



SOCIETY OF
ACTUARIES®

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MEETING**
& EXHIBIT

October 27-30
Toronto, Canada

Session 043: Auditing your Models for Bias

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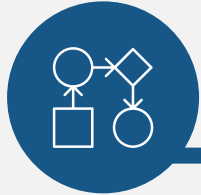
Auditing your Models for Bias

October 2019

NOT IF, BUT HOW

Munich RE 

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Data Science Framework

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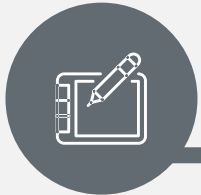
Fairness Metrics

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Demo

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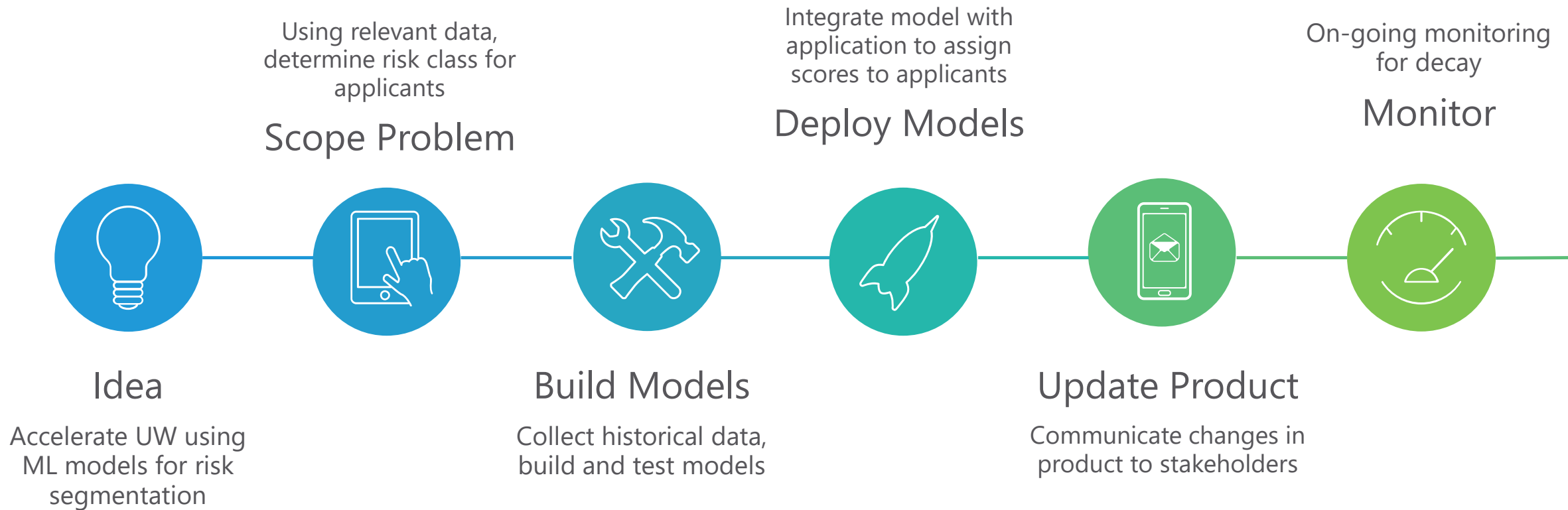


Questions

Data Science Framework



From Idea to Application: Data Science Life Cycle



Important Touchpoints for Privacy and Bias

- Data Sourcing & 3rd Party Data
 - Decide on appropriate data (internal and external) to build model; talk with subject matter experts to define relevant data sources
- Fairness Considerations
 - Based on data, decide on appropriate model design
 - Based on possible interventions, define metrics for model selection
 - Query model results for transparency and bias

3 questions to think about when using 3rd party data

1. What is the benefit of external data for the use case?

- In some cases, we want to use supplemental information to request less information from clients and make for an easy application process
- In some cases, want to use it to verify statements that people make

2. Do you satisfy specific policy requirements around the use of 3rd party data?

3. Are there proper procedures in place for storage and access to 3rd party data?

- Is there access control? Procedures in case of breach?
- When matching external data to internal data, is this done in a robust, reproducible way?

Measuring Fairness



Fairness and Model Audits is a new industry

- Cathy O’Neill, author of Weapons of Math Destruction offers a “Model Audited for Bias” certification through her consulting firm ORCAA
- Other consulting firms like McKinsey also offer a model audit solution
- Aequitas, developed by center for Data Science and Public Policy is an open source tool that can help you audit your models for bias
- IBM AI 360, developed by IBM can calculate many fairness metrics
- All of these approaches specify metrics that can be used to determine if your model is fair/biased

In addition to a model performance metric, how do you incorporate a fairness metric in your model selection process?

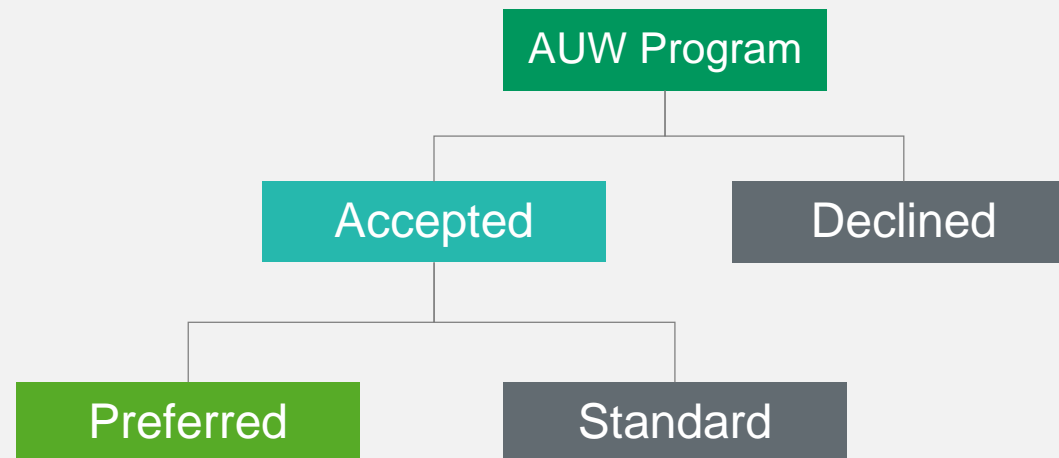
What are the Tradeoffs?

- A model may perform better on some metric of accuracy but perform worse on a bias metric
 - How do you make the decision of which model to use?

Case Study: Model Development

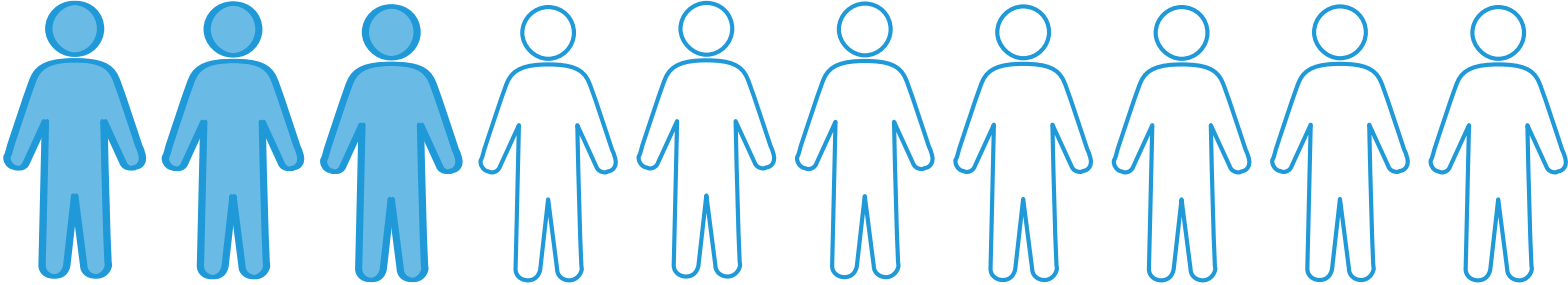
Exercise: Identify Privacy and Bias Concerns at each stage in the model and product cycle

- Problem: For an AUW program, how can we increase STP of Preferred candidates?
- Intervention: Based on a model score, the top scoring accepted candidates will be assigned a Preferred Class.



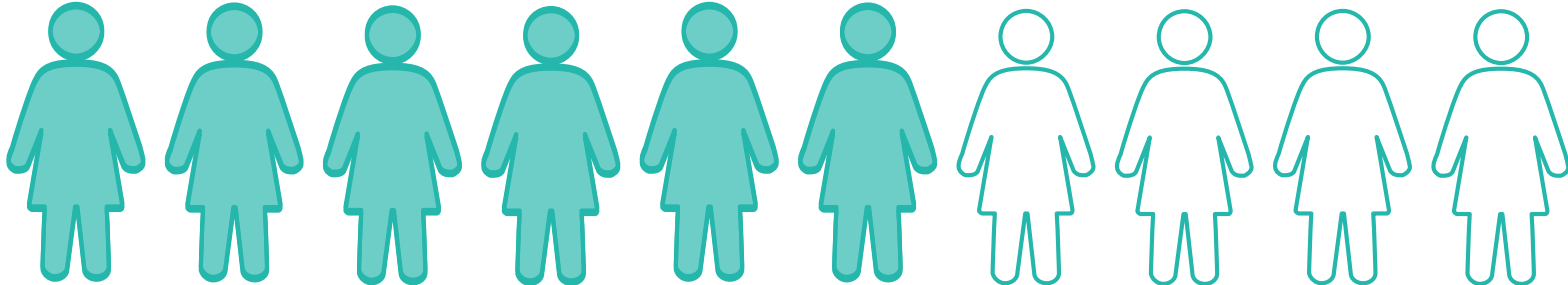
Model Results

Protected Attributes



30%

Men are flagged as Preferred



60%

Women are flagged as Preferred

FAIRNESS TREE

Do you want to be fair based on disparate representation or based on disparate errors of your system?

Representation

Errors

Do you need to select equal # of people from each group OR proportional to their percentage in the overall population?

Equal Numbers

Proportional

Equal Parity

Also known as Demographic or Statistical Parity

Proportional Parity

Equivalent to Disparate Impact

Are your interventions punitive or assistive?

Punitive (could hurt individuals)

Assistive (will help individuals)

Are you intervening with a very small % of the population?

Yes

No

False Discovery Rate Parity

Equivalent to Precision (or PPV) Parity

False Positive Rate Parity

Equivalent to True Negative Rate Parity

Are you intervening with a very small % of the population?

Yes

No

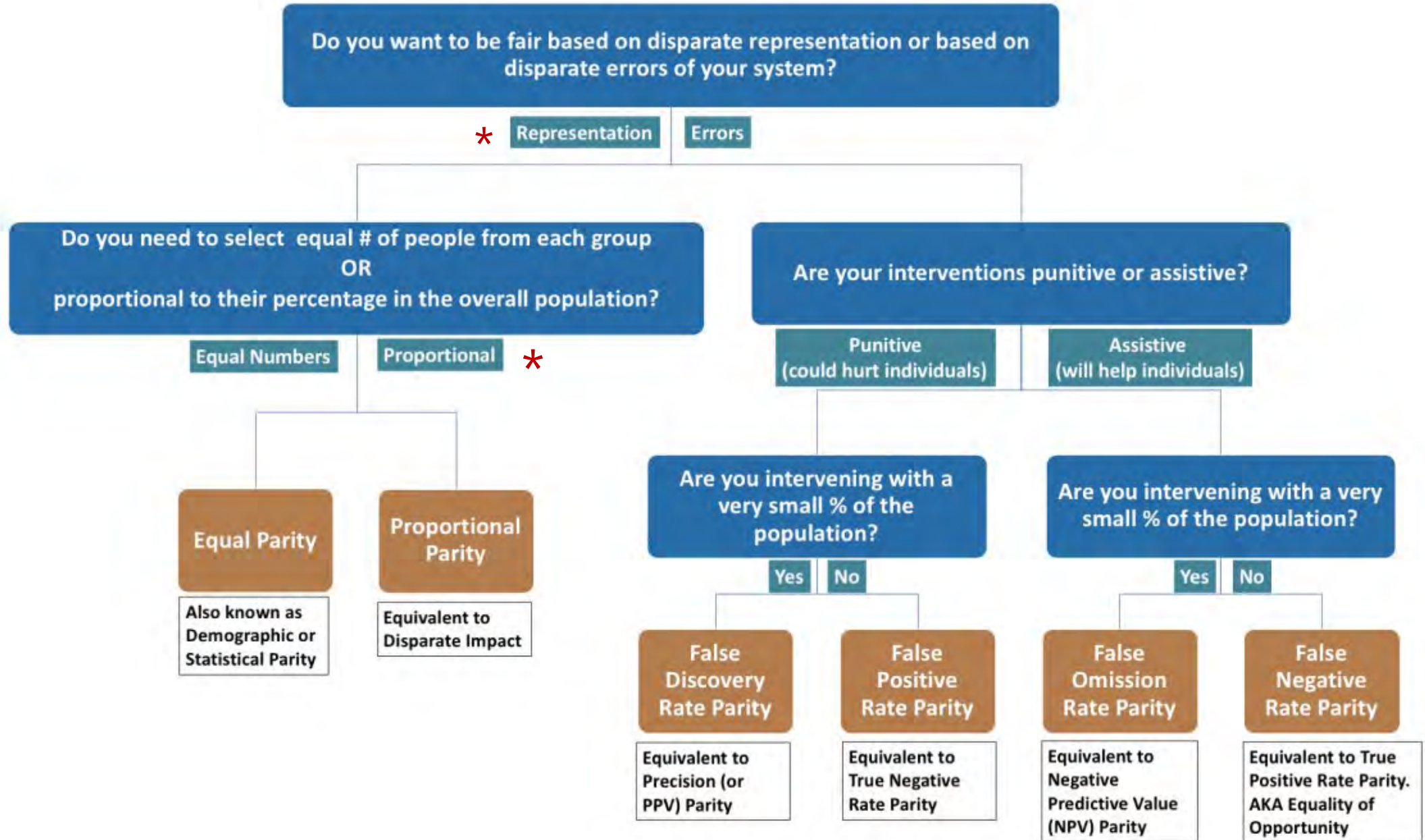
False Omission Rate Parity

Equivalent to Negative Predictive Value (NPV) Parity

False Negative Rate Parity

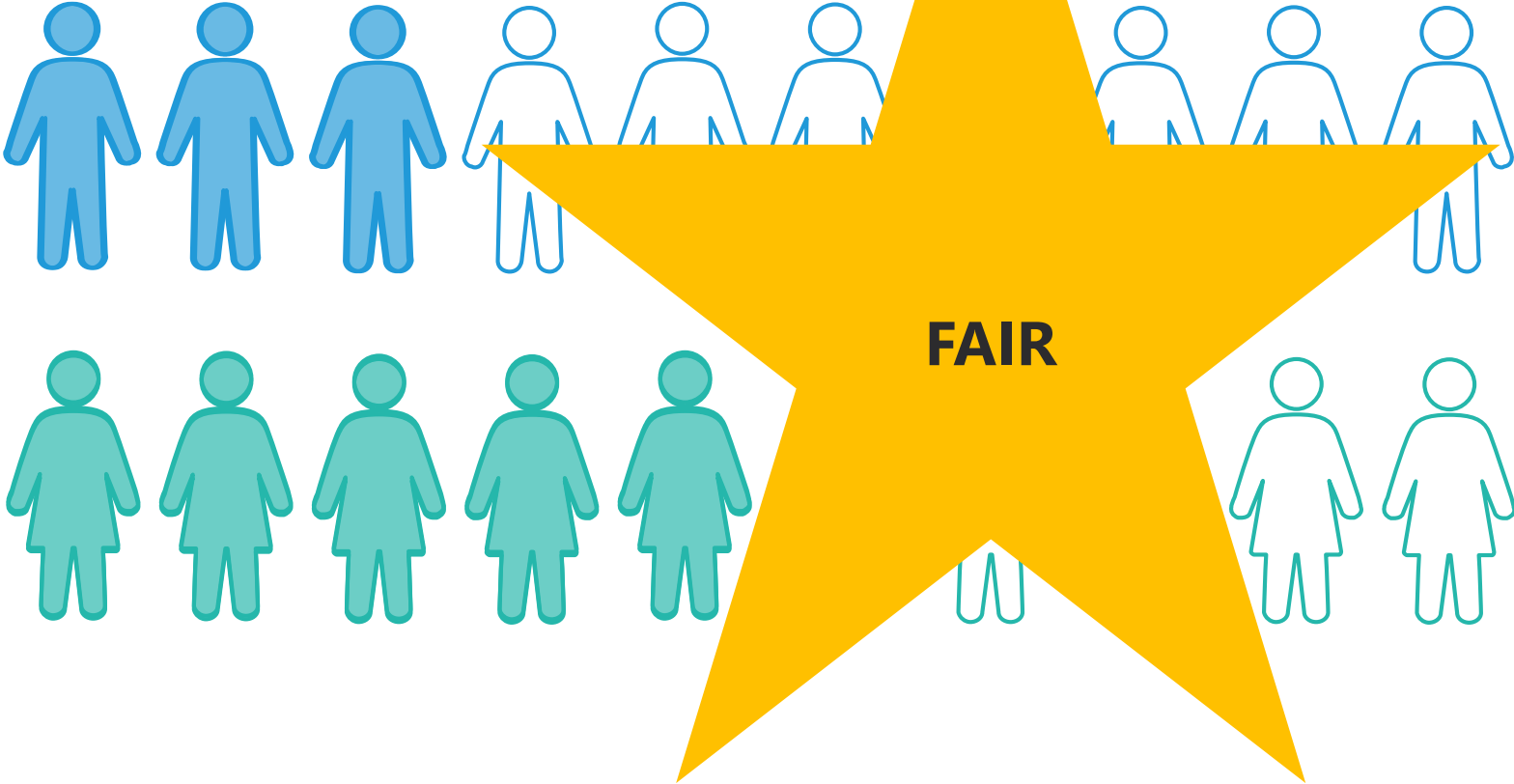
Equivalent to True Positive Rate Parity. AKA Equality of Opportunity

FAIRNESS TREE



Model Results

Protected Attributes



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- Privacy and bias considerations of the modelling process are real
- Uncertainty about what is required from a regulatory perspective
- To account for such considerations:
 - Design a model that takes into account the process which it supports
 - Document all decisions made around model selection
 - Audit models for bias and incorporate bias metrics into model selection process
 - Work with legal to be in compliance with policy requirements around 3rd party data

Questions?





Thank you.

NOT IF, BUT HOW

Munich RE 

Reviewing your models for bias

April Shen

October 28, 2019



Agenda



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Why is it important to reviewing actuarial models for bias

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Potential biases for different components of actuarial models

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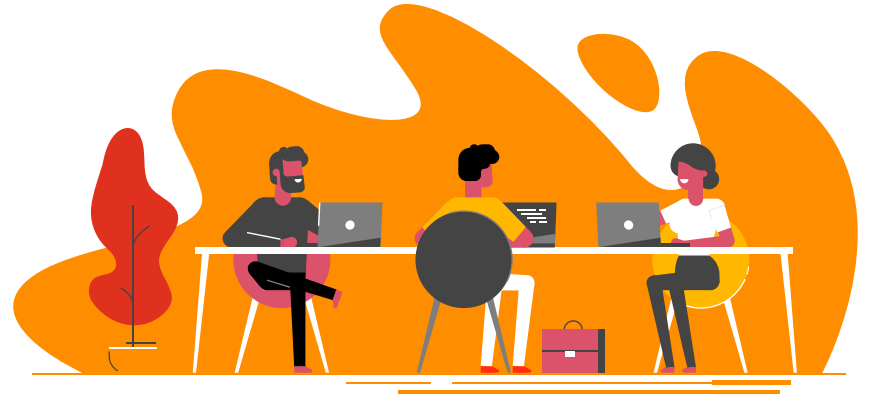
04

Model governance practice

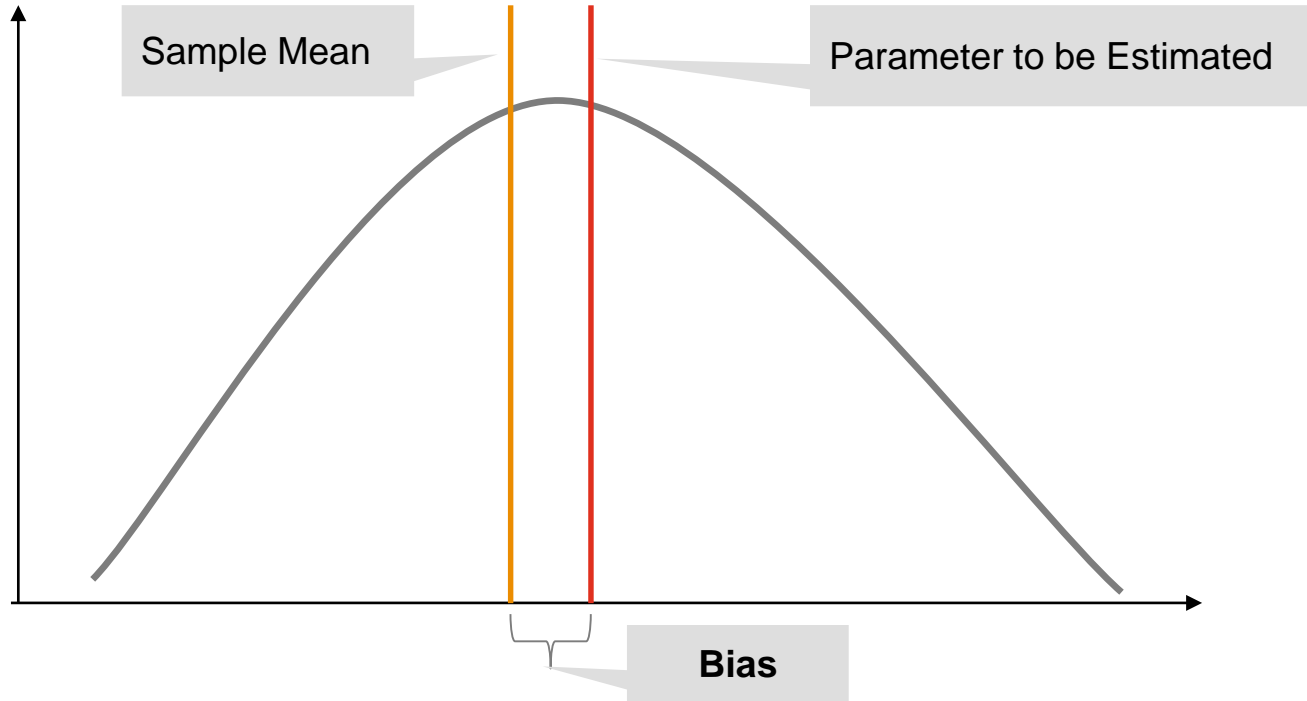
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What is bias in actuarial model

- Bias is a statistical term. Bias refers to the tendency of a measurement process to over- or under-estimate the value of a population parameter.
- For a point estimator, statistical bias is defined as the difference between the parameter to be estimated and the mathematical expectation of the estimator.
- When applied to actuarial models, bias could be reflected in the following places:
 - Parameter calibration.
 - Scenario validation.
 - Metric aggregation.



What is bias in actuarial model (continued)



Why is it important to reviewing actuarial models for bias

- Reviewing models for bias is an important component of model validation processes.
- Unbiased estimates are inherently required in financial reporting.
- Unbiased estimates are critical to the accuracy of actuarial metrics, especially in the principals-based framework.
 - Actuarial assumptions are largely estimated with large population datasets and statistical methodologies.
 - Economic assumptions should coherently reflect company's view on economic condition.
 - In actuarial modeling, many metrics are calculated by projecting out along various paths and calculating the expected metrics.

Potential biases for different components of actuarial models



Actuarial assumption calibration



Economic assumption calibration and scenario generation



Aggregation for actuarial metrics

Reviewing actuarial assumptions for bias

- Actuarial assumptions are usually derived within the company's experience study unit or from industry survey.
- For company's own experience study, possible causes for biases include:
 - Incomplete data – survivorship bias.
 - Truncated data – data not reported under or above a threshold.
 - Cohorting methodology – algorithms to group data are dependent on the parameter estimation from data samples.
- For companies who use industry survey to form it's policyholder behavior assumptions:
 - Industry population may not be representative of company's own underwriting population.

Reviewing actuarial assumptions for bias (continued)

- There are a few strategies to review for biases for actuarial assumptions:
 - Perform regular actual – expected analyses to adjust the estimation.
 - Dynamically adjust the algorithms for cohorting as the inforce changes
 - Have a protocol on tolerances for bias.
 - Consider more variables. When we assume X causes Y, consider variable Z that may cause both X and Y.



Review economic assumptions for bias

- Companies may use the following strategies to implement their economic assumptions:
 - Calibrate economic assumption parameters.
 - Consult vendor system for canned calibration methodology.
 - Develop best estimate assumptions and recalibrate when new information is available.
 - Assume correlations of certain market assumptions.

Review economic assumptions for bias (continued)

- There are a few strategies review for biases for economic assumptions:
 - Create a set of protocols to validate the calibration process.
 - Stress-test vendor solutions or cross compare from multiple sources.
 - Perform consistency checks on economic assumptions, both cross-sectional and time-dependent.
 - Perform actual – expected analysis to see how the assumption is realized.



Review metric aggregation for bias

- It's a common practice to calculate certain actuarial metrics under various scenarios and then take the average or tail measure as the final metric.
- Whether the final metric aggregation is biased or not is key to the validity of the result.
- Some questions to consider regarding metric aggregation:
 - How to estimate the effect of assumptions used in the model from the results.
 - What sensitivities should be run to be most effective in identifying model biases.
 - What to do if there's bias in the model inputs and how this will impact the metric aggregation.

Review metric aggregation for bias (continued)

There are a few strategies to review metric aggregation for biases:

- Does the same scenario dominate the results at different points in time? If so, peer review the scenario sets in focus.
- When there's known bias in the inputs for assumptions, the output measures should have a corresponding adjustment.
- Detailed testing for a given scenario and peer reviewing the time impact by performing attribution.

Independent review vs. In-house review

Independent review

- Models are reviewed with a different angle.
- Industry best practices can be leveraged for model build.
- Model enhancement ideas can be generated and implemented.
- Independence is maintained between modelers and testers.

In-house review

- Retain institutional knowledge on actuarial models in-house.
- Leverage existing model stewardship and testing resources.

First line and second line roles

First line - model developer

- Key part of developer's review and testing.
- Document work, findings and decisions.
- Communicate issues and resolution to second line.

Second line - model risk management

- assessment of first line's review.
- independent perspective.
- consistency with similar issues in non-actuarial models.

Thank you

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