



# Explainable AI and the Future of Underwriting

## SPEAKER

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# Explainable AI And The Future of Underwriting

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Douglas  
Merrill,  
CEO &  
Founder

“Since 2009,  
our mission has  
been to **make fair  
and transparent  
credit available  
to everyone**”

## Who is ZestFinance?

### TOP TALENT



**100+**  
EMPLOYEES

100+ Employees primarily comprised of Data Scientists, Engineering and Business Analysts  
- based in Los Angeles, CA

Google amazon CapitalOne EQUIFAX Forbes Morgan Stanley UBS

### SUPPORTIVE INVESTORS

 **LIGHTSPEED**  
VENTURE PARTNERS

**matrix**  
PARTNERS

  
**FLYBRIDGE**  
CAPITAL PARTNERS

**upfront**  
VENTURES

## Three things I'm going to talk about today

- Why ML works
- What the barriers to adoption are
- Why explainability is the only way past those barriers

Machine learning helps find subtle, non-intuitive patterns in data  
For example, let's create a model that predicts gender.



?

Height: On average, men are taller than women.

◀..... More likely to be **men**

More likely to be **women** .....▶



But there are tall women and short men, so our height model is not great.

Accuracy: 0.6

Height + Weight: Most men are heavier than women, so accuracy improves.



But our height-weight model would still misclassify most children as women.

Accuracy: 0.8

Height + Weight + Birthdate: Incorporating date of birth helps account for the child issue. Our model now looks pretty good.



But if we started by saying that date of birth would help predict gender, you would have thought we were nuts.

**Accuracy: 0.9**



# ML Works: Real Results From Real Customers

15%

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Average increase  
in approvals

30%

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Average decrease  
in charge-offs

\$800m

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Credit expansion  
for top 10 credit card  
provider over 2 years

# ML Works Across All Credit Domains... And All Geographies

**Commercial**



**Credit Card**



**Auto**



**Student**



**Insurance**



**Mortgage**



**Telecom**



**Personal Loans**



# ML Works In A Tough Lending Climate: Subprime Auto



7 out of 10  
borrowers were  
getting turned  
down by legacy  
model

Identified more than 2,700  
unique borrower  
characteristics, 100x the  
23 indicators of the  
legacy model

**Results:**  
**33% reduction**  
in credit losses  
**14% increase**  
in approvals

# More Data Is Everything

ML uses **80x** the number of data points

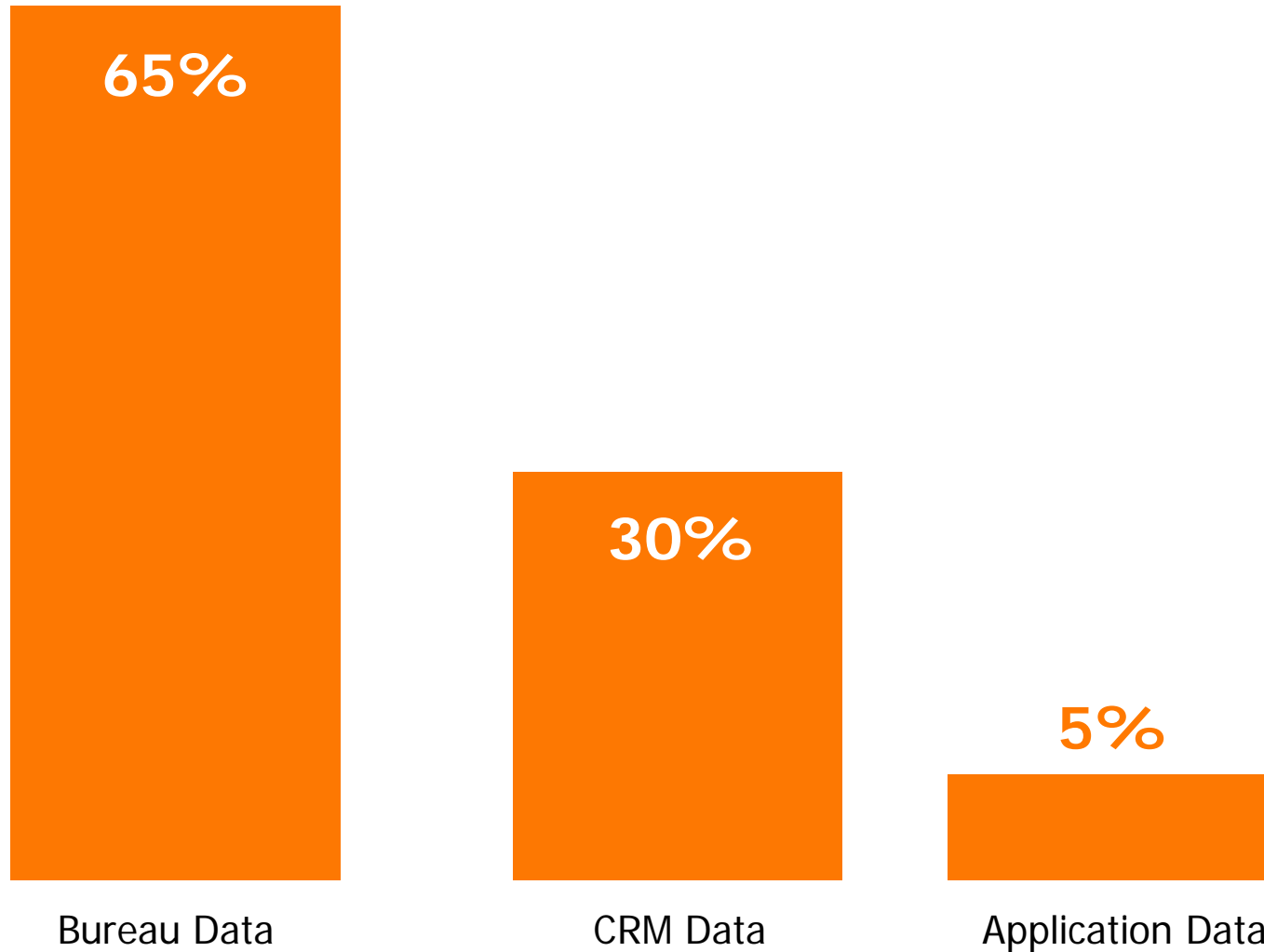
	Bureau	CRM	Application	Total
Old Model	19	0	2	21
ML Model	1,219	428	42	1,689

# More Data Is Everything

## More signal from the noise

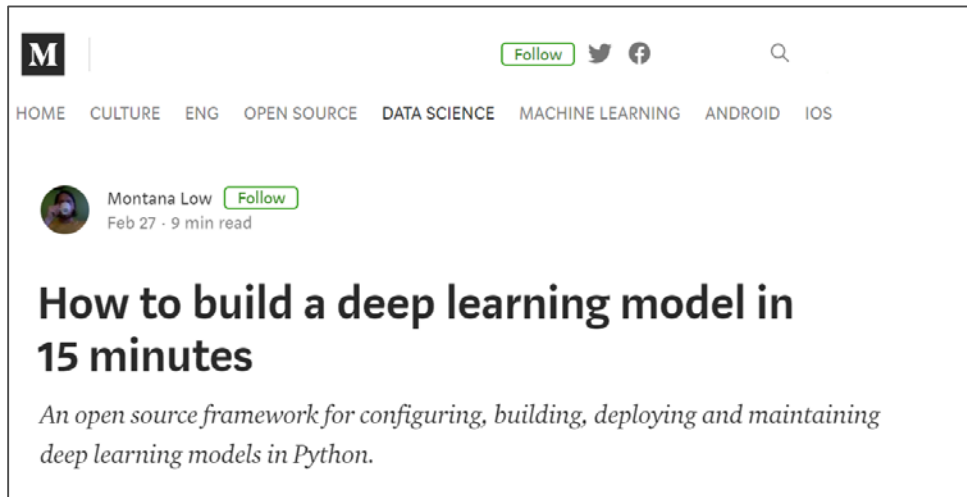
### Performance Contribution by Data Type

Results from top 10 credit  
card engagement



# Challenges To ML Adoption

It's NOT the math. Decent model build tools are everywhere.

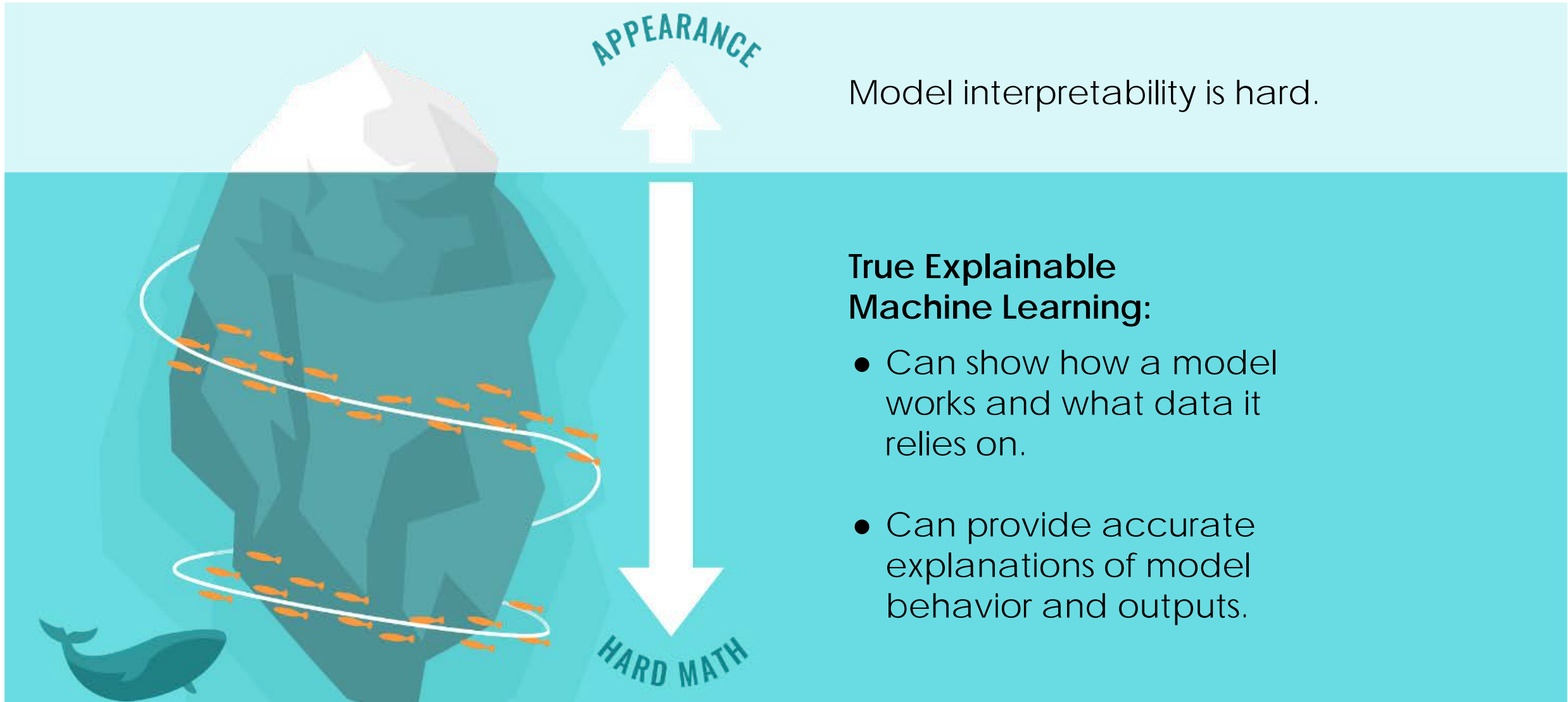


Blogs are filled with ML examples



Proprietary and open-source tools target users with varying levels of sophistication

# Explainability Is The Real Challenge. And It's Hard



Model interpretability is hard.

## True Explainable Machine Learning:

- Can show how a model works and what data it relies on.
- Can provide accurate explanations of model behavior and outputs.

# Three common approaches to explainability just don't cut it...

METHODOLOGIES	
<b>Permutation Impact</b> (PI)	<ul style="list-style-type: none"><li>• Does not work on overlapping data sources</li><li>• Does not capture variable interactions which leads to incorrect interpretations</li><li>• Not scalable due to strict latency requirements.</li></ul>
<b>Linear Proxy Models</b> (e.g., Lime)	<ul style="list-style-type: none"><li>• Requires subjective judgement to set parameters</li><li>• Does not work on outliers because there isn't a comparative</li></ul>
<b>Monotonic Constraints</b>	<ul style="list-style-type: none"><li>• Artificial constraints sacrifice performance and limit predictiveness</li><li>• Requires subjective judgement to determine which variables to increase or decrease</li></ul>

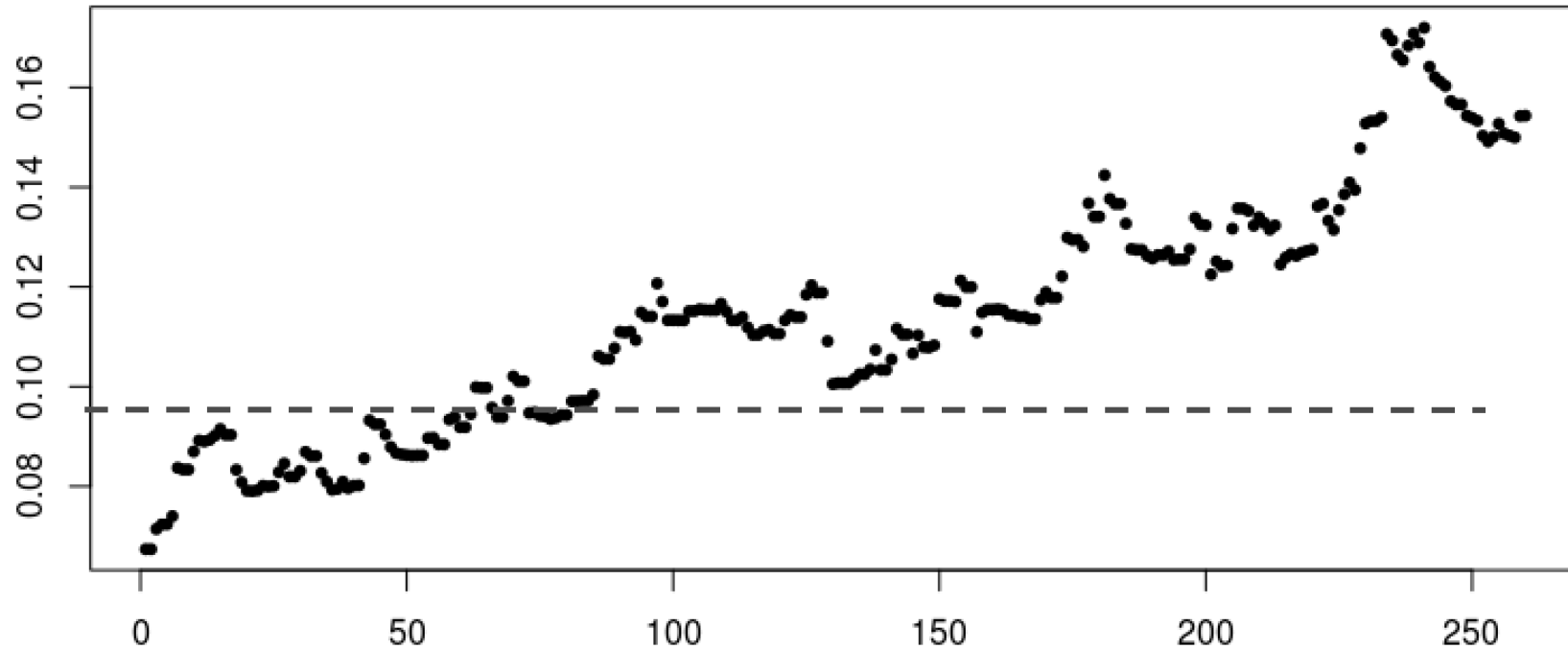


# ZAML Overcomes Core Explainability Challenges

- New method based on recent deep learning research and competitive game theory
- Directly inspects a model's structure to generate explanations with respect to a baseline
- Enables consistent and accurate explanations for:
  - A single score
  - A model
  - A population segment
- Works with:
  - Trees (Random Forest, Gradient Boosted Trees)
  - Neural Networks, including Deep Networks (Tensorflow)
  - Linear Models (Logistic Regression and the like)
  - Ensembles (Combinations of any of the above)
- Sensitive
- Implementation Invariant
- Handles interactions
- Handles correlated variables

**ZAML model explainability is the only method that is reliable and accurate for complex ML models**

# Explainability Enables Production Model Monitoring



ZAML detected that this model needs to be refit -- the client's marketing activity has attracted a new population that has caused the input characteristics, scores, and reason codes to diverge from expectations set during model build.

- Model build tools capture input variable and score distributions
- Reason codes associated with each score are also captured
- This gives the system baseline data about how the model should operate
- When the model is promoted to production we can alert the business when inputs, scores or reasons begin to drift and explain what happened and how important it is

# Explainability Enables Everything



- Fair Lending
- Disparate Impact Analysis
- Data/Feature Contribution
- MRM Documentation

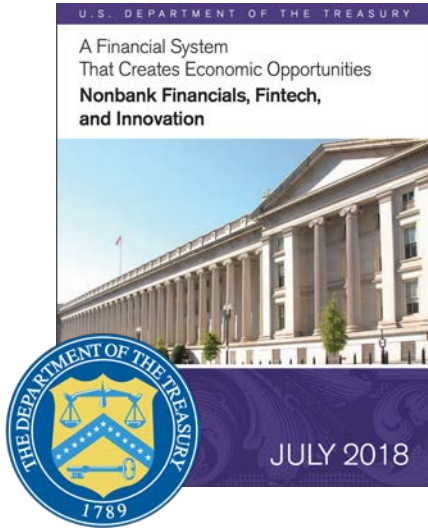


- FCRA-Adverse Action
- Complete Decision/Scope Auditability



- Feature Drift
- Outlier Detection
- Population Stability

# Regulators Support the Use of AI, As Long As Fairness is Ensured



“AI will increasingly be a driver of competitive advantage for firms”

“**Treasury** recognizes that these new credit models and data sources have the potential to meaningfully expand access to credit and the quality of financial services, and therefore **recommends that financial regulators further enable their testing.**”

Source: 2018 Dept. Of The Treasury Innovation Report



“Big data should not be viewed as monolithically good or bad.”

“**Institutions should** conduct a thorough analysis to **ensure compliance with consumer protection laws** before implementing new data and modeling methods.”

Source: 2017 Federal Reserve Board of Governors Compliance Outlook Report



Thanks

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