Turning insights into applications

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Agenda

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1. Creating data-driven insurance propositions
2. Example case studies
   - Propensity to Buy
   - Streamlined Underwriting
   - Dynamic Risk Calculator

Creating data-driven insurance propositions

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The four pillars of data analytics

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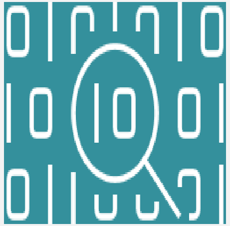
Data



- Internal Data
- External Data
- Structured Data
- Unstructured Data

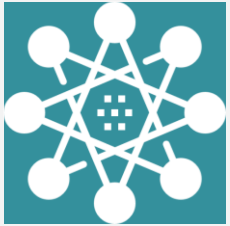
Technology

- Hardware
- Software

People

- Data Scientists & Engineers
- Actuaries
- Business People
- IT Architects

Methods



- Regression Models
- Machine Learning Models
- Text Mining

… Creating data-driven business value requires an integrated proposition…

Integrated analytics:

- ✓ Gains stakeholder buy in
- ✓ Implementable
- ✓ Treats customers fairly
- ✓ Risk acceptance

Integrated analytics:

Data-driven business value in four integrated steps

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Digital transformation

Digitisation

Conversion of analogue data into digital form that can be used by a computer

Automation

Manual to automated processes

Data management

Data Capture

Analysis

Digital transformation

Analytics

Descriptive analytics

What happened?

Diagnostic analytics

Why did it happen?

Prescriptive analytics

What should happen?

Predictive analytics

What will happen?

Proposition development

Gather data

Perform analytics

Risk assessment

Risk categorisation

Targeted underwriting based on insights and risk assessment

Customised products based on customer insights

Model deployment, customised campaign design & execution

Risk acceptance

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Underwriting & Product

Deploy Model

Campaign Design & Execution

Monitoring

How to get the **balance right?**

Integrated analytics (a holistic solution)

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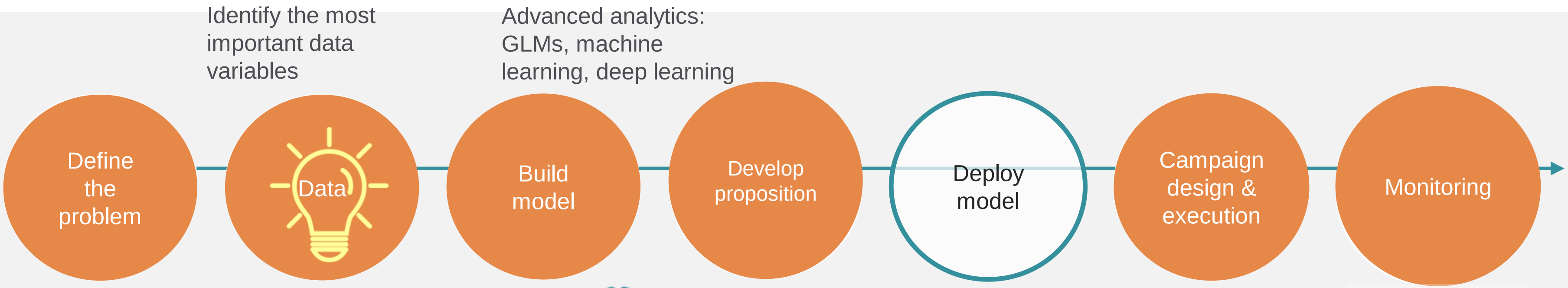

Likelihood to purchase

Enhance customer experience

Eliminate underwriting requirements

Remove some or all traditional underwriting questions

How to use bank or physical activity data in underwriting

Predict which customers smoke

Predict fraudulent claims

Automate claim decisions

Customised sales execution method

Trends to monitor

New business profile and agent analysis

Random holdout sample

Claims experience

Deployment of model

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Define the problem → Data → Build model → Develop proposition → **Deploy Model** → Campaign design & execution → Monitoring

Deployment options

Solution in the Cloud

Own Deployment & Integration System

Historic records | Known outcome

DOB	Gender	Smoker	Income	Marital Status	BMI	UW Decision
7/24/1975	F	N	240000	Married	30	S
7/17/1969	F	S	552000	Widow	22	NS
7/18/1973	M	N	180000	Married	30	S
3/18/1971	F	N	200000	Married	20	S
2/27/1970	F	S	352000	Married	20	S
12/29/1975	F	S	460000	Married	19	NS
7/22/1986	M	N	850000	Married	34	S
7/24/1975	F	N	240000	Married	30	S
7/17/1969	F	S	552000	Widow	22	NS
7/18/1973	M	N	180000	Married	30	S
3/18/1971	F	N	200000	Married	20	S
2/27/1970	F	S	352000	Married	20	S
12/29/1975	F	S	460000	Married	19	NS
7/22/1986	M	N	850000	Married	34	S

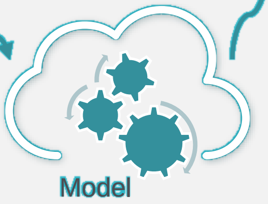
New customer record

DOB	7/27/1975
Gender	F
Smoker	N
Income	240000
Marital Status	Married
Real Weight	70

Predict outcome

P(Standard)	0.78

1 Build model → 2 Deploy model → 3 Consume model



Sample case studies

Case study: Propensity to buy

Sales and marketing

Cross-selling motor insurance through a banking partner

Our client's need:

"I want to increase my motor business sales by cross-selling motor business to my banking partners clients"

Our approach:

- Developed a predictive model of the banking customers' propensity to buy a motor insurance
- Ranked banking customers by their propensity to purchase motor insurance – target top X
- 2.4 million monthly observations from 190 000 bank customers

>25	Original and derived variables (socio-economic, banking and insurance)
5	Machine learning methods tested

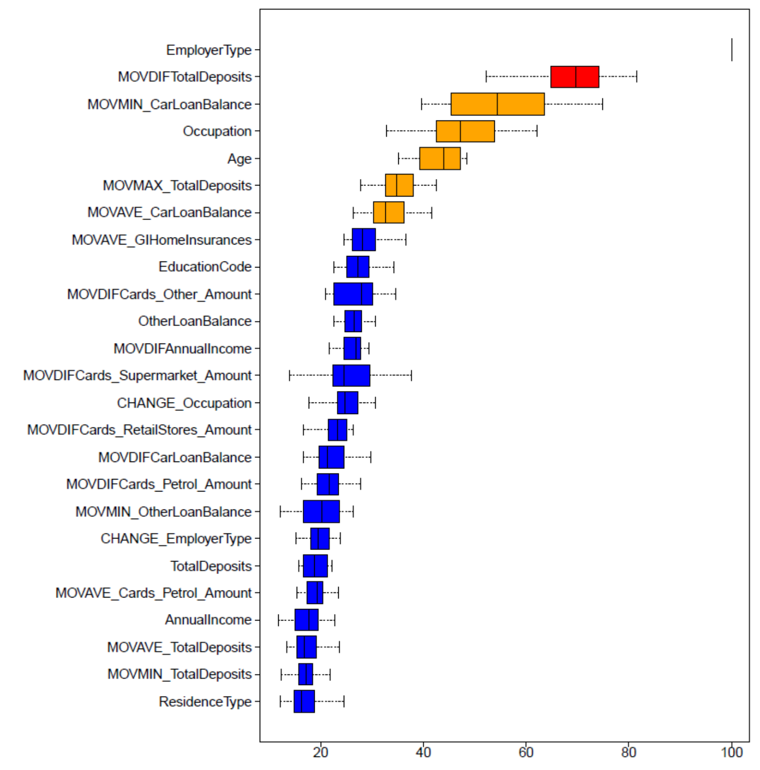
The outcome *(in progress)*:

Conclusion: It is possible to predict the propensity to purchase using banking data. Campaign ongoing…

5 000	Top customers targeted
3	Customer segments defined for marketing
>70%	Predictive power metric

Propensity to buy – insights

Predictor variables



- Variable importance –
  - The importance of each covariate has been calculated over 20 simulations
  - The plot shows the most important predictors

- Important predictors –
  - Employer type
  - Biggest movement in total deposits in last 3 months
  - Minimum car loan balance in last 3 months
  - Occupation / Age
  - Maximum total deposits over last 3 months
  - Average car loan balance in last 3 months

Case study: Streamlined underwriting

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Streamlined underwriting

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Our client's need:

"I want to significantly reduce the underwriting requirements with a minimal price impact while retaining sound risk management."

"Which variables from my loyalty programme data can streamline an up- and cross-selling campaign?"

Our approach:

- Developed predictive models of the underwriting decision with machine learning methods using a limited number of variables
- Applied the models to the data to identify eligible customers for streamlined underwriting

100 000 lives analysed

150 Application form and loyalty programme variables analysed

15 Variables predict decision with similar accuracy to 150

The outcome:

>80%

Reduction in underwriting application questions to identify standard risks

(with **<3%** error rate)

>60%

of customers qualify for streamlined uw / up-selling / cross-selling

Live campaign ongoing

Data

Generating the study dataset – data is prepared to be “model ready”

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If answered **“YES”**, sub-conditions questions left blank are missing and need to be generated as **“NO”**

If answered **“NO”**, all sub-conditions are missing and need to be generated as **“NO”**

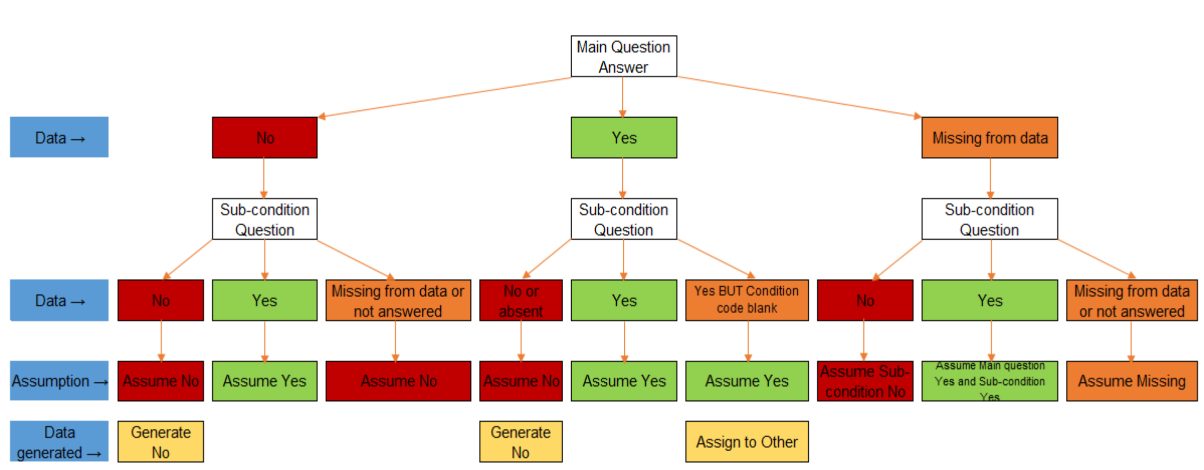
Section 4: Underwriting (continued)

G. Medical history

Do you currently or have you ever suffered from any of the following?

1. Heart or blood circulation Yes ☐ No ☐

1.1	High blood pressure ☐	1.2	Raised cholesterol ☐	1.3	Palpitations ☐
1.4	Heart attack ☐	1.5	Heart murmur ☐	1.6	Rheumatic fever ☐
1.7	Stroke ☐	1.8	Any cardiac procedure ☐	1.9	Chest pain ☐
1.10	Other ☐				



Missing underwriting data is generated using our understanding of how the client’s internal systems record application data.

Making your data “model ready”

Data

Benchmark checks

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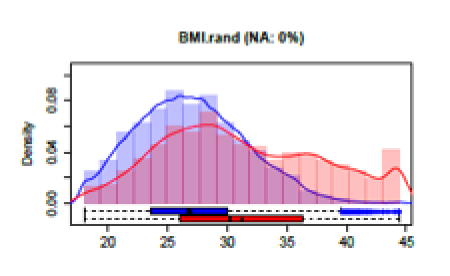
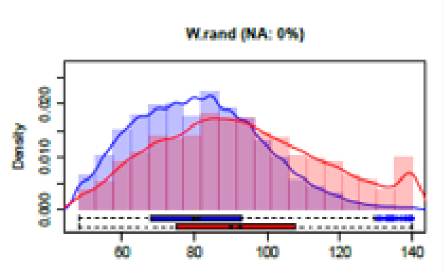
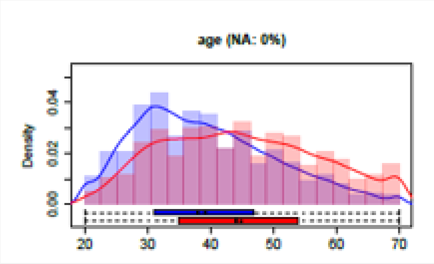
BMI



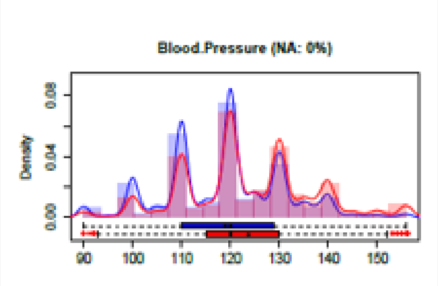
Weight



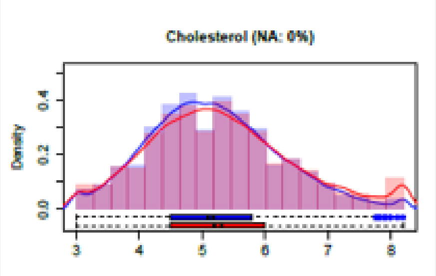
Age



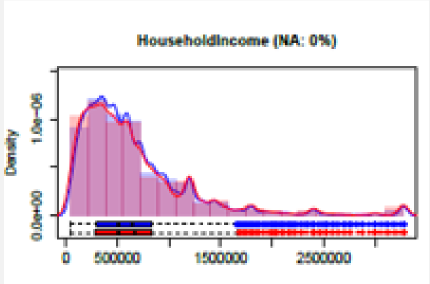
Systolic Blood Pressure



Cholesterol



Household Income



This section shows the reasonability checks of the variables and input the missing data

Model

Ranking questions based on importance for predictive underwriting decision

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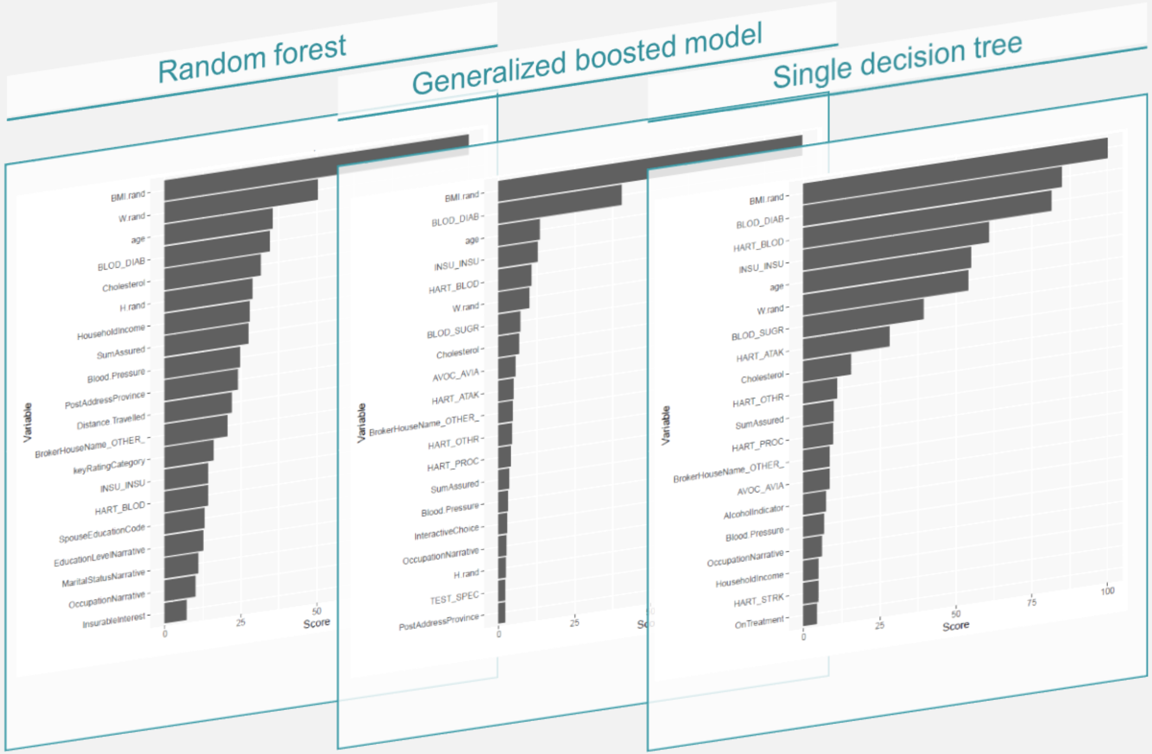


Which model is most appropriate?

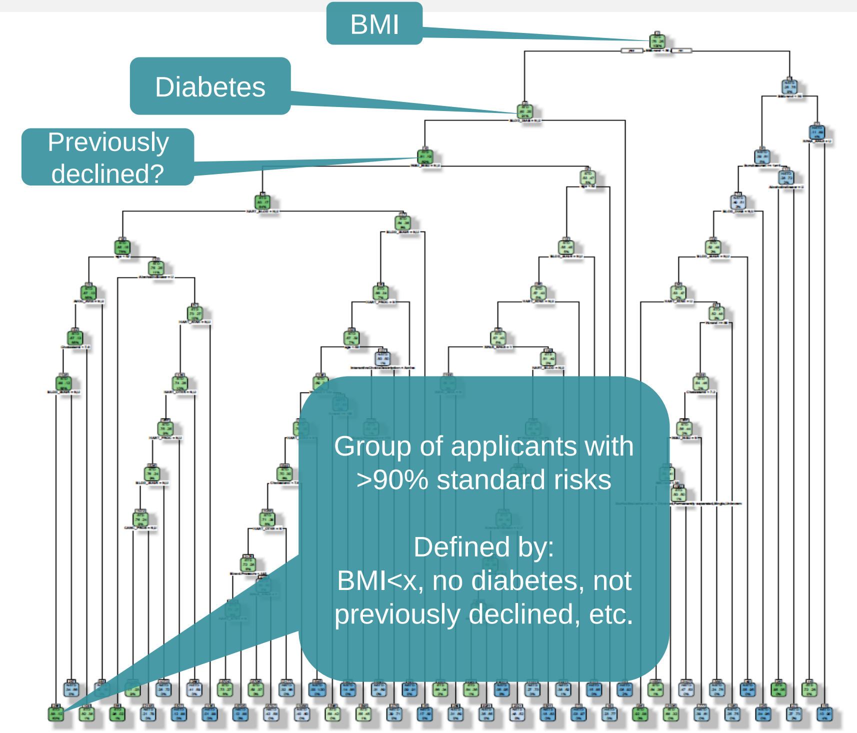
What questions are most important in making underwriting decisions?

How consistent the results across models?

Top questions include: BMI, diabetes, age, previous declines, high blood pressure, raised blood sugar

Develop proposition – Decision Tree model

identifies which customers should be targeted with GIO or SIO offers



Which group of applicants should receive standard rates with significantly less or no underwriting questions?

Decision Tree is more interpretable

Just 10 - 20 variables identify >60% of customers within which >90% are standard risks!

Develop proposition – Random Forest model

identifies which customers should be targeted with GIO or SIO offers

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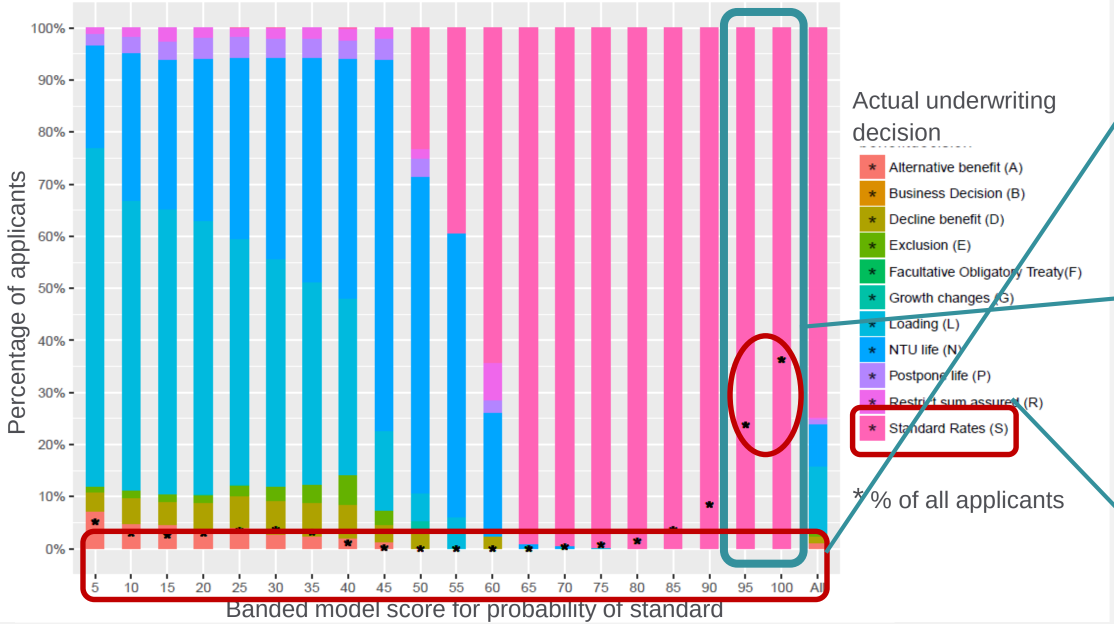
Random forest model predicts the likelihood (score) of an applicant being standard



This chart shows the comparison between the actual underwriter decision vs. predicted decision from the Random forest model:

- The horizontal "X" axis shows the predicted probability of standard within the random forest model (i.e. "90" shall mean that predicted probability of standard (y) is 86% < y < 90%).
- The black bullet point inside the bar chart indicates the volume of cases as % of all cases (i.e. if we add up the "95" and "100 which means predicted probability of standard > 90%, we could see 60% applicants meet this standard)
- For this 60% of applicants, the actual underwriting decision is 100% standard.

Insight: > 60% of applicants have a score > 90%

Application: offer customers with high scores a standard decision with significantly reduced underwriting questions

Develop proposition – potential impact to pricing

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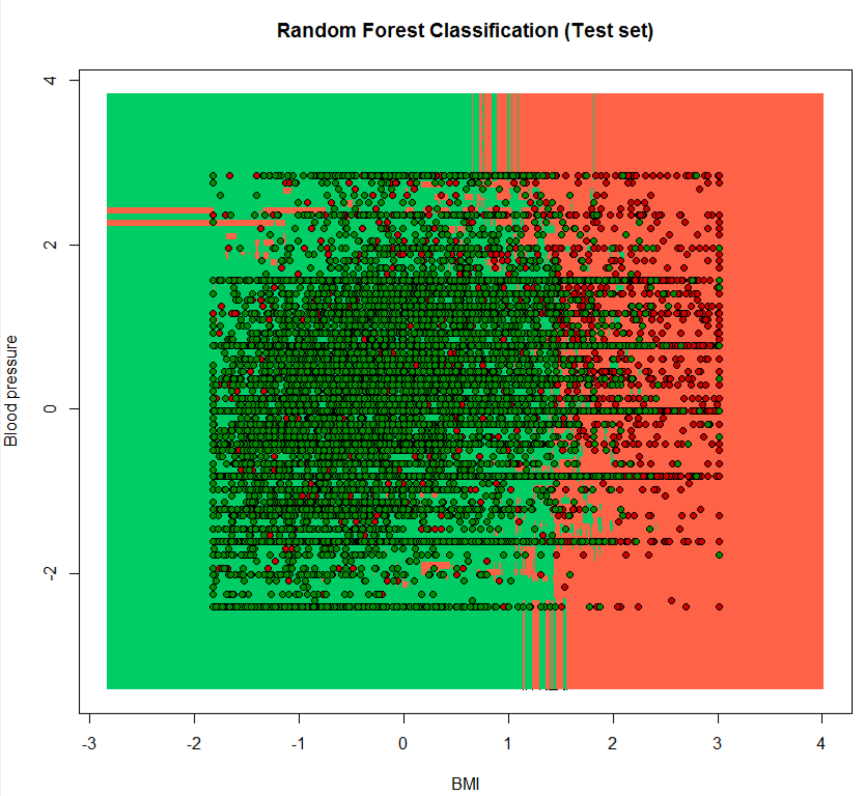

	Predicted decision	
Actual decision	Standard	Non-standard
Standard		
Non-standard	**False positive**	

- Deeper dive into false positives
- Use insights to develop knock-out questions

- Random checks to compare model to actual underwriting – no downside for client
- Specifically monitor false positives and their profile
- Relate false positive impact to pricing

Deployment

through Munich Re's cloud hosted model deployment

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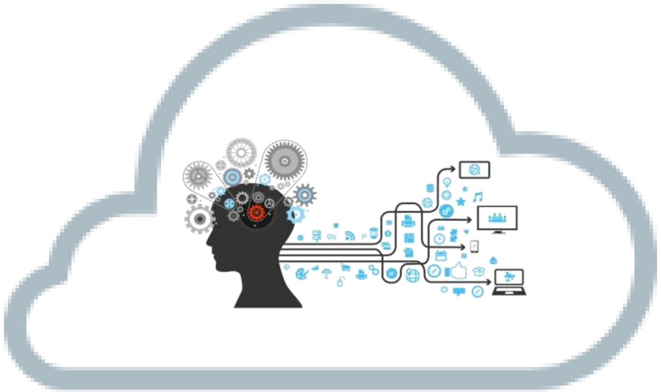
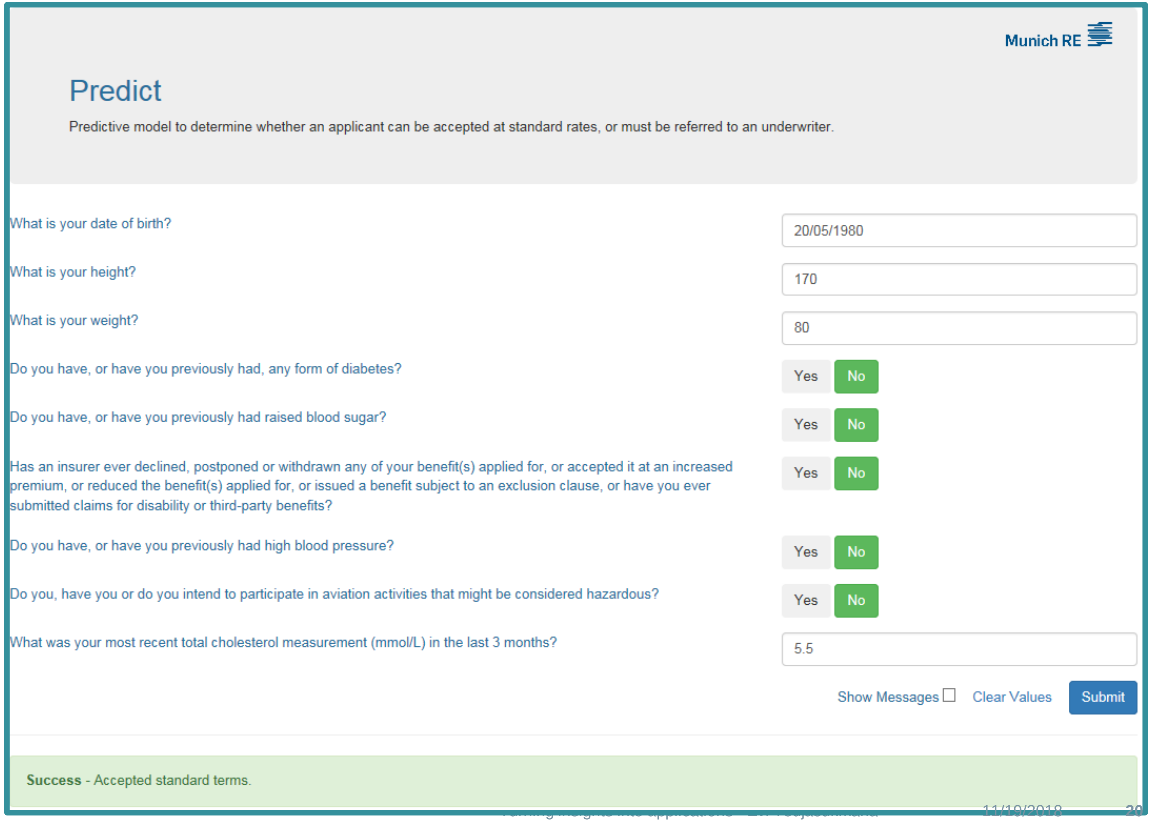
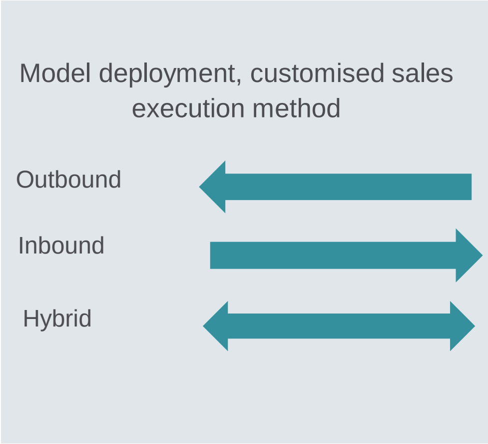
- Stand-alone solution
- Integrates with various auto-underwriting engines
- Real-time underwriting decisions





Campaign design

Customized sales execution method

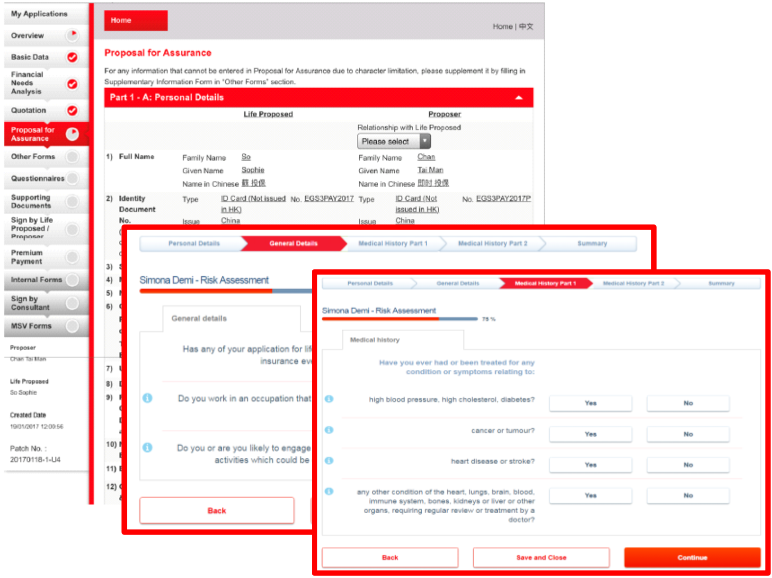


Outbound:

Pre-approve customers with offers through direct marketing channel (lower risk)

Inbound:

Open to new business based on predictive variables with offers through digital channel (higher risk)



Monitoring

Agent-driven behavior

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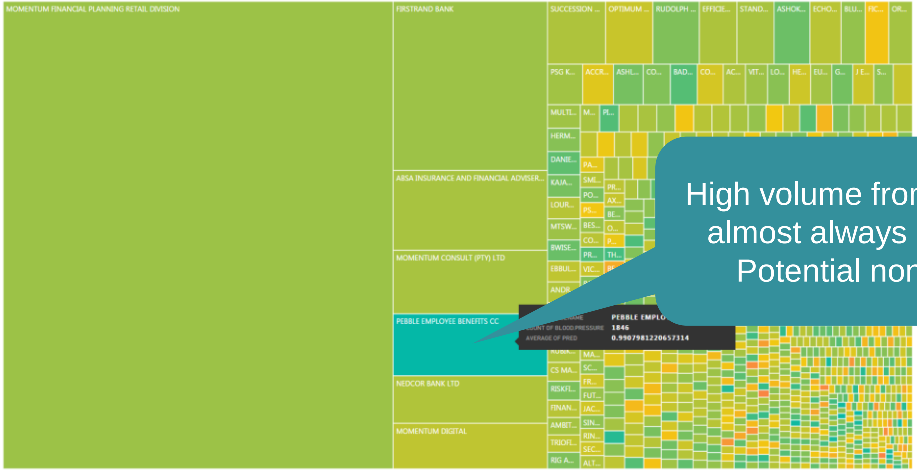
Which agents bring the lowest risks?



Which agents bring high-sum assured, high-risk cases?

Analytics can flag agents for non-disclosure and anti-selection investigations

Pre- and post customer journey

Simplifying customer journey for those who are eligible

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Before

- Many pages, 150 fields to be completed!
- Blood tests, invasive
- Lengthy
- Inconvenient

150 fields!

Really?!

After

150 fields

<20 fields - potentially from loyalty programme – no pain point for client

Best risks (standard)

Worst risks (declines)

Top X customers

Target standard rates with significantly reduced underwriting

Refer to underwriter

Rated

Referred

Declined

Case study: Dynamic Risk Calculator

2b

Underwriting and risk management

Risk categorisation at the time of policy issuance

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Our client's need:

"I want to reduce the incidence of fraudulent/early claims by identifying potentially risky profiles at the policy <u>inception</u> stage, while simultaneously offering smoother on boarding experience to low risk profiles. "

"Which profile characteristics indicate higher risk of anti-selection and fraud?
How can the process of policy issuance be seamless?"

Our approach:

- Developed a predictive model to estimate the propensity to fraud/early claim, based on the profile parameters available at the time of policy issuance (using Tree-boosting algorithm)
- Categorised policies into risk profiles.

300,000	Policies analysed
80%	Repudiated Sum Assured captured by the model
74%	Repudiated claims captured by the model
5	Risk profiles created

The outcome:

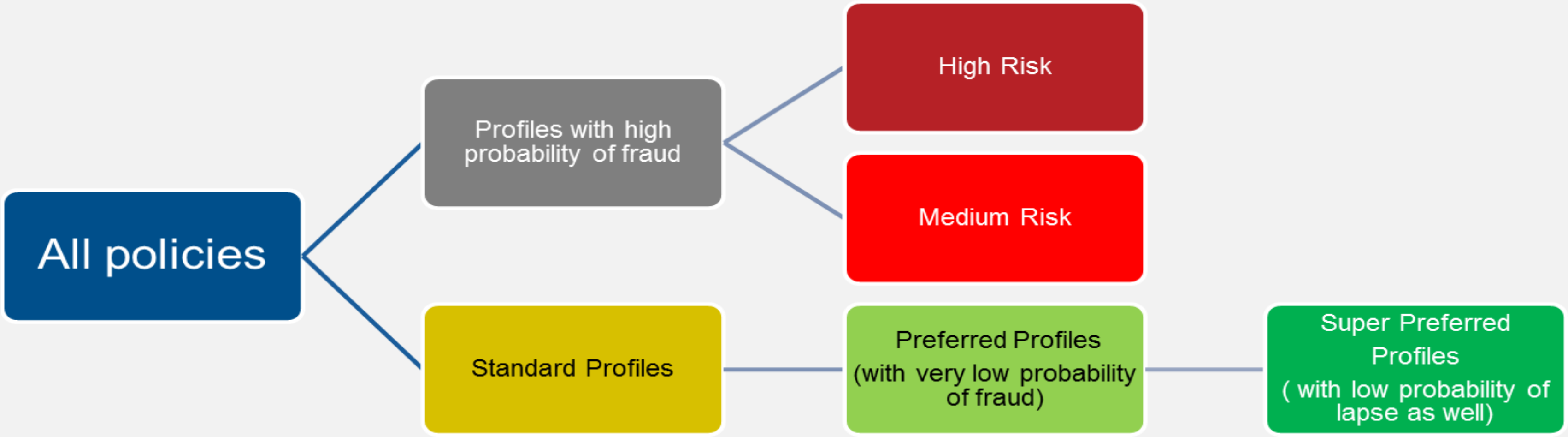
Predicted the risk profile for policies issued in the next year using the trained model

Potential reduction in claim repudiations, reducing the litigation cost and reputation risk.

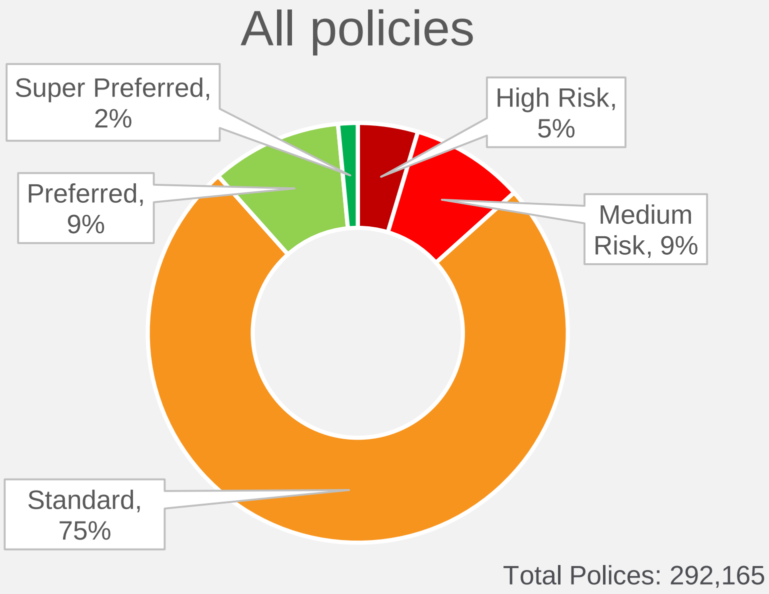
Improved on boarding experience for potentially low risk profiles.

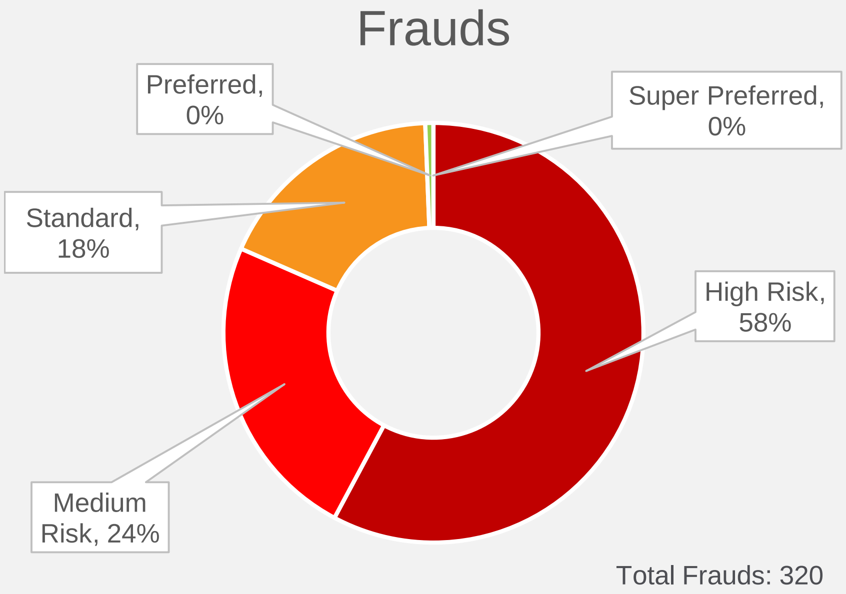
DRC (Dynamic Risk Calculator) categorization

- Each policy is assigned a profile based on the channel through which it is sourced and its predicted probabilities of fraud and lapse.
- **High risk** category represents the **poorest risk profile**, having the highest probability of resulting a fraudulent claim.
- **Super Preferred** profiles exhibit the **best risk profiles** which have least propensity of fraud as well as lapse.



Evaluating risk profiles – fraudulent claims

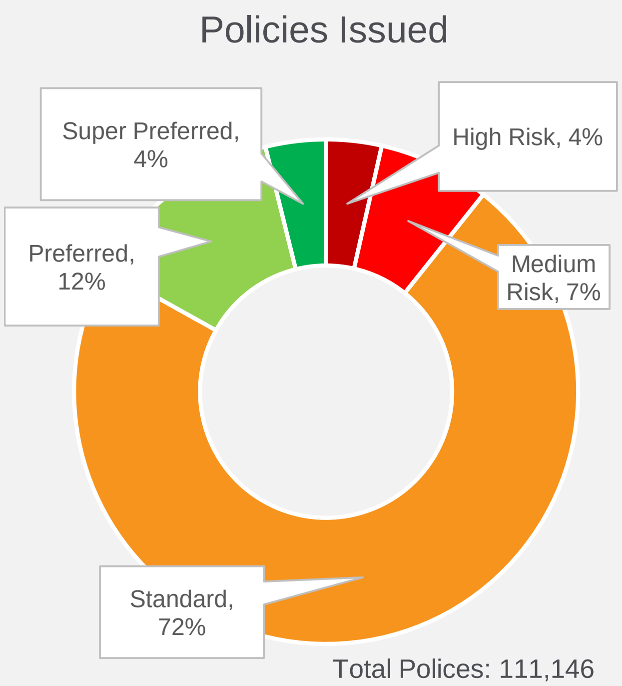


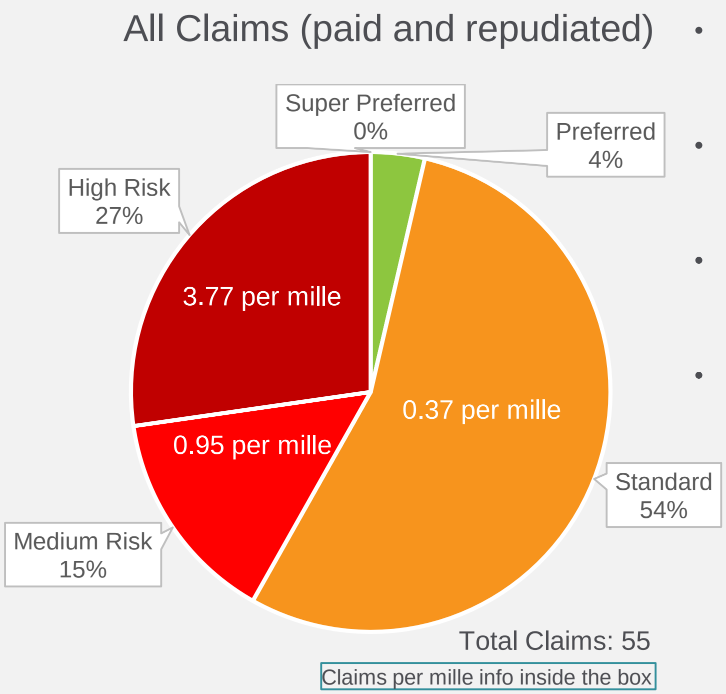


- **58%** of the fraud claims originated from the High Risk category.
- Risky profiles together constitute **14%** of the portfolio, but contribute to **82%** of the total fraudulent claims.

Assessing model effectiveness

Testing model of policies issued in 2017





- Proportion by risk profiles remain largely similar with risky profiles make up ~ 12% of total policies.
- Profiles marked as "Preferred" and "Super Preferred" did not result in any fraudulent claims.
- Out of 55 claims, 7 are repudiated: 2 / 2 / 3 from standard / medium / high risk respectively.
- The categorization allows the Company to:
  - Decide whether additional documentation is required for the risky profiles
  - Decide whether to rate or decline those risky profiles
  - Decline those with high propensity to claim

The early claims and repudiated claims experience is poor for "High Risk" profiles as expected

Summary

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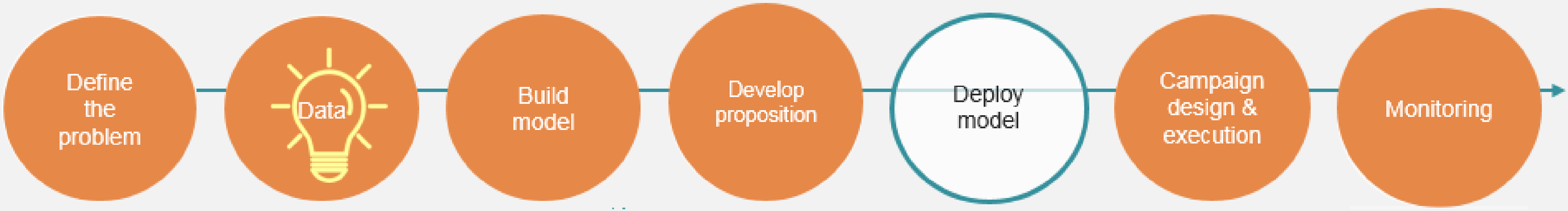
1. Creating data-driven insurance propositions



2. Case studies

- **Propensity to Buy** – *ranking potential customers based on their observed needs and / or the predicted likelihood of purchasing an insurance product*
- **Streamlined Underwriting** – *developing revised and simplified underwriting processes or guidelines by using existing data, without a negative impact on the price charged or level of risk accepted.*
- **Dynamic Risk Calculator** – *segmenting customers based on the likelihood of fraudulent/early claims at the policy <u>inception</u> stage*

Please get in touch

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“War is ninety percent information.”

Napoleon Bonaparte

“You can have data without information, but you cannot have information without data.”

Daniel Keys Moran, Computer programmer and science fiction author

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Source: McKinsey