

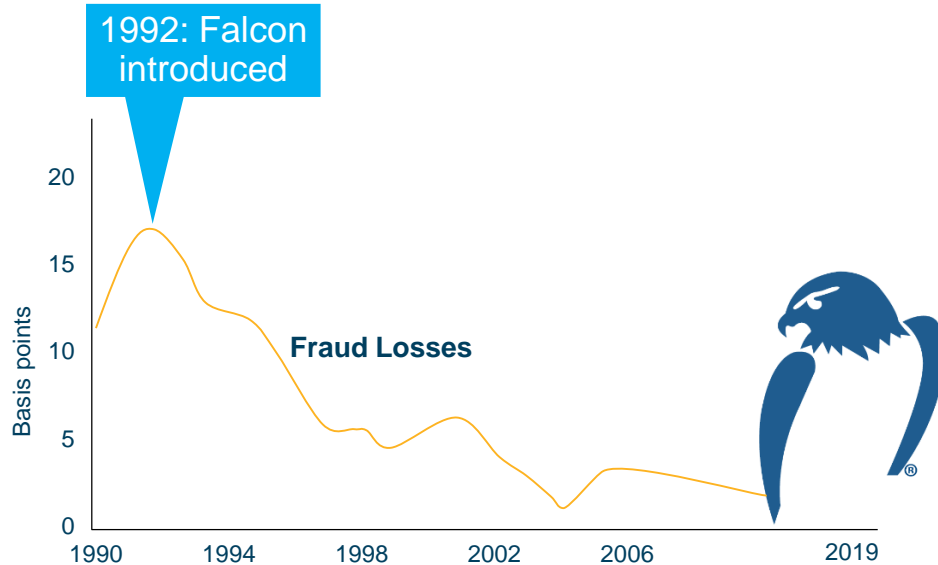
Deep But Explainable: Explainable Latent Feature Neural Networks

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Chief Analytics Officer, FICO

Shafi Rahman
Sr. Principal Scientist, FICO

FICO has 30+ years of Machine Learning Experience

1992: First ML based patent issued for FICO® Falcon® Fraud Manager



3000 ML research years

197 issued patents

102 pending patent applications

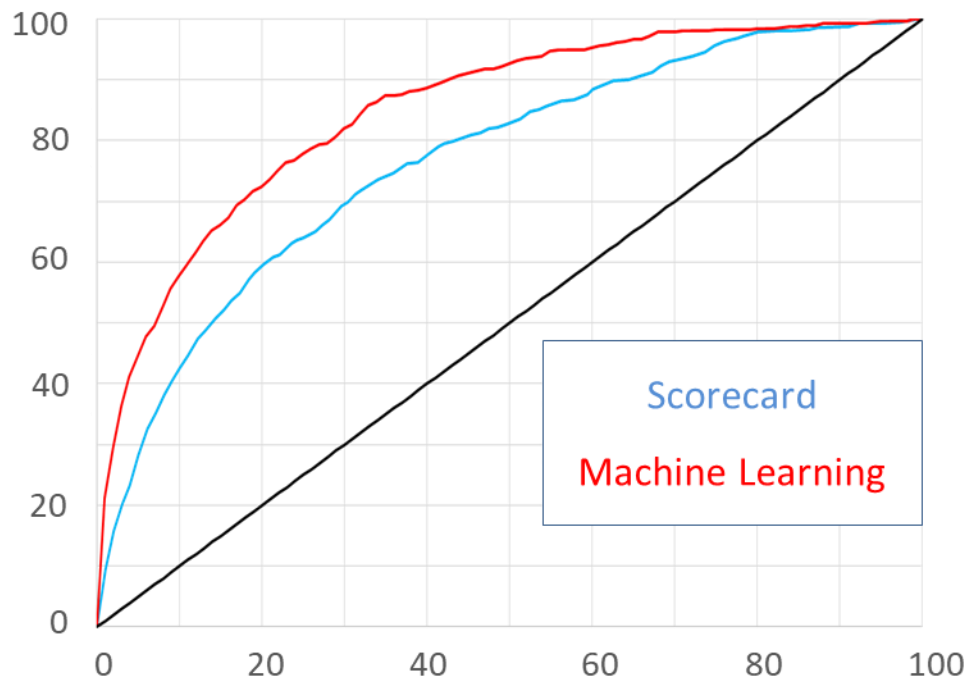
125+ patents in ML to date

Substantial Improvements in Credit Risk Space with Machine Learning Models

Home Equity Portfolio

— Bad rate of 7.7%

~15% improvement in KS
over Scorecard



FICO® Score Using Neural Networks

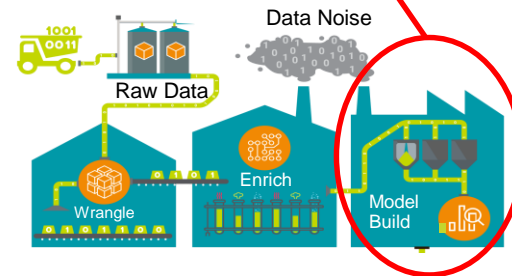
Neural Networks Yield Modest Predictive Lift; Significantly More Streamlined Model Build

< 2%*

Predictive Lift

40 vs 800

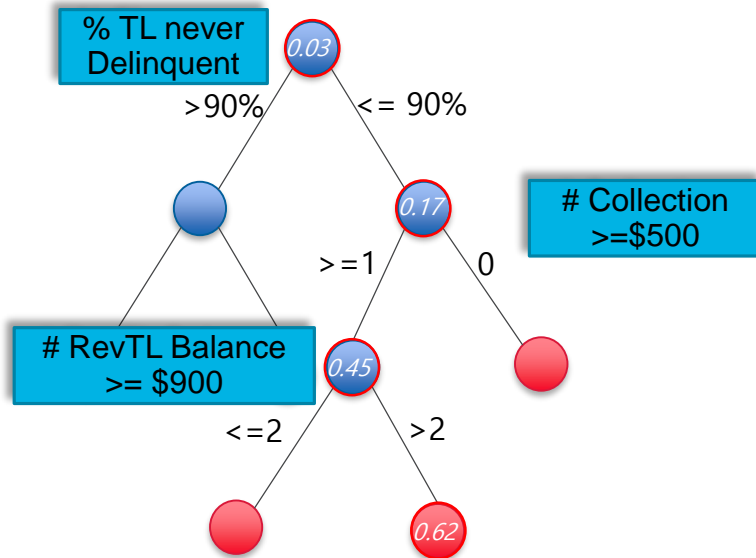
Resource hours required to build model
(vs status quo approach)

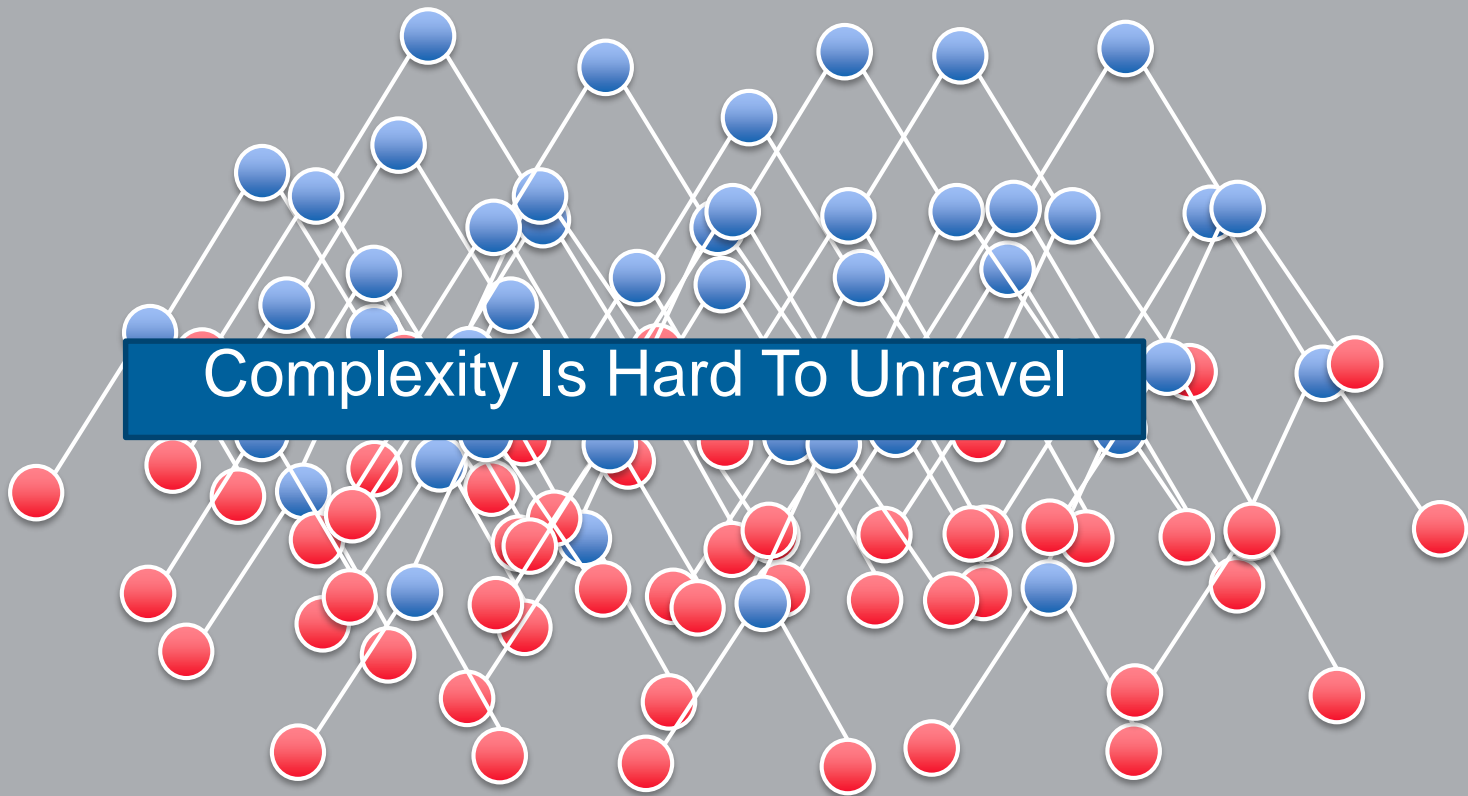


* Measured by relative % improvement in KS statistic on in-time holdout sample

Decision Tree

Probability of Default







Regulatory Requirements

Executive Acceptance

Avoiding Biased Decisions

Neural Network Technology



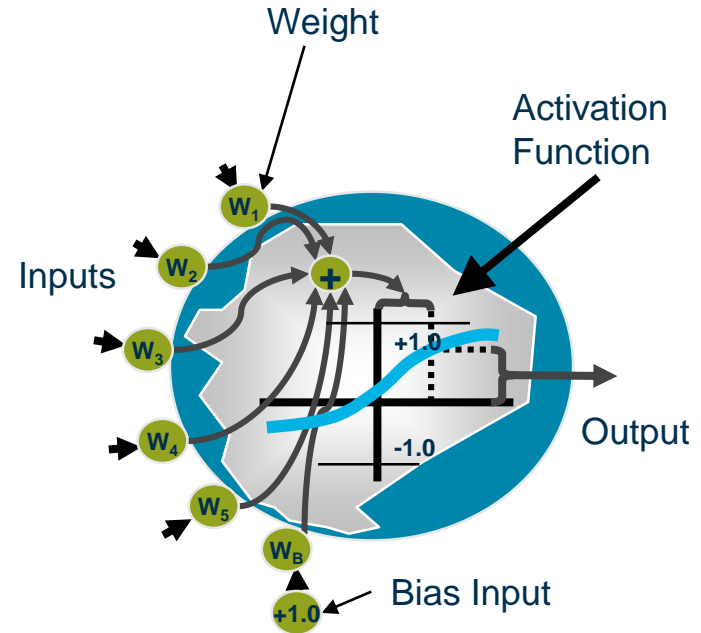
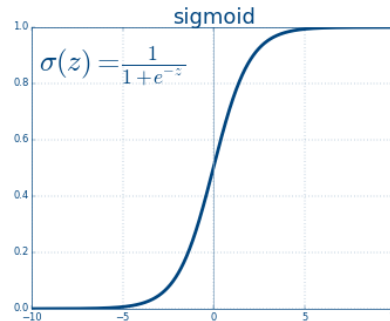
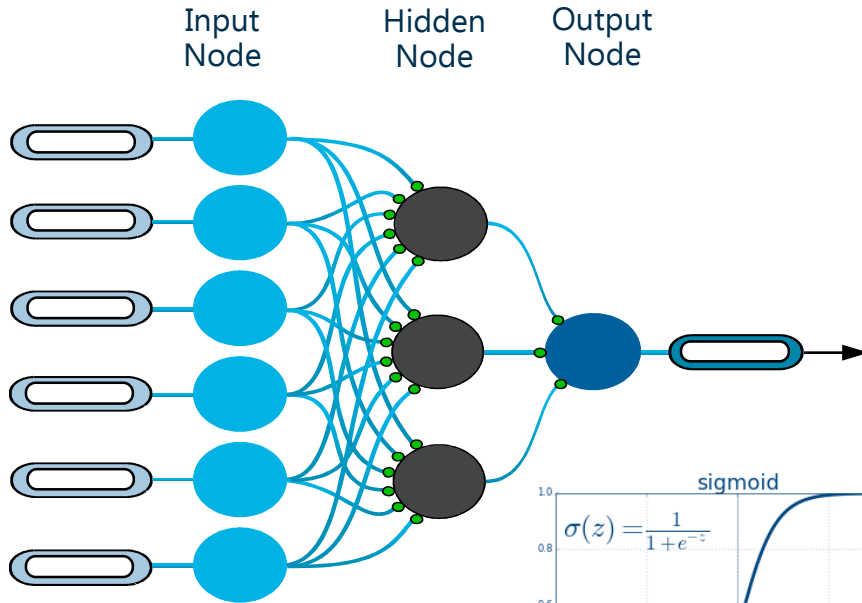
90%

Percentage of the US payment cards covered by FICO fraud solutions

2.6B

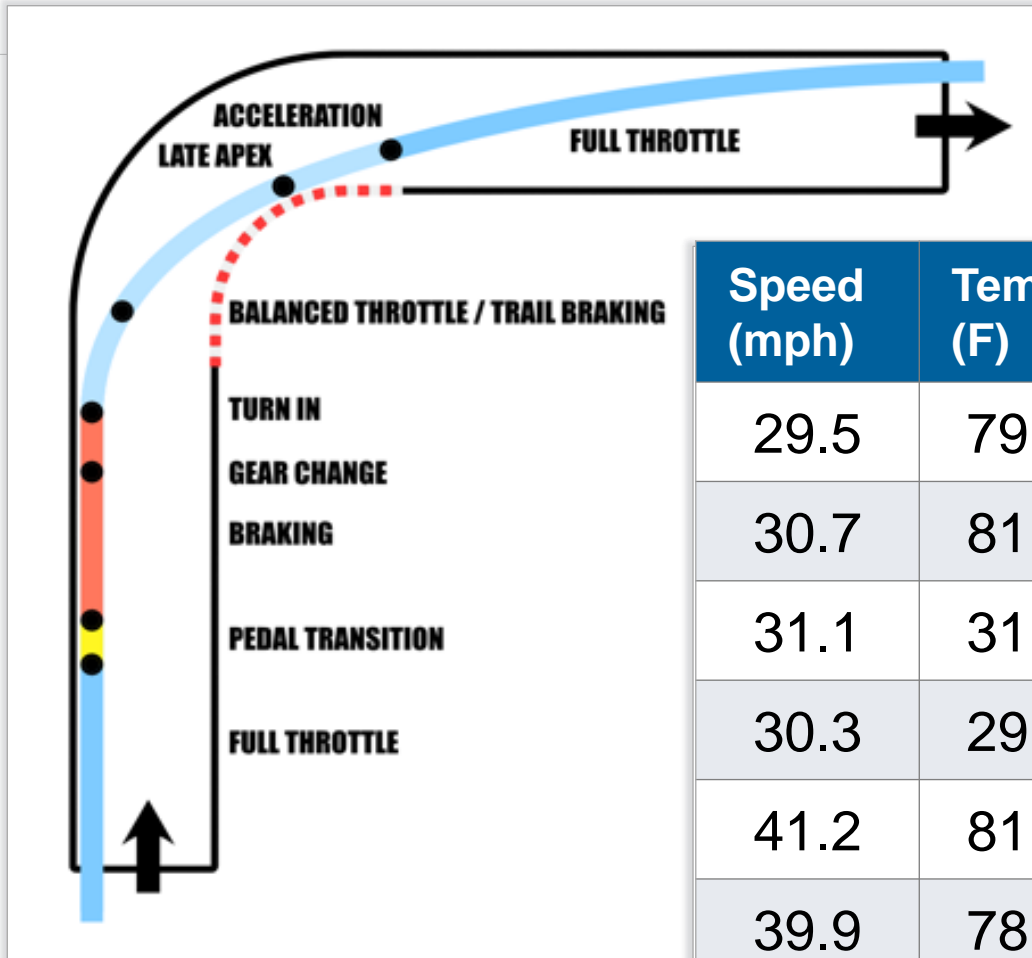
Active financial accounts protected by FICO worldwide

Neural Networks Are The Most Classic Machine Learning Technique

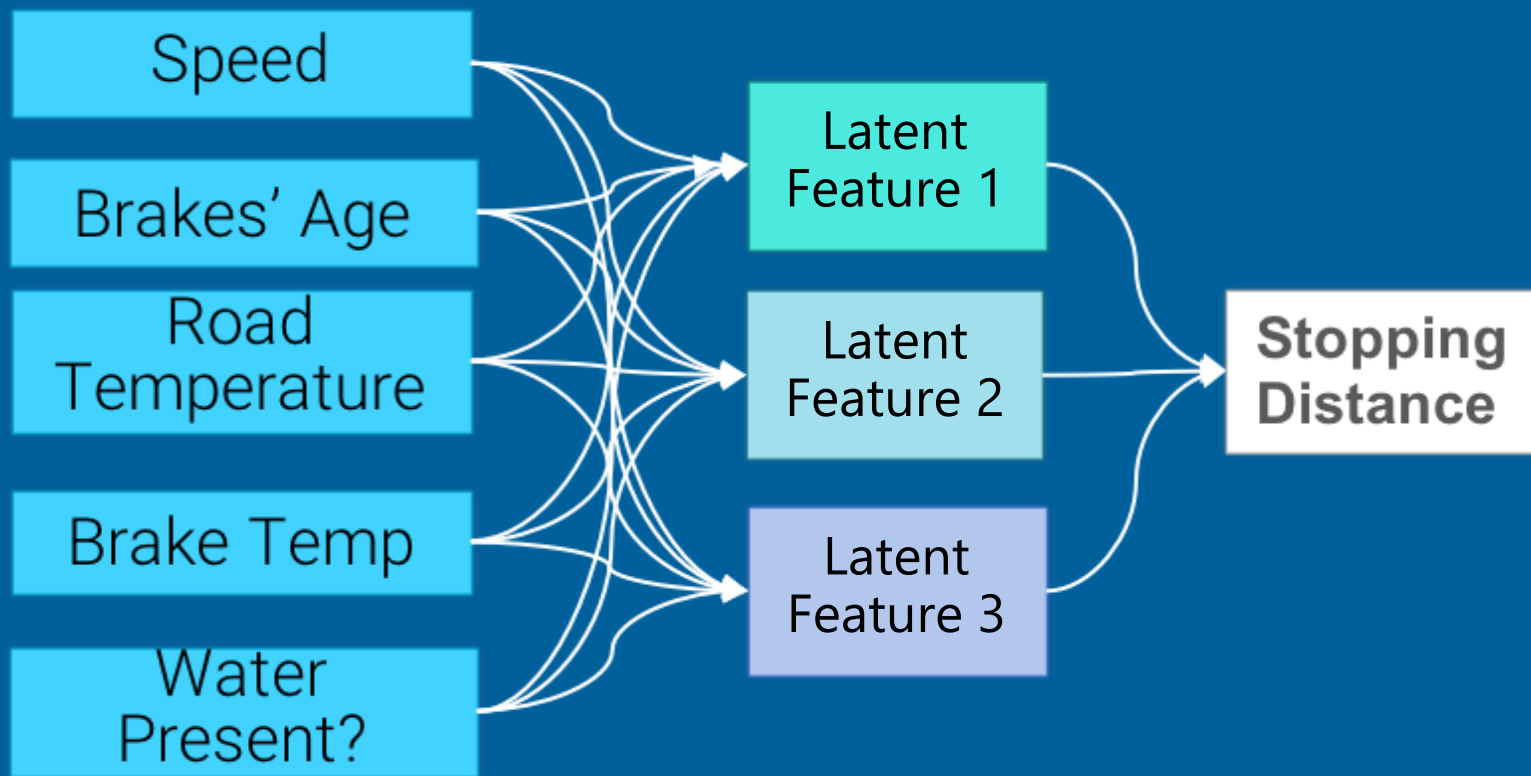


Learns non-linear relationships

How do Neural Networks Work?

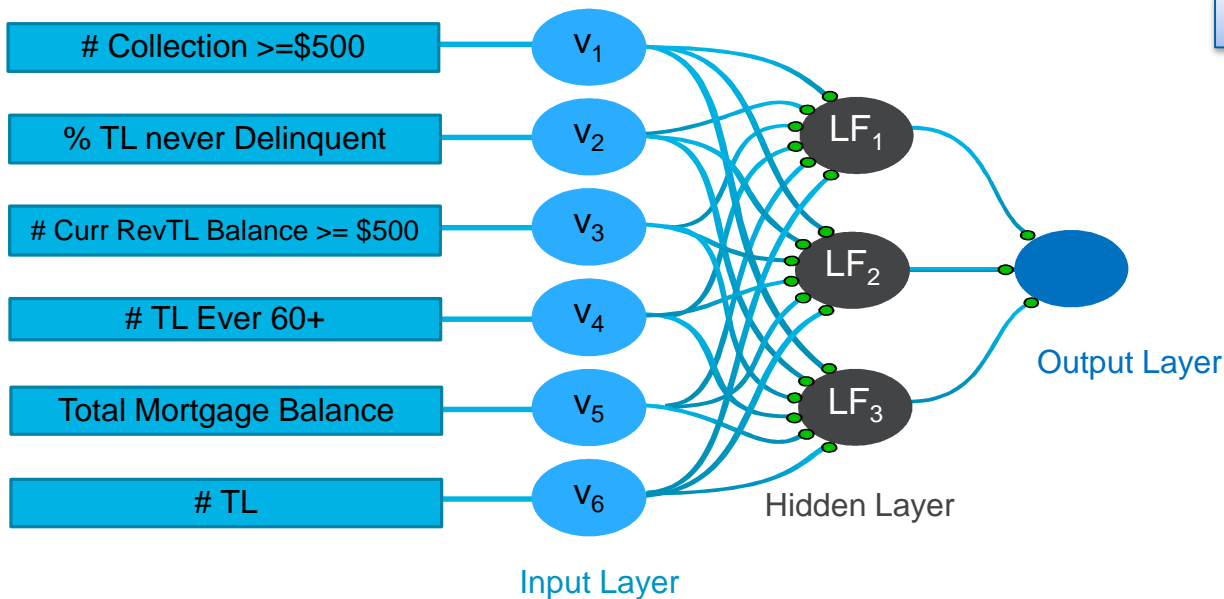


| Speed (mph) | Temp (F) | Water ? | ... | Stopping dist (ft) |
|-------------|----------|---------|-----|--------------------|
| 29.5 | 79.9 | No | ... | 45 |
| 30.7 | 81.0 | Yes | ... | 91 |
| 31.1 | 31.9 | No | ... | 51 |
| 30.3 | 29.8 | Yes | ... | 269 |
| 41.2 | 81.1 | No | ... | 82 |
| 39.9 | 78.7 | Yes | ... | 159 |



WHAT DID IT LEARN? Do we know?

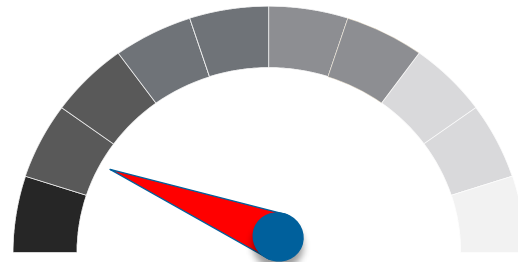
Applying Machine Learning To Mortgage Origination Problem



Cost Function

$$C(w) = \frac{1}{2p} \sum_x \|y(x) - a(x)\|^2$$

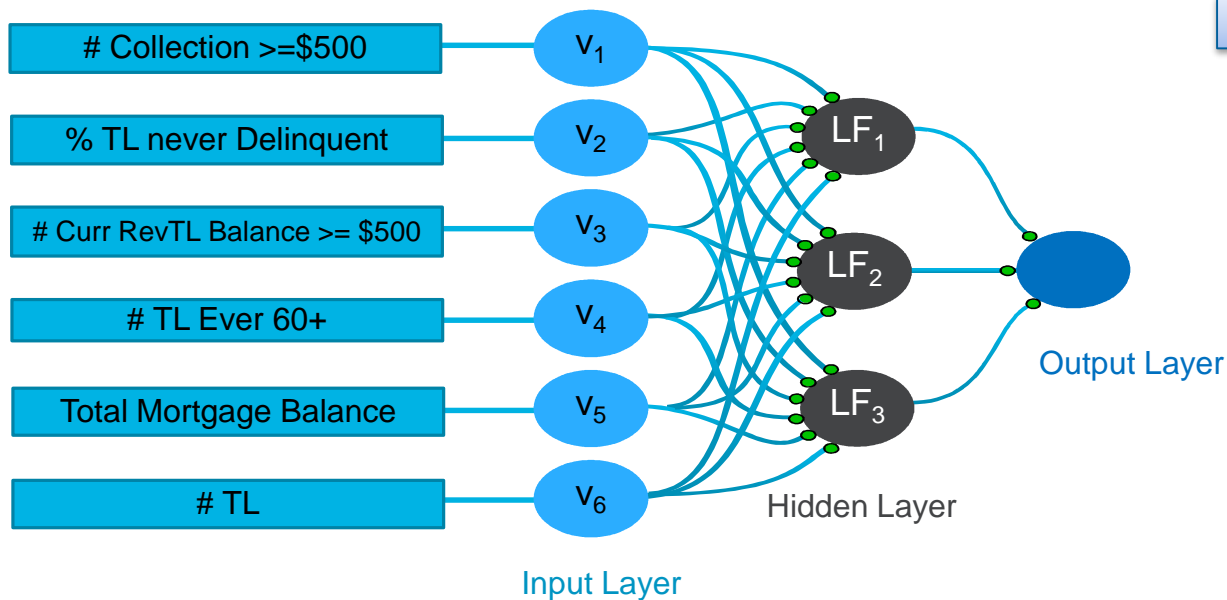
~15% improvement in
KS over Scorecard



Interpretability Meter

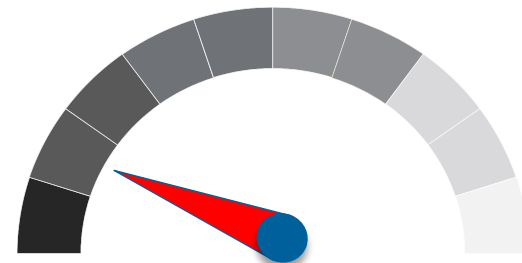
Patent 15/985,130 (USA)

Change The Cost Function



Cost Function

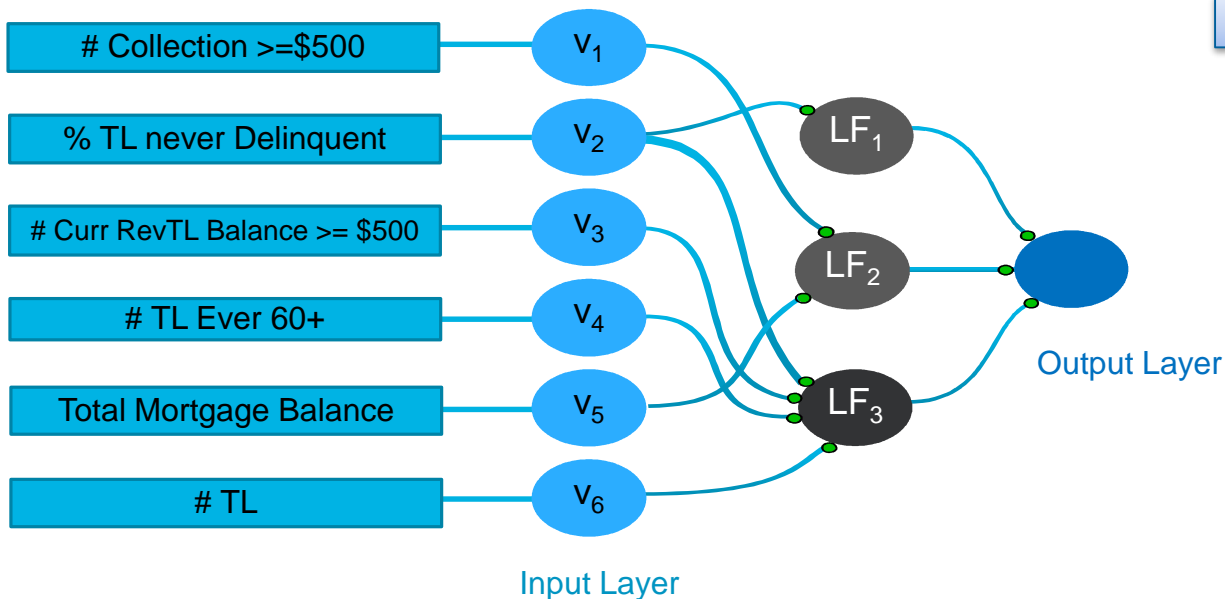
$$C'(w) = C(w) + \frac{\lambda}{p} \sum |w|$$



Interpretability Meter

Patent 15/985,130 (USA)

Determine Edges That Don't Contribute



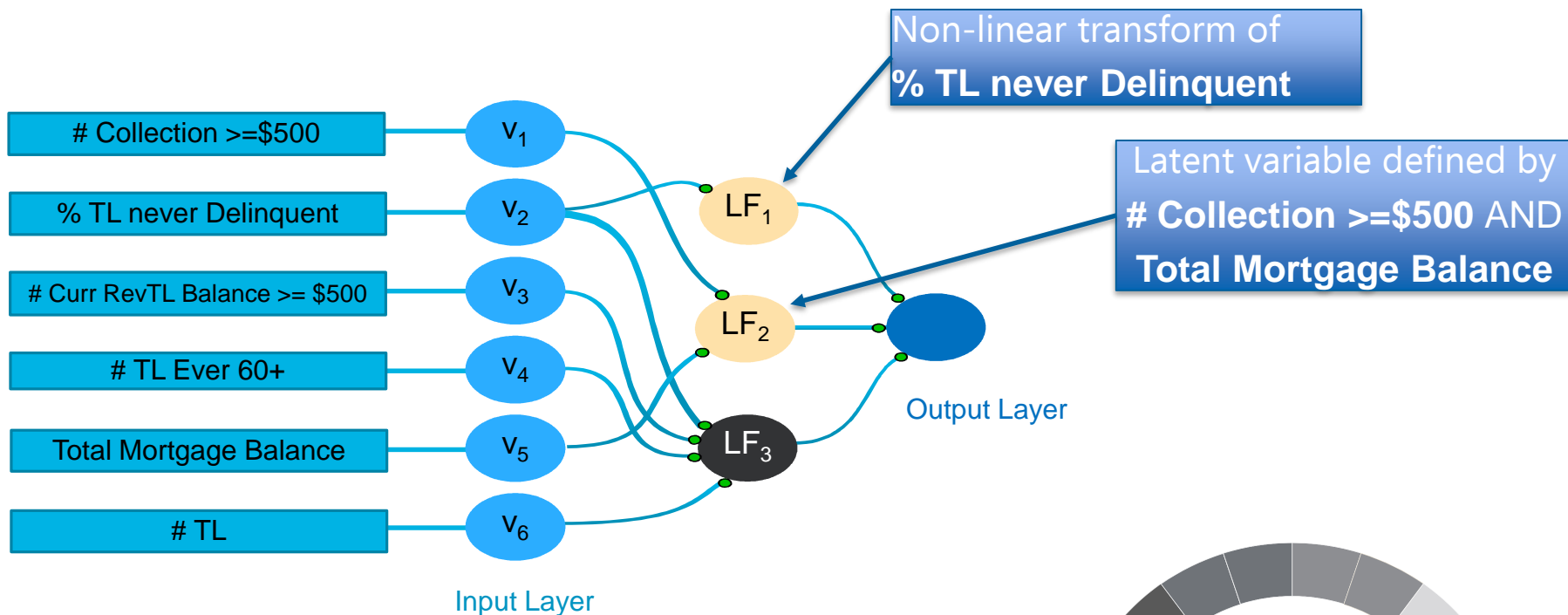
Cost Function

$$C'(w) = C(w) + \frac{\lambda}{p} \sum |w|$$



Patent 15/985,130 (USA)

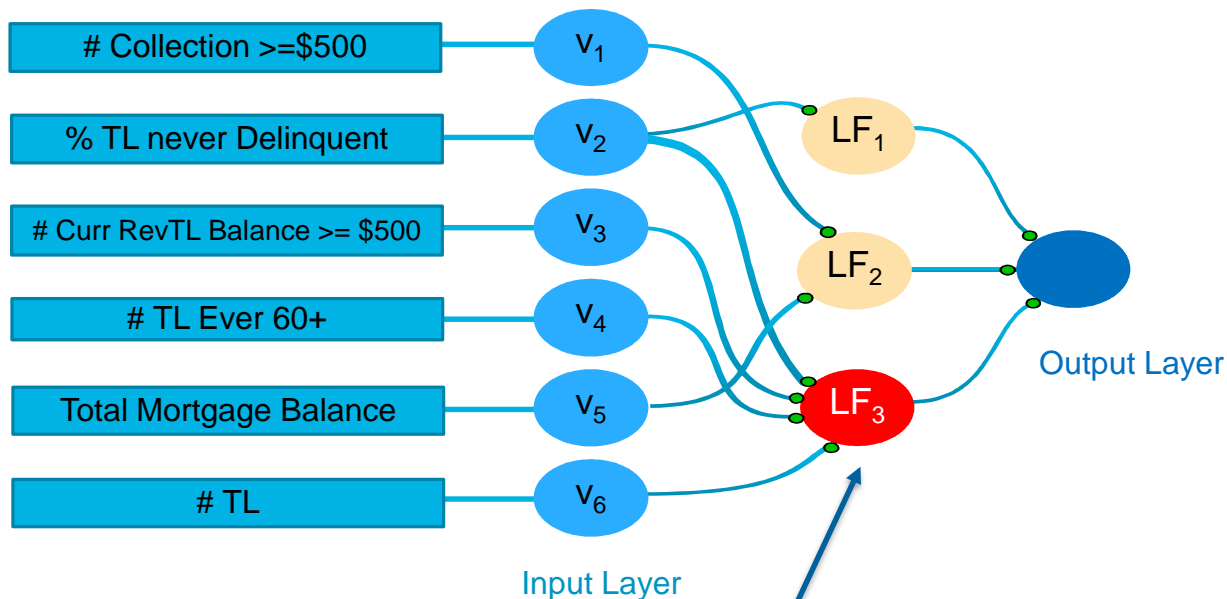
Some Hidden Nodes Are Interpretable Functions of Input Variables



Patent 15/985,130 (USA)



Identify All Complex Hidden Nodes



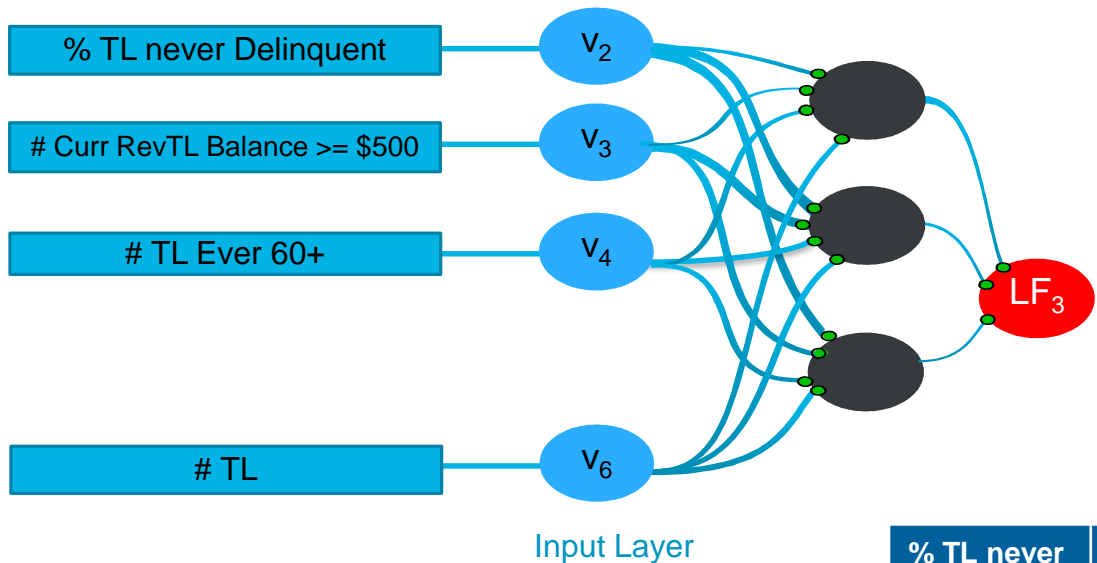
Complex hidden node

Patent 15/985,130 (USA)



Explode the Complex Nodes

Train a Fully Connected Neural Network with complex hidden node's activation as the target

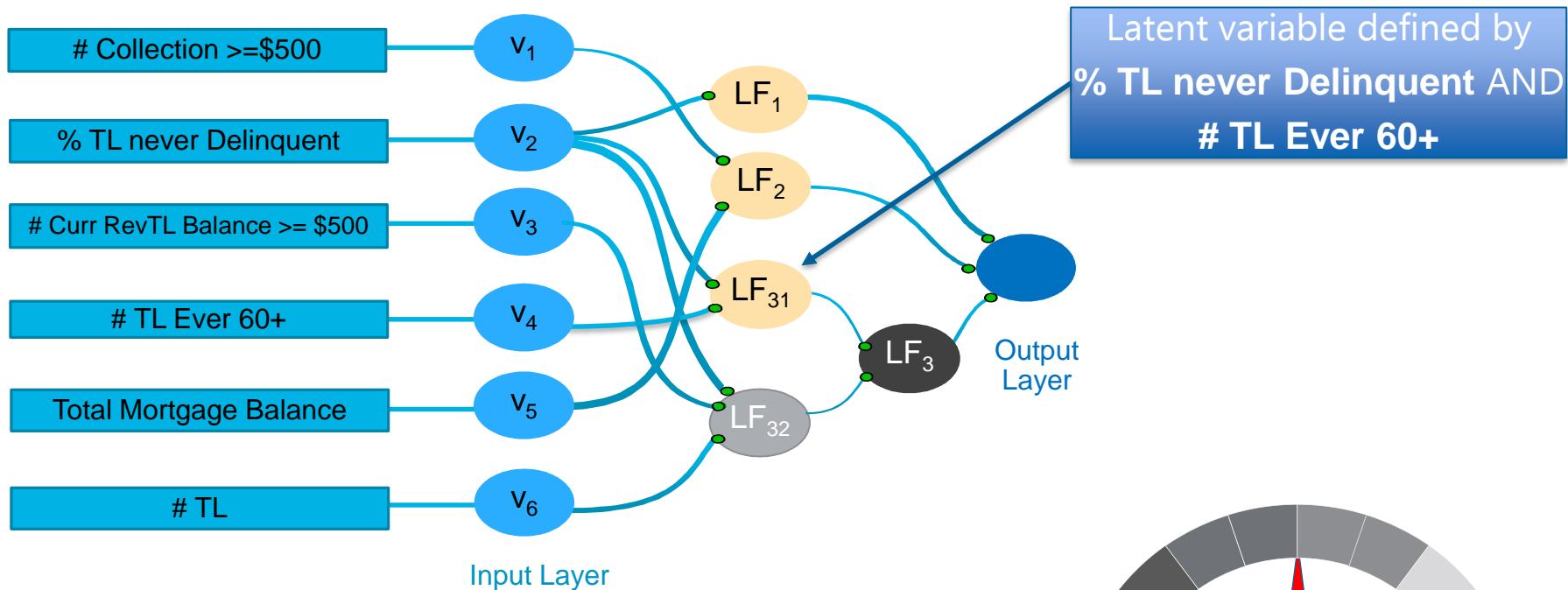


New Training Dataset

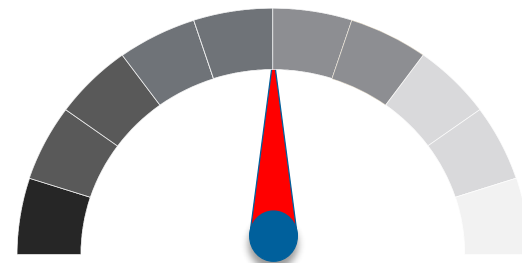
| % TL never Delinquent | # Curr RevTL Balance >= \$500 | # TL 60+ Overdue Ever | # TL | LF_3 |
|-----------------------|-------------------------------|-----------------------|------|--------|
| 77.8 | 3 | 0 | 9 | 0.41 |
| 100 | 1 | 0 | 5 | -0.3 |
| 83.3 | 2 | 1 | 6 | 0.89 |

Patent 15/985,130 (USA)

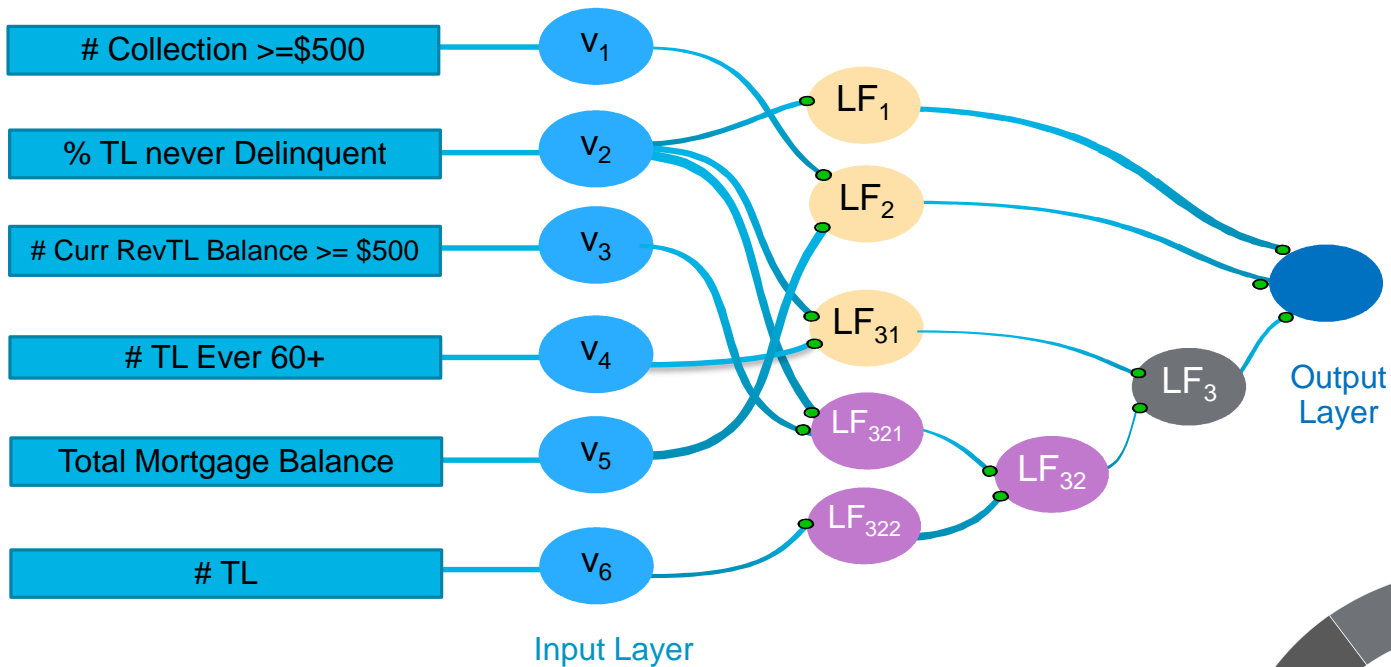
Superimpose Rest of the Interpretable Model



Patent 15/985,130 (USA)



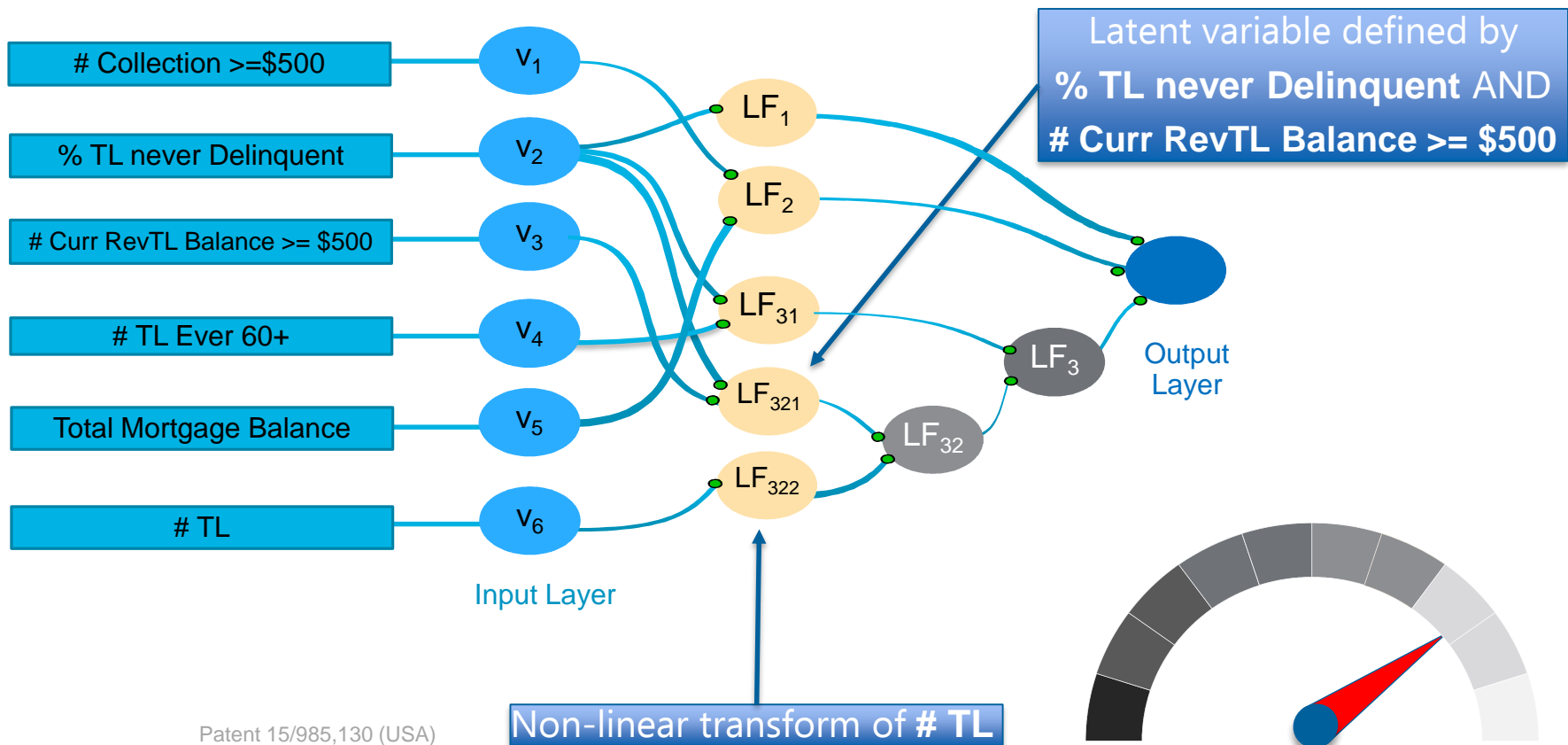
Final Model Has No Complex Nodes



Patent 15/985,130 (USA)



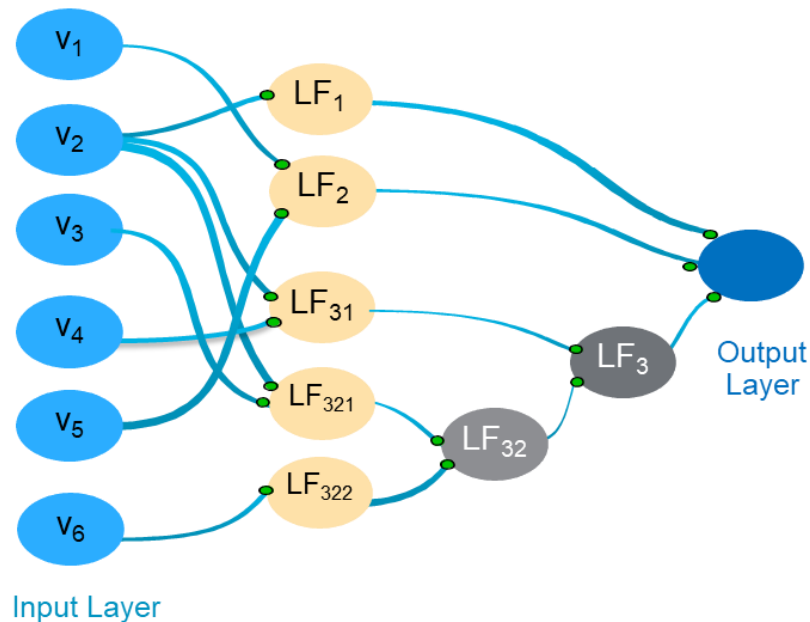
Final Model Has No Complex Nodes



Patent 15/985,130 (USA)

Use Case #1: Using Interpretable Latent Features Models Directly

Brave New World of Explainable Neural Network Models



Use The Explainable Neural Network
Directly for Origination Decisions

Patent 15/985,130 (USA)

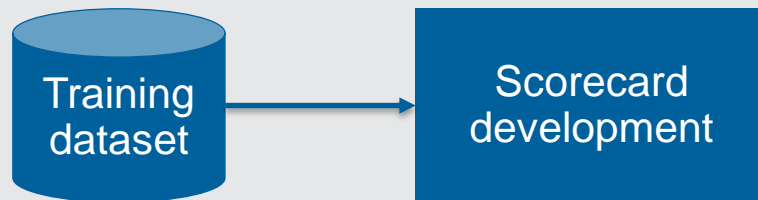
A hand in a dark suit and light-colored shirt is pointing towards the center of the image. The background is a blurred office scene with a hexagonal grid overlay. The word "Risk" is written in a large, bold, white font inside a central dark hexagon. Surrounding this central hexagon are several other hexagons, each containing a white icon: a handshake, a globe, a stack of money with a dollar sign, a bar chart with an upward arrow, a group of three people, and a document with a checkmark.

Risk

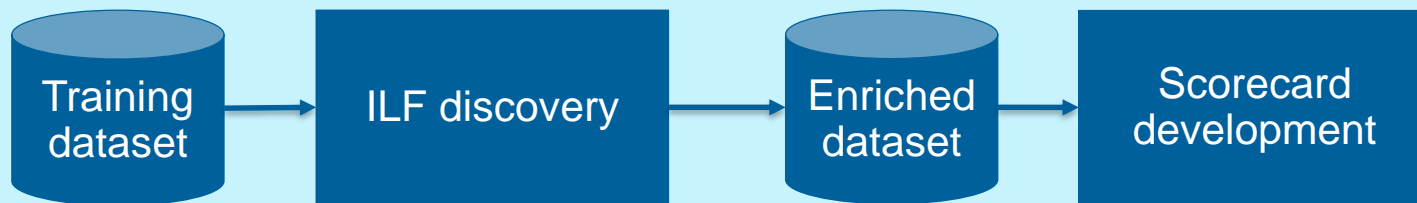
Brave New World of Credit Risk

Use Case #2: Scorecards Enhanced by Interpretable Latent Variables

Traditional approach



New approach



Scorecards Enhanced by Interpretable Latent Variables

Supplement

with

Explainable
Latent
Variables

Collection \geq \$500
AND
Total Mortgage Balance

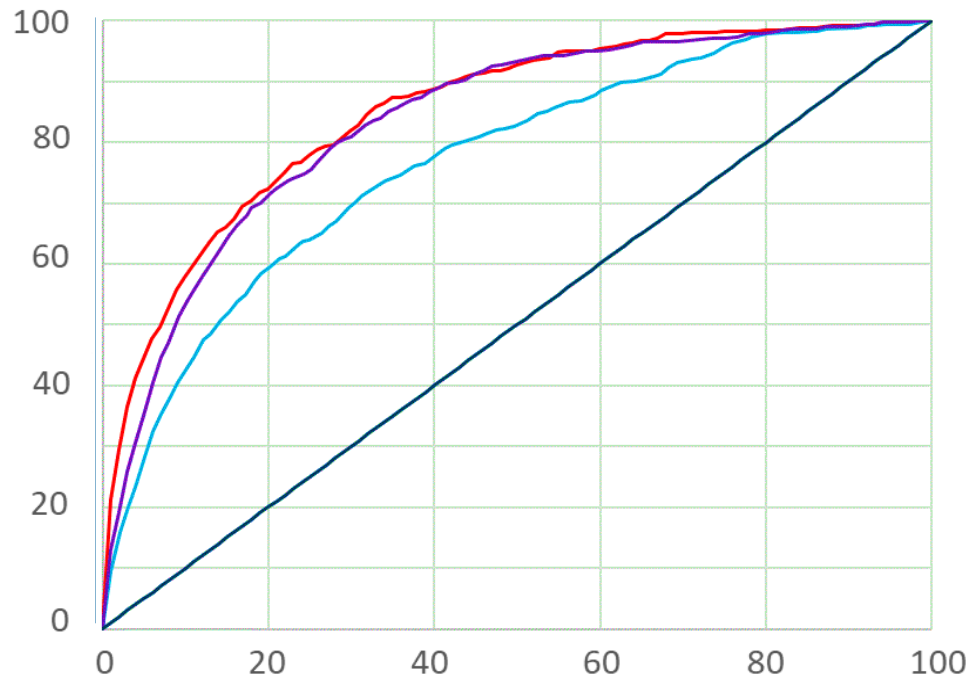
% TL never Delinquent
AND
TL Ever 60+

% TL never Delinquent
AND
Curr RevTL Balance \geq \$500

| Variable | Bin | Score Weight |
|----------|--------------------|--------------|
| | Missing, unknown | 53 |
| | 0 | 53 |
| | 1 - 4 | 64 |
| | 5 - 9 | 75 |
| | \geq 10 | 81 |
| | Baseline score: 81 | |
| | Missing, unknown | 78 |
| | No missed payments | 85 |
| | 0 - 1 | 50 |
| | 2 - 5 | 63 |
| | 6 - 11 | 71 |
| | 12 - 23 | 76 |
| | \geq 24 | 79 |
| | Baseline score: 85 | |
| | Checking & savings | 56 |
| | One account only | 52 |
| | None | 41 |
| | Missing, unknown | 43 |
| | Baseline score: 56 | |

Patent 15/985,130 (USA)

Impact of Using Interpretable Latent Features On Model Performance



ILF XNN Model
ILF enhanced Scorecards
Scorecards

Bringing It All Together

Machine Learning Is Here To Stay

Machine Learning Provides Incredible Performance

Need To Explain The Machine Learning Decisions

Interpretable Latent Features Provide Powerful Way to Bring Machine Learning into Credit Risk



Thank You!

Shafi Rahman
Sr. Principal Scientist, FICO