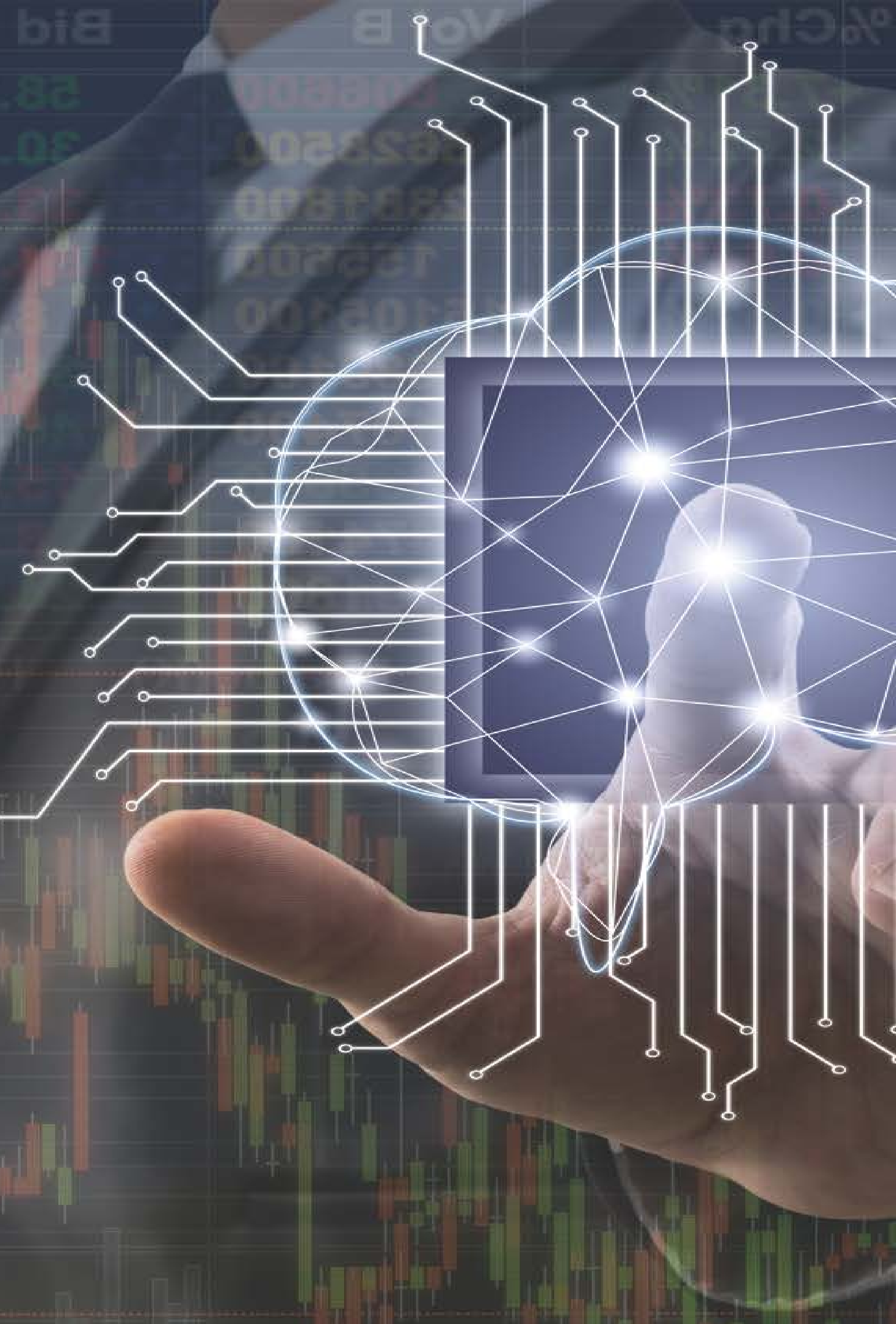
KPMG

A Paradigm Shift in Insurance Analytics



AI Modeling with Micro-Segmentation (AIMS)

Midwest Actuarial Forum

March 2021

Introductions

Ian Sterling
Managing Director
M: +1 856 912 7242
E: isterling@kpmg.com

Ian is a Managing Director in the KPMG actuarial practice with almost 19 years of experience in the industry working with a variety of domestic and international property and casualty carriers. In addition, he has led multiple innovation and transformation projects.

Nate Loughin
Director
M: +1 610 348 5126
E: nloughin@kpmg.com

Nate is a Director with KPMG in the P&C Actuarial Practice, specializing in predictive analytics, large account pricing, and E&S Reserving and Operations.

Disclaimer

Note that the views expressed today are those of the presenter, and don’t necessarily represent the views of KPMG, the CAS, or the sponsors of this conference.

Agenda

The case for change

Issue: A Paradigm shift in insurance analytics

Insurers' current state:

- Rapidly changing insurance market with Insurtech and disruptive technology
- Need to reduce expenses and quote times, improve risk selection, increase speed to market, product flexibility
- Exploring artificial intelligence and machine learning to remain competitive and increase margins
- Siloed tools hinder cross-sharing of augmented intelligence across underwriting, claims, actuarial, and finance

Insurance industry's challenge for modernizing:

- Lifting traditional analytical modeling to a more granular claim and exposure level approach through micro-segmentation requires resources and time to build. Implementing these new analytics is challenging due to competing priorities, manual processes, and older non-automated tools.

Business issue

The winners are those that are continuously moving forward.

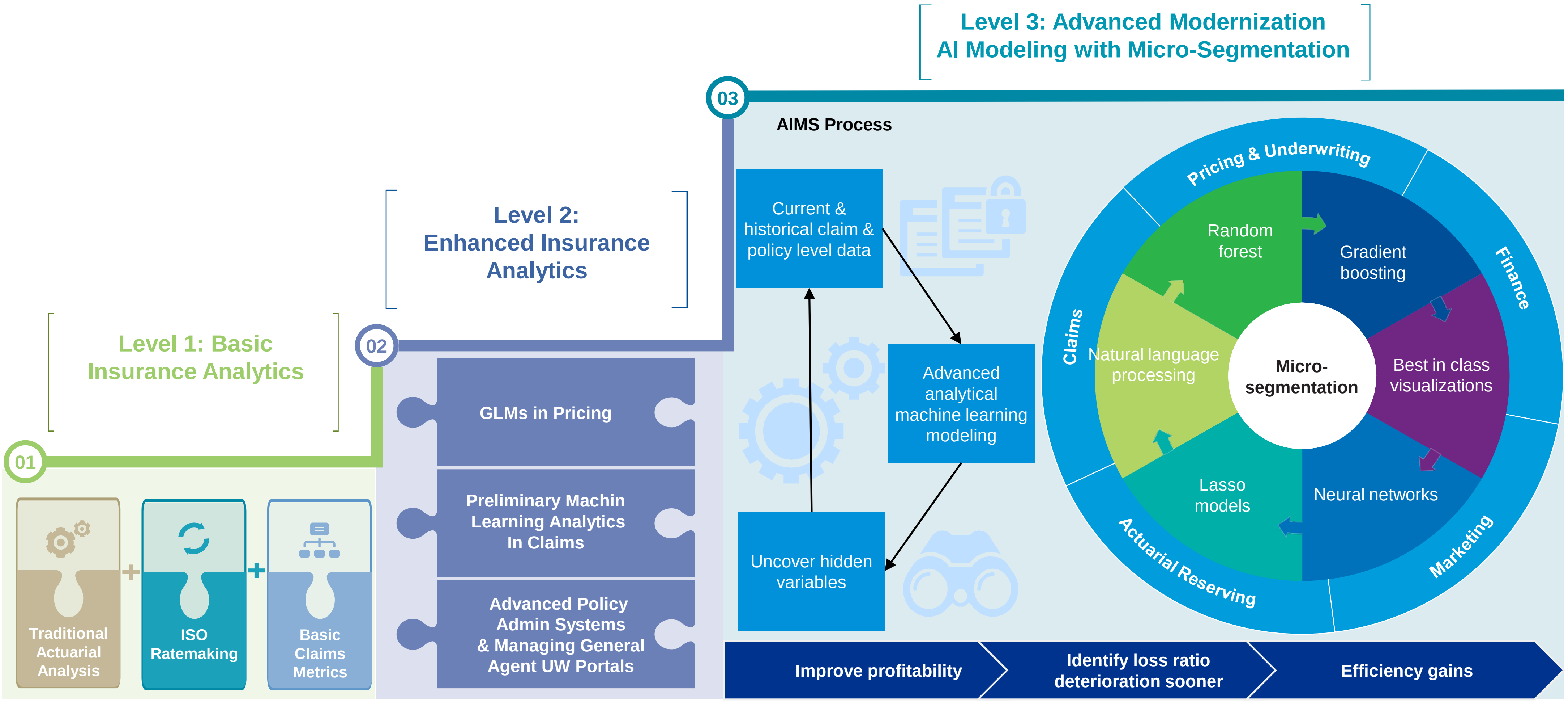
Clear winners are those that

- Best utilize data to drive insights for improved risk selection
- Execute efficiently to reduce wasted costs
- Move insight to action to bring the right product to the right customer
- Align across the organization for coordinated, responsive actions
- Optimize operations to increase speed to market

If you don’t act now

- How will you remain competitive against peers and those with scale?
- How will you explain to the board or the street actions being taken to advance the organization?
- How will you increase profitability – lower loss and/or expense ratio?
- How will you avoid being a victim of aggressive M&A activity?
- How will you remain flexible and best positioned to consistently adapt?

The changing analytics landscape

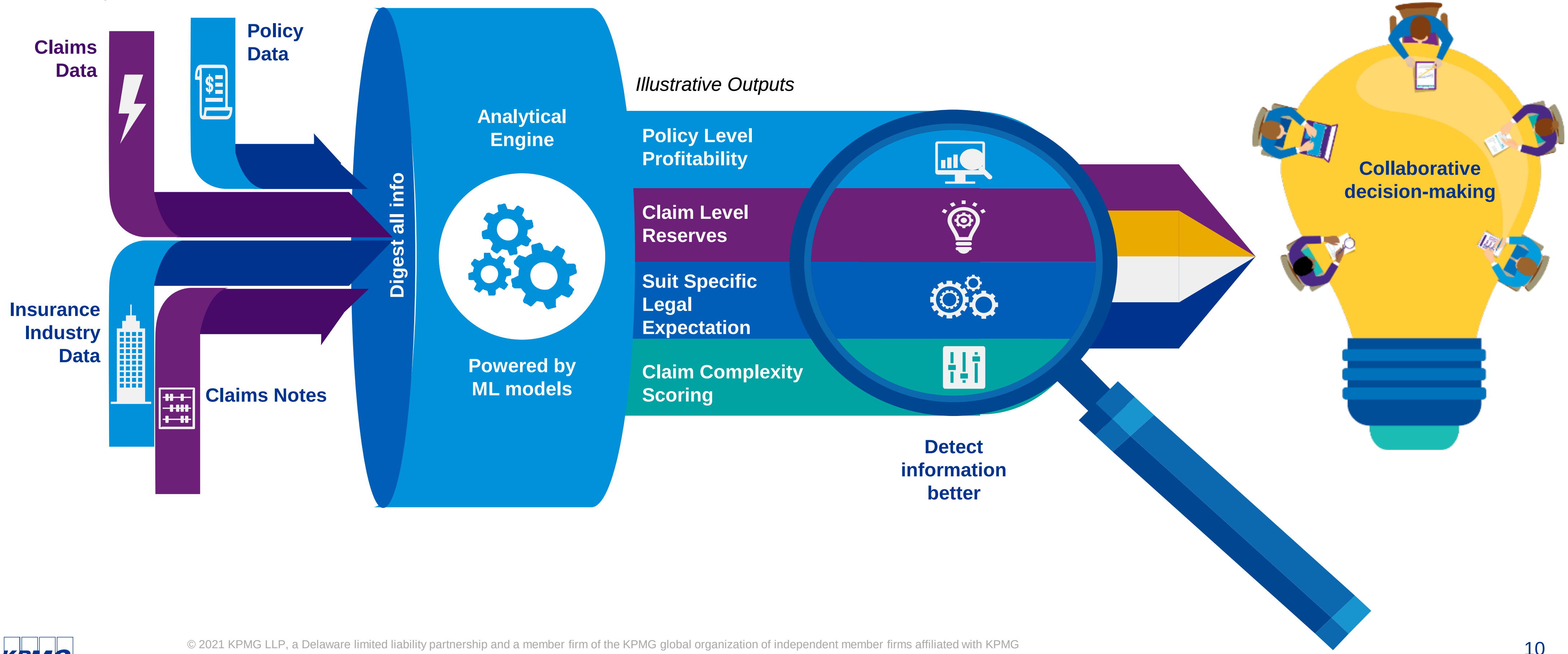


Driving Value with Micro-Segmentation

What is Micro-Segmentation?

Granular modeling using advanced statistical models can help create a single view of profitability across Claims, Underwriting, Finance, and Actuarial

Illustrative Inputs



Case Study

When a major property and casualty insurance carrier experienced significant deterioration in one of its books of business, an investigation led to antiquated actuarial approaches that caused slow response times and ongoing performance issues. The Company was seeking to rectify the problem with advanced analytics and technologies.

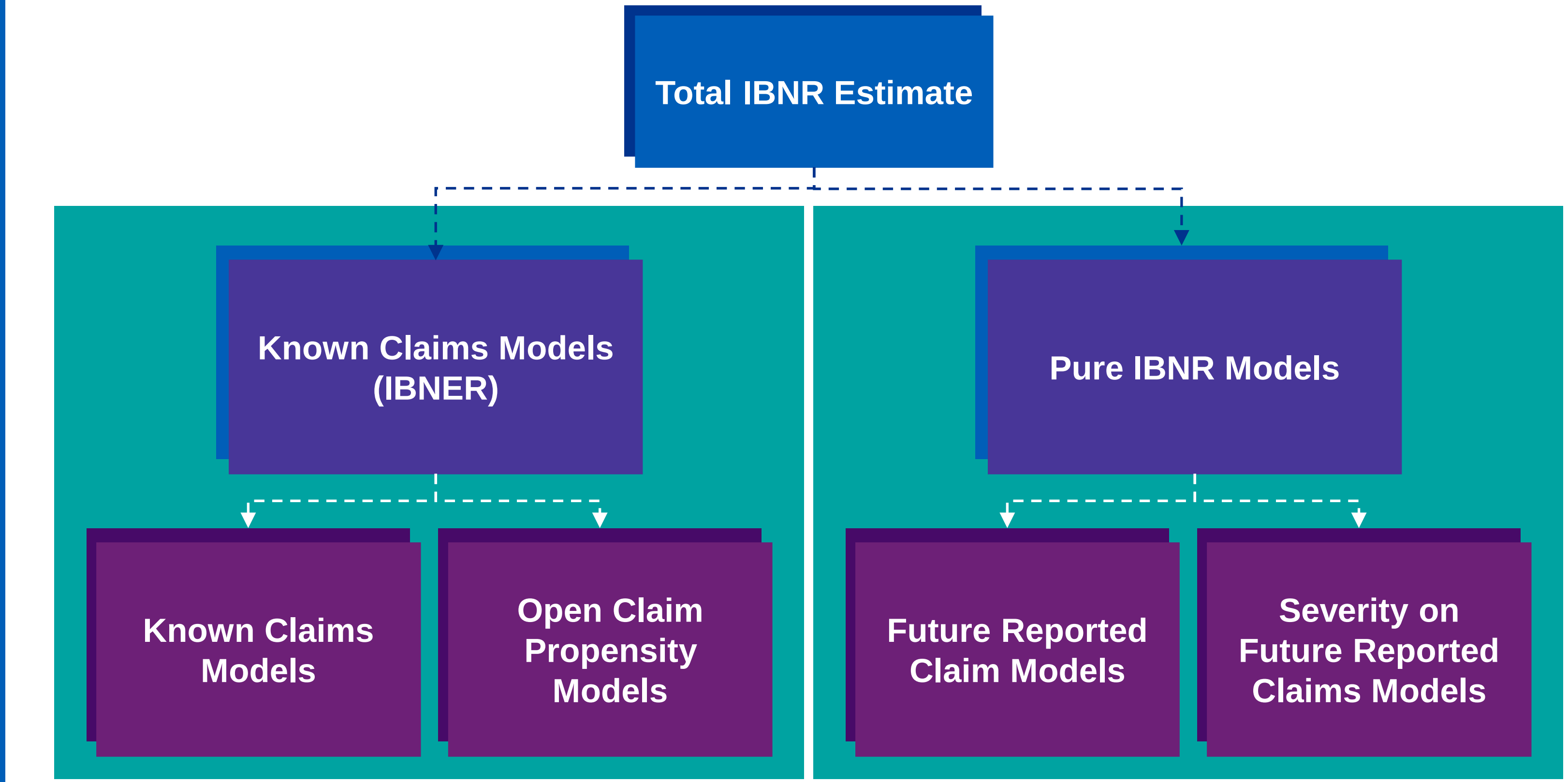
Interviews were conducted with key underwriters, actuaries, product managers, claims handlers, litigation practitioners, and various executive stakeholders. Acting on this information, a machine learning model was built using claims and policy-level data to analyze the carrier's loss of performance at a granular level. This enhanced view helped more accurately analyze its profitability by class, state, and other dimensions not previously available for study.

The increased transparency and enhanced output improved trust in the actuarial model and resulted in potential annual savings of tens of millions of dollars.

Case Study

Model overview

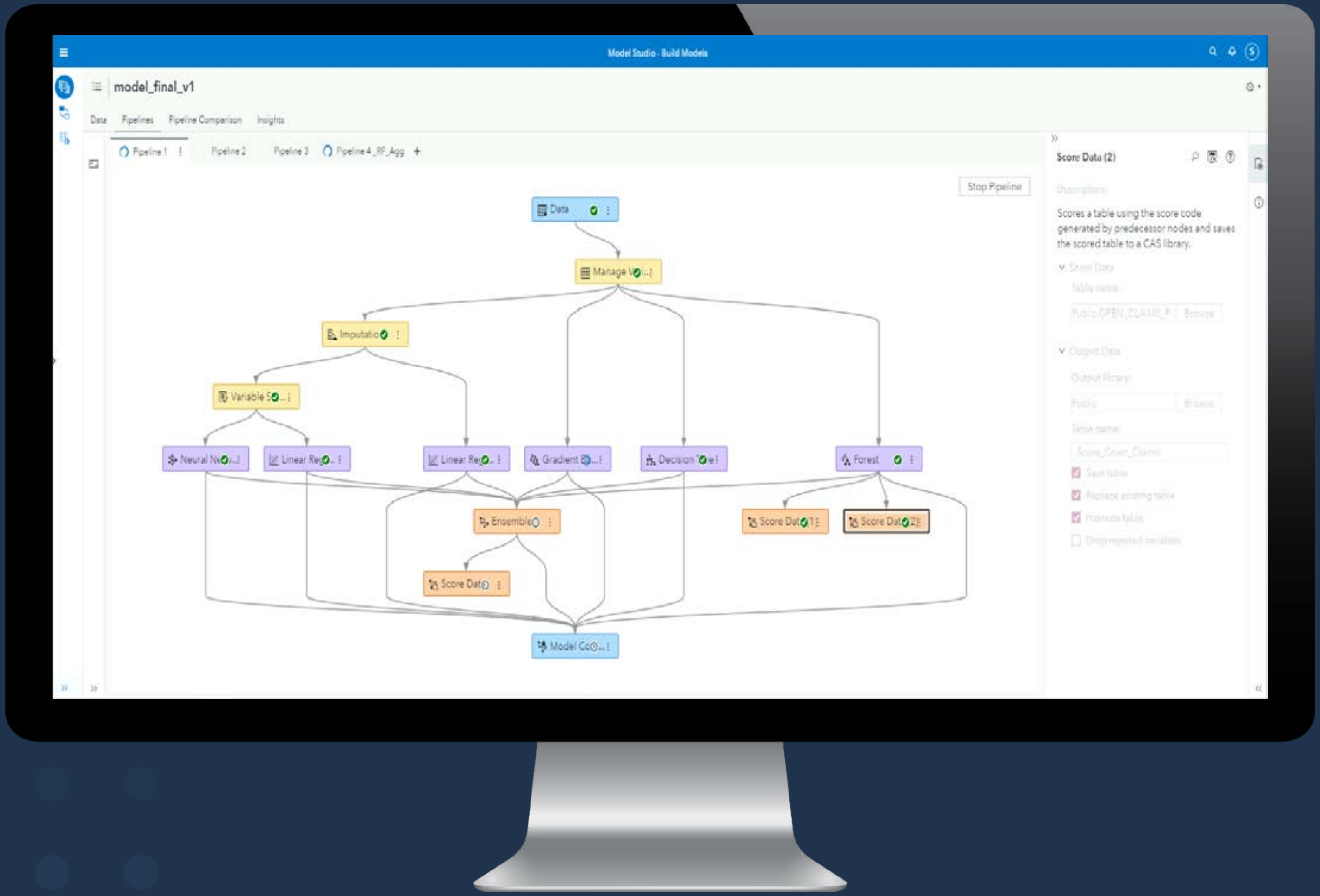
Generalized machine learning framework for Micro-segmentation



Case Study

Modeling Process

- — Significant lift with readily available data
- — Consider a variety of models
- — Data structure is key to success
- — Model validation
  - \- statistical measures
  - \- rigorous back-testing



Case Study

IBNER Approach

Calculation is performed at low level of granularity (e.g. Claim) – leveraging granular data assets

IBNER

	Actual Experience			Future Predicted Experience			
Period	**1**	**2**	**3**	**4(F)**	**5(F)**	**6(F)**	**7(F)**
Actual Incremental Paid Losses	2500	0	3000	NA	NA	NA	NA
Known Claims Model Estimate	NA	NA	NA	3000	4000	7000	7500
Open Claim Propensity Estimate	NA	NA	NA	25%	21%	18%	15%
Conditional Probability of Open Estimate[1]	NA	NA	NA	100%	84%	72%	60%
Estimated IBNER[2]	NA	NA	NA	3000	3360	5040	4500

Example – not derived from any company sources

[1]Conditional probability of claim open at the beginning of each future period given that the claim is open at the beginning of period 4. (e.g. Conditional Probability of Open for Period 5 = 0.21/0.25 = 0.84)

*[2]Estimated IBNER = Known Claims Model Estimate * Conditional Probability of Open*

Case Study

Using Generalized Approach for Pure IBNR Estimation

Calculation is performed at portfolio level (can be allocated to policy)

Pure IBNR

	Actual Incremental Experience			Future Predicted Experience			
Period	**1**	**2**	**3**	**4(F)**	**5(F)**	**6(F)**	**7(F)**
Actual Newly Reported Claims	1000	300	100	NA	NA	NA	NA
Future Reported Claims Model Estimate	NA	NA	NA	30	20	12	5
Severity on Future Reported Claims Model Estimate	NA	NA	NA	35,000	38,000	42,000	47,000
Estimated Pure IBNR	NA	NA	NA	1.05M	760k	504k	235k

Total IBNR = IBNER + Pure IBNR

Example – not derived from any company sources

Case Study

Sample Insights and Visuals

— Results provide insights in aggregate in recent years

— Key back-test is convergence in older years

— Significant detail under the surface

— Excel at identifying mix-shifts

Tiering – Illustrative Analysis Results

Profitable Classes

Accident Year	"A Classes" Earned Premium (000s)	Ultimate Loss Ratio
2016	20,000	45.0%
2017	21,000	43.5%
2018	22,000	46.3%
2019	23,000	44.7%
2020	24,000	42.8%
Total	**110,000**	**44.4%**
2016-2018	63,000	45.0%
2019-2020	47,000	43.7%

- Often decreasing as a portion of portfolio
- Traditional methods & allocations may show false adverse trends

Unprofitable Classes

Accident Year	"C Classes" Earned Premium (000s)	Ultimate Loss Ratio
2016	35,000	115.0%
2017	42,000	108.6%
2018	50,000	121.7%
2019	60,000	125.0%
2020	72,000	128.8%
Total	**259,000**	**121.4%**
2016-2018	127,000	115.5%
2019-2020	132,000	127.1%

- Often growing faster than other segments
- Traditional methods & allocations may show false favorable trends

Remaining Classes

Accident Year	"B Classes" Earned Premium (000s)	Ultimate Loss Ratio
2016	100,000	57.0%
2017	102,000	59.1%
2018	104,040	63.3%
2019	106,121	59.4%
2020	108,243	61.7%
Total	**520,404**	**60.1%**
2016-2018	306,040	59.8%
2019-2020	214,364	60.6%

- Often stagnant as a portion of the portfolio
- Traditional methods & allocations are often flat

Total Portfolio

Total All Total All Business		
Accident Year	Earned Premium (000s)	Ultimate Loss Ratio
2016	155,000	68.5%
2017	165,000	69.8%
2018	176,040	77.7%
2019	189,121	78.4%
2020	204,243	83.1%
Total	**889,404**	**76.0%**
2016-2018	496,040	72.2%
2019-2020	393,364	80.9%

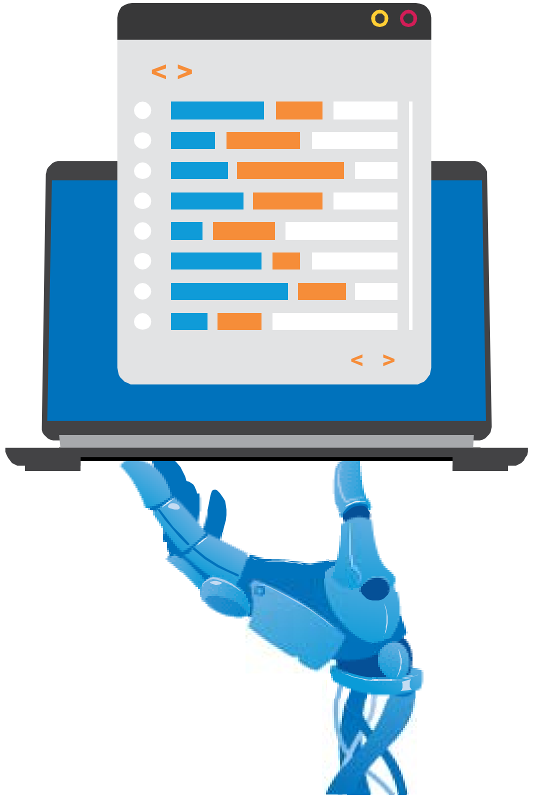
- Loss experience has deteriorated
- Primarily driven by growth and deterioration of C Classes
- Failure to grow A Classes

Lessons learned

Machine Learning is Not a Magic Bullet

Significant Levels of Actuarial Judgment & Expertise are Still Required

- Does the data need to be adjusted to consider the presence of distortions? Examples include:
  - Case Reserve Strengthening
  - Changes in Closure Rates
  - Portfolio Acquisitions
- How credible is the data?
  - Is the historical database sufficient for modeling?
  - Is the entire claim life cycle reflected in the data?
- How much historical data should we consider?
  - Trade off between focusing on recent trends and credibility
- Is the resulting model statistically valid?



Lessons learned

1. **Perfect data** and data system upgrades are **not needed** to achieve significant benefits
2. Build models that are **accessible** and can be run by all frequently
3. **Identify purpose** of model and output to explain findings and drive action
4. **Leadership** buy-in is key to drive importance and communication around anticipated use of models
5. In model design include personnel that understand both **AI/ML modeling** and **business needs**
6. Deploy a solution that is **scalable** with multiple techniques

Some or all of the services described herein may not be permissible for KPMG audit clients and their affiliates or related entities.

kpmg.com/socialmedia