

# From Data Issues to Insurance Solutions: Machine Learning's Potential

Brandon Schwab

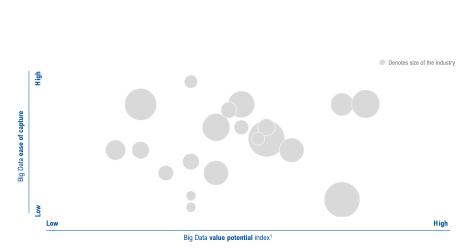
Institute for Risk and Insurance, Leibniz University Hannover

Hannover, October 19, 2023

**1** The Importance of Asking the Right Questions

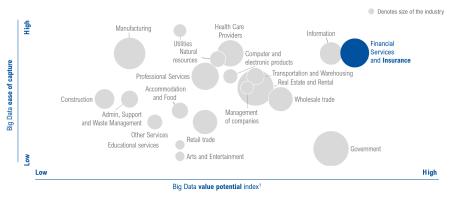
- 2 Machine Learning in Insurance: Potential Use Cases
- 3 Types of Data Issues
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- 6 Practical Example

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1 Determined by industry average of transaction intensity, amount of data per firm, variability in performance, customer and supplier intensity, and turbulence Source: McKinsey

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# The Importance of Asking the Right Questions

#### **<sup>(C)</sup>** Start with the End in Mind Define clear business goals before data considerations.

B Demand Analysis Identify data essentials by understanding business needs

**Different Problems, Different Data** Tailor data collection to the specific insurance issue.

The Risk of Wrong Data Irrelevant data increases noise and wastes resources.



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# Machine Learning in Insurance: Potential Use Cases

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#### Fraud Detection

Identifying potentially fraudulent activities by analyzing patterns that deviate from the norm.

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- Detailed claim information
- Behavioral data
- Previous fraud markers

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## **O:** Customer Churn Prediction

Forecasting the likelihood of a customer discontinuing their policy before its expiration.

### **(**)

- Detailed contract information
- Renewal history
- Customer service interactions

## Loss Reserving

Predicting the claim developments and the ultimate claim amount for a portfolio of claims.

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- Detailed claim information
- Sufficient loss history
- Macroeconomic indicators

## 🚇 Optimized Pricing

Adjusting insurance premiums using a vast array of factors to attract and retain customers while ensuring profitability.

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- Detailed claim information
- Detailed contract information
- Macroeconomic indicators



# Types of Data Issues

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Data Issue	Description	Example		
Completeness	All attributes of a vari- able are available.	<sup>vari-</sup> Height: NA		
Consistency	Consistent values for the same entity.	Date: 05.09.2016 / 20160905		
Validity	Data matches with the syntax of its definition.	Age: -3		
Accuracy	Data is correct.	Birthday: 05.09.1919		
Timeliness	Data is received at the right time and interval.	Event: 14:14, Notice: 23:59		

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# Enhancing Data Quality

## Data Imputation

ML can predict and fill missing values based on patterns in existing data.

#### Anomaly Detection

Automatically identify and flag outliers or inconsistencies.

Data Validation
Use predictive models to verify and correct data entries in real-time.

**Temporal Analysis** ML can track and update time-sensitive data, ensuring timeliness.

## **\*** Feature Engineering

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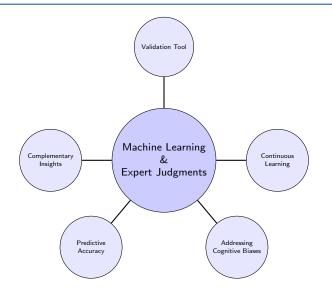


# Synergy: Machine Learning & Expert Judgments

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# Practical Example

## Research Objective

Enhance the accuracy of claim development predictions by leveraging individual claim and contract information through ML.

## Graditional Approach

Classic actuarial methods are based on simple heuristics that use aggregate data to make predictions.

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Our research deploys machine learning models to tap into the richness of individual claim & contract data, ensuring a more granular and informed prediction.

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## Example:

Accident Year	Development Year					
Accident real	1	2	3	4	5	6
1	100	150	180	200	210	215
2	95	140	170	190	200	-
3	90	135	165	185	-	-
4	85	130	160	-	-	-
5	105	90	-	-	-	-
6	75	-	-	-	-	-

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Chain Ladder



Accident Year	Development Year					
	1	2	3	4	5	6
1	0	0	0	0	0	0
2	0	0	0	0	0	2.1% / 1.4%
3	0	0	0	0	2.8% / 0.1%	5.4% / 0.6%
4	0	0	0	9.2% / 4.0%	10.4% / 4.1%	13.0% / 3.1%
5	0	0	3.2% / 2.2%	10.1% / 3.9%	11.9% / 3%	13.8% / 0.7%
6	0	6.2% / 0.2%	4.2% / 1.3%	2.3% / 1.0%	4.6% / 3.3%	7.7% / 3.7%