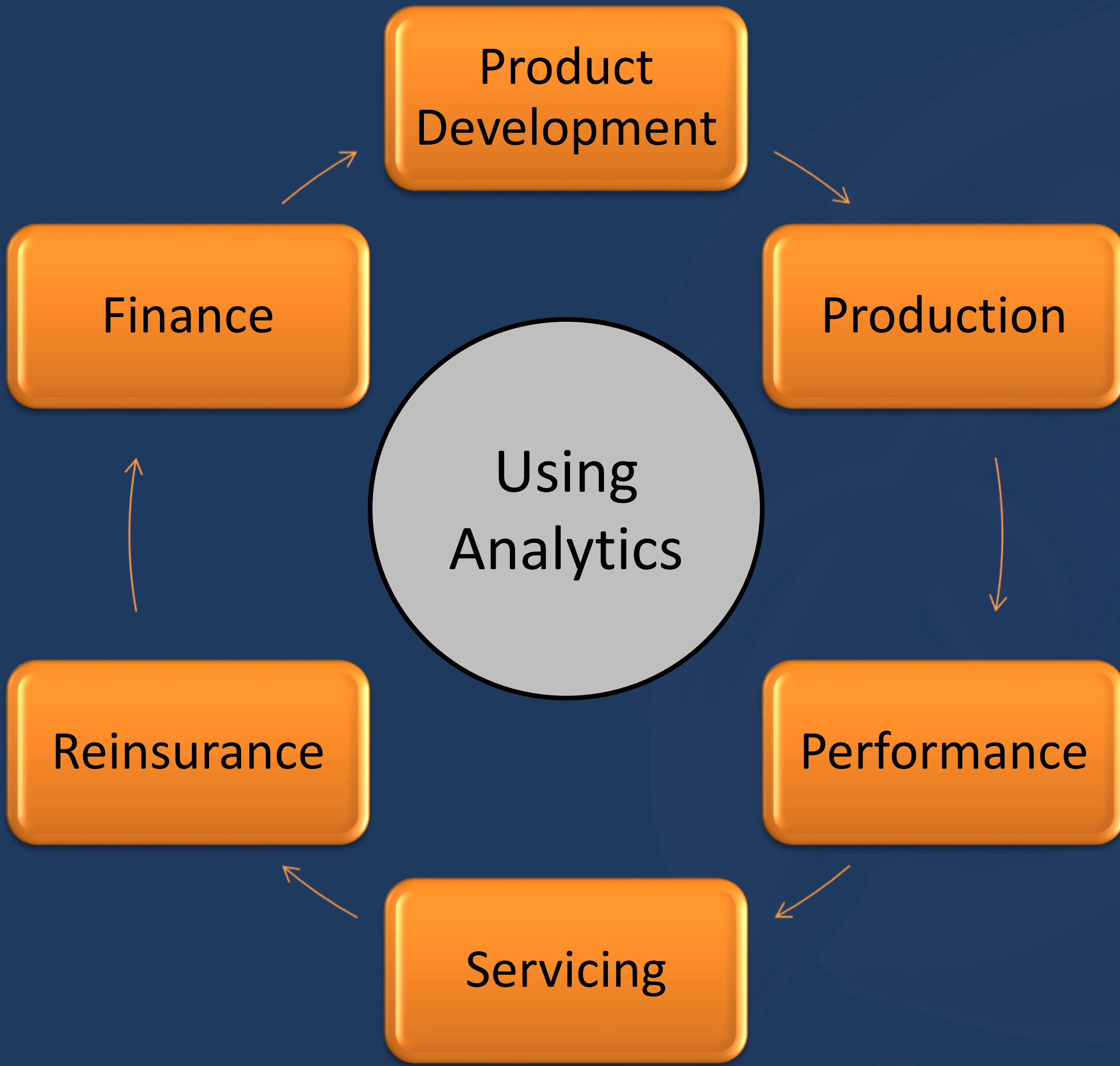
- High level
- KPIs
- Something which gives you an overall picture in two minutes

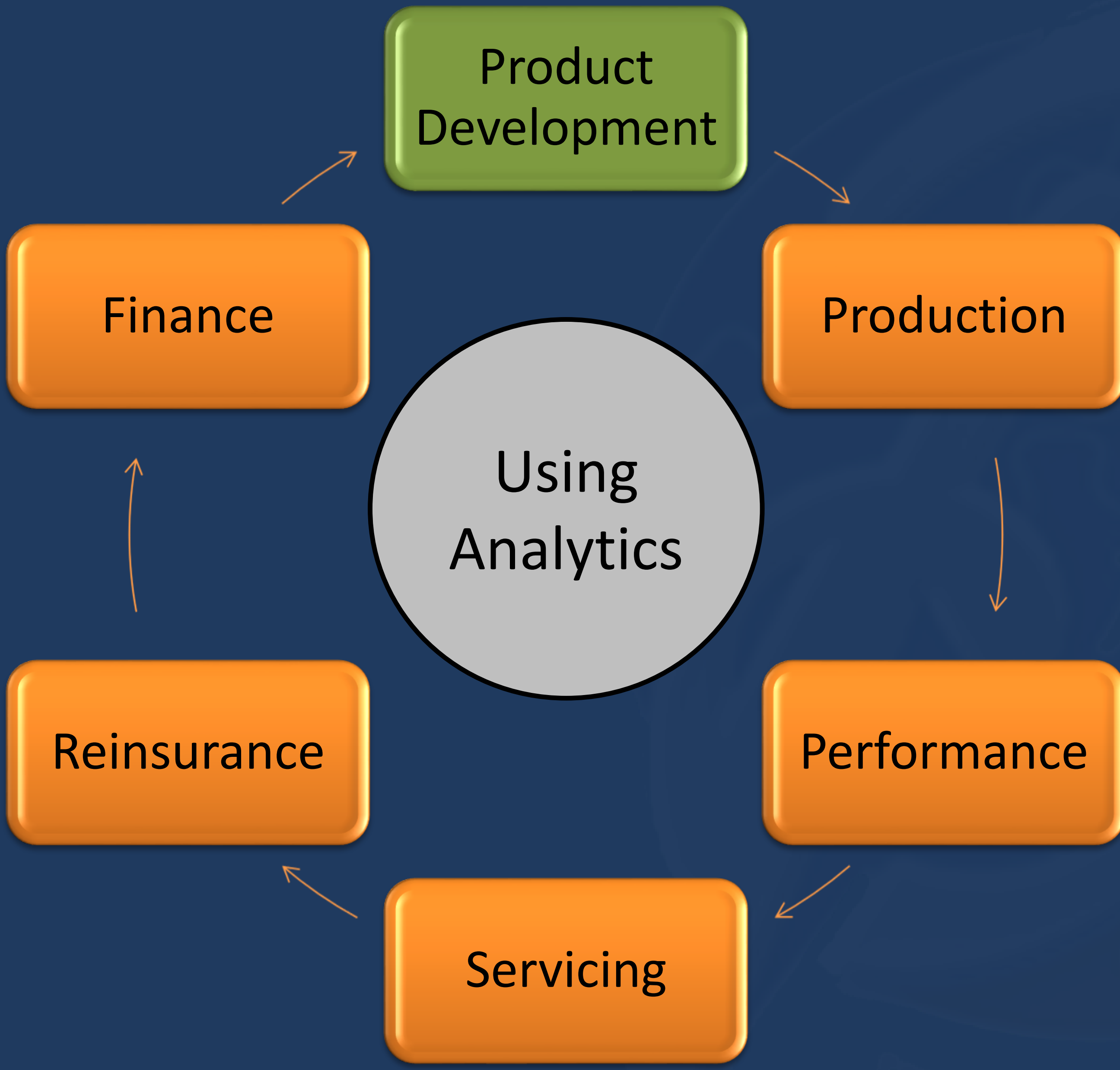
Analysis

- Has graphs and tables and tells the users “how” or “why”

Report

- Transactional level information
- Has more details like policy details, claim details


Product Development
Production
Performance
Servicing
Reinsurance
Finance
Using Analytics


Product Development
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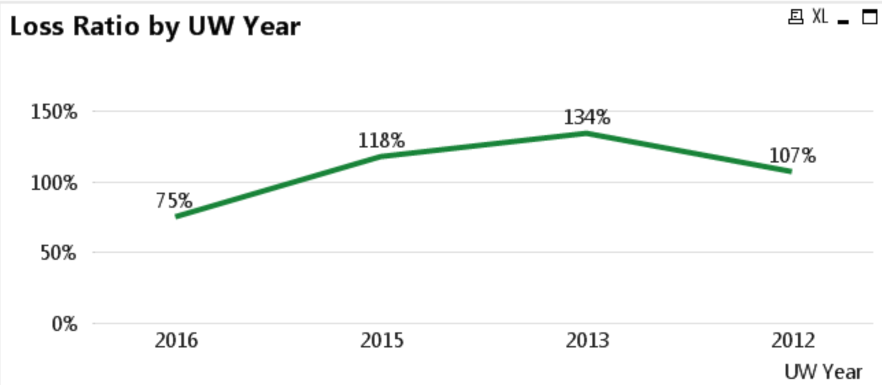
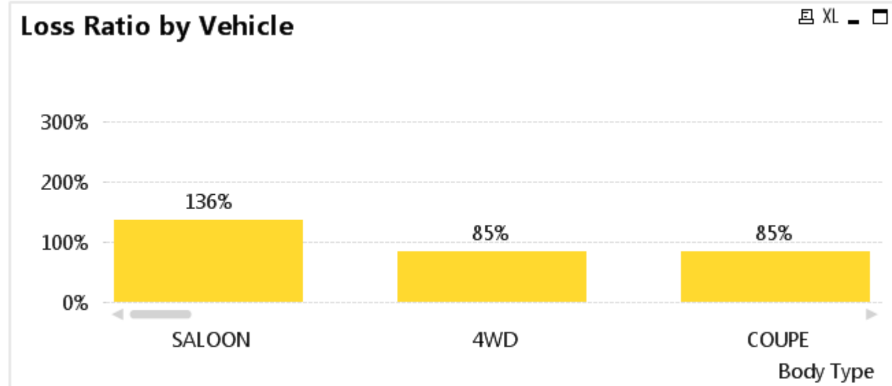
Using Analytics

Product Development

- Health/Motor insurance has become extremely data oriented
- Pricing / decision making should be analytics driven. Always validate perceptions with data
- Start at the top and drill down
- Pricing factors and pricing tool
- Use of pricing tool will provide standardised rates

Deeper Pricing Analysis

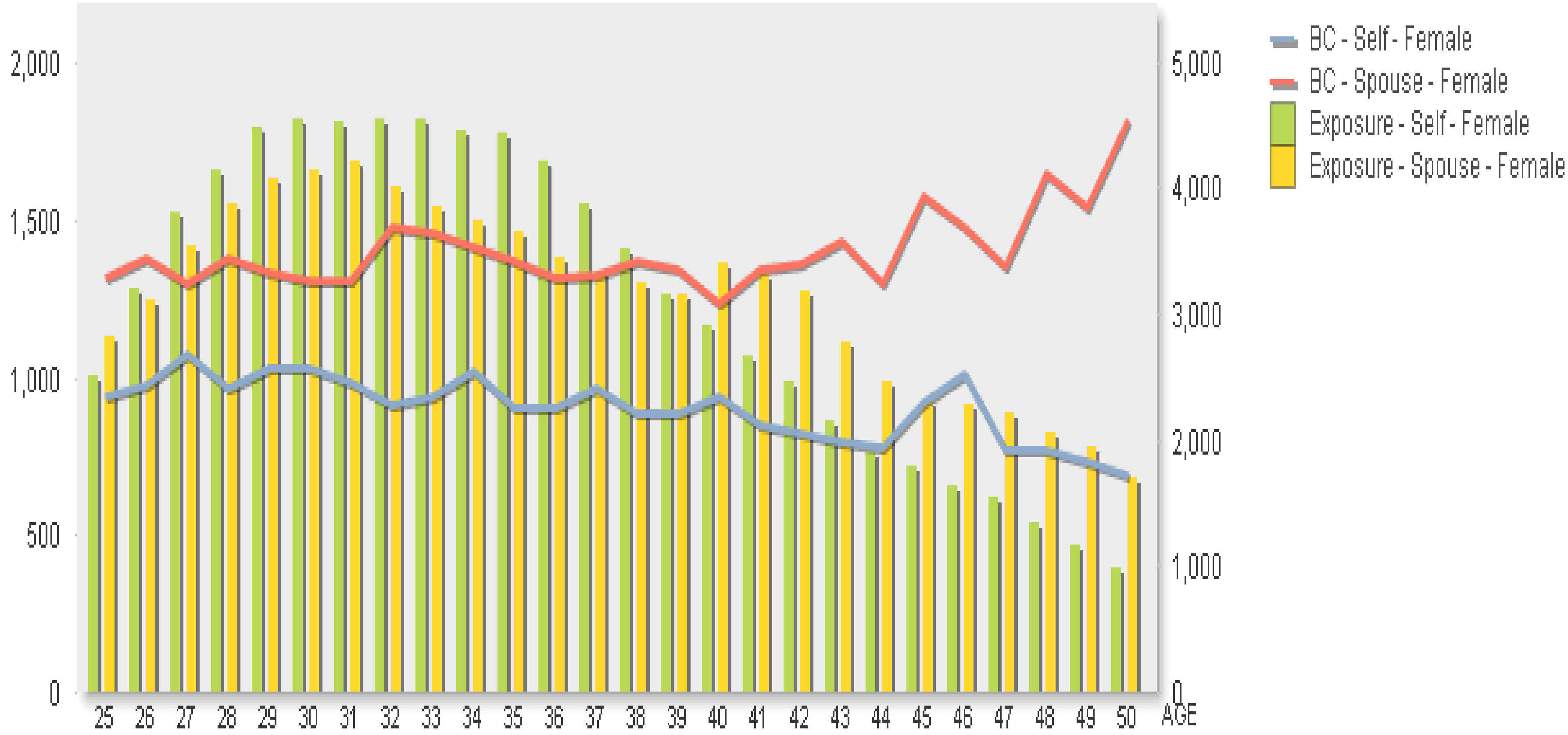


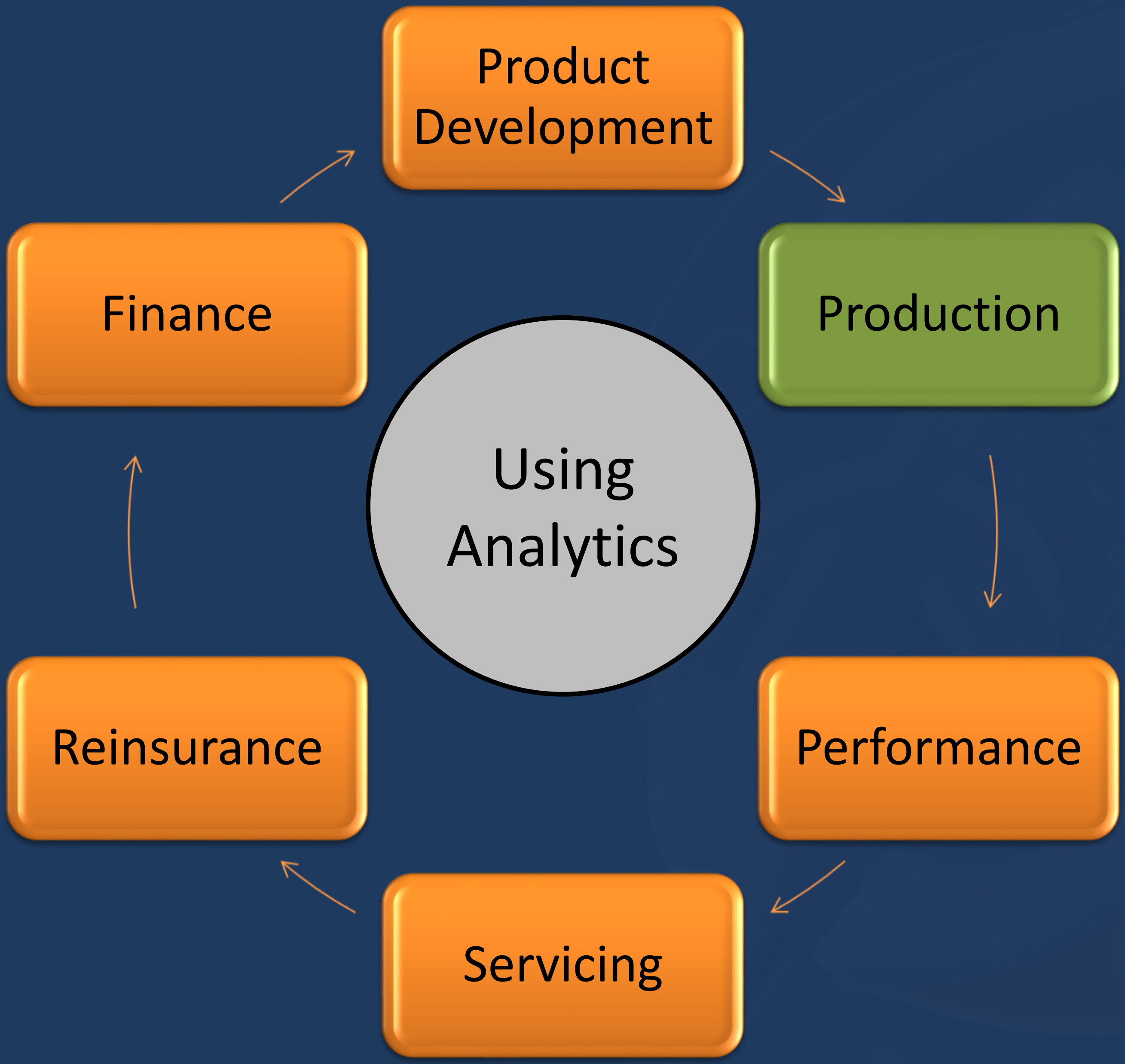


Loss Ratio by Vehicle (RSD 19) | Loss Ratio by Make Model RSD 23 | Burning Cost by Body Type RSD...

Body Type	Type	Claims	Exposure	Burning Cost
		392,364,124	224,324	1,749
SALOON	Private	182,398,867	98,849	1,845
4WD	Private	98,920,612	35,578	2,780
STATION WAGON	Private	30,523,779	30,081	1,015
STATION	Private	18,788,598	23,479	800
HATCHBACK	Private	31,955,034	17,346	1,842
PICKUP	Private	8,165,271	5,054	1,616
BUS	Private	6,025,650	4,509	1,336
VAN	Private	8,783,796	4,496	1,954
COUPE	Private	4,226,907	1,827	2,314
Trailer	Private	325,530	521	625
TRUCK	Private	635,552	358	1,775
Motor Cycle	Private	9,050	265	34
CHILLER VAN	Private	38,750	237	164
Forklift	Private	4,200	205	20
MIXER	Private	81,460	197	414
Concrete Mixer	Private	657,497	193	3,407
Wheel Loader	Private	6,800	143	48
Sedan 4 Door	Private	81,850	108	758
Shovel	Private	16,500	78	212
Tipper	Private	1,200	62	19
JEEP	Private	20,840	48	434
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Deeper Pricing Analysis




Product Development
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Reinsurance
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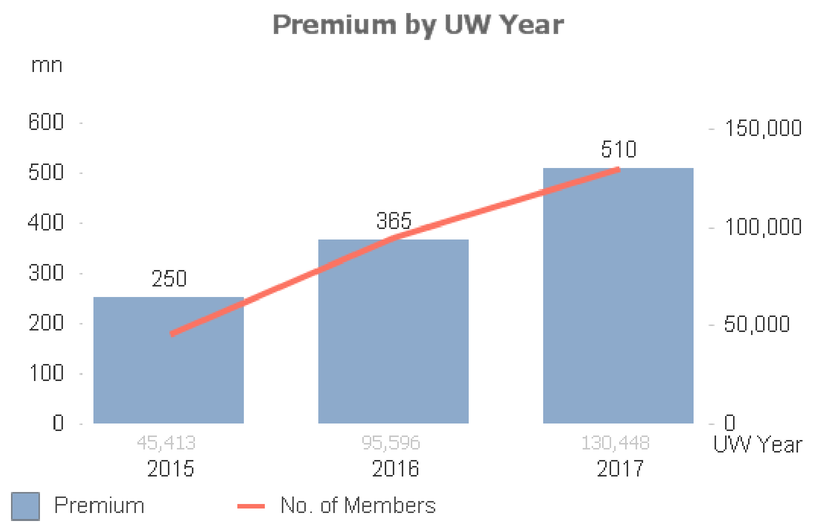
Using Analytics

Sales - Client

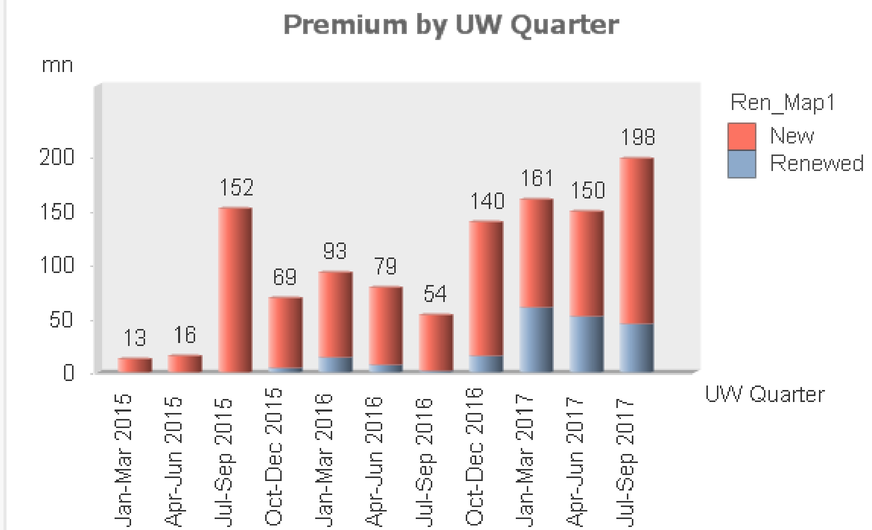
- Client segmentation
  - By size – analyse your existing portfolio to find out which segments are profit making
  - By industry – generally difficult to evaluate. Can be done as part of data cleaning or one time exercise
- Campaign optimization / lead generation
- Where to cross sell
- What to upsell

Sample Production

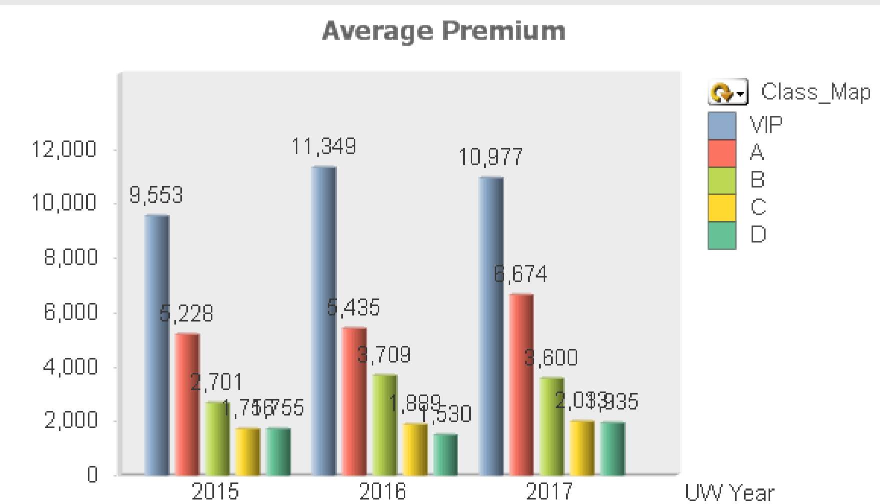
Premium by UW Year



Premium by UW Quarter



Average Premium

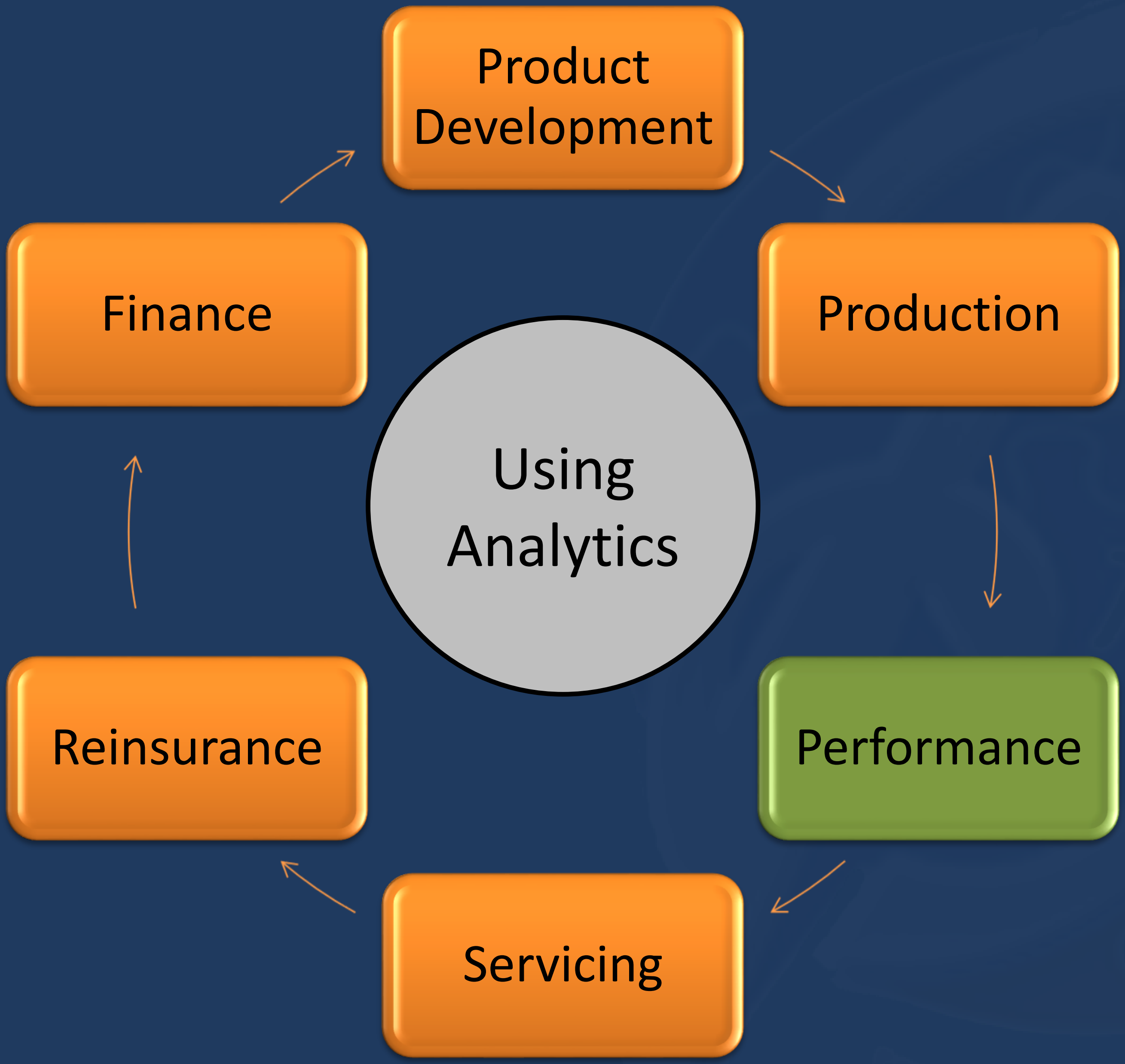


Persistency - Volume

UW_Year	New Business	Renewed B...	Total	Persistency	Growth
	924,152,058	**200,500,806**	**1,124,652,864**	-	-
2015	245,090,074	4,562,095	249,652,169	-	-
2016	327,266,603	38,229,707	365,496,310	15%	34%
2017	351,795,382	157,709,004	509,504,386	43%	7%

Persistency - No. of Policies

UW_Year	New Business	Renewed Bus...	Total	Persistency	Growth
	1,607	**266**	**1,873**	-	-
2015	162	1	163	-	-
2016	612	59	671	36%	278%
2017	833	230	1,063	34%	36%



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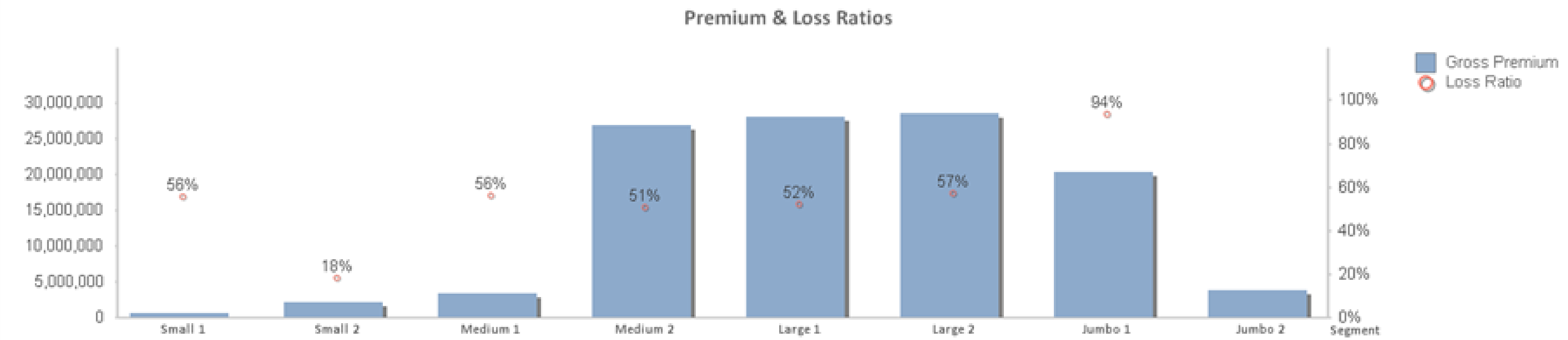
Sample Health Performance

Premium & Loss Ratios



Loss Ratio

UY	POLICYNO	Gross Premium	Risk Premium	Earned Risk Premium	Paid Claims	Loss Ratio
		113,438,815	91,400,558	91,400,558	53,513,083	59%
2014	VK/07/1600/34/51527	4,582,010	3,711,428	3,711,428	6,083,552	164%
2014	KP/05/8668/17/96803	4,094,342	3,562,077	3,562,077	3,381,689	95%
2014	QT/43/1979/35/97922	1,959,188	1,694,698	1,694,698	2,768,308	163%
2014	DJ/46/4286/51/94834	2,701,558	2,026,168	2,026,168	2,440,724	120%
2014	PC/22/0152/16/29683	1,524,131	1,310,753	1,310,753	2,118,911	162%
2014	MZ/16/1238/92/80609	1,247,733	898,368	898,368	1,868,370	208%
2014	JN/15/6122/42/02469	2,037,370	1,721,573	1,721,573	1,791,749	104%
2014	FN/93/5638/19/27748	2,018,576	1,630,004	1,630,004	1,671,699	103%
2014	PH/43/3401/18/27157	2,496,458	1,859,863	1,859,863	1,655,586	89%
2014	YD/23/9064/14/70432	1,700,188	1,283,642	1,283,642	1,525,946	119%
2015	NI/30/7940/91/28621	1,572,585	1,407,462	1,407,462	1,521,446	108%
2014	FK/99/4237/51/04467	1,081,788	805,931	805,931	1,395,486	173%
2014	XZ/97/9110/38/64096	1,192,530	959,988	959,988	1,373,905	143%
2014	HE/08/2765/09/78120	2,275,206	1,581,268	1,581,268	1,347,840	85%

Segmentation

Group Size	Number of Policies	Active Members	Premium Booked (AED mn)	% of Total	Claims Incurred (AED)	Loss Ratio
Small	200	5,000	27.5	11%	18.75	68%
Medium	150	15,000	67.5	28%	56.25	83%
Large	50	37,500	150.0	61%	140.63	94%
Jumbo	-	-	-	0%	-	
	400	**57,500**	**245.0**		**215.63**	**88%**

Segmentation

- 2 more clients – portfolio grows:
- Active Members – 52%
- Premium – 37%

ASSUMPTIONS

Group Size	Average Burning Cost AED pppy	Average Premium AED pppy
Small	3,750	5,500
Medium	3,750	4,500
Large	3,750	4,000
Jumbo	3,750	3,500

Segmentation

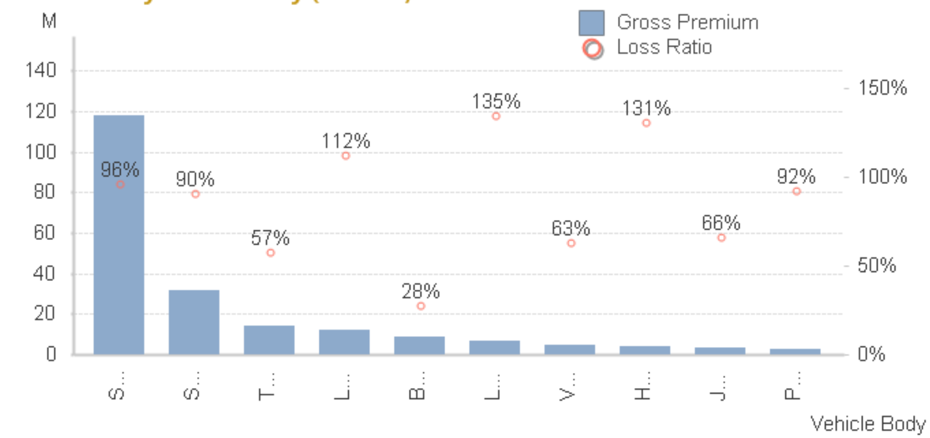
Group Size	Number of Policies	Active Members	Premium Booked (AED mn)	% of Total	Claims Incurred (AED)	Loss Ratio
Small	200	5,000	27.5	8%	18.75	68%
Medium	150	15,000	67.5	20%	56.25	83%
Large	50	37,500	150.0	45%	140.63	94%
Jumbo	2	30,000	90.0	27%	112.50	125%
	402	**87,500**	**335.0**		**328.13**	**98%**

Loss Ratio goes from 88% to 98%
Only because of 2 policies

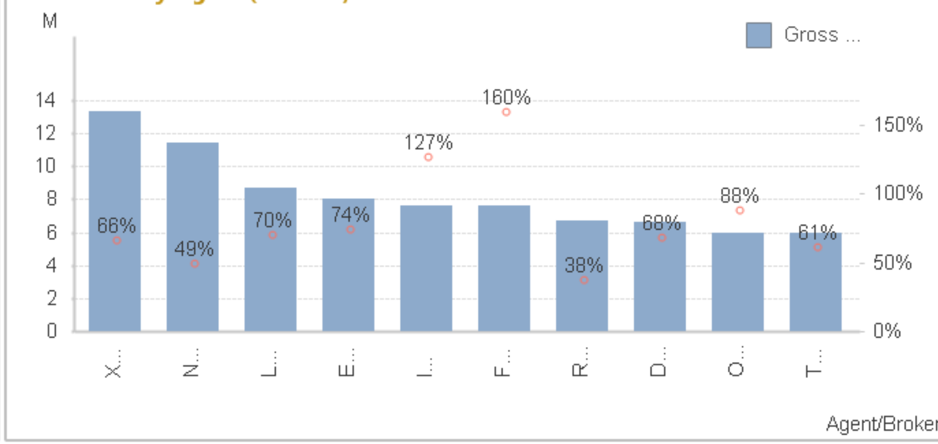
Sample Motor Performance

BADRI

Loss Ratios by Vehicle Body (Millions)



Loss Ratios by Agent (Millions)

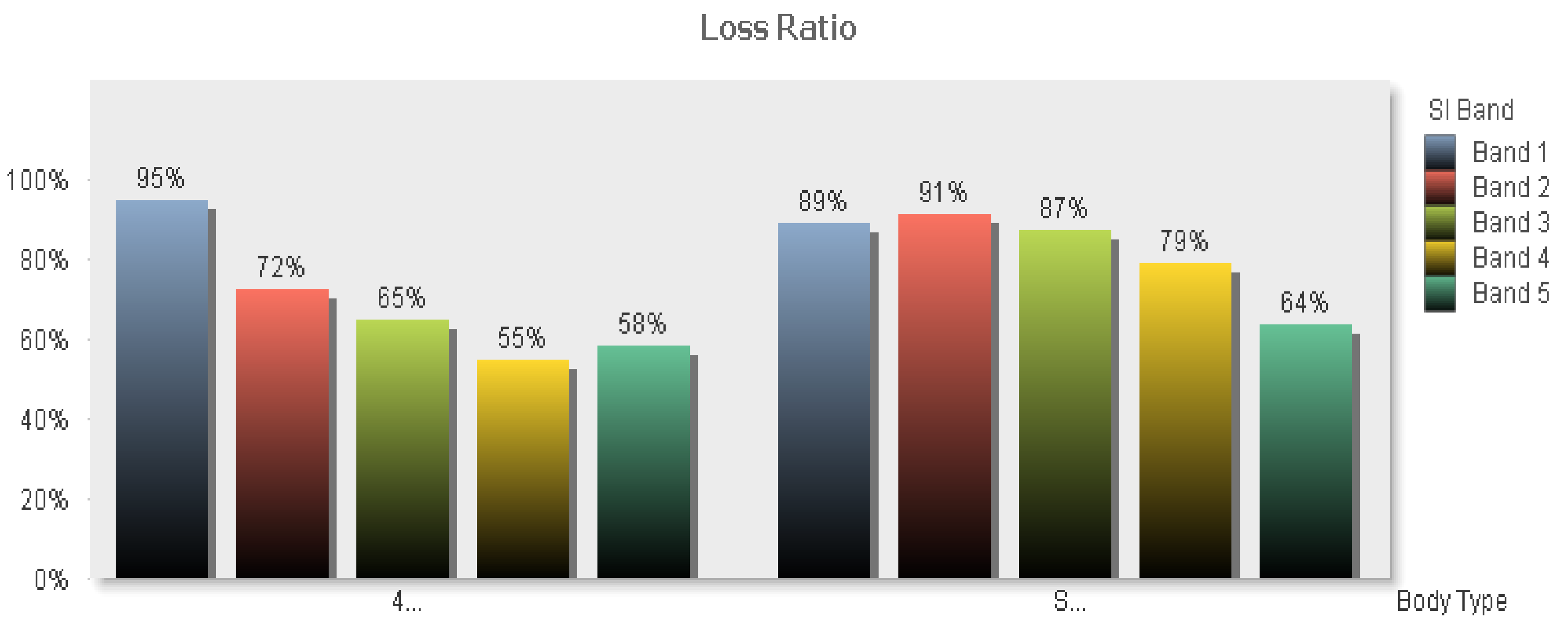


Loss Ratios by Policy Type

Loss Ratios by Repair Condition

	Gross Premium			Loss Ratio		
RA_Year	2012	2013	2014	2012	2013	2014
Repair Condition						
Outside Agency	42,650,118	44,812,667	32,002,941	74%	75%	60%
N/A	6,962,666	22,826,401	16,263,219	93%	115%	86%
Inside Agency	5,328,446	9,700,746	6,477,703	106%	114%	99%
Repair Condition	-128	-	-	0%	-	-

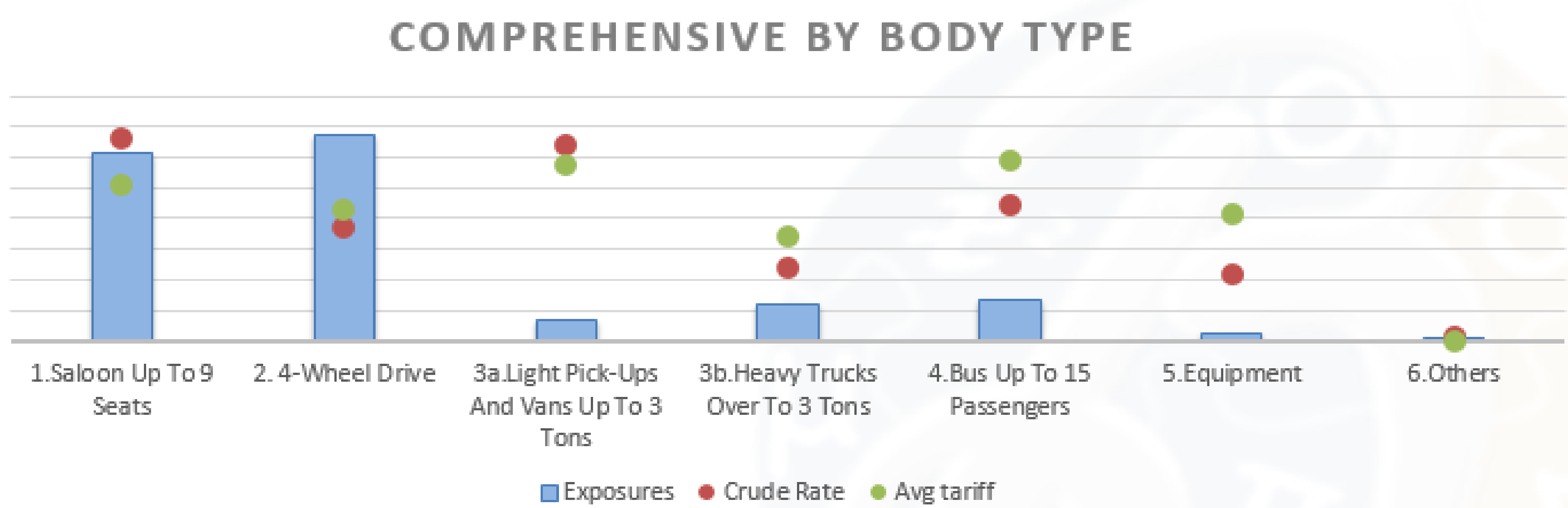
Loss Ratio by Body Type and Sum Insured Bands

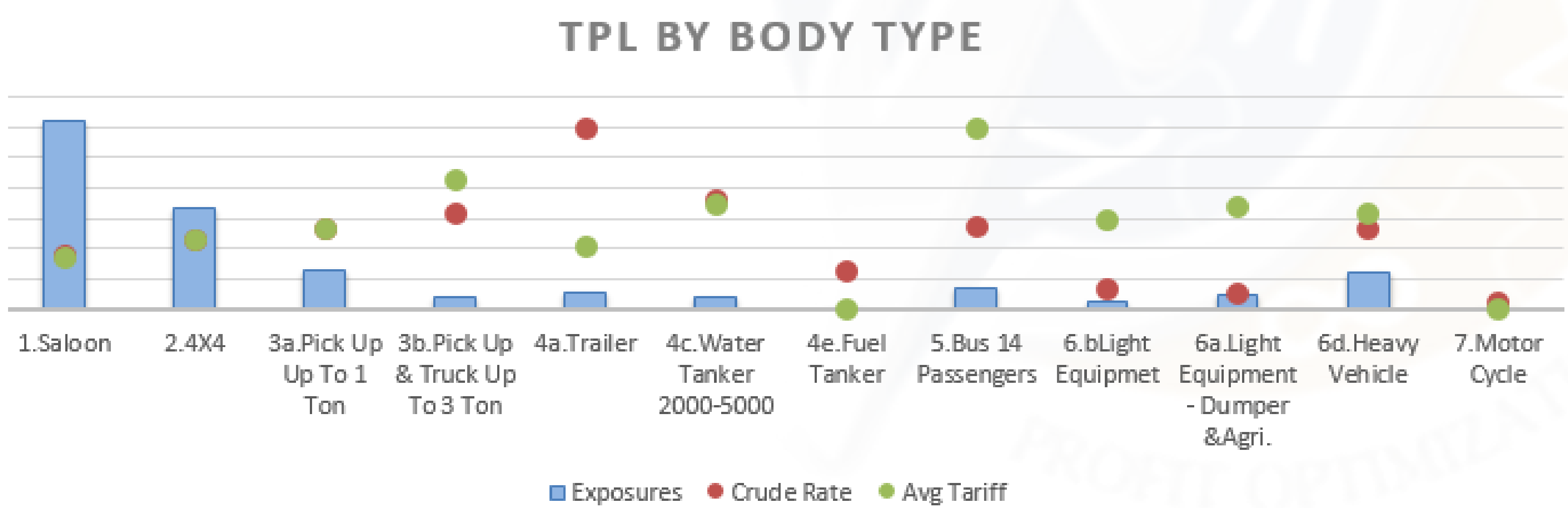


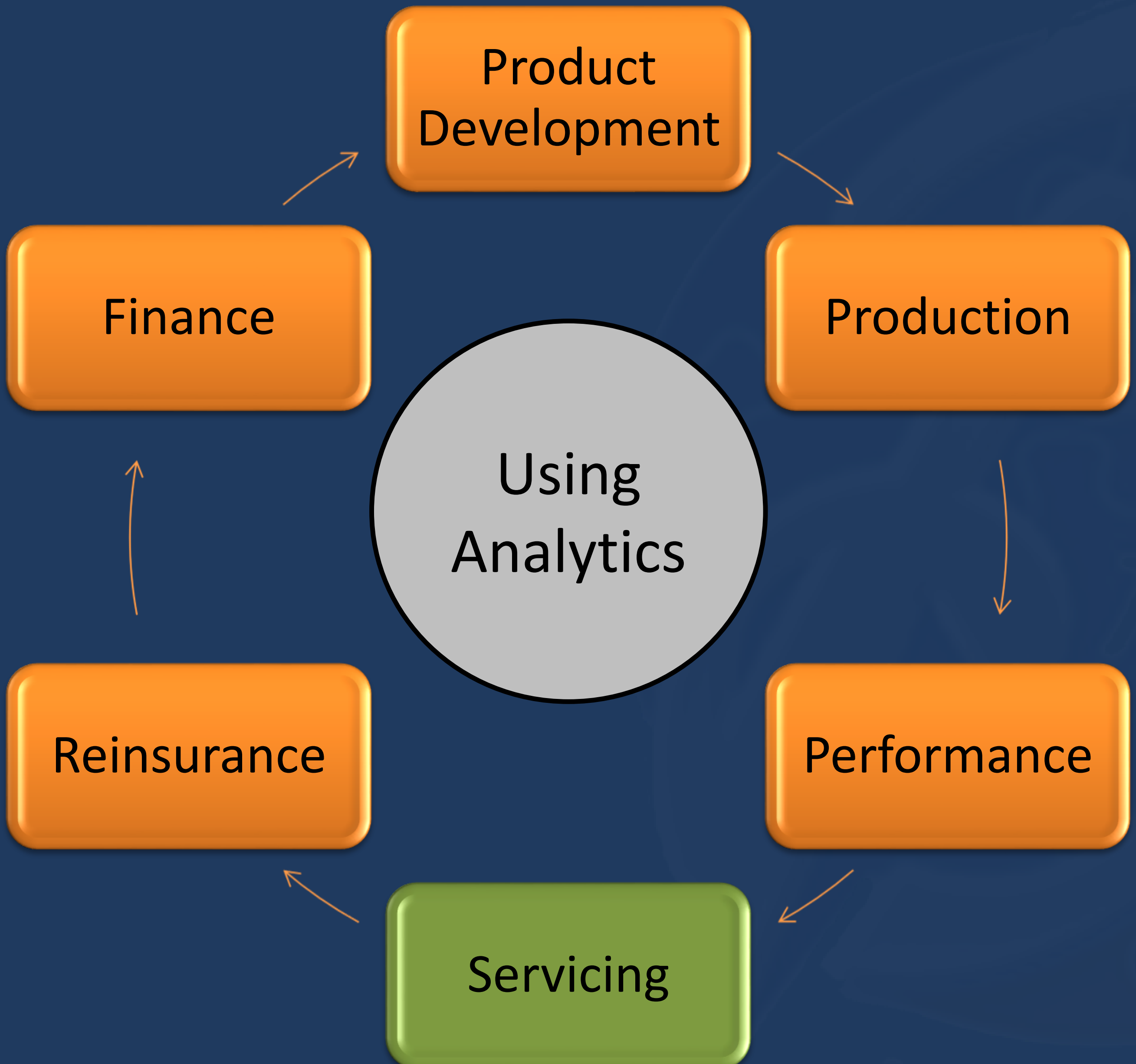
Performance Monitoring

Vehicle Model	Claims Incurred	Exposure in Vehicle Years	Burning Cost	Proposed Technical Premium
ACCENT	19,337,618	18,892	1,024	1,365
COROLLA	12,569,979	12,238	1,027	1,370
ELANTRA	11,530,433	8,854	1,302	1,736
HEAD	9,145,724	7,218	1,267	1,690
YARIS	8,164,967	9,094	898	1,197
CAMRY	7,821,214	9,595	815	1,087
SONATA	5,822,573	4,065	1,432	1,910
ACCORD	5,292,685	3,478	1,522	2,029
PICKUP 2C	5,285,424	7,389	715	954
PICKUP 1C	3,891,814	7,315	532	709
TRAILOR HEAD	3,021,683	2,544	1,188	1,583
SUNNY	2,898,089	3,444	842	1,122
CHARGER	2,655,949	972	2,731	3,642
Truck	2,633,754	3,146	837	1,116
CROWN VICTORIA	2,430,861	3,313	734	978
YUKON	2,184,290	5,091	429	572
LOGAN	2,157,216	2,815	766	1,022
CAPRICE	2,110,150	2,226	948	1,264
GRAND MARQUIS	2,052,200	2,497	822	1,096
CERATO	1,969,749	1,698	1,160	1,547
AVALON	1,750,839	1,300	1,346	1,795
GXR	1,732,495	2,603	665	887
AVEO	1,662,674	3,201	519	693
FJ CRUISER	1,538,324	1,075	1,431	1,908
AZERA	1,497,969	669	2,241	2,988
LAND CRUISER	1,491,042	1,820	819	1,093
TRUCK	1,459,788	2,260	646	861
TAHOE	1,414,980	2,748	515	686
DYANA	1,378,942	1,078	1,279	1,706
RIO	1,366,075	1,815	753	1,003
FORTUNER	1,334,525	1,610	829	1,105

Analysing Target Segments



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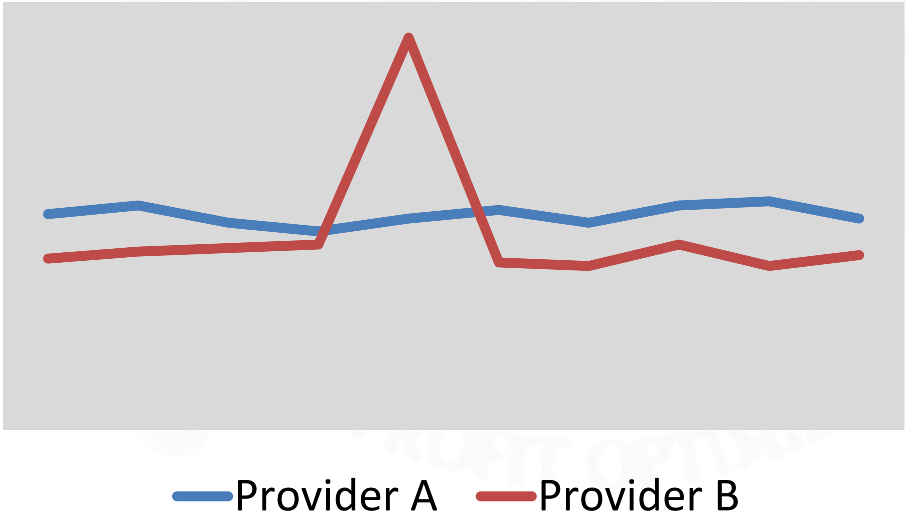
Customer Service

- Customers are less loyal and more price conscious
- Insurance managers are looking for more insights / advices
- Clients wants transparency / more analytical reports
- Need proper analytical tools which can handle big data

Claims

- Finding fraud is like finding a needle in the haystack.
- With big data it's a big stack



Use of Systems for Fraud

Historical / Retrospective

Predictive / Real Time

Standard Reports

- Utilization per provider
- Provider KPIs
- Averages per diagnosis

Statistical Reports

- Distribution of claims by provider
- By diagnosis / treatment

Determ-inistic Rules

- Rule edits
- Diagnosis / treatment rules

Complex Probab-ilistic Rules

- Calculate scores for claim
- Calculate scores for patient based on past history

Historical data / experience will help create new rules and setup complex probabilities.

The Solution

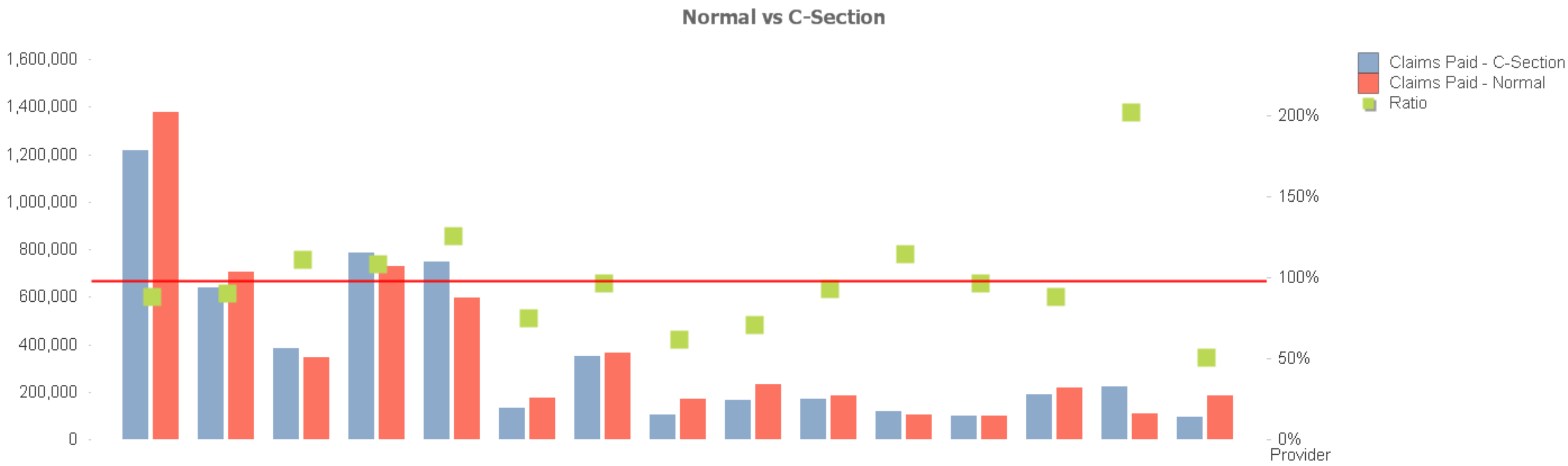
- Develop and test rules e.g.
  - No pharmacy /test with IR-DRG
  - Pharmacy claims without consultation
- Need to create exceptions
  - Speciality hospitals
  - Client industry

- It needs to be handled in a structured manner.
- Have regular data discovery meetings between actuary, claims and SIU
- Get the right tools

Gap within Consultations

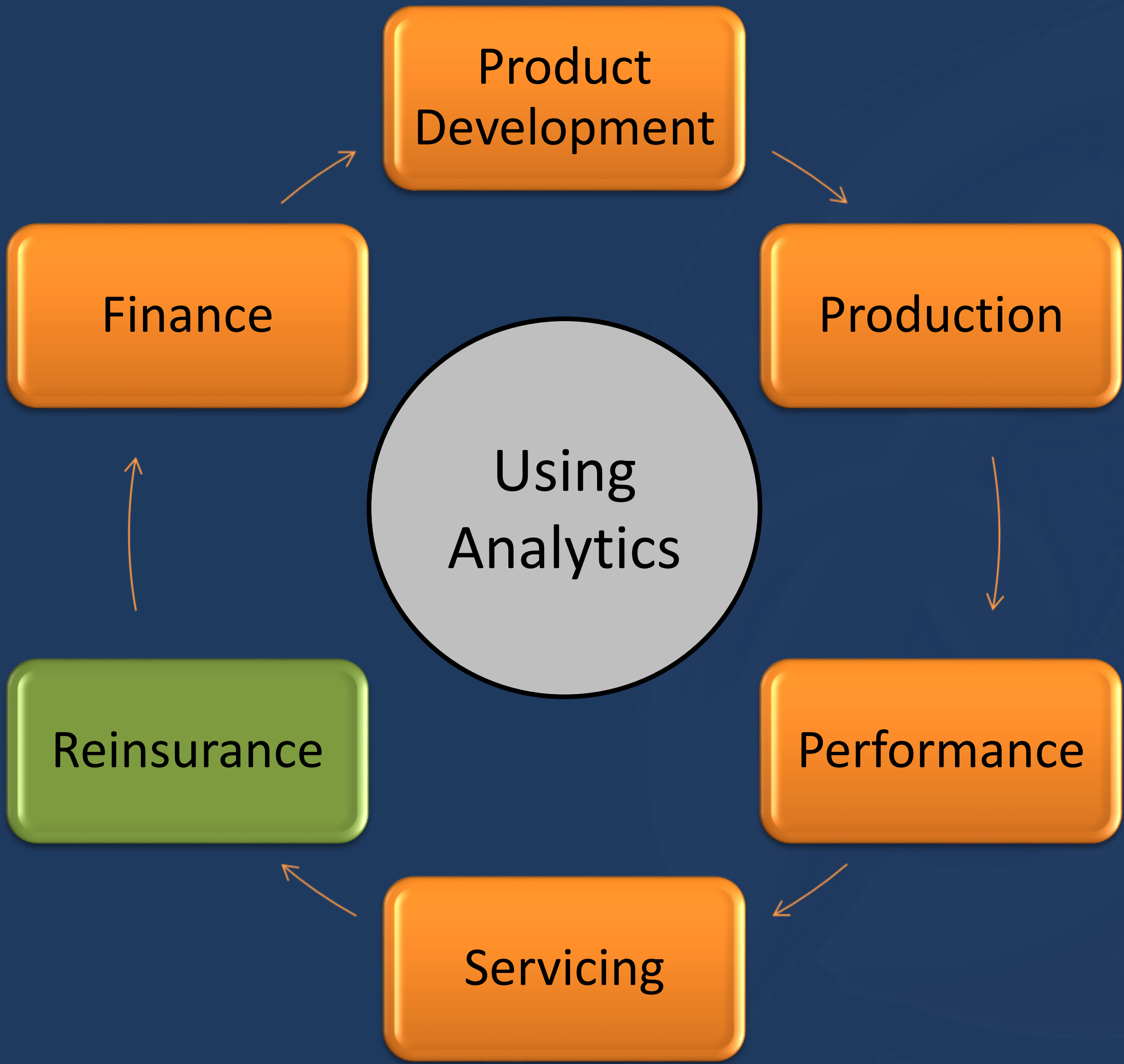
Clinician	Member No	TREATMENT...	Consultation	Gap within Tr...	Less than 8 days	Eight day	Ninth day	Tenth day
			110,490	-	39	7	6	2
MOHD		23/Oct/2013	269	-	-	-	-	-
MOHD		29/Sep/2014	311	341	-	-	-	-
MOHD		02/Apr/2014	311	-	-	-	-	-
MOHD		01/Jul/2014	311	90	-	-	-	-
MOHD		11/Oct/2014	311	102	-	-	-	-
MOHD		24/Jan/2015	311	105	-	-	-	-
MOHD		28/Jan/2015	361	4	1	-	-	-
MOHD		23/Feb/2015	311	26	-	-	-	-
MOHD		28/Feb/2015	269	5	1	-	-	-
MOHD		09/Jul/2014	311	-	-	-	-	-
MOHD		14/Dec/2014	311	-	-	-	-	-
MOHD		27/Nov/2014	311	-	-	-	-	-
MOHD		06/Oct/2013	269	-	-	-	-	-
MOHD		27/Oct/2013	269	21	-	-	-	-
MOHD		19/Jan/2014	269	84	-	-	-	-
MOHD		29/Jan/2014	226	10	-	-	-	1
MOHD		05/Feb/2014	226	7	1	-	-	-
MOHD		18/Feb/2014	226	13	-	-	-	-
MOHD		22/Nov/2014	311	277	-	-	-	-
MOHD		06/Oct/2013	269	-	-	-	-	-
MOHD		19/Jan/2014	269	105	-	-	-	-
MOHD		01/Mar/2014	269	41	-	-	-	-
MOHD		10/Mar/2014	226	9	-	-	1	-
MOHD		21/May/2014	311	72	-	-	-	-
MOHD		01/Jun/2014	269	11	-	-	-	-
MOHD		26/Nov/2014	311	178	-	-	-	-
MOHD		16/Dec/2014	311	-	-	-	-	-
MOHD		09/Apr/2014	311	-	-	-	-	-
MOHD		01/Oct/2014	311	-	-	-	-	-
MOHD		01/Oct/2014	289	-	-	-	-	-
MOHD		08/Feb/2015	311	-	-	-	-	-
MOHD		25/Feb/2014	269	-	-	-	-	-
MOHD		13/Apr/2014	311	-	-	-	-	-
MOHD		19/Apr/2014	269	6	1	-	-	-
MOHD		25/Oct/2014	311	189	-	-	-	-
MOHD		17/Oct/2013	269	-	-	-	-	-
MOHD		04/Dec/2013	269	48	-	-	-	-
MOHD		22/Dec/2013	226	18	-	-	-	-

Normal vs C-Section



Rank Analysis on Drugs

Drug	Claim Paid ::: Year: 2016	Number of Claims ::: Year: 2016	Average Claim ::: Year: 2016	Claim Paid ::: Year: 2015	Number of Claims ::: Year: 2015	Average Claim ::: Year: 2015	Rank Current :: : Year:...	Rank Previous ::: Year: 2015	Rank Variance
	887,599	2,833	313	764,331	2,877	266	1	1	0
	840,212	597	1,407	358,287	319	1,123	2	14	-12
	824,579	3,075	268	718,978	2,848	252	3	2	1
	646,601	4,821	134	594,452	4,884	122	4	4	0
	601,097	126	4,771	585,267	134	4,368	5	5	0
	578,218	8,879	65	598,056	9,638	62	6	3	3
	562,877	5,554	101	477,654	4,912	97	7	7	0
	526,117	70	7,516	509,705	83	6,141	8	6	2
	454,774	2,582	176	427,284	2,898	147	9	8	1
	440,633	2,011	219	408,186	2,080	196	10	10	0
	426,787	3,507	122	411,554	3,773	109	11	9	2
	401,152	4,569	88	397,588	4,876	82	12	11	1
	356,443	40	8,911	285,362	37	7,712	13	21	-8
	346,788	3,386	102	375,101	4,165	90	14	12	2
	344,933	1,012	341	369,912	1,095	338	15	13	2
	338,229	3,551	95	309,939	3,218	96	16	16	0
	320,968	23	13,955	232,514	18	12,917	17	32	-15
	313,056	938	334	293,108	1,072	273	18	18	0
	310,056	1,870	166	256,640	2,612	98	19	27	-8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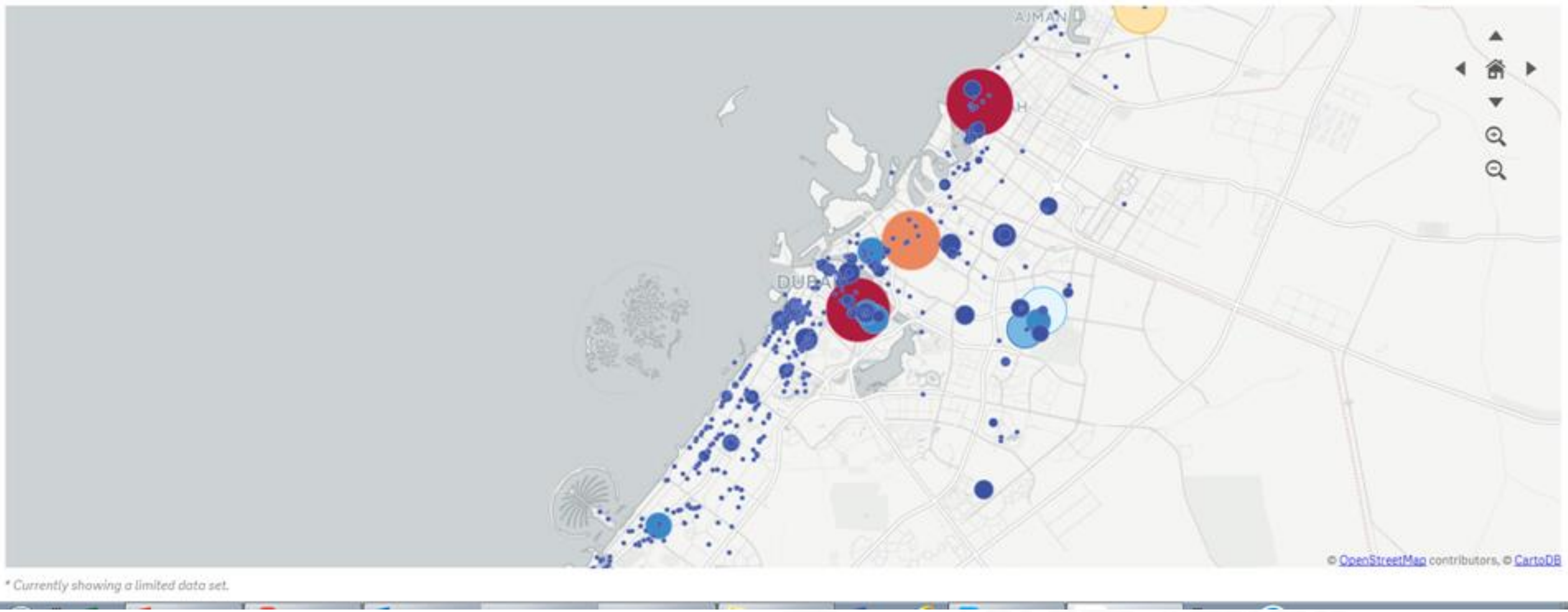
Risk Accumulation Visually

We can show accumulation by geography also and the spots would be updated based on selections. The size and colour can represent different dimensions.



Risk Accumulation Reports

Risk Accumulation Concentration Report (RSD 29)

UW Year	Country	City	State	Area	Street	Premium	Sum Insured
						125,565,115	33,577,539,337
2015	United Arab Emirates	Abu Dhabi	Abu Dhabi	Al Souq	-	780	1,950,000
2015	United Arab Emirates	AL GHAYATHI	Abu Dhabi	AL GHAYATHI	-	2,617	1,900,000
2015	-	Bahia	-	-	K7	2,822	1,888,647
2015	United Arab Emirates	Dubai	Dubai	DIP Dubai	-	463	1,850,000
2015	United Arab Emirates	Dubai	Dubai	Al Wasl Square-Opp:Safa Park	-	1,089	1,815,000
2015	-	Fujairah	-	-	U13	3,167	1,752,170
2015	-	-	-	-	1-13	52,501	1,688,320
2015	United Arab Emirates	Dubai	Dubai	Building Lago Vista, Dubai	-	700	1,675,000
2015	United Arab Emirates	Ras al-Khaimah	Ras Al khaimah	Work Street	-	1,250	1,600,000
2015	-	Al Ain	-	-	1-34	1,956	1,564,677

TOP 5 Location By Concentration

By Country

Country	Sum Insured
	33,577,539,337
United Arab Emirates	24,376,959,923
-	8,956,918,198
GCC Countries	191,437,837
Lebanon	29,435,000
Oman	14,355,150
Others	8,433,229

By City

City	Sum Insured
	33,577,539,337
Abu Dhabi	10,374,121,555
Dubai	8,691,733,869
-	8,353,324,822
Sharjah	2,482,128,686
Al Ain	1,161,220,374
Others	2,655,505,902

By State

State	Sum Insured
	33,577,539,337
Abu Dhabi	10,503,036,867
-	8,957,818,198
Dubai	8,720,389,750
Sharjah	2,481,415,351
Al Ain	1,003,082,904
Others	1,911,796,266

Area

Area	Sum Insured
	33,577,539,337
-	8,957,818,198
Abu Dhabi	2,589,936,100
Dubai	2,457,094,328
Mussafah	1,294,578,855
Electra Street	1,018,704,000
Others	17,259,407,855

Alert For Location Approaching Defined Concentration

Please Enter Concentration Amount . =1000000000

By Country

Country	Sum Insured
	33,577,539,337
United Arab Emirates	24,376,959,923
-	8,956,918,198
GCC Countries	191,437,837
Lebanon	29,435,000
Oman	14,355,150
Qatar	8,051,000
Bahrain	382,229

By City

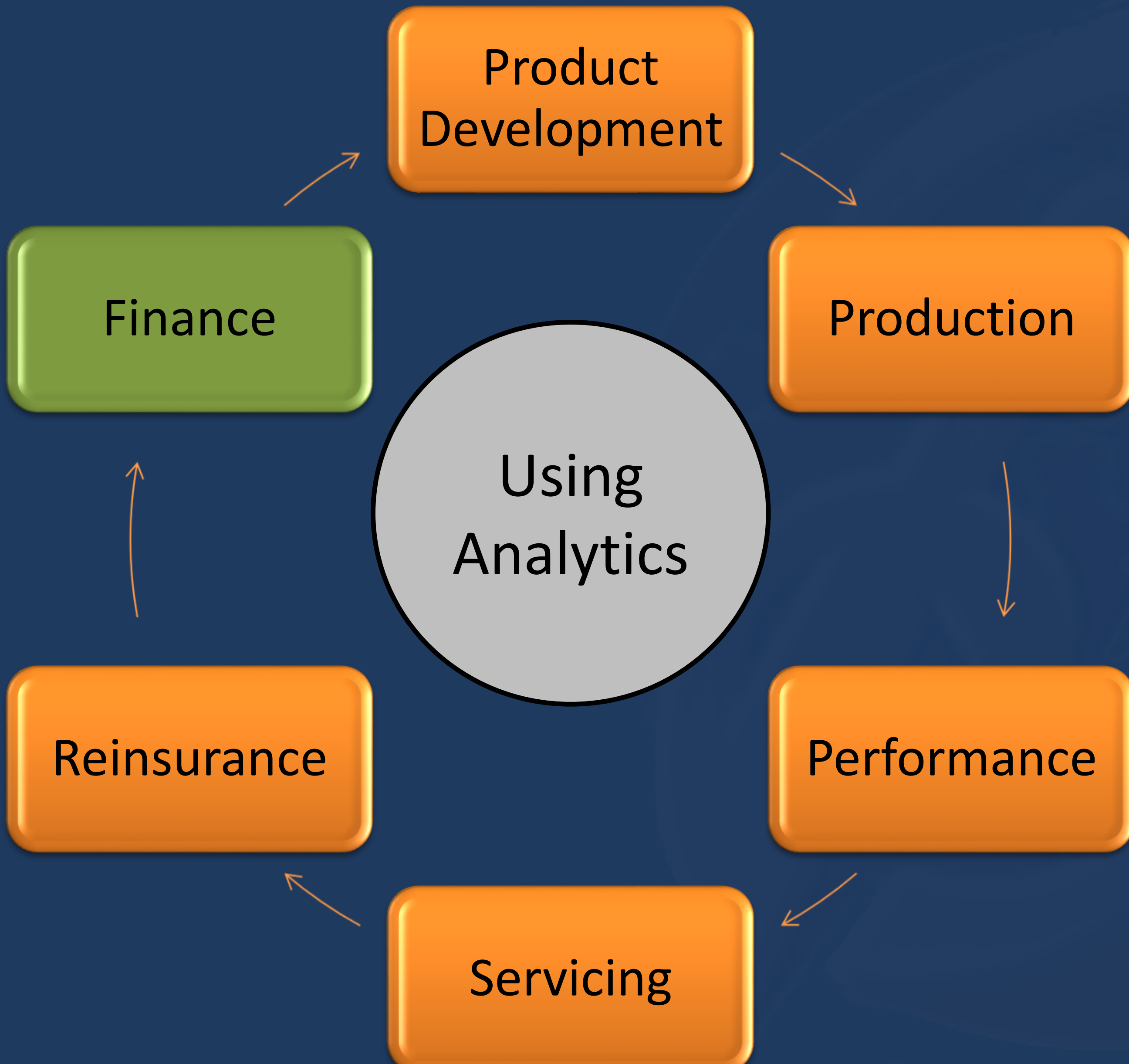
City	Sum Insured
	33,577,539,337
Abu Dhabi	10,374,121,555
Dubai	8,691,733,869
-	8,353,324,822
Sharjah	2,482,128,686
Al Ain	1,161,220,374
Various Cities in UAE	747,380,220
Ajman	678,240,514

By State

State	Sum Insured
	33,577,539,337
Abu Dhabi	10,503,036,867
-	8,957,818,198
Dubai	8,720,389,750
Sharjah	2,481,415,351
Al Ain	1,003,082,904
Various States in UAE	747,231,620
Ajman	648,339,293

By Area

Area	Sum Insured
	33,577,539,337
-	8,957,818,198
Abu Dhabi	2,589,936,100
Dubai	2,457,094,328
Mussafah	1,294,578,855
Electra Street	1,018,704,000
Jabel Ali	933,547,387
Al Ain	893,264,077
Various Locations in ...	713,909,132


Product Development
Production
Performance
Servicing
Reinsurance
Finance
Using Analytics

Automated Financial Reports

BADRI

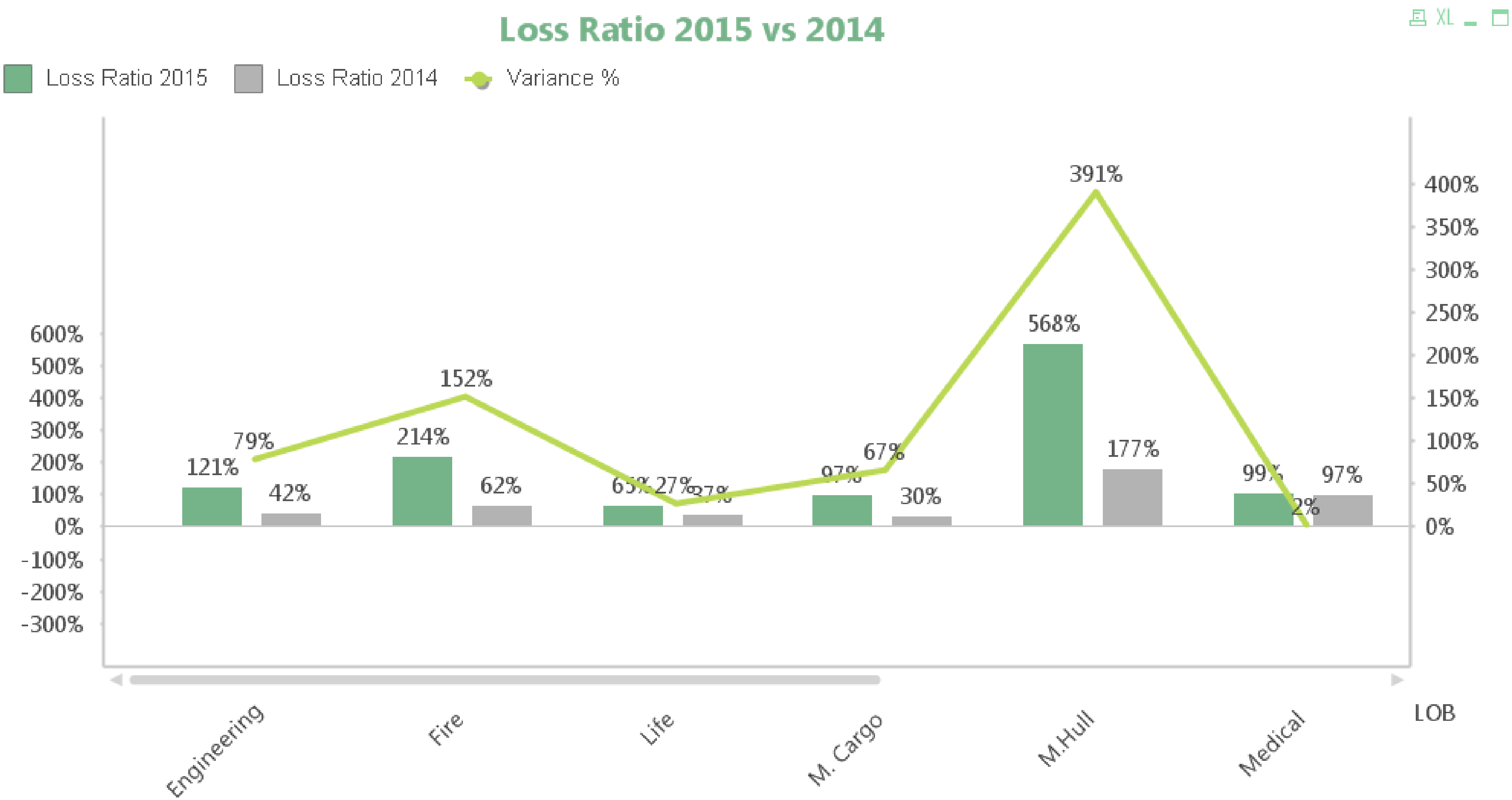
Revenue of Year - By LOB

LOB	Engineering	Fire	Life	M. ...
Premiums written	25,273,770	34,149,025	21,215,632	
Less: Reinsurance Share	23,603,647	31,652,787	18,939,399	
Net retained premiums	1,670,123	2,496,238	2,276,233	
Change in Net UPR	-246,734	-117,670	-188,326	
Net Commission earned and others	4,602,987	6,297,624	8,442,836	
Net Claims Paid	776,621	1,546,054	656,169	
Change in Net OSLR	177,142	1,357,408	245,248	
Change in Net IBNR	59,000	171,000	188,000	

Revenue of Year - By Branch

Branch	Dubai	Abu Dhabi	Sharjah
Premiums written	680,738,160	-7,286	-11,352
Less: Reinsurance Share	263,354,474	0	0
Net retained premiums	417,383,687	-7,286	-11,352
Change in Net UPR	-12,772,914	0	0
Net Commission earned and others	103,921,408	-611,488	103,022
Net Claims Paid	273,877,083	53,955,679	32,429,969
Change in Net OSLR	40,273,333	0	0
Change in Net IBNR	-27,096,997	0	0
Expenses	79,597,562	-852	-1,327
Gross Profit/(Loss)	**141,881,200**	**-54,573,601**	**-32,336,972**

Financial Loss Ratio



Are you data driven

Data Denial	Data Indifferent	Data Informed	Data Driven
• You distrust data and avoid using it	• You don’t care about data and have no need for it	• You use it only when it supports your opinions or decisions	• You use it to shape and evaluate all your decisions

- This is one time cost that reaps ongoing benefits. No use reinventing the wheel
- To become a Data Driven Company it has to come from top

Q&A

Analysis paralysis is an anti-pattern, the state of overanalysing a situation so that a decision or action is never taken

BADRI

MANAGEMENT CONSULTANCY

ACTUARIES | RISK MANAGERS

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