

CASTF BOOK CLUB PREDICTIVE MODELING VARIABLES AND POTENTIAL IMPLICATIONS

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PRESENTER

Dave Heppen, FCAS, MAAA

Actuarial Partner

Key areas of expertise include ERM, financial reporting, reinsurance, and the use of complex models in ratemaking and reserving.



- Chair of the American Academy of Actuaries' (AAA) ERM/ORSA committee, Chair of the AAA's Workers' Compensation Committee, member of the AAA's Committee on Property and Liability Financial Reporting, member of the AAA's Casualty Practice Council, and member of the AAA's Risk Management and Financial Reporting Council
- Frequent speaker at industry conferences; author of numerous publications on Property/Casualty risks.

PRESENTER

Jennifer Balester, FCAS, MAAA

Actuarial Consultant

Key areas of expertise include reserving, financial reporting, process improvement and documentation, and implementation of complex models for underwriting, pricing, and other uses.



Member of AAA Data Science and Analytics Committee and Casualty Actuarial Society Syllabus & Examination Committee

OBJECTIVES

- Provide overview of use of complex models for ratemaking
- Provide examples of rating variables we have encountered in reviews of complex models used for P&C ratemaking
- Discuss potential implications of the use of such variables
- Receive feedback from CASTF members on follow-up information that would be useful in thinking about the issues raised during the discussion

PRINCIPLES OF RATEMAKING

PRINCIPLE 1

A rate is an estimate of the expected value of future costs

PRINCIPLE 2

A rate provides for all costs associated with the transfer of risk.

PRINCIPLE 3

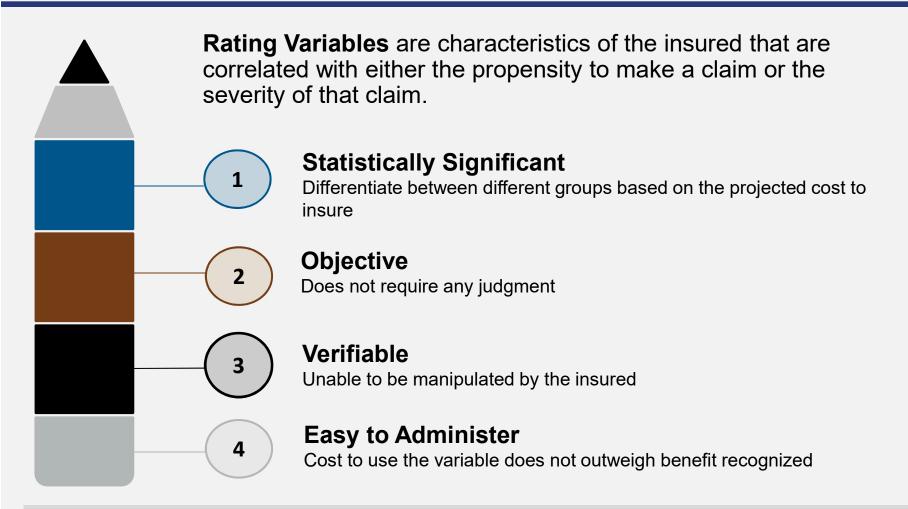
A rate provides for the costs associated with an individual risk transfer.

PRINCIPLE 4

A rate is reasonable and not excessive, inadequate, or unfairly discriminatory if it is an actuarially sound estimate of the expected value of all future costs associated with an individual risk transfer

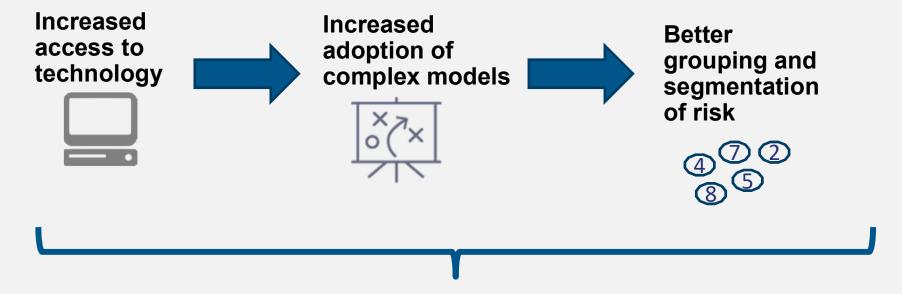


RATING VARIABLES





CHANGING WORLD







REGULATION OF COMPLEX MODELS

- Regulators may reject or prohibit variables if they differentiate between policyholders based on prohibited characteristics whether that differentiation is intentional or unintentional.
- Examples of protected classes:
 - Federal: race, color, sex, sexual orientation, gender identity and expression, national origin, religion, age, military status, equal pay, pregnancy, disability, or genetic information
 - Most states: race, religion, national origin
 - Life insurance in NY State: race, color, creed, national origin, status as a victim of domestic violence, past lawful travel, sexual orientation

DISPARATE TREATMENT VS. DISPARATE IMPACT

- Discrimination does not have to be overt to be disallowed
- Disparate treatment: intentionally treating someone differently because of a given characteristic
- Disparate impact: causing a disproportionate result on a certain group
- The NAIC's Special (EX) Committee on Race and Insurance scope includes these considerations

POTENTIAL PITFALLS

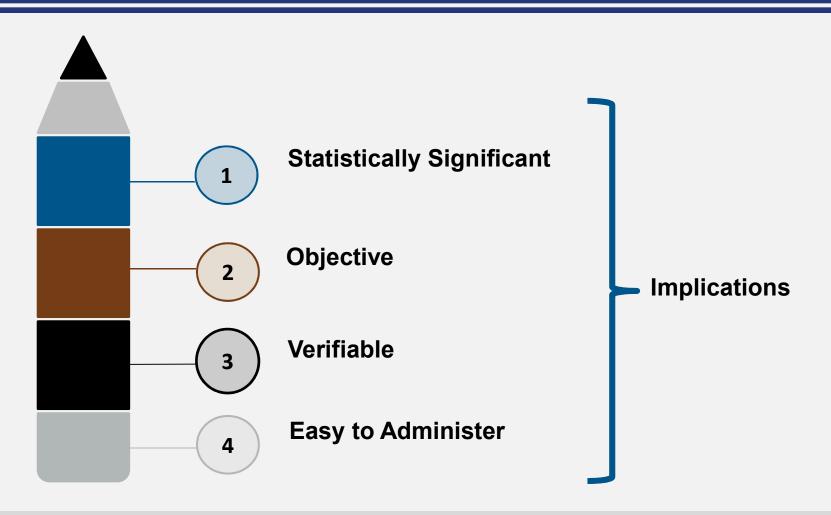
- Variable that represents a prohibited characteristic
- Another variable takes the place of the variable that represents a prohibited characteristic
- Some insureds subsidize other insureds when the company is not allowed to differentiate between them despite different costs
- Adverse selection
- Company rejects risks that they cannot adequately price

Sources of Variables

- Policy Characteristics Deductible, Limit, Coverage Amount
- Characteristics of Insured (or Insured Property) location, age of home, vehicle model, violations
- Financial Characteristics payment history, credit score
- Claims History number of claims, dollar value of claims, type of claims
- Demographic data general characteristics often based on zip code



EXAMPLE 1 – PRIOR CLAIMS HISTORY



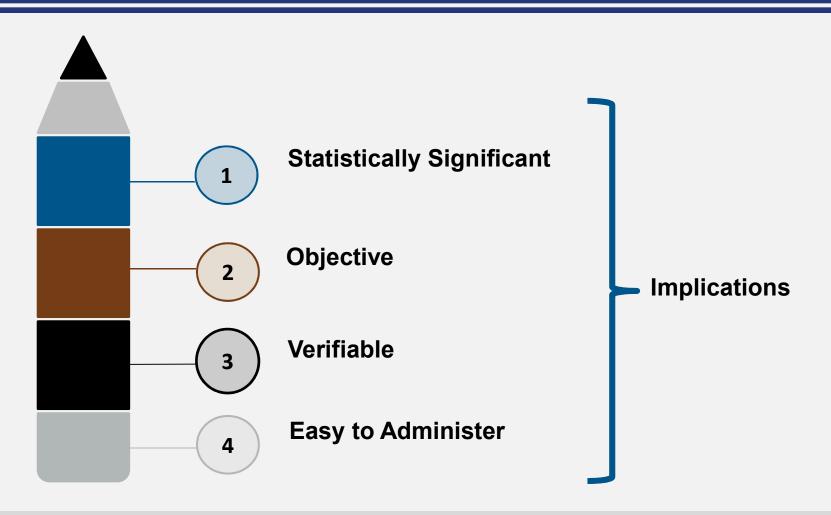


EXAMPLE 1 – PRIOR CLAIMS HISTORY

- Rating Variable Construction
 - Data may come from internal claims history or from external sources such as Comprehensive Loss Underwriting Exchange (CLUE)
- Industry View of Variable Relationship to Loss Propensity
 - Generally highly correlated with future loss potential
- Usage
 - Commonly accepted variable



EXAMPLE 2 – CREDIT SCORE



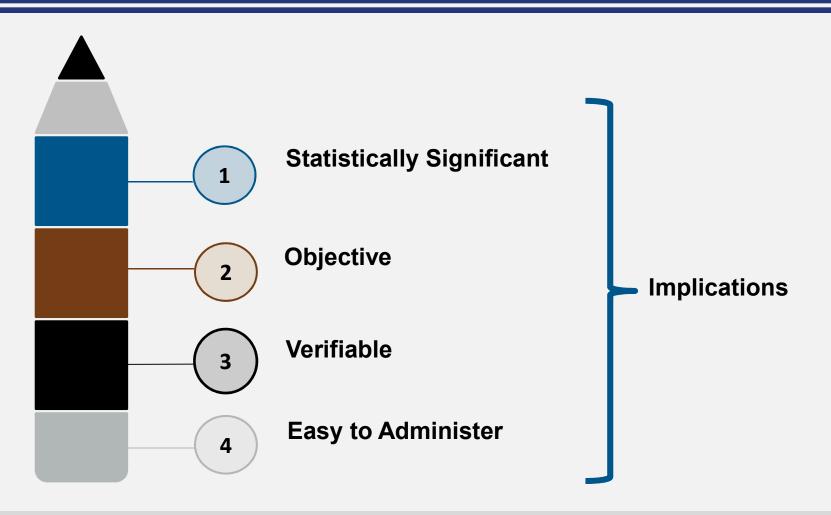


EXAMPLE 2 – CREDIT SCORE

- Rating Variable Construction
 - Data from external sources such as Experian
- Industry View of Variable Relationship to Loss Propensity
 - Generally correlated with future loss potential
- Usage
 - Used in most states, but often subject to strict guidelines



EXAMPLE 3 – MOTOR VEHICLE VIOLATIONS



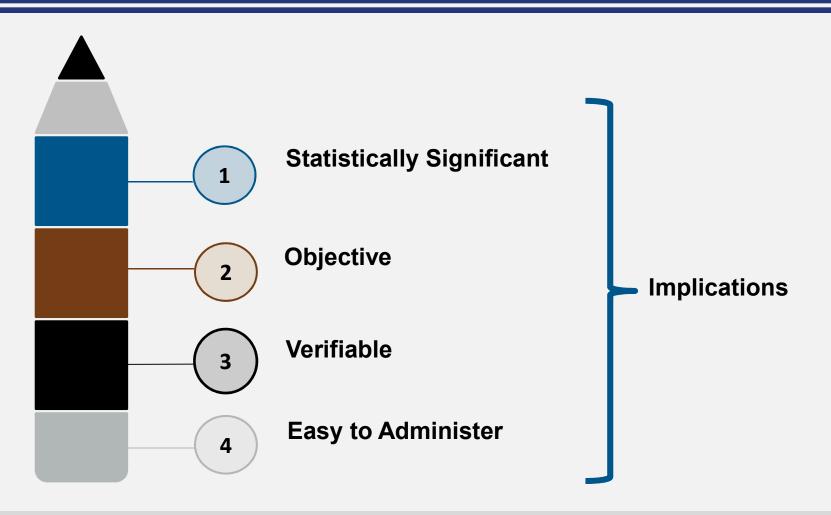


Example 3 – Motor Vehicle Violations

- Rating Variable Construction
 - External data from Motor Vehicle Report (MVR)
- Industry View of Variable Relationship to Loss Propensity
 - Generally highly correlated with future loss potential
- Usage
 - Commonly accepted variable



EXAMPLE 4 – DRIVER AGE

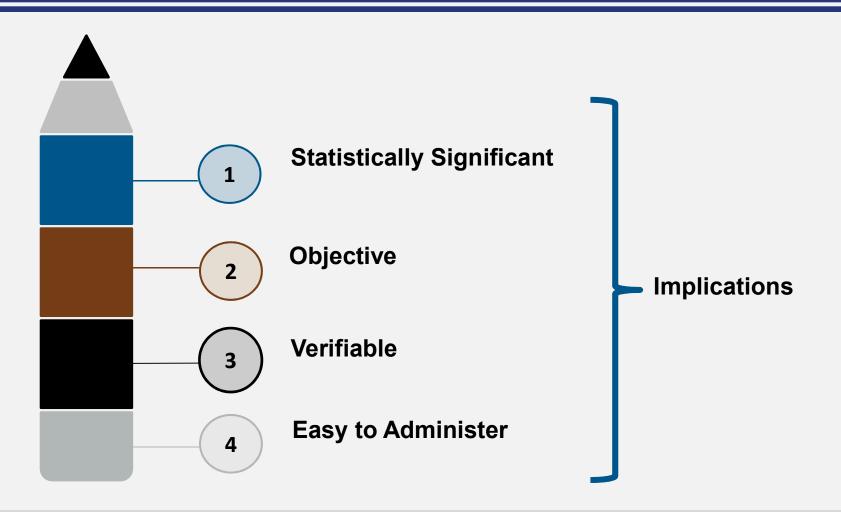


EXAMPLE 4 – DRIVER AGE

- Rating Variable Construction
 - Internal policy data
- Industry View of Variable Relationship to Loss Propensity
 - > Generally highly correlated with future loss potential
- Usage
 - Protected class, but has become acceptable for certain uses in insurance



EXAMPLE 5 – AMOUNT OF INSURANCE

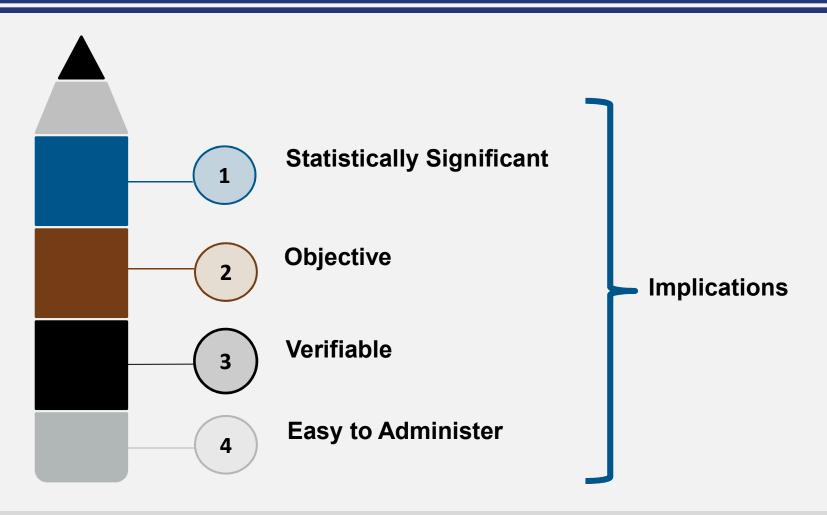


EXAMPLE 5 — AMOUNT OF INSURANCE

- Rating Variable Construction
 - Internal policy data
- Industry View of Variable Relationship to Loss Propensity
 - Direct relationship to severity of losses
- Usage
 - Commonly accepted variable



EXAMPLE 6 — POPULATION DENSITY





EXAMPLE 6

- Rating Variable Construction
 - External demographic data, such as Census
- Industry View of Variable Relationship to Loss Propensity
 - Not an obvious direct causal link to loss, but often correlated with loss
- Usage
 - Demographic variables are commonly accepted



REVIEWING A MODEL

- Understand the target variable
- Understand the predictive variables
- Assess the model output and validation
- Understand how the model is used and whether any judgment can be layered on top of the model results
- Understand triggers for model recalibration or update



QUESTIONS AND CONTACT INFORMATION

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We welcome any feedback you have on this presentation or the topic in general.

Sources:

Insurance Rating Variables: What They Are and Why They Matter, Casualty Actuarial Society and Insurance Information Institute, July 2019

CASTF Regulatory Review of Predictive Models White Paper, Casualty Actuarial and Statistical Task Force, September 2020 Statement of Principles Regarding Property and Casualty Insurance Ratemaking, Casualty Actuarial Society Insurance Circular Letter No. 1 (2019), New York State Insurance Department, January 18, 2019

