

What Does Machine Learning Mean for the Life Insurance Industry?

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Agenda

State of the Life Insurance Industry

How Are We Evaluating Risk Today?

Can We “Amazon-ify” the Life Market?

Exploring Possible Applications of Machine Learning

- Artificial Neural Networks
- Genetic Algorithms
- How AIR Applies Machine Learning Techniques

Q&A

State of the Life Insurance Industry



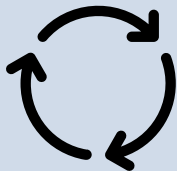
The Race to Digitization and Automation

- Customer-centric focus on millennials
- Less invasive underwriting
- Processes becoming more digital



- Accelerated underwriting comes with more risk
- Heavy regulation of new technology
- Still dealing with siloed decision-making

Transformations in Process, Data, Society, and Analytics



Then:

- Full underwriting and holding pension risk

Now:

- Real-time policy quotes, PRT, and increased solvency demands



Then:

- MIB, medical data, driving, credit

Now:

- Avocation, voice, social media, marketing data

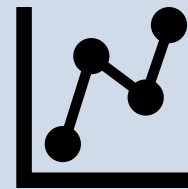


Then:

- Lower smoking rates

Now:

- Obesity, opioids, e-cigarettes



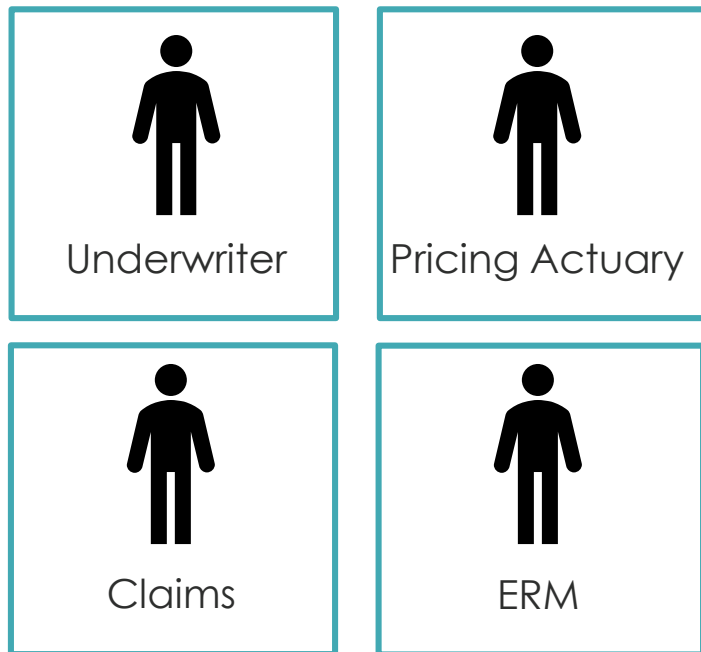
Then:

- Mortality tables, adjustment factors

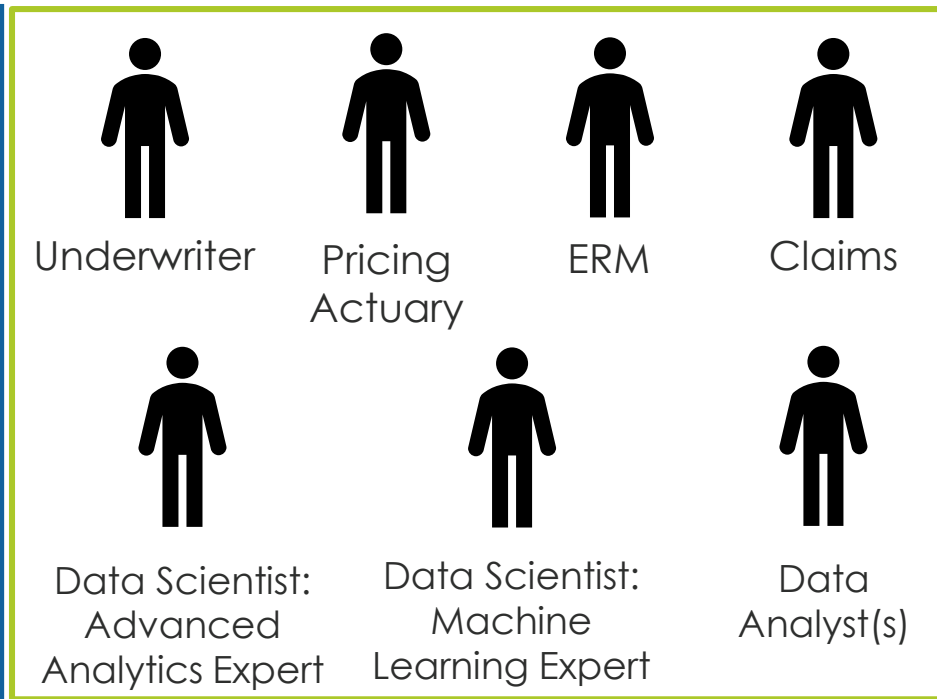
Now:

- Probabilistic models and machine learning

Technology Shifts Require New Skill Sets



Today

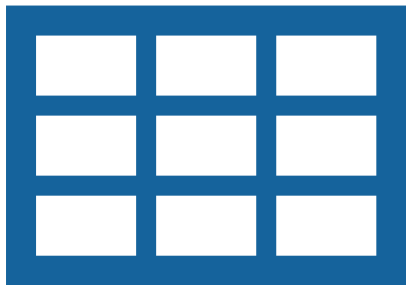


Tomorrow



How Are We Evaluating Risk Today?

How Are We Evaluating Risk Today?

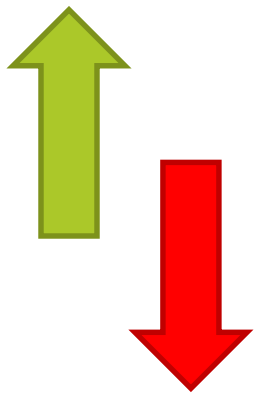


- Mortality tables built with limited information, e.g., age, sex, and smoking status and duration



- Underwriting often performed to meet minimum criteria for individual
- Designed to force firms to focus on an individual market and product
- Credit and debit systems require greater and greater expertise

How Current Methods Can Impact Your Business



Over- or under-
valuing risk

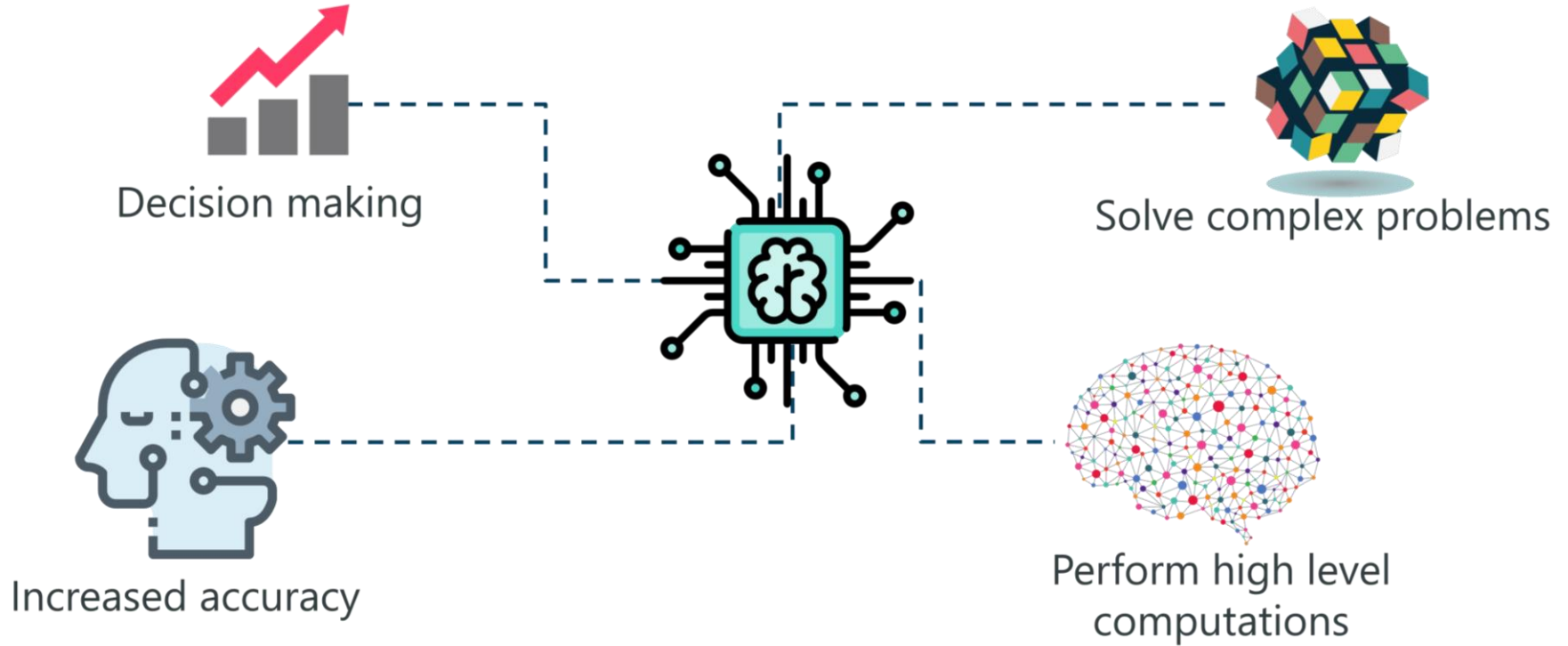


Anti-selection



Lack of accounting
for socioeconomic
factors

Machine Learning Offers Numerous Benefits



What Can We Learn from Amazon?



Recommended items other customers often buy again



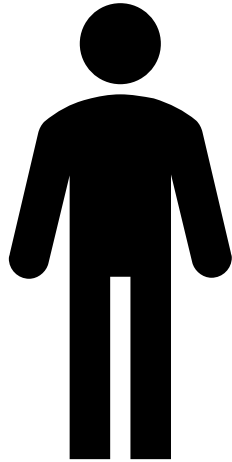
How do they know their customers—and why does it matter?

Can We “Amazon-ify” the Life Industry?



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Behaviors Can Be Independent or Correlated



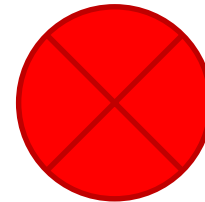
Buying
baseball
tickets



Looking up
directions to
the stadium

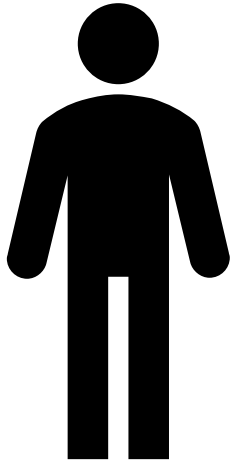


Buying a tube
of toothpaste
on Amazon



Leaving for
work at
8:30 a.m.

Behaviors Can Be Independent or Correlated



Buying
baseball
tickets

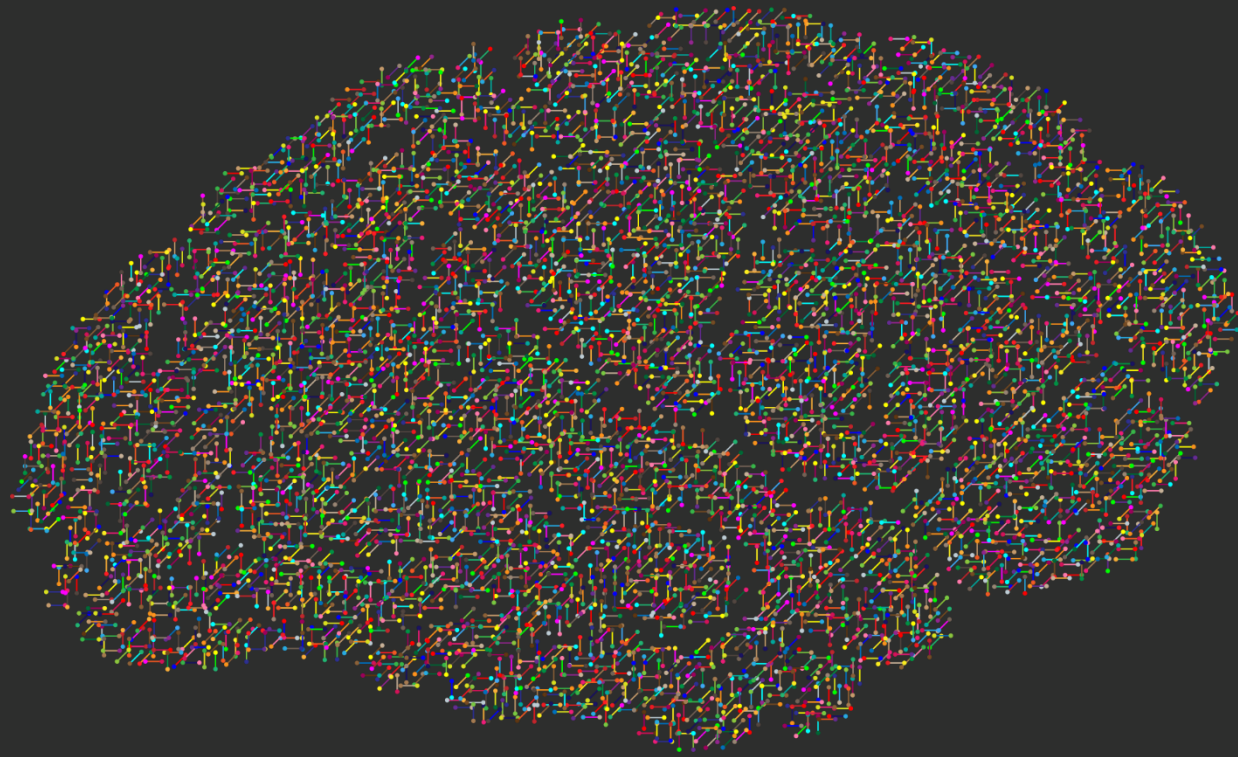


Looking up
directions to
the stadium



How Do We Find and Weigh Correlations in Mortality Risk Factors?





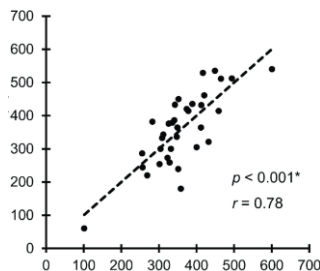
Exploring Possible Applications of Machine Learning

Comparing Modeling Methods

- **Traditional Statistical**

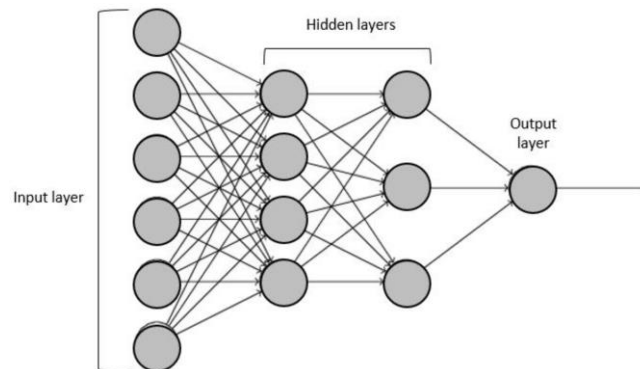
- Regression, multi-variable regression, distribution fitting, etc.
- Objective: understanding inference in the results

$$Y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + u_i.$$



- **Machine Learning**

- Artificial neural networks (ANNs), deep neural networks, heuristic algorithms, etc.
- Objective: predictability



Comparing Modeling Methods

	Traditional Statistical	Machine Learning
Advantages	<ul style="list-style-type: none">• Easily assess parameters and relationships• Control model format• Compare against other known relationships	<ul style="list-style-type: none">• Can smoothly take on very complex relationships• Often—not always—better at predicting outcomes
Disadvantages	<ul style="list-style-type: none">• Must decouple any correlations• Model limited by modelers' knowledge• Complex relationships may be omitted, smoothed, or captured poorly	<ul style="list-style-type: none">• Testing parameter output is complicated• Difficulty discerning some correlations• Subsequent testing can be problematic• Requires significant computational power

Multivariable Regression: Complexity Grows Quickly

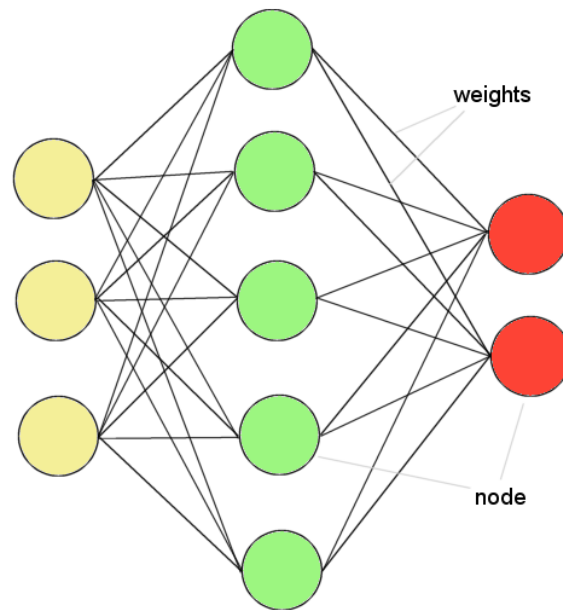
- Most simplistic form:
 - $mortality = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \varepsilon$
- Alternatively:
 - $mortality = \beta_0 + \beta_1 * (x_1)^2 + \beta_2 * \log(x_2) + \dots + \varepsilon$
 - $mortality = \beta_0 + \beta_1 * (x_1)^2 + \beta_2 * (x_1) + \beta_3 * \log(x_2) + \dots + \varepsilon$
- What if x_1 and x_2 are related?
 - $f(x_2) = \beta_0 + \beta_1 * (x_1) + \varepsilon$
 - $mortality = \beta_0 + \beta_1 * (x_1) + \beta_2 * \varepsilon_{f(x_2)} + \beta_3 * (x_3) + \dots + \varepsilon$

Artificial Neural Networks (ANN)

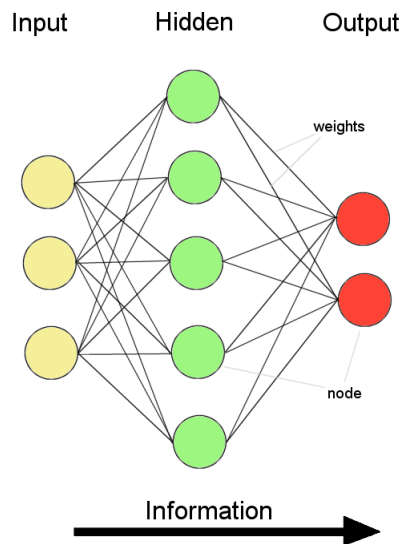
ANN: The Basics

ANNs incorporate the **two fundamental components** of biological neural nets:

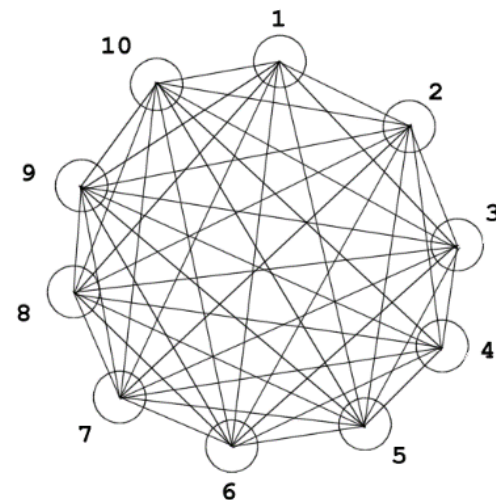
1. Neurons (*nodes*)
2. Synapses (*weights*)



ANN: The Basics



**Feed Forward
Networks**



Recurrent Networks

How Is a “Simple” ANN Model Applied?



1. User

- Defines data for training and testing
- Defines input data, number of neurons, their shape, and model output



2. Model

- Derives initial weights for each synapse
- Compares the estimated output vs. the actual
- Updates the weights for each synapse, with the updates being more refined over time
- Iterates through this process until it achieves its overall objective

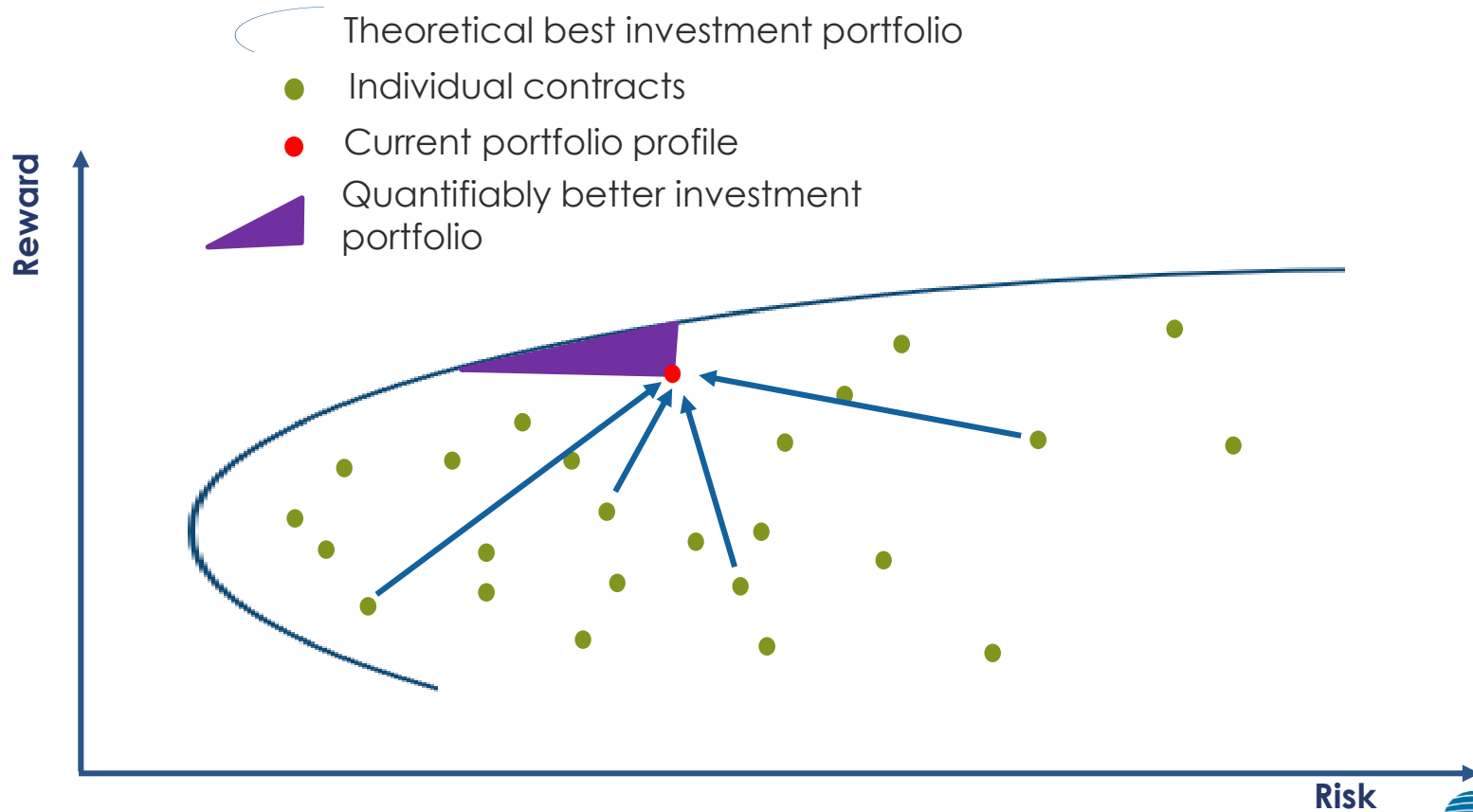
Testing an ANN Model

- Compare against testing data set to determine if the model is designed appropriately
- Run select data inputs to understand the output
 - Allows you to perform comparative analyses on specific iterations of data



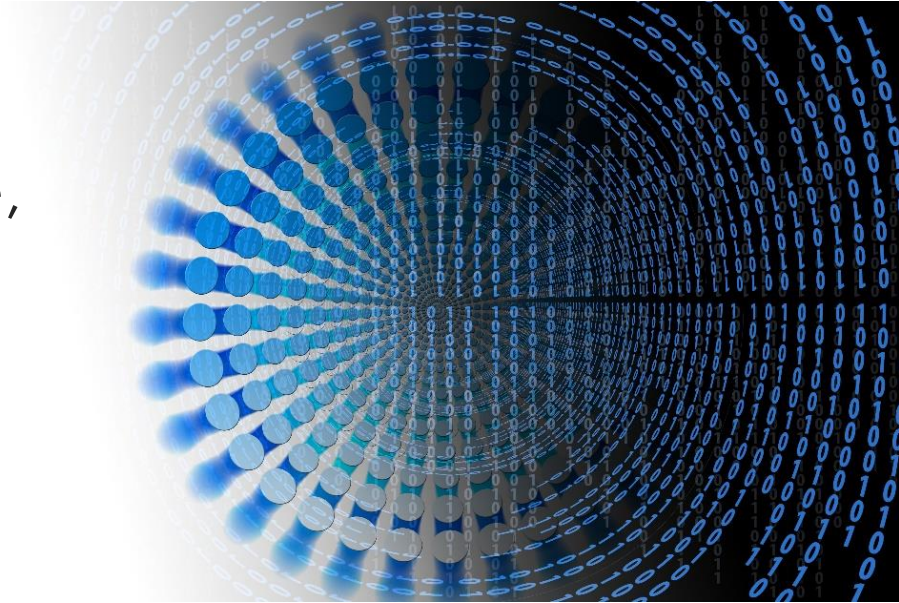
Genetic Algorithms (GA)

Envisioning the Efficient Frontier

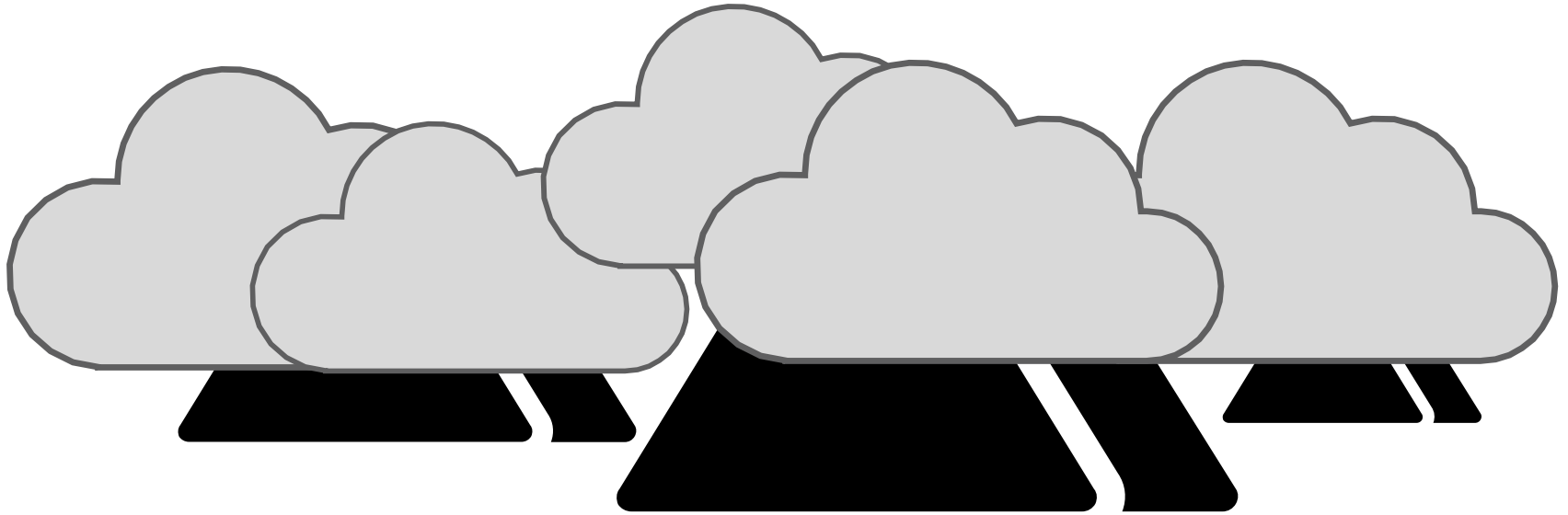


Quantifying the Size of the Problem

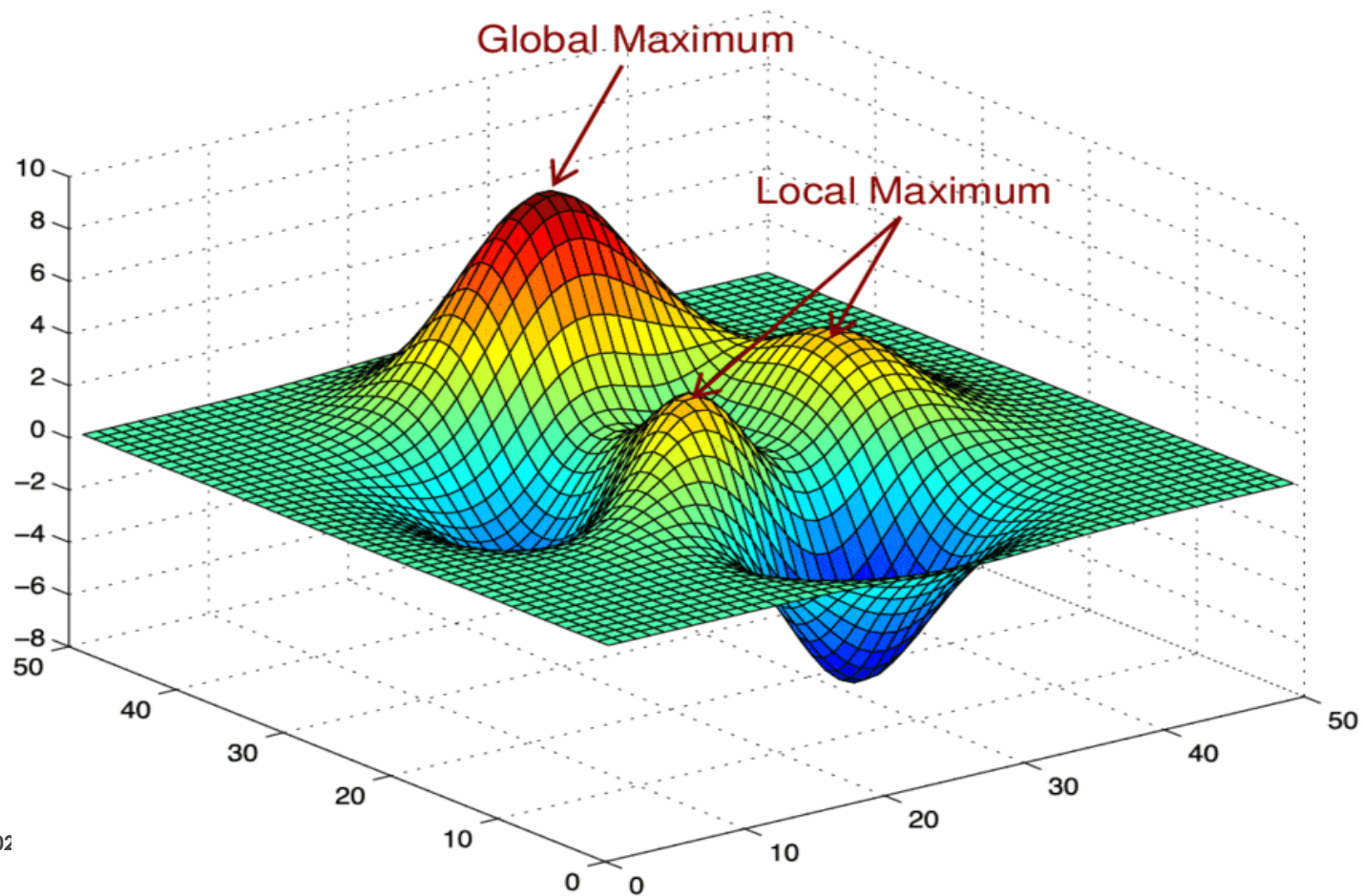
- With a fixed number of contracts, if each contract can only be sold as a whole, the resulting theoretical combinations will be:
 - 5 contracts = 32
 - 10 contracts = 1,024
 - 100 contracts = $1.27 * 10^{30}$



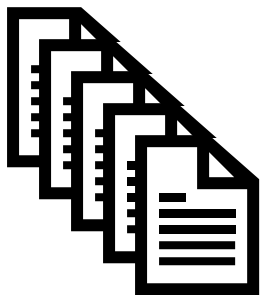
Can We Deduce Which Is the Highest Peak?



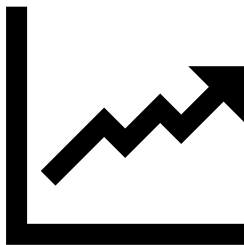
Global Maximum vs. Local Maximum



How It Works: Reinsurance Example



- Problem
 - Investor has USD 1 billion to invest in the reinsurance market
 - There are 1,000 contracts, each with their own price, expected return, risk profile, and correlation with other contracts



- Objective
 - What is the best investment portfolio I can derive?

Genetic Algorithm Method

Available Investments

A	B	C	D	E	F	G	H	I	J	K	L	M	...
---	---	---	---	---	---	---	---	---	---	---	---	---	-----

Each has its own **expected return**, **risk profile**,
and **correlation** to other investments

Simulated Investments

Sim. 1	1	0	0	0	1	1	0	1	0	0	0	1	1	...
--------	---	---	---	---	---	---	---	---	---	---	---	---	---	-----

Sim. 2	1	0	1	1	1	0	0	0	0	1	0	0	1	...
--------	---	---	---	---	---	---	---	---	---	---	---	---	---	-----

Sim. 3	0	1	1	1	0	1	0	0	1	1	0	0	0	...
--------	---	---	---	---	---	---	---	---	---	---	---	---	---	-----

Sim. 4 ...

Genetic Algorithm Method: Rank and Order

Iteration 1

Sim. 1
Sim. 2
Sim. 3
Sim. 4
•
•
•
Sim. n



Rank Iteration 1

Sim. 111
Sim. 12
Sim. 405
Sim. 8
•
•
•
Sim. #

} Keep

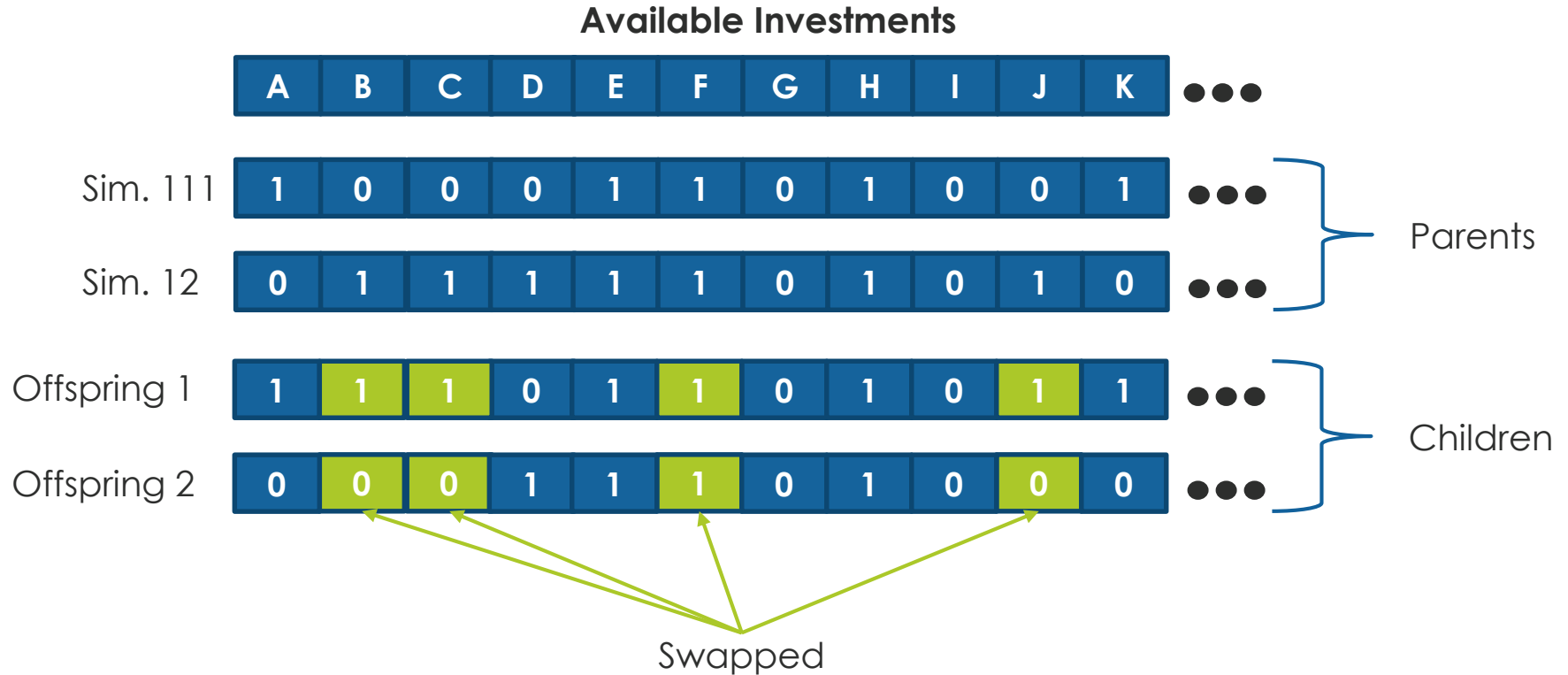
} Discard

Genetic Algorithm Method: Offspring

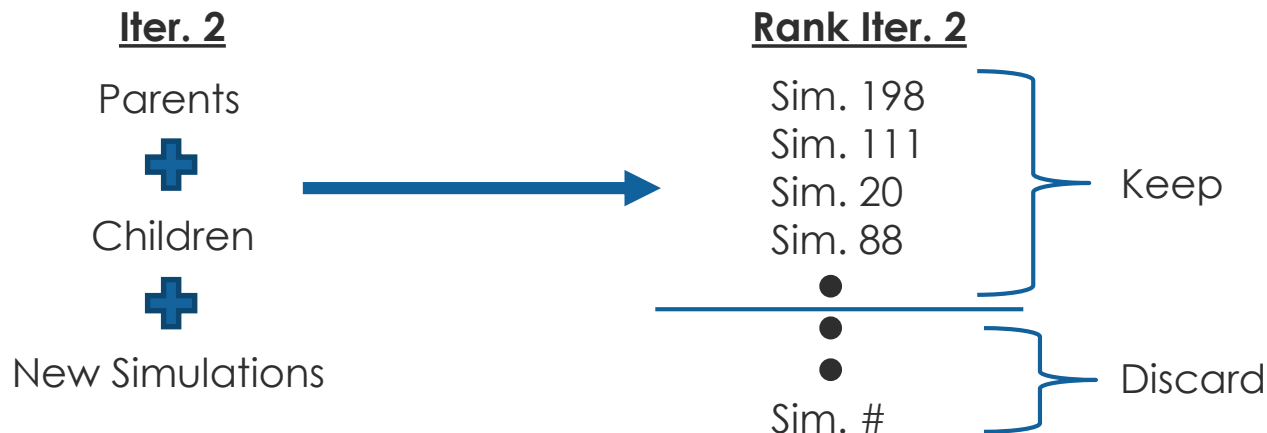
Available Investments

	A	B	C	D	E	F	G	H	I	J	K	...
Sim. 111	1	0	0	0	1	1	0	1	0	0	1	...
Sim. 12	0	1	1	1	1	1	0	1	0	1	0	...
Offspring 1	1	0	0	0	1	1	0	1	0	0	1	...
Offspring 2	0	1	1	1	1	1	0	1	0	1	0	...

Genetic Algorithm Method: Offspring

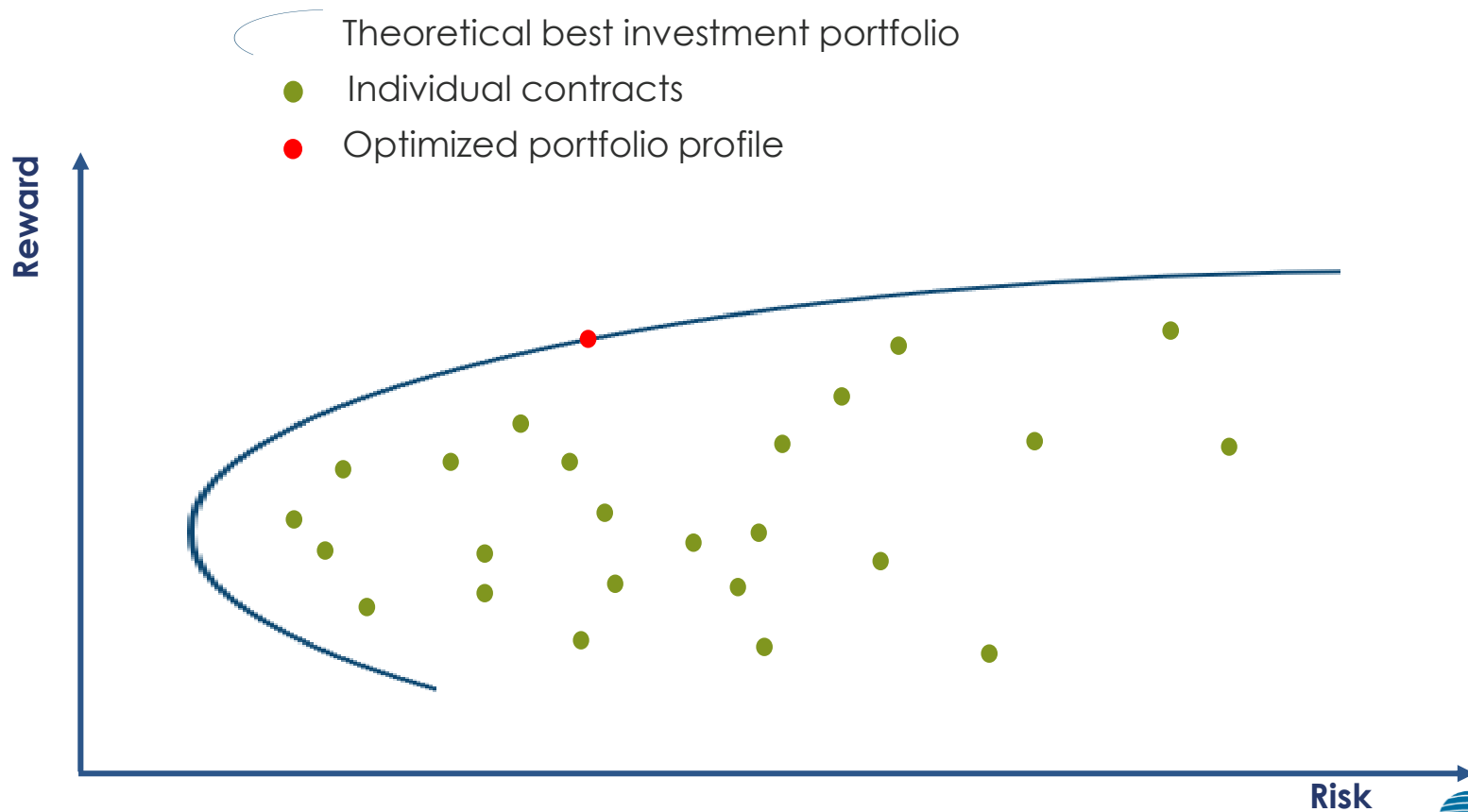


Repeat with Subsequent Iterations



This iterative process can consider **constraints** as well as **objectives**, e.g., life insurance limit, age restrictions, disease restrictions, broker caveats, percent change from current investments, etc.

Reaching the Efficient Frontier



How AIR Applies Machine Learning Techniques

How AIR Applies Machine Learning Techniques

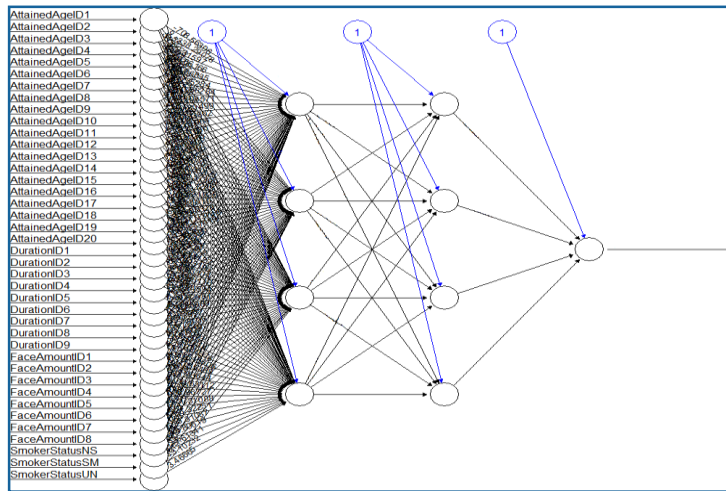
INPUT

- Age
- Sex
- Duration of policy
- Face amount/annuity amount
(income level predictor)
- Health status
 - Smoking status
- Socioeconomic status
- Post-term period
- Geographical location
- Policy options
- ...

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METHODOLOGY

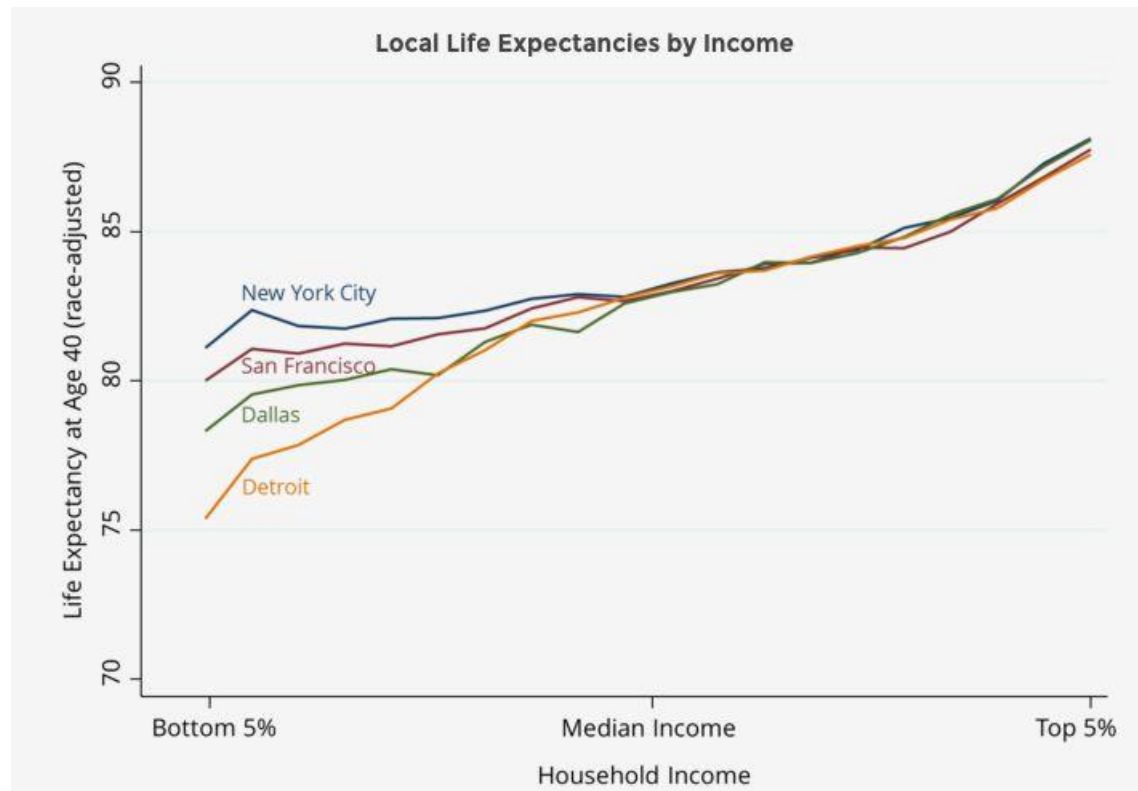
Artificial Neural Network



Logistic Regression

$$\begin{aligned}
 \text{Log}(\text{mort}_{x,\text{gender}}) = & \beta_0^{x,\text{gender}} + \beta_1^{x,\text{gender}} \text{Age} + \beta_2^{x,\text{gender},\text{terms}} \text{Policy Terms} \\
 & + \beta_3^{x,\text{gender}} \text{Duration} + \beta_4^{x,\text{gender}} \text{Duration}^2 \\
 & + \beta_5^{x,\text{gender}} \text{PostTerm} + \beta_6^{x,\text{gender}} \text{PostTerm}^2 \\
 & + \beta_7^{x,\text{gender},\text{group}} \text{Age}_{\text{Smk}} + \beta_8^{x,\text{gender},\text{InsGroup}} \text{InsuranceUnderwriting} \\
 & + \beta_9^{x,\text{gender},\text{Face}} \text{FaceAmount}
 \end{aligned}$$

Improvement Rates Vary Across Demographics



Source: *The Health Inequality Project*

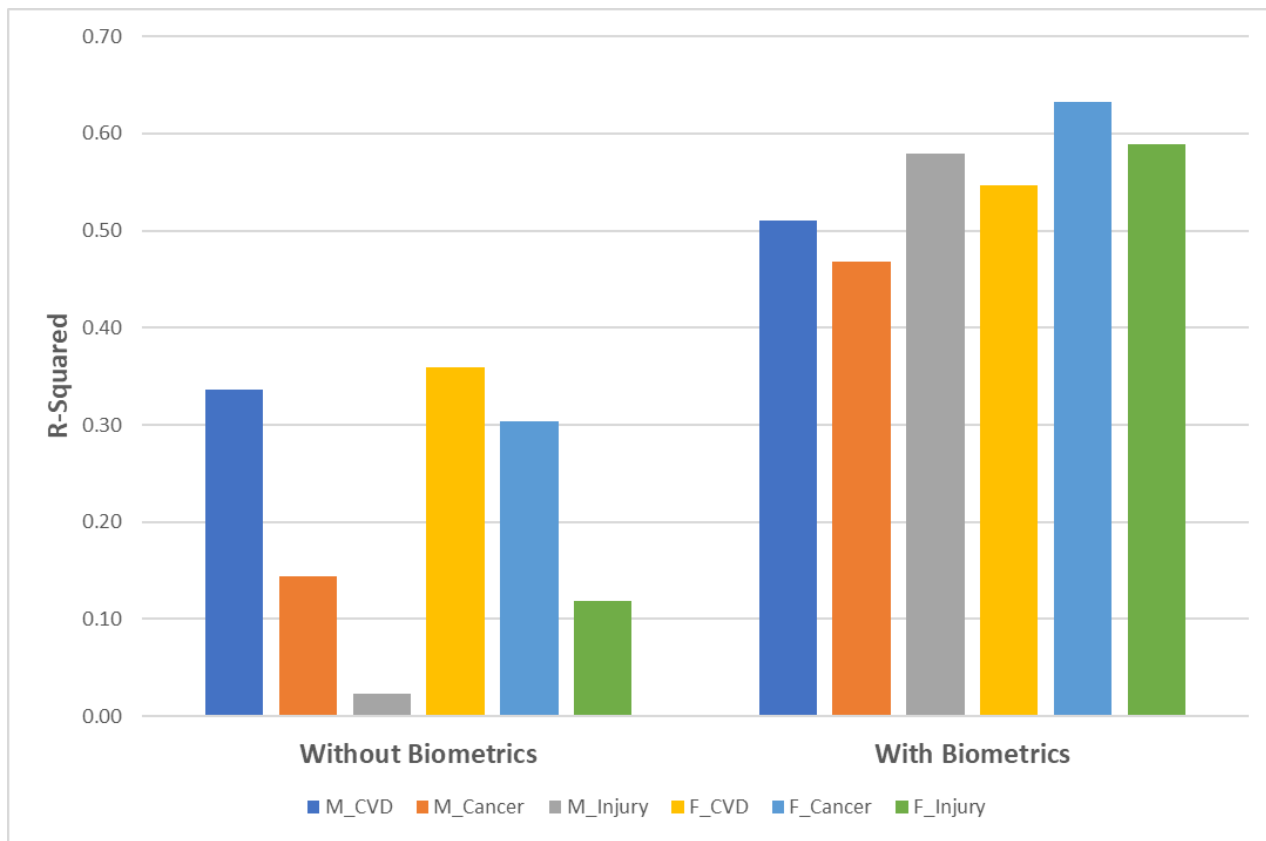
Mortality Improvements Are Not Simply a Function of Income

- Income is related to mortality, but is also correlated with other factors

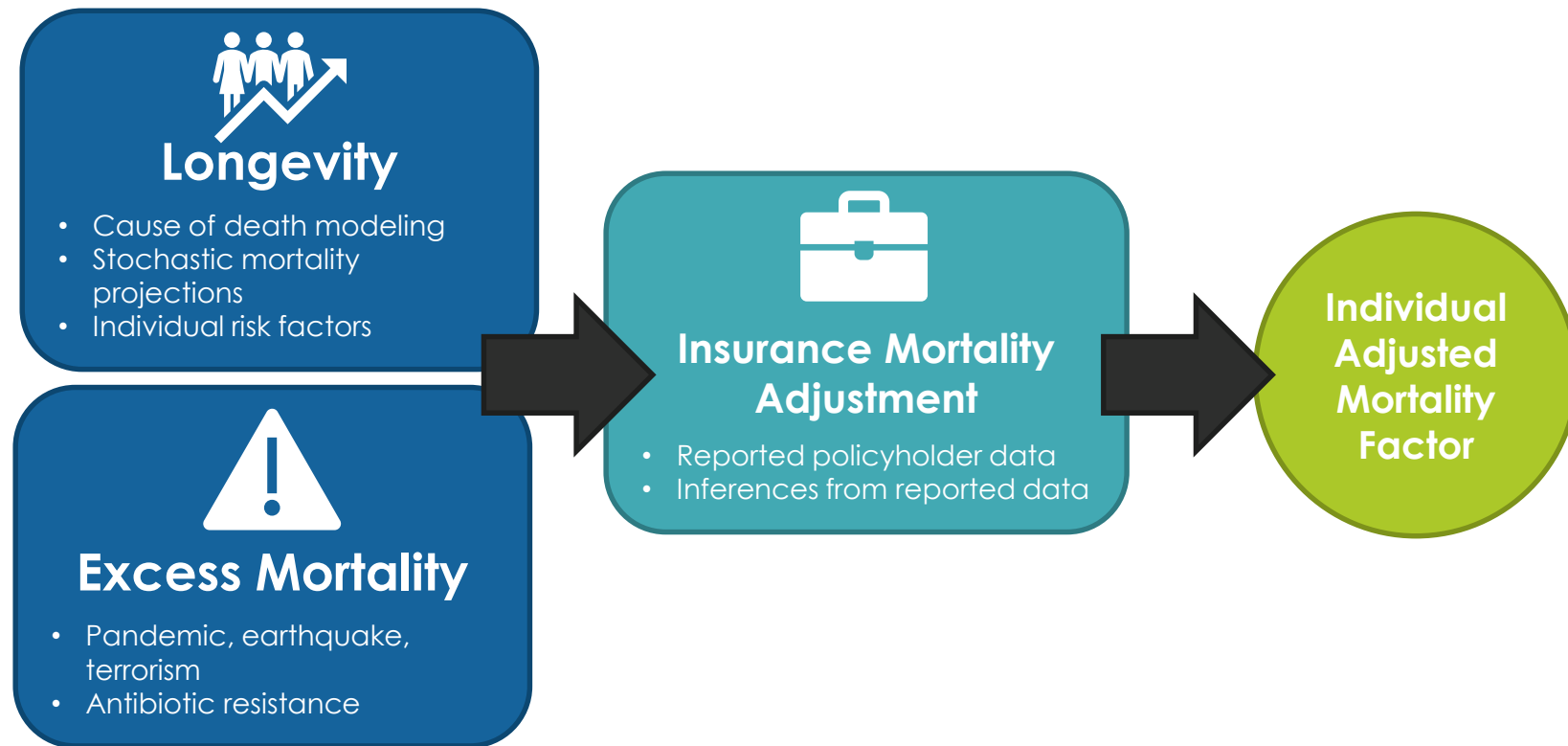


- Breaking down biomedical information and using a multi-variable dynamic model provides a better view of risk

Biometric Data Enhances Understanding of Trends



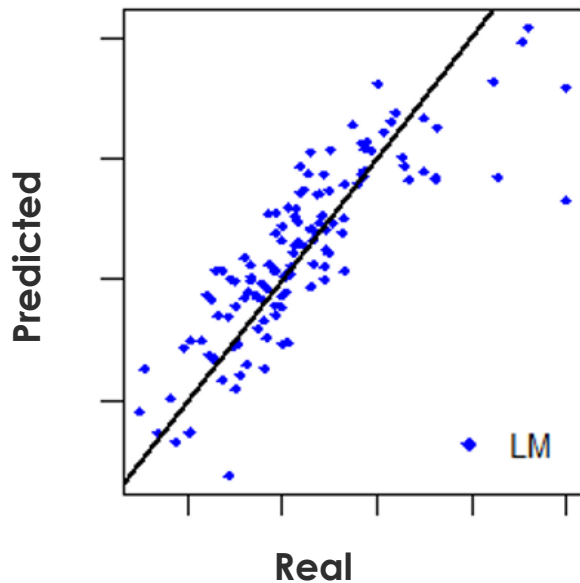
Life Risk Models



Hypothetical Fits

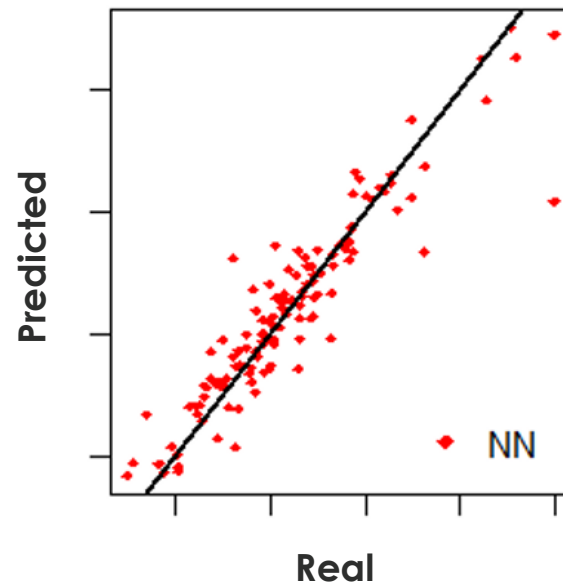
Linear Model (LM)

$$\sigma = 4.66$$



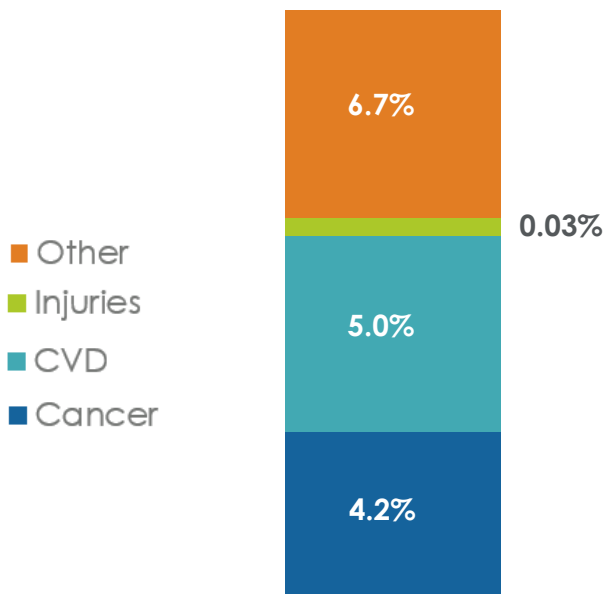
Neural Network (NN)

$$\sigma = 3.97$$



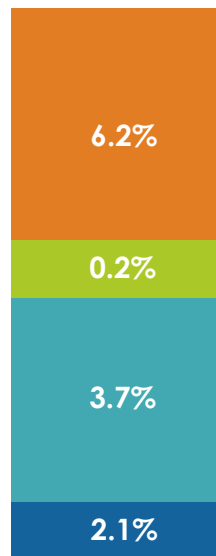
Mortality Adjustment for Insured Individuals

Mortality rate: 15.9%



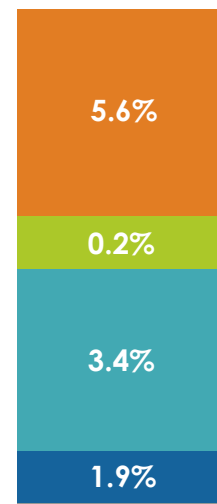
Average
85-year-old female

Mortality rate: 12.2%



Non-smoker
85-year-old female

Mortality rate: 11%



Insured – 85-year-old female
Whole Life
Preferred NN

Key Takeaways

1

Machine learning is already changing our world—and it shows no signs of slowing down

2

Machine learning applications in the life insurance industry are helping us rethink risk

3

The value of AI underwriting will surpass USD 20 billion by 2024 from USD 1.3 billion in 2019 (Juniper Research)

An aerial photograph of a busy pedestrian crossing in Times Square, New York. The image shows a large crowd of people walking across the street. Overlaid on the image is a network of thin, light blue lines connecting various points, with small colored dots (blue, green, pink, yellow) at the nodes, suggesting a data network or connectivity theme.

Verisk Life Seminar

The Westin New York at Times Square

March 10, 2020

- Industry perspectives on an evolving life insurance landscape
- Innovations using machine learning and predictive analytics
- Capturing the impact of shifting life expectancy trends
- Leveraging emerging data sources to better understand and manage risk
- Enhancing underwriting, claims, and portfolio management workflows

\$125 Early Bird Rate available now



Thank you!
Questions?

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