

## — VISION 2016 — TAKE CONTROL A ROADMAP FOR GROWTH







#vision2016

# Chasing a score credit score migration





#### **Industry challenges**

- Resources
- Posting inquiries
- Updating selection logic
- Choosing most predictive
- Variety
- Compliance
- Where to start













#### **Setting the stage**

- Overview of generic risk scores
- Attributes that feed scores

#### What is score migration

- Trends in migration
- How to look for migration
- Identify lost opportunity

#### What action should be taken

- Model and attribute governance
- **Validations**









## TAKE CONTROL A ROADMAP FOR GROWTH #vision2016

## Overview of generic scores and attributes





#### **Generic risk scores**

#### How they have changed



Began appearing in the 1950's

1989 true acceptance of credit score





No update last 12 months

Universe expansion



What's next?



1971 FCRA became more prevalent, but still manual

No update last 6 months



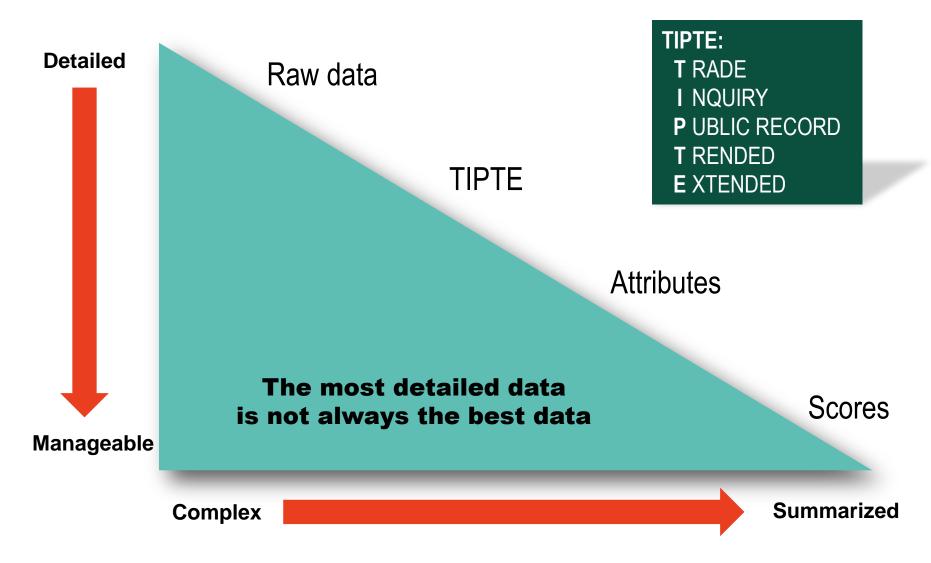
Course Creditions of Course Co

Authorized user trades

Medical collections

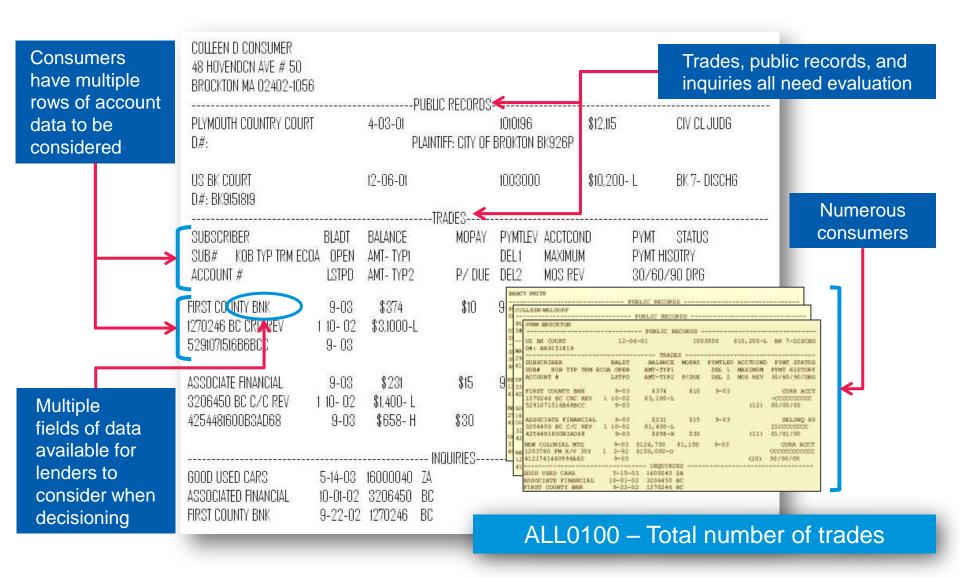








#### Complex consumer credit data



### Attributes the feed scores Premier Attributes<sup>SM</sup>

**Premier Attributes<sup>SM</sup>** is the credit industry's most robust, accurate and comprehensive set of tri-bureau leveled attributes that enable organizations to make more strategic and data-driven decisions across the Customer Life Cycle.

#### Predictive power and analytical precision

- Enhanced modeling opportunities and lending decisions
- Innovative attribute concepts and attributes as new data elements become available

#### Patented tri-bureau leveling

- Efficient model development build one model on one data source
- Consistent decisioning across all three data sources

#### **Attribute governance**

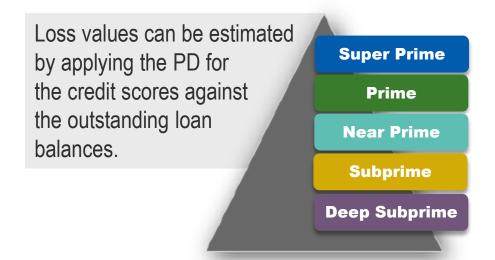
- Development protocol and documentation stands-up to regulatory scrutiny
- Rigorous monthly validation process to ensure continue integrity of attributes



#### **Generic risk scores**

#### **Leading brands in the market:**

- Predict the likelihood of future serious delinquencies (90 days late or greater) on any type of account
- 24-month performance window
- Score range of 300-850 (higher scores represent a lower likelihood of risk)



VantageScore <sup>®</sup> 3.0 FDIC Probability of Default Mapping Table						
Product Group	Score	Probability of Defaul				
Auto	850	0.0048				
Auto	849	0.0049				
Auto	301	1.0000				
Auto	300	1.0000				
Mortgage	850	0.0125				
Mortgage	849	0.0126				
Mortgage	848	0.0127				
Mortgage	302	1.0000				
Mortgage	301	1.0000				
Mortgage	300	1.0000				
HELOC	850	0.0062				
HELOC	849	0.0063				
HELOC	848	0.0063				
HELOC	302	1.0000				
HELOC	301	1.0000				
HELOC	300	1.0000				
HE loan	850	0.0120				
HE loan	849	0.0122				
HE loan	848	0.0123				
HE loan	302	1.0000				
HE loan	301	1.0000				
HE loan	300	1.0000				
Bankcard	850	0.0075				
Bankcard	849	0.0076				
Bankcard	848	0.0077				
Bankcard	302	1.0000				
Bankcard	301	1.0000				
Bankcard	300	1.0000				
Student loan	850	0.0099				
Student loan	849	0.0100				
Student loan	848	0.0101				
Student loan	302	1.0000				
Student loan	301	1.0000				
Student loan	300	1.0000				
All Other	850	0.0048				
All Other	849	0.0049				
All Other	848	0.0049				
All Other	302	1.0000				
All Other	301	1.0000				
All Other	300	1.0000				

— VISION 2016 —— A ROADMAP FOR GROW









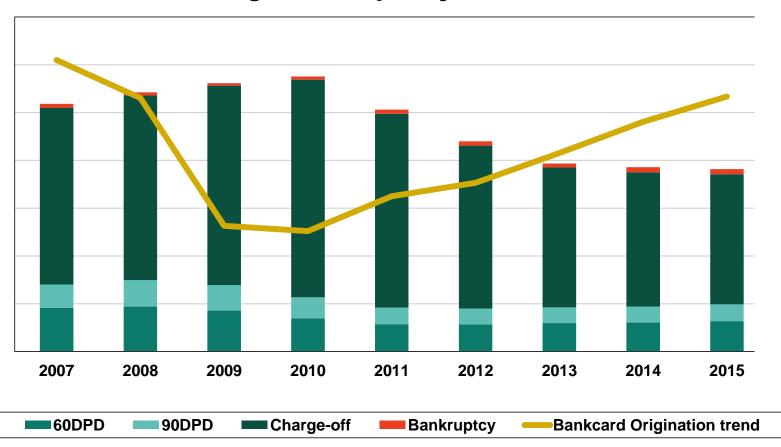


#### **Trends in migration**





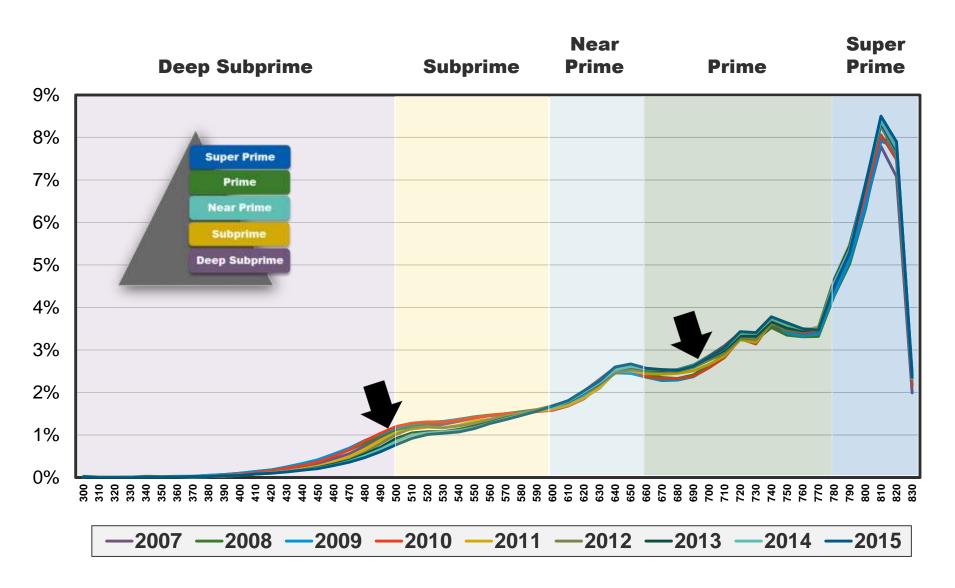
#### Change in delinquency over time





#### How to look for migration

Generic score cohort frequencies 2007-2015



## WHAT DO YOU THINK?





#### 2014-2015 (1 year)

- 27% moved +/- at least one tier
- 15% moved up at least one segment
- Those age 18-34 had the greatest upward movement ~19% moving up at least one tier

		Linked consumers from 2014 - 2015							
		2015							
		661-780	781-850						
	300 - 499	0.90%	1.29%	0.12%	0.03%	0.00%			
4	501-600	0.97%	6.15%	2.82%	0.82%	0.01%			
2014	601-660	0.22%	2.28%	5.71%	4.28%	0.10%			
,	661-780	0.08%	0.89%	3.68%	28.03%	5.46%			
	781-850	0.00%	0.03%	0.17%	4.28%	31.69%			

#### 2007-2015 (8 years)

		Linked consumers from 2007 - 2015							
		2015							
		300-499	500-600	601-660	661-780	781-850			
	300 - 499	0.30%	0.88%	0.46%	0.38%	0.01%			
_	501-600	0.67%	3.27%	2.60%	2.91%	0.24%			
2007	601-660	0.35%	2.49%	3.15%	5.53%	1.02%			
	661-780	0.32%	2.62%	4.73%	18.95%	13.49%			
	781-850	0.03%	0.29%	0.85%	6.48%	27.98%			

- 46% moved +/- at least one tier
- 27% moved up at least one segment
- Those age 18-34 had the greatest upward movement about 37% moving approximately one tier

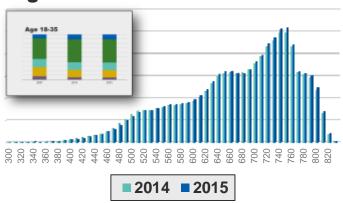


#### How to look for migration

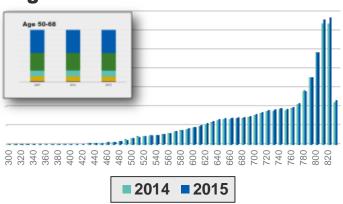
#### Cohort age by score frequencies (1 year)



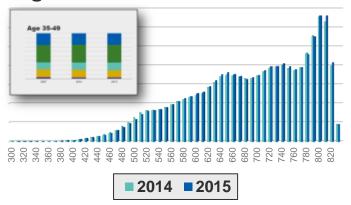




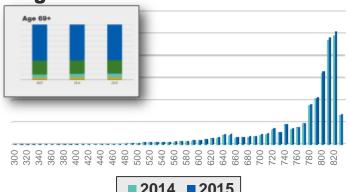
#### Age 50-68



#### Age 35-49



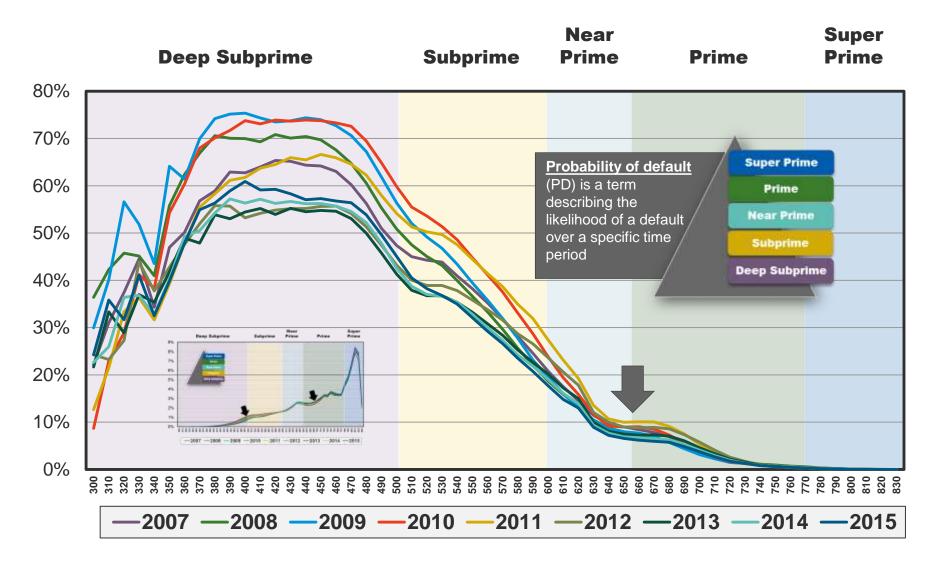
Age 69+



## WHAT DO YOU THINK?



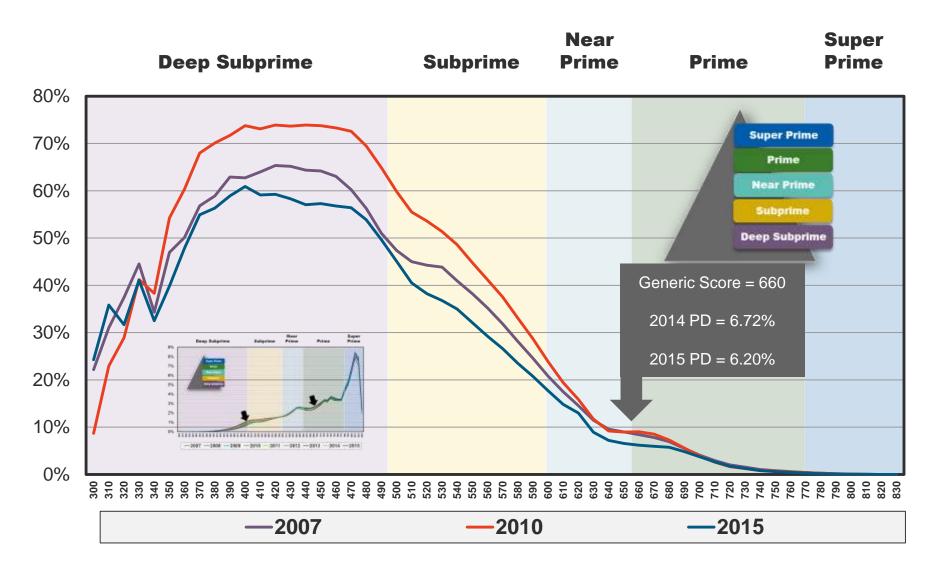
## How to look for migration Probability of default





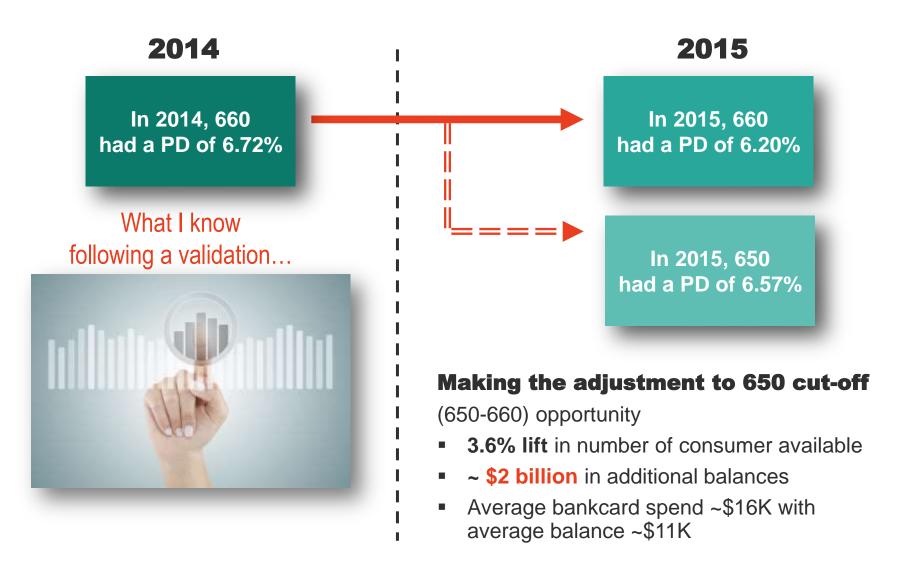
#### How to look for migration

Probability of default pre-recession to recovery





#### **Identify lost opportunity**





## TAKE CONTROL A ROADMAP FOR GROWTH #vision2016

#### **Take ACTION!!**





#### What is a model validation?

- A process designed to measure how well a model works on a portfolio
- In an historical validation, accounts booked or monitored are scored at an observation date
  - For **new accounts**, this is typically at time of acquisition (e.g., accounts booked 12-24 months ago)
  - For **existing accounts**, this is typically all accounts that are open at a certain point in time
- The scores at observation date are then compared to the accounts' actual account performance during the performance window to validate how well the model performs









#### How does it work?

- Evaluates all scores and attributes selected and ranks which are the most predictive
- The analysis looks within a score or attribute to evaluate at what range it is the most predictive

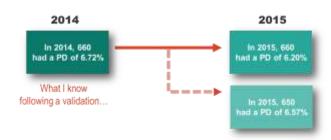
10.08 13.18 13.24

5.73

								が対象		
Т	IND PERCENT	CELL FREQ	KNO WN G/B	KNO WN G/B		D F	WGTOF	INFO INC REMEN	BAD RATE	
	(F)	(G)	O DDS (H)	INDEX (I)	***************************************	RATIO	(J)	T (K)	(L)	6 (8 (8 (8 K)
0	0	2.81	8.54	331G	< 3.31	>	1.2	2.92	10.48	
0	0	0.55	2.63	102G	< 1.02	>	0.02	2.92	27.54	
0	0	0.08	2.32	111B		>	-0.1	0	30.09	
0	0	7.96	1.83	141B	< -1.41	>	-0.35	1.02	35.37	
0	0	11.61	2.15	120B	< -1.20	>	-0.18	0.39	31.7	
0	0		2.27	114B	< -1.14	>	-0.13	0.21	30.6	
0	0	11.41	2.36	110B	< -1.10	>	-0.09	0.1	29.8	CONTRACTOR OF THE PARTY OF THE
0	0		2.52	102B	< -1.02	>	-0.02	0.01	28.39	Company of the Compan
0	0		2.71	105G	< 1.05	>	0.05	0.03	26.95	
0	0	4.62 6.55	2.88 3.09	112G 120G	< 1.12 < 1.20	>	0.11	0.05	25.77 24.44	The same of the sa
0	0	5.36	3.36	120G	< 1.20	>	0.18	0.21	22.93	
0	0	5.06	4.18	162G	< 1.62	>	0.48	1.05	19.31	
0	0	100	4.18	.020	1.02		3.48	6.33	17.31	
		.00					لنصا			

THE REPORT OF STREET AND ADDRESS OF THE PARTY OF THE PART





#### Comparing the probability of default at different score ranges or points is one way to evaluate transition score cutoffs

SCORE1 SCORE2

Score 1	Sum of _FREQ_	Sum of good	Sum of bad	Bad Rate %	Score 2	Sum of _FREQ_	Sum of good	Sum of bad	Bad Rate %
1	500	100	400	66.73%	1	500	50	450	66.73%
2	450	100	350	63.78%	2	450	50	400	£1.56%
3	400	100	300	EO 28%	3	400	50	350	54.72%
4	350	100	250	56.07%	4	350	50	300	45.30%
5	300	100	200	50.95%	5	300	50	250	31.90%
6	250	100	150	44.67%	6	250	200	50	11.33%
7	200	100	100	37.00%	7	200	175	25	7.00%
8	150	100	50	28.33%	8	150	145	5	3.33%
9	100	75	25	23.33%	9	100	95	5	3.33%
10	50	40	10	20.00%	10	50	50	0	0.00%

- A score of 4 in the in SCORE1 translates to a score of 3 in SCORE2.
   The bad rate of SCORE2 does not go above the bad rate of SCORE1 maintaining the same risk tolerance
- Transitioning from SCORE1 to SCORE2 will provide the client with 400 additional customers within their current risk strategy



#### What causes a score to migrate:

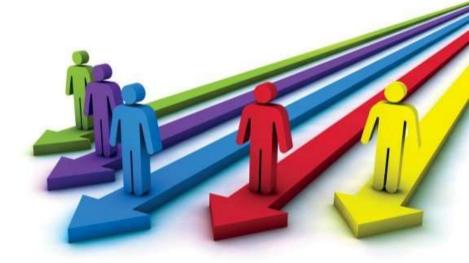
- Economic trends
- Credit trends
- Regulatory trends

#### How to look for migration

Validation

#### An historical validation can be used to:

- Compare different models and attributes
- Increase portfolio volume
- Lower portfolio bad rates
- Determine cutoff scores
- Assign various strategies or credit limits













## For additional information, please contact:

Brodie.Oldham@experian.com



#### **Follow us on Twitter:**

@ExperianVision | #vision2016



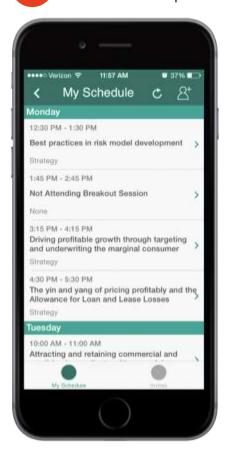
©2016 Experian Information Solutions, Inc. All rights reserved. Experian Public.

#### **Share your thoughts about Vision 2016!**

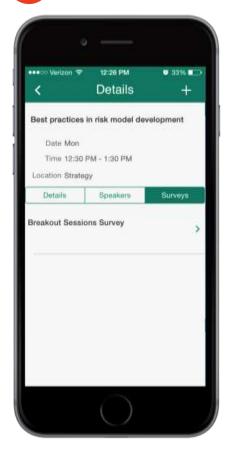
Please take the time now to give us your feedback about this session. You can complete the survey in the mobile app or request a paper survey.



Select the Survey button and complete



2 Select the breakout session you attended





**VISION 2016 ——** 

## TAKE CONTROL

A ROADMAP FOR GROWTH









