



Outcome Focused Analytics – Moving AI from the White Paper to the Board Paper

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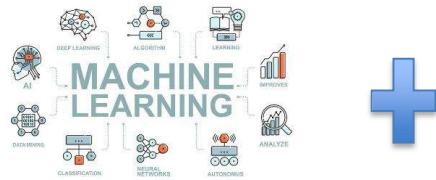
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Outcome Focused Analytics

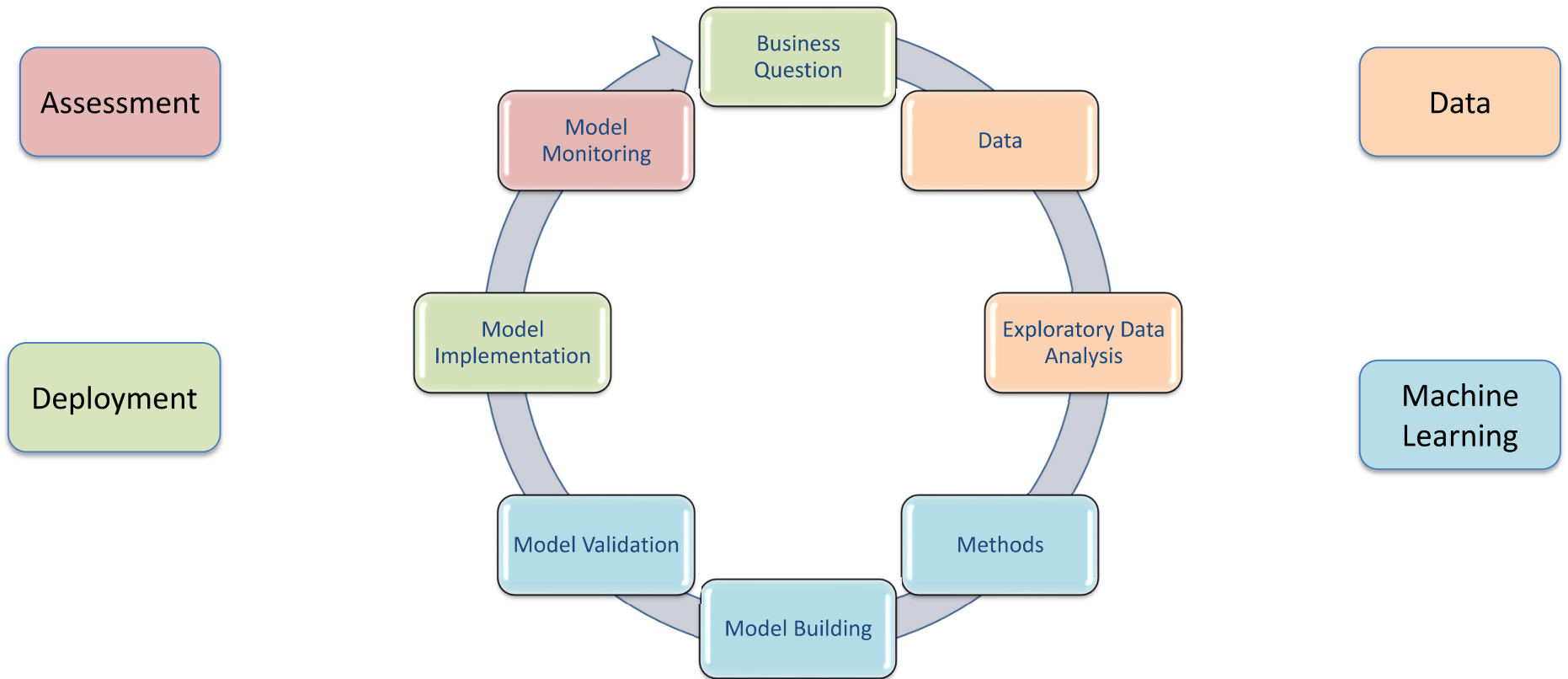
- ▶ Definition of AI
- ▶ Keys to Successful Execution of AI Initiatives
- ▶ Examples

Various Definitions of AI

- **Oxford Dictionary**: the theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages
- **IBM**: field, which combines computer science and robust datasets, to enable problem-solving
- **Wikipedia**: intelligence—perceiving, synthesizing, and inferring information—demonstrated by machines, as opposed to intelligence displayed by humans or by other animals
- **SAS**: Artificial intelligence (AI) makes it possible for machines to learn from experience, adjust to new inputs and perform human-like tasks



Modeling Lifecycle



Keys to Successful Execution of AI initiatives

Complete

- Across all key areas in an organization
- Championed from the top executive levels
- Include balance of targeted analytics and data exploration

Consistent

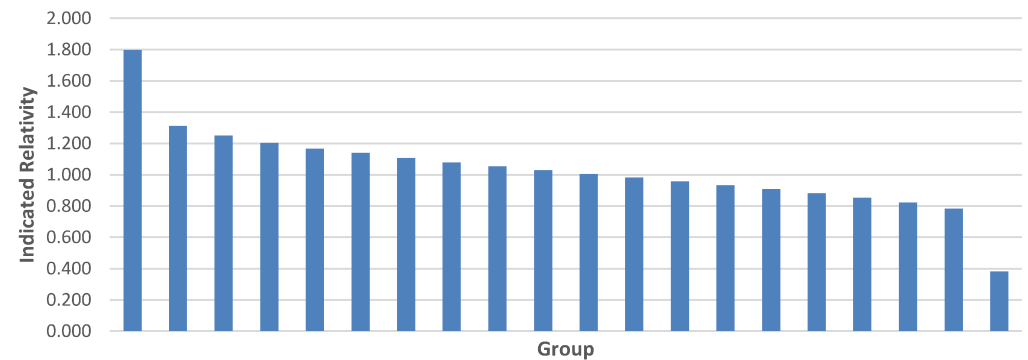
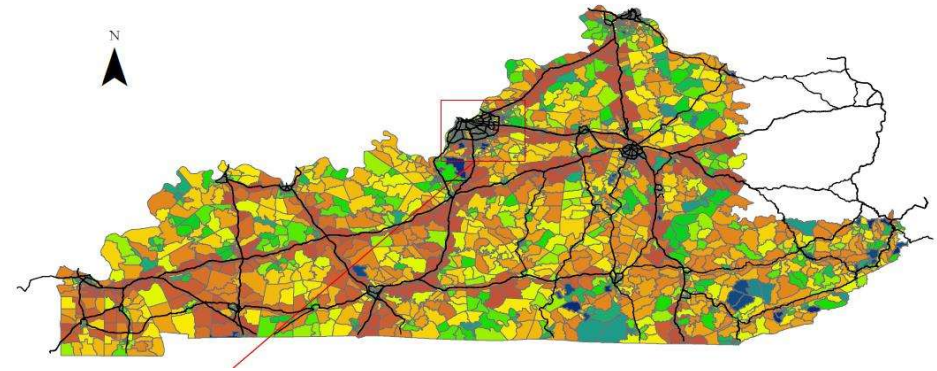
- Analytics should be focused on the overall strategy
- Analytics in different areas should be coordinated
- Championed from the top executive levels

Intentional

- Begin with the end in mind
- Data collection, processing analytics and implementation are all done in purposeful manner
- Buy-in and change management
- Outcome measurement

TomTom – Road Characteristic Data

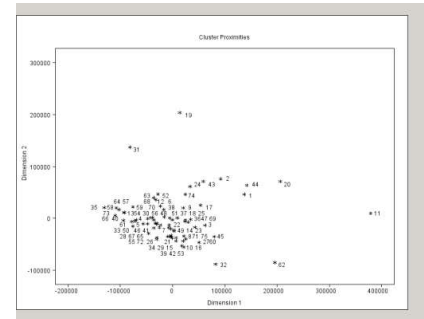
- **Business problem** – incorporating the geographical risk associated with automobile insurance
- **Examples of data**
 - Speed (median, average, harmonic average)
 - Speed limit
 - Time traveled on road segments
 - Traffic density
 - Speed variability
 - Ratio of speed to speed limit
- **Possible Solutions**
 - Dynamic risk assessment
 - Dynamic risk mitigation



Claims – Fraud Detection Model

- **Business Problem**

- Claim referral can be inconsistent – heavy dependence on claim adjuster
- **False positives**
- Claim adjuster may not be aware of all suspicious relationships
- Not all historical fraud has been identified
- Prioritization of potentially fraudulent claims



Suspicion Score	
Root Mean Square Error	99.7%
Distance to Nearest Cluster	99.4%
Distance from Mean	96.5%
Combined	98.3%

- **Multiple analytics solutions**

- Predictive analysis of historical referrals (consistent referrals)
- Predictive analysis of historical fraudulent claims (false positives)
- Association analysis (recognition of claim patterns)
- Clustering methods (missed claims, prioritization)
- PRIDIT (consistent referrals, prioritization)

Factor Name	Description	Input Value
insured_kids_2	Y, N, or U	u
peril_2	Cause of Loss	Fire
public_adjuster	0 or 1	0
IMP_REP_Coverage_C	Coverage C Amount	190,500
IMP_REP_Insured_Home_Bathrooms	Number of Bathrooms	2
IMP_REP_Insured_Home_Bedrooms	Number of Bedrooms	3
IMP_REP_Insured_Home_SqFt	Square Footage	1,412
IMP_REP_Insured_Home_YearBuilt	Year Built	1973
IMP_REP_Insured_Homeowner	Homeowner (Y or N)	Y
IMP_REP_acvloss_rcttotal	Ratio of ACV Loss to RCT Total	1.13
IMP_REP_create_lag	Delay in Creating Record	9
IMP_REP_insured_age_2	Insured Age	50
IMP_REP_insured_educationlevel_2	Years of Education	12
IMP_REP_insured_homevalue_calc_r	Home Value Calculation Rounded	149
IMP_REP_insured_yearsinhome_2	Insured Years in Home	6

Model Fairness

The latest research in model fairness and model de-biasing is introducing an additional component to the **concept of model bias that transcends the purely statistical context**. The central theme in this additional dimension of bias detection and bias mitigation is attempting to provide practitioners of analytics with mechanisms and mathematical constructs to **minimize the social inequalities that their models may capture through data** and **ensure that the model does not unfairly discriminate against certain protected classes**.

Independence	Separation	Sufficiency
$\hat{Y} \perp A$	$\hat{Y} \perp A Y$	$Y \perp A \hat{Y}$

A - protected attribute

Y - observed value of target variable

\hat{Y} - predicted value of target variable

CAS Research Series on Race and Insurance Pricing

<https://www.casact.org/publications-research/research/research-paper-series-race-and-insurance-pricing>

The image displays four research paper covers from the CAS Research Series on Race and Insurance Pricing. Each cover features a background illustration of a scale of justice. The covers are arranged in a row and each includes the following text:

- Cover 1:** CAS RESEARCH PAPER SERIES ON RACE AND INSURANCE PRICING. **DEFINING DISCRIMINATION IN INSURANCE**. Kudakwashe F. Chibanda, FCAS.
- Cover 2:** CAS RESEARCH PAPER SERIES ON RACE AND INSURANCE PRICING. **UNDERSTANDING POTENTIAL INFLUENCES OF RACIAL BIAS ON P&C INSURANCE: FOUR RATING FACTORS EXPLORED**. Members of the 2021 CAS Race and Insurance Research Task Force.
- Cover 3:** CAS RESEARCH PAPER SERIES ON RACE AND INSURANCE PRICING. **METHODS FOR QUANTIFYING DISCRIMINATORY EFFECTS ON PROTECTED CLASSES IN INSURANCE**. Roosevelt Mosley, FCAS, and Radost Wenman, FCAS.
- Cover 4:** CAS RESEARCH PAPER SERIES ON RACE AND INSURANCE PRICING. **APPROACHES TO ADDRESS RACIAL BIAS IN FINANCIAL SERVICES: LESSONS FOR THE INSURANCE INDUSTRY**. Members of the 2021 CAS Race and Insurance Research Task Force.

At the bottom of each cover, the text "CASUALTY ACTUARIAL SOCIETY" and the CAS logo are displayed.

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