



Society of Actuaries in Ireland

Good Practices in the Application of Predictive Analytics

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Disclaimer

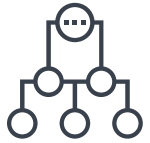
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Agenda

- Applications of predictive analytics
- SOA research objectives
- Findings from SOA survey
- Good practices for predictive modelling
- Case Study
- Q&A



Data Science and Predictive Analytics



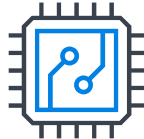
Machine Learning



Artificial Intelligence



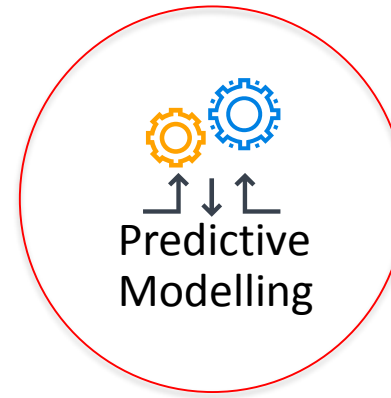
Data Collection



Data Cleaning



Data Analytics



Predictive Modelling

“The process of developing a mathematical tool or model that generates an accurate prediction”
– Max Kuhn



Resourcing and governance



Data Strategy



Business Intelligence



Applications of Predictive Analytics

Cross Selling and Discounts

- Offering discounts for purchasing multiple product types

Data Validation and Imputation

- Identifying unexpected data patterns & dealing with missing data

Quotations and Pricing

- Deriving better rating factors and asking fewer u/w questions

Model Validation

- Forecasting future exposure in internal model

Customer Behaviour

- Identifying key drivers of option take-up, fund switches, lapses, etc.

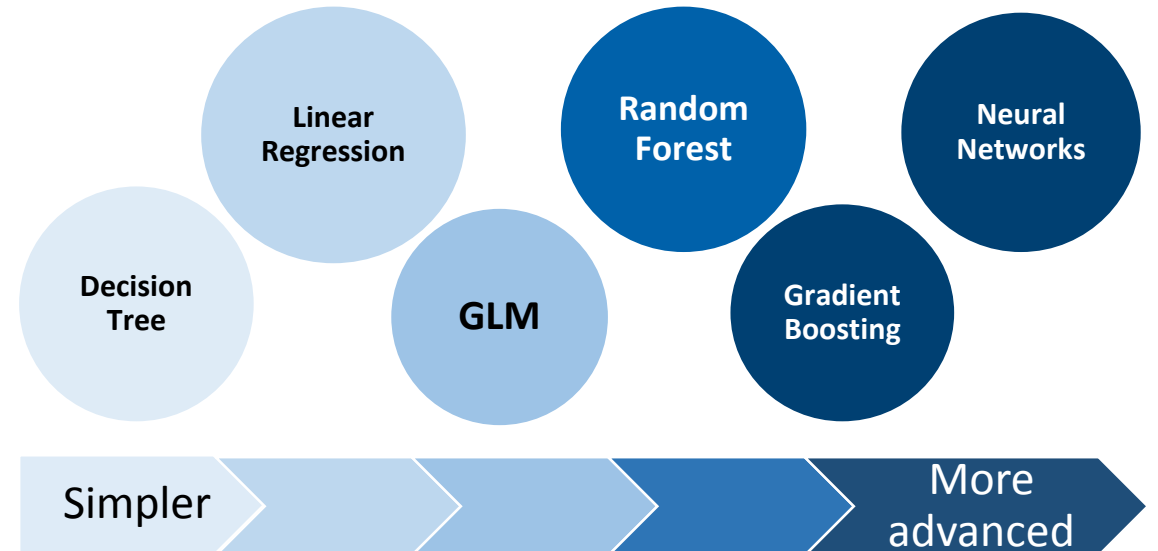
Inforce Management

- Creating behavioural profiles for distinct customer segments

Programming languages

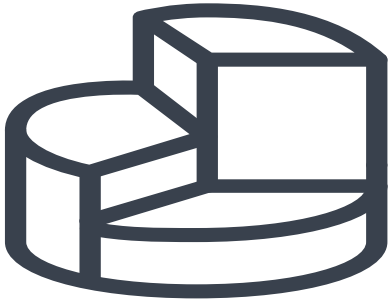


Data Science Tools





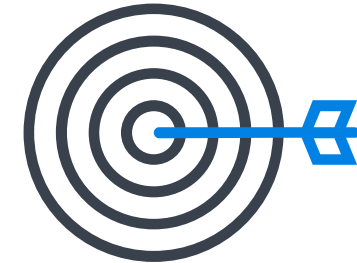
SOA Research Objectives



Survey: Capture leading practices among industry participants



Literature review: Research sources internal and external to life insurance



Considerations: Distill findings into areas to specifically address



Case study: Demonstrate leading practices via a case study



Survey Design

- SOA Survey
 - Predictive Analytics
 - Approx. 150 Responses from SOA members
 - Focused on
 - Business applications
 - Data acquisition and preparation
 - Algorithm and software selection
 - Model evaluation, implementation and governance
- Milliman Irish Client Survey
 - Data Science
 - 22 Irish-based life and health insurers and reinsurers
 - Focused on
 - Overall data science strategy
 - Data collection
 - Process and technical application
 - Resourcing and governance
 - Benefits and challenges



Key Findings

- SOA Survey

- No standardised approaches to applying predictive analytics techniques
- Wide variety of applications of predictive analytics
- Business/domain knowledge is very important at a number of stages
- Simplicity and transparency are key determinants in algorithm selection
- R is the leading language used
- Work to do on model governance

- Milliman Irish Client Survey

- Over 75% expect to be using data science within the next 3 years, with over 35% already making it a point of focus
- Most common uses of data science right now involve either assessment of customer behaviour or assumption setting
- Biggest challenges facing companies involve a lack of infrastructure and technology, cyber risks, regulatory expectations, a shortage of talent, data quality, and access to data



Business Applications

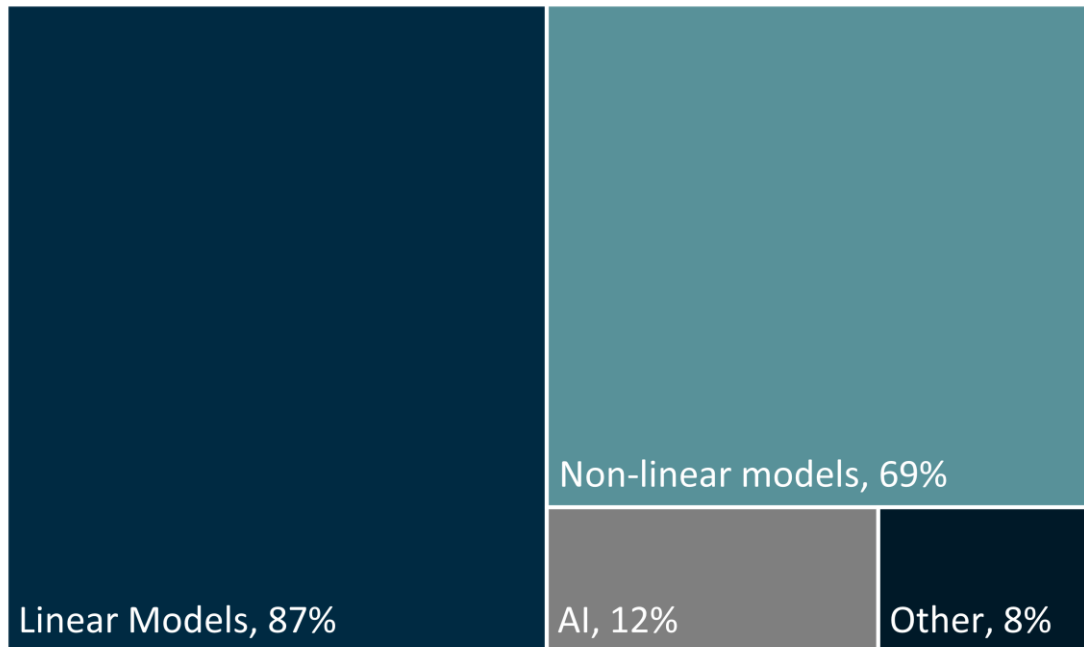
AREA	SOA STUDY		IRISH SURVEY	
Actuarial	Pricing	51%	Actuarial assumption setting	32%
Risk	Underwriting	33%	Monitoring for fraud	27%
Operations	Claims	32%	Optimising operational processes	27%
Customer Service	In-force management	24%	Understanding customer behaviour	41%
Compliance	Compliance	0%	Ensuring compliance standards	14%
Other	Other	8%	Other	14%

- Milliman – For which business decisions or applications is Data Science used at your company?
- SOA – To which of the following business areas have you applied predictive modelling?

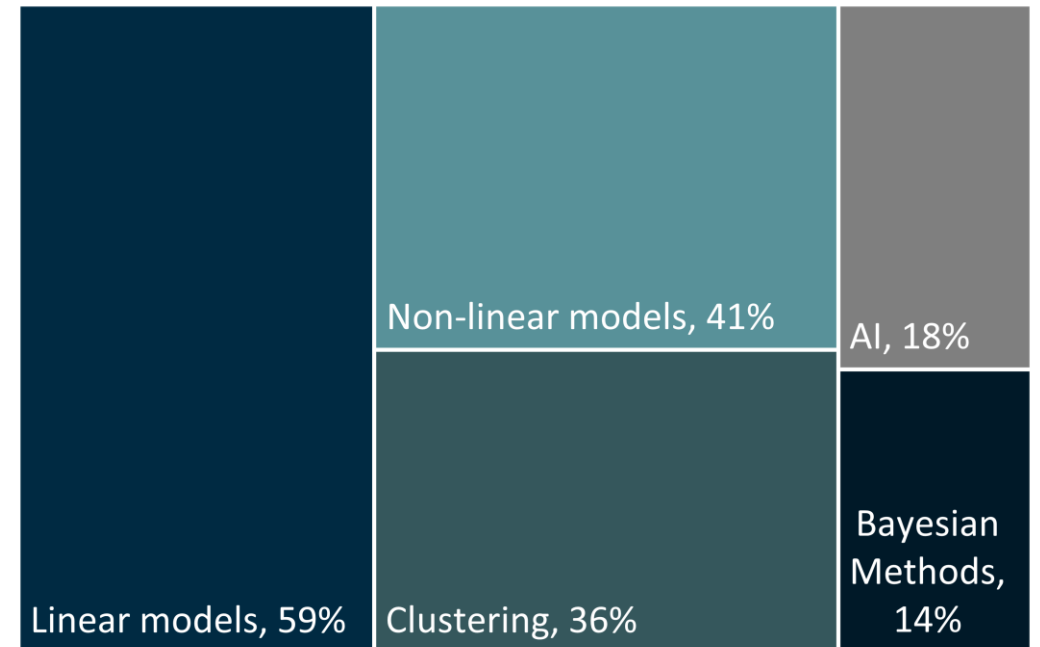


Techniques

- SOA – which technique(s) do you use for predictive modelling?



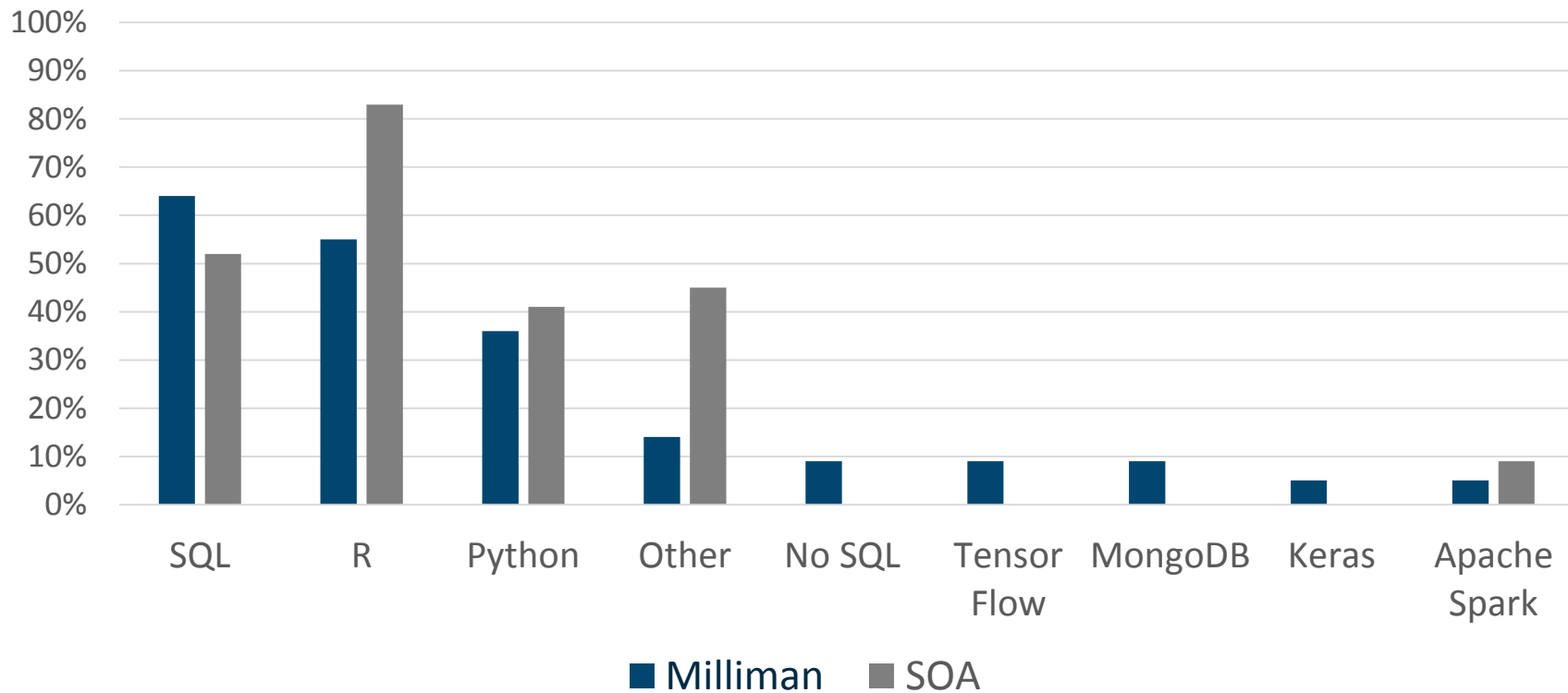
- Milliman – which of the following types of tools or techniques have you used in the application of Data Science (or plan to use in the next 3 years)?





Software Selection

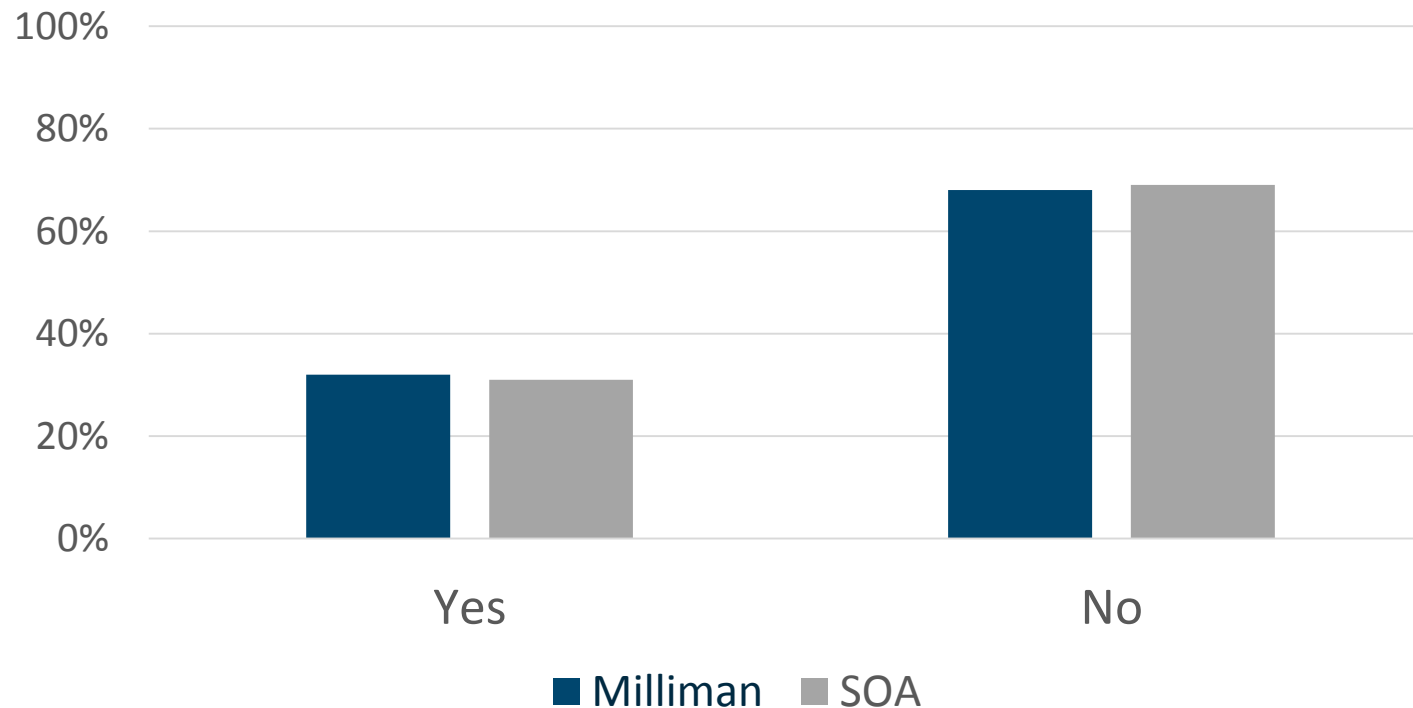
- SOA – What software/language(s) do you use for predictive modelling?
- Milliman – Which of the following types of tools or techniques have you used in the application of Data Science (or plan to use in the next 3 years)?





Governance

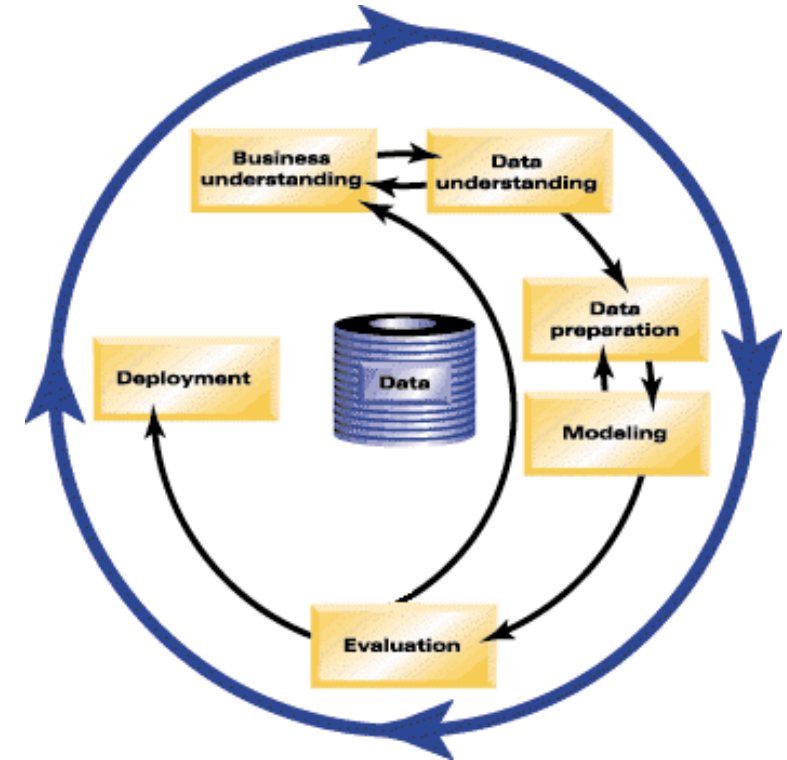
- SOA – Does your company have a modelling governance framework for your predictive modelling work?
- Milliman – Does your organisation have internal standards governing the use of data science?





Areas of focus

- Project objective
- Data acquisition and preparation
- Algorithm selection
- Feature engineering and selection
- Model evaluation and measurement
- Model deployment
- Model governance
- Software selection



Cross-Industry Standard Process for Data Mining (CRISP-DM)
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**Project
objective**



Project objective

- **What are the primary business objectives?**
- How will this provide value to the business and to the customers?
- What are the specific modeling objectives?
- **What is the organizational context?**
- What data will be needed?
- Are there existing limitations to accessing and using the data?
- What resources are available?
- What is the contingency plan for unexpected delays?
- How do we define and measure the model's success?
- What is the end state?

**Data
acquisition
and
preparation**





Data acquisition and preparation

- **What data is available internally and externally?**
- Who will gather the data? Depending on the breadth of data sources, this may be one for several people.
- Where will the data be stored once acquired and how will it be accessed?
- What issues and challenges are anticipated, and what is the plan for addressing them?
- What checks can be automated?
- **What will happen if the person familiar with the data leaves the company or the team?**
- What will happen if the data warehouse or underlying data source changes?
- How will the team handle data security, HIPAA compliance, General Data Protection Regulator (GDPR) and other confidentiality requirements?

Algorithm selection





Algorithm selection

- What is your methodology for selecting an algorithm?
- What are the pros and cons of your candidate and selected algorithms?
- Does your selection fit within requirements of stakeholders?
- **Will your chosen algorithm allow you to maximize predictive accuracy relative to requirements for interpretability?**
- **How will you identify and document limitations? How will you effectively communicate them to other stakeholders and model users?**



Feature engineering and selection



Feature engineering and selection

- What is your plan for feature engineering?
- **What steps can you take before feature selection to ensure a smooth process?**
- What is your plan for addressing collinearity of variables?
- **What method will you use for feature selection?**
- What limitations are implied by regulatory, legal, or privacy considerations?
- How will your model evaluation plans affect the preparation of your modeling data?
- How will you verify that the data support your assumptions about the underlying relationships between features and the response, e.g., linearity?
- How will you identify and document limitations?

Model evaluation and measures of success





Model evaluation and measures of success

- How will you ensure you do not overfit the model, balancing the bias-variance trade-off?
- **What metrics will you use to evaluate the relative performance among your candidate models?**
- What visualizations will you use to evaluate the relative performance among your candidate models?
- Will you address credibility of the model predictions, and if so, what measures of credibility will you use?
- Do the training and testing data sets reflect a diversity of scenarios?
- What other considerations will help you choose between models?
- How will you measure the performance of the model in production?
- What are your business measures of success?
- **How will you communicate the value and limitations of your model to all stakeholders?**

Model deployment





Model deployment

Implementation

- How will you document the model and associated assumptions to communicate to users?
- Will all the data required by the model be available once it is deployed?
- **How will the model be operationalized?**

Validation

- How will you check that the model is performing as expected? How frequently will these checks be done?

Updates

- How often or under what circumstances will you retrain the model on updated experience?
- How will you recognize and handle new data that implies the conditions under which you originally fit the model are changing?
- **If you find an error in your modeling process, how will you implement a fix to the model in production?**

Model governance





Model governance

- Will your predictive models be recorded in your company's model inventory?
- **How does your predictive model fit into your company's model governance policy?**
- How will you work with IT on data governance and establish a balance of responsibility and information sharing?
- How will you approach version control to ensure that no unintended changes make their way to the end user?
- **If you are just getting started, what is a minimum requirement for model governance based on the risk level of the model, and what is your plan for improving governance in the future?**
- Who will be responsible for each portion of model governance?
- How will you audit compliance with your model governance policy and procedures?
- How will the risks and/or limitations of your model be communicated?

Software selection

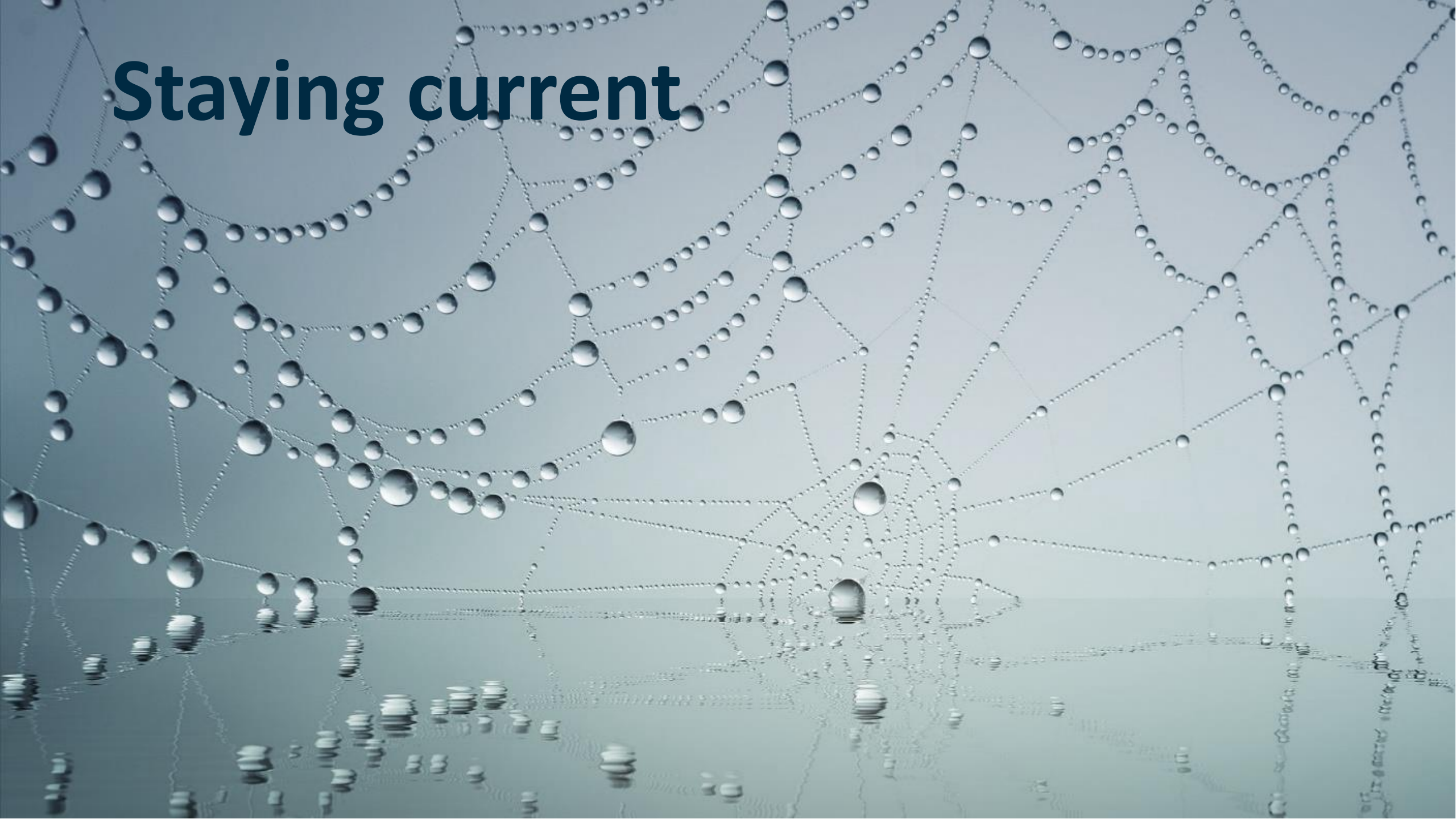
```
20 <?php language_attributes(); ?>
21 </html>
22 <meta charset="<?php bloginfo( 'charset' ); ?>" />
23 <meta name="viewport" content="width=device-width" />
24 <title><?php wp_title( '|', true, 'right' ); ?></title>
25 <link rel="profile" href="http://gmpg.org/xfn/11" />
26 <link rel="pingback" href="<?php bloginfo( 'pingback_url' ); ?>" />
27 <?php fruitful_get_favicon(); ?>
28 <!-- [if lt IE 9]><script src="<?php echo get_template_directory_uri(); ?>/js/html5.js"></script></if-->
29 <?php wp_head(); ?>
30 </head>
31 <body <?php body_class(); ?>
32 <div id="page-header" class="hfeed site">
33 <?php
34 $theme_options = fruitful_get_theme_options();
35 $logo_pos = $menu_pos = "";
36 if (isset($theme_options['logo_position']))
37 $logo_pos = esc_attr($theme_options['logo_position']);
38 if (isset($theme_options['menu_position']))
39 $menu_pos = esc_attr($theme_options['menu_position']);
40 </?php
41 </div>
42 </body>
43 </html>
```



Software selection

- **Core competency: Do you want to build your software solution, or do you prefer to purchase an application or framework that does not require programming?**
- Cost: What is your budget, and what is the scope of the project?
- Analytics: What predictive modeling capabilities will you need?
- Visualization: How do you want to deliver your data, models, and results? Who will want to view them? How interactive does the delivery mechanism need to be?
- Other: Processing speed and distributed computing, cross-functionality, client or stakeholder standards, availability of support for software, **existing knowledge within company or modeling team, ability to hire additional qualified practitioners**

Staying current

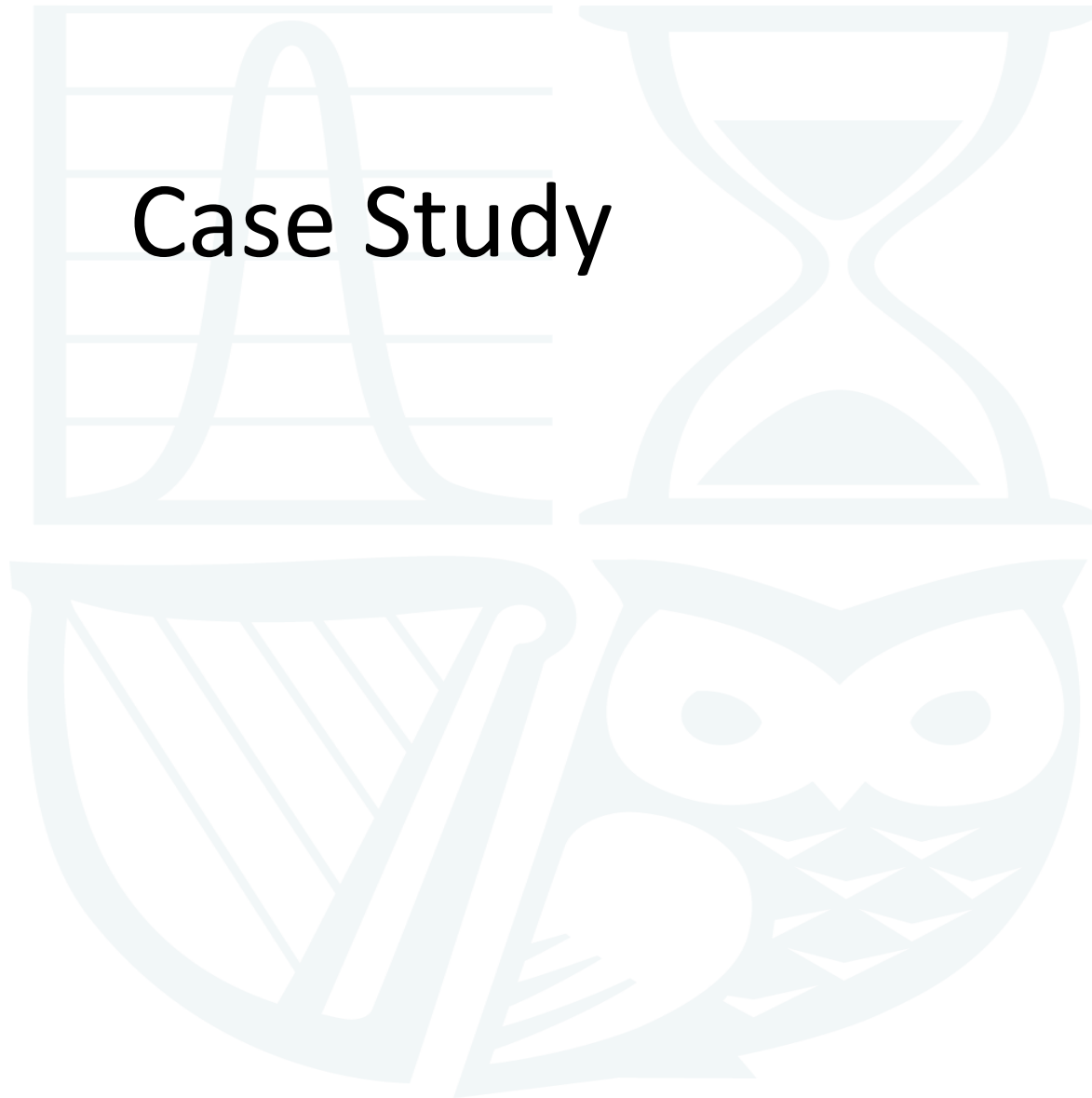




Staying Current

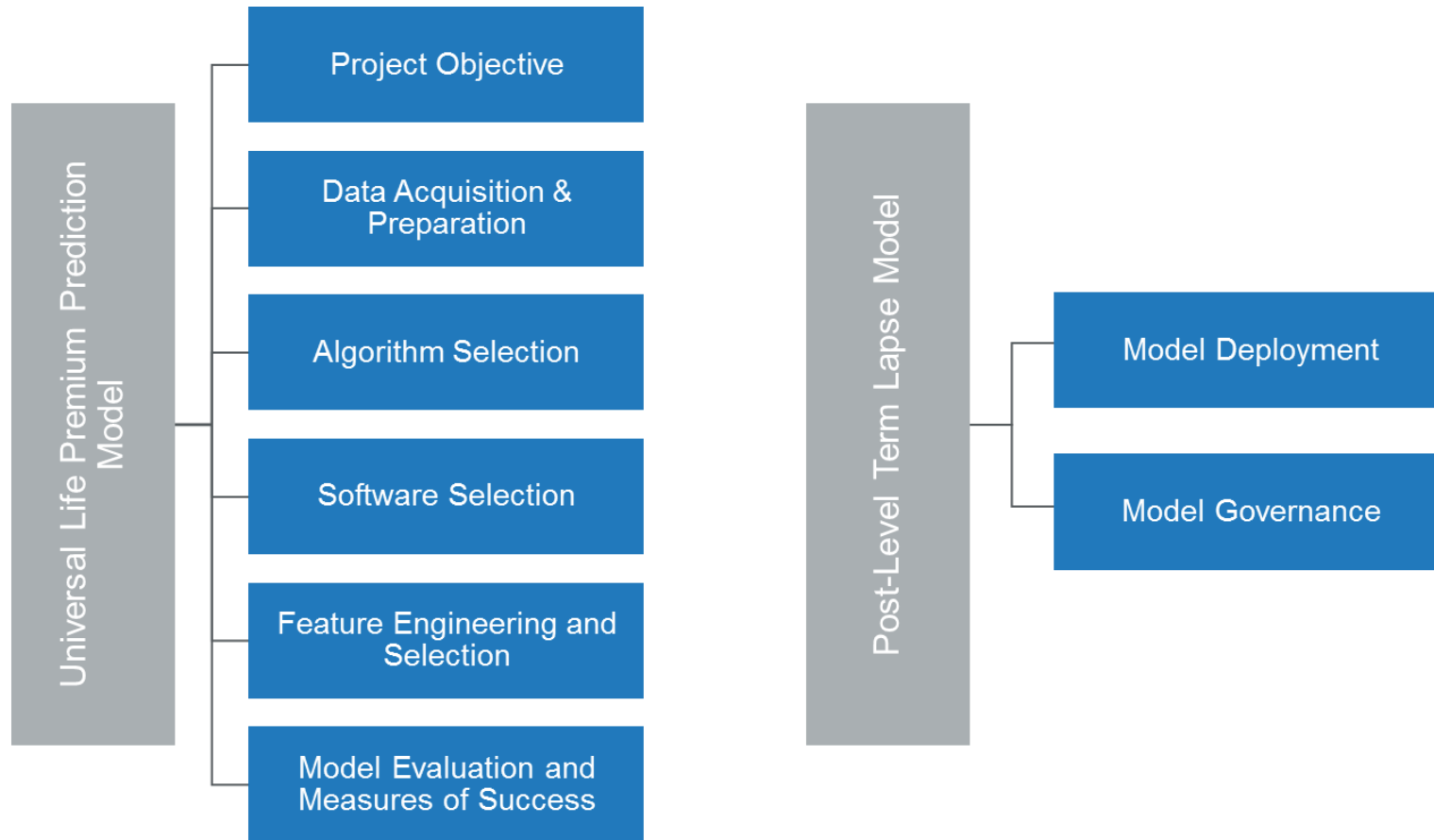
- Web resources
- Social media
- Community
- SOA Predictive Analytics and Futurism Section!

Case Study



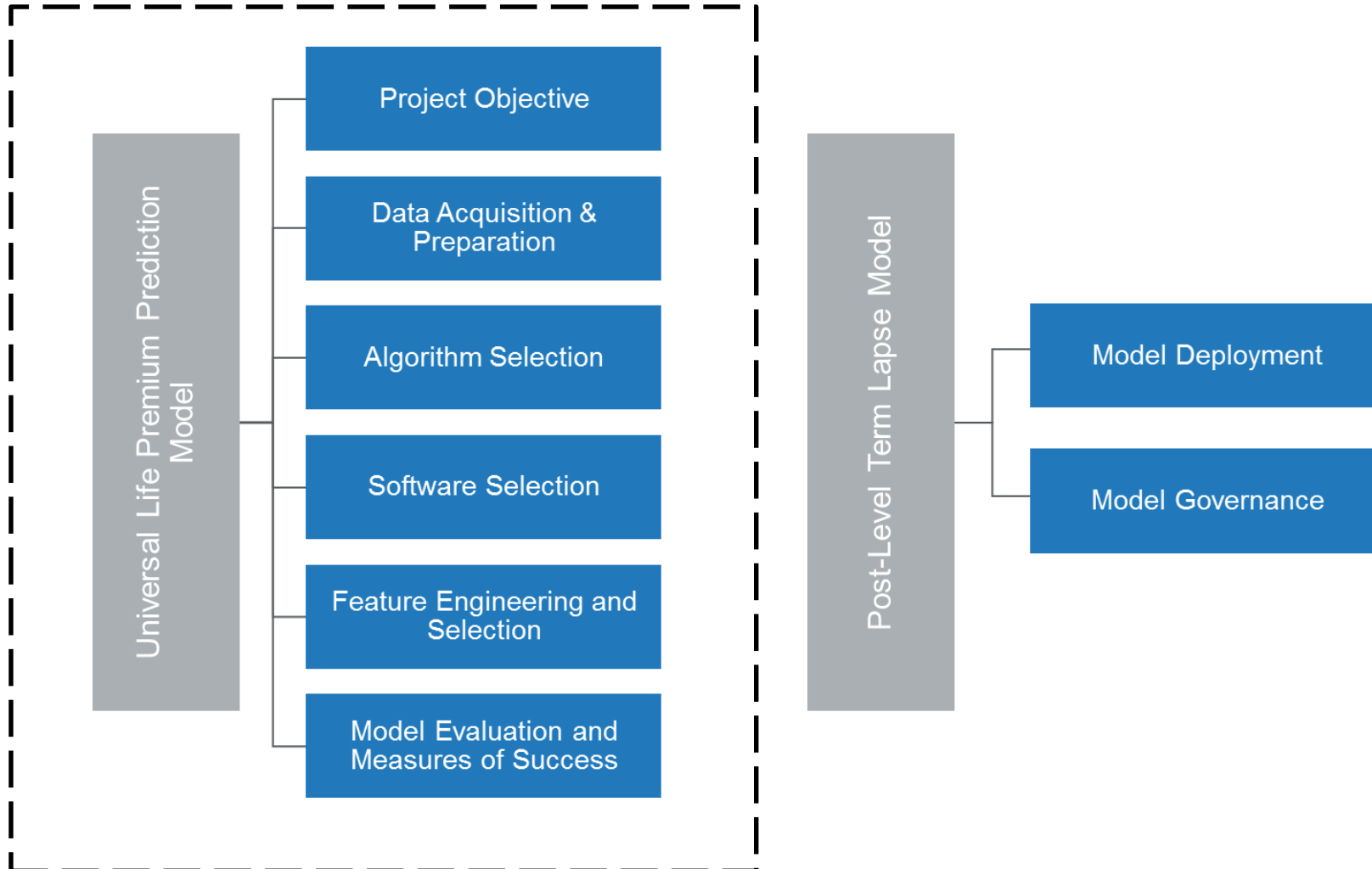


Case study structure





Case study structure





Project objective

- Predict a policyholder's premium payment amount for the next month on a universal life (UL) policy
- Eventually, predict monthly payment patterns several years in advance



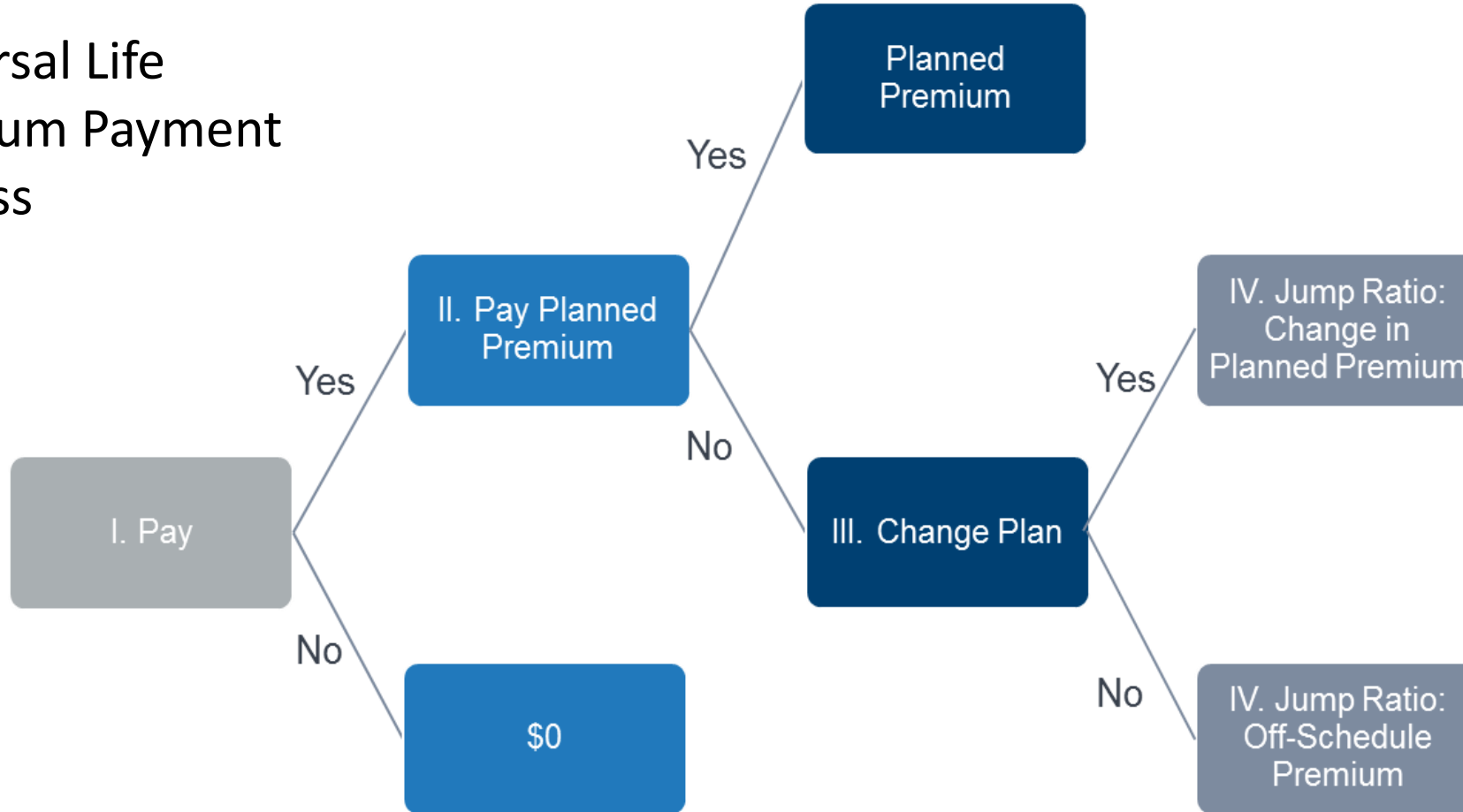
Data acquisition and preparation

- Three data stores:
 - Legacy data store
 - Current data warehouse
 - Reserving data warehouse
- Reconciliation:
 - Data stores reconciled against each other
 - Data set reconciled against official policy system



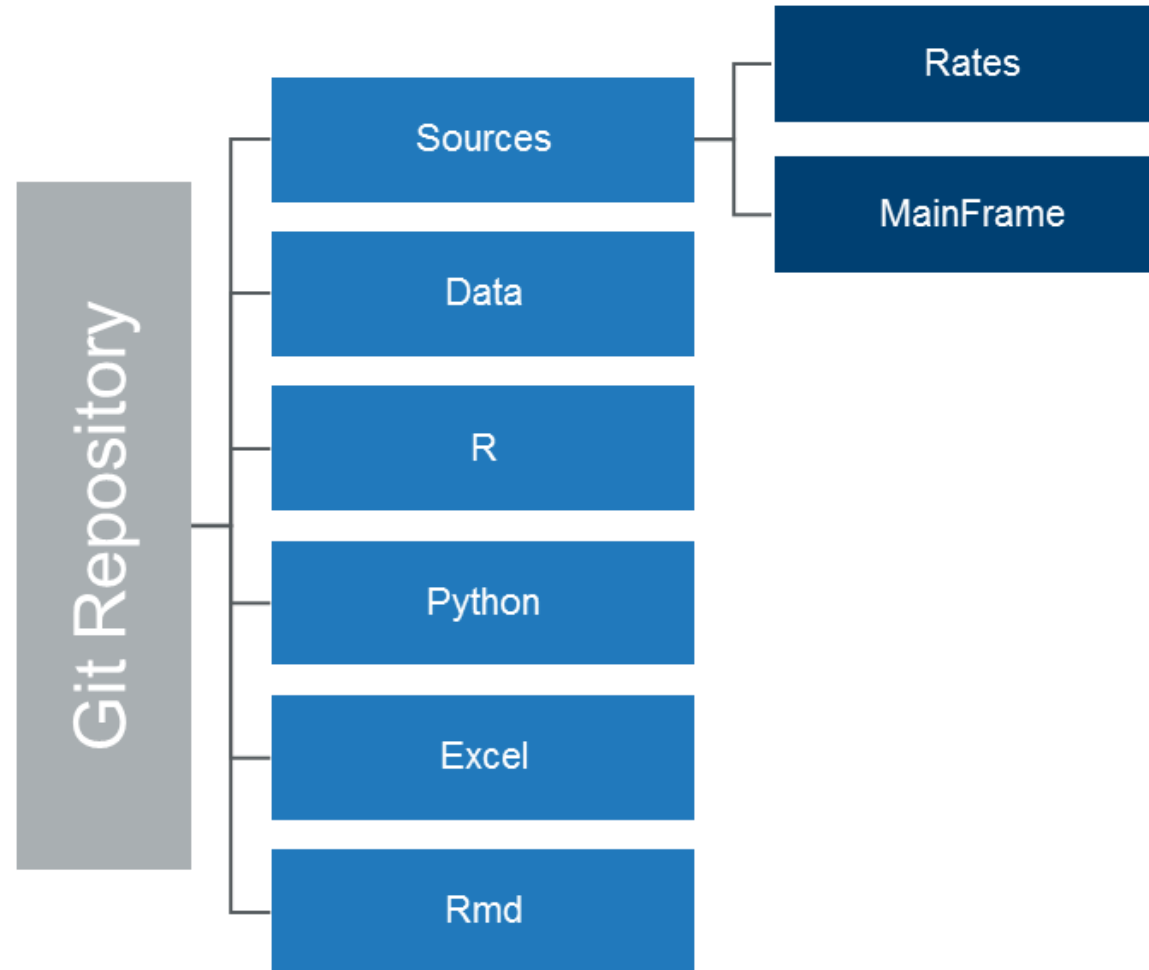
Algorithm Selection

Universal Life Premium Payment Process





Project structure





Feature engineering and selection

Base Model: $P(\text{Pay}) = 1/(1+\exp(-\eta))$, $\eta = 1.710445$. Negative log-likelihood: 1,540,701.

Model 1: $P(\text{Pay}) = 1/(1+\exp(-\eta))$, $\eta = 1.66682267 + 0.00038814 * \text{Funded_Ratio}$. NLL = 1,539,993.

Coefficients	Estimate	Standard Error	P-Value
(Intercept)	1.66682267	0.00186506	< 2e-16
Funded_Ratio	0.00038814	0.00001054	< 2e-16

Model 2: $P(\text{Pay}) = 1/(1+\exp(-\eta))$, $\eta = 1.3307445 + 0.0977192 * \log(1+\text{Funded_Ratio})$. NLL = 1,535,759.

Coefficients	Estimate	Standard Error	P-Value
(Intercept)	1.3307445	0.0039985	< 2e-16
log(1+Funded_Ratio)	0.0977192	0.0009758	< 2e-16

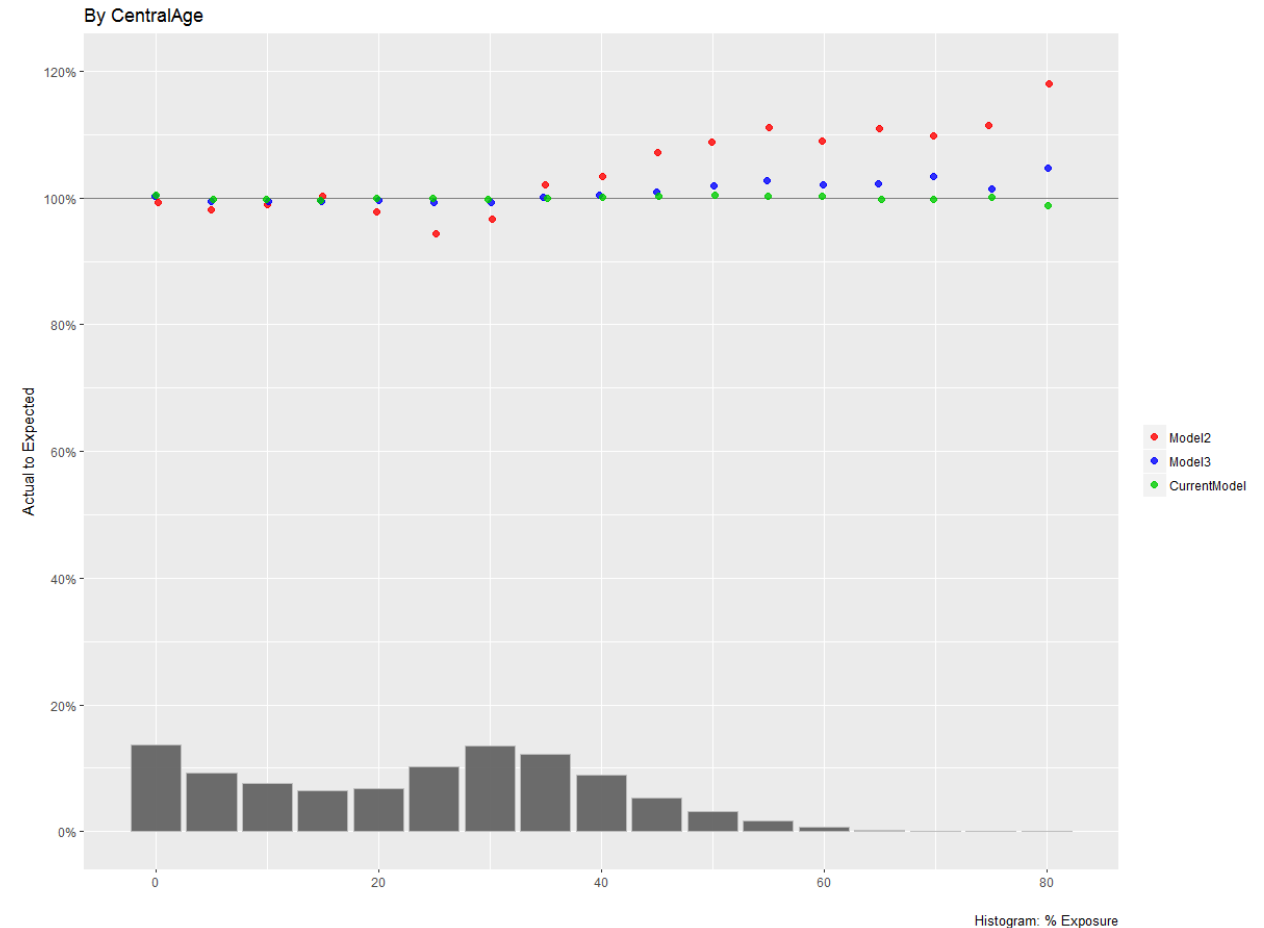
$\eta = 1.331047 + (-0.266503 - 0.993250 I_{NP} + 0.923363 I_{RP}) * \log(1+\text{Funded_Ratio})$. NLL = 556,227

Coefficients	Estimate	Standard Error	P-Value
(Intercept)	1.331047	0.005407	< 2e-16
log(1+Funded_Ratio)	-0.266503	0.001765	< 2e-16
StateNP:log(1 + Funded_Ratio)	-0.993250	0.002858	< 2e-16
StateRP:log(1 + Funded_Ratio)	0.923363	0.001721	< 2e-16



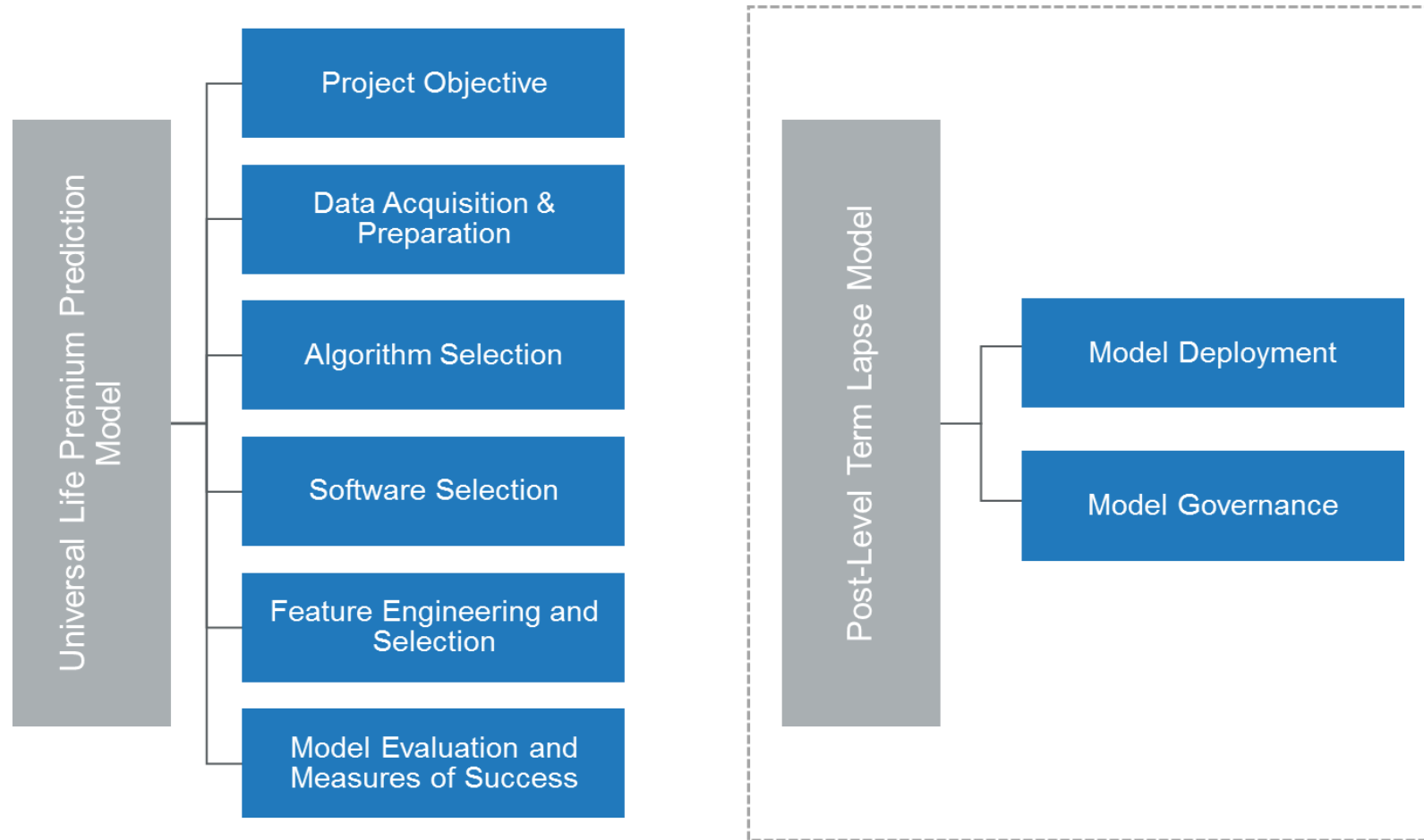
Measures of success

- Actual vs. Expected
- Mean Absolute Percentage Error (MAPE)





Model in production





Model deployment

- Model implemented in company's projection platform
- Company has a dedicated deployment team consisting of programmer actuaries



Model governance

- Model Assumptions Committee
- Executive Finance Committee
- Model Oversight Committee



Model governance

- Model Assumptions Committee
- Executive Finance Committee
- Model Oversight Committee



Questions?

