Future Score Projection

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Introduction

- Typically, Credit Scores assess an individual’s ability to pay back a specific credit product based on a Snapshot view of a customer’s existing bureau data.

- The ability to predict how a credit score may look in the future based on the profile today could allow clients the ability to assess the direction and therefore likely future risk level of a consumer.

- The value of this may be realised when assessing borderline Accept/Reject applications for credit products where consumers just under a score cut-off may be considered more favourably if there is a higher propensity of them improving their financial situation in the next year.

- The typical risk assessment of an applicant at the point of applying for credit also does not take into account how the profile may change once the customer actually takes out the loan. The risk projection may help improve discrimination on these customers

- The ability to infer a future score may be derived from ‘Trended’ rather than ‘Static’ metrics

Trended Data

Problem: Knowing a consumer's credit information at a single point in time only tells part of the story and doesn't help with thin credit files

Solution: To better understand the consumer, lenders need the ability to assess **credit behaviour over time**

Consumer A

Trade Data

February	
Credit Score	850
Balance	£3,500
Status	Good standing

Trended Data

Month	Balance	Min Pay Due	Actual Pay
Jan	£3,500	£175	£1,000
Dec	£4,000	£200	£800
Nov	£4,750	£238	£1,000
Oct	£5,500	£275	£1,000
Sep	£6,000	£300	£750
Aug	£6,750	£338	£750
Jul	£7,000	£350	£500

✓ Paying well over minimum payments

✓ Demonstrated ability to pay

✓ **No payment stress**

Consumer B

Trade Data

February	
Credit Score	850
Balance	£3,500
Status	Good standing

Trended Data

Month	Balance	Min Pay Due	Actual Pay
Jan	£3,500	£175	£175
Dec	£2,900	£145	£145
Nov	£2,500	£125	£125
Oct	£2,250	£113	£125
Sep	£1,750	£88	£100
Aug	£1,500	£75	£150
Jul	£1,600	£80	£150

X Making minimum payments for the last three months

X Payment amounts vs. minimum due is decreasing over time

X **Increasing payment stress**

Can the additional Trended Data above be used to inter a likely Future Risk level of a customer based on Trajectory?

Trended Characteristics

Alongside typical Credit Bureau data metrics, new variables have been defined on a new Trended Data block and are used in order to help project the likely direction of a consumers score.

Rather than looking at a static view of a consumers Balance or Arrears Status across their credit products, we instead look at the shift historically over time which may help to infer the likely direction in the future.

Previously-

Current Balance on Active Accounts

Worst Arrears Status on Active accounts Last 6 Months

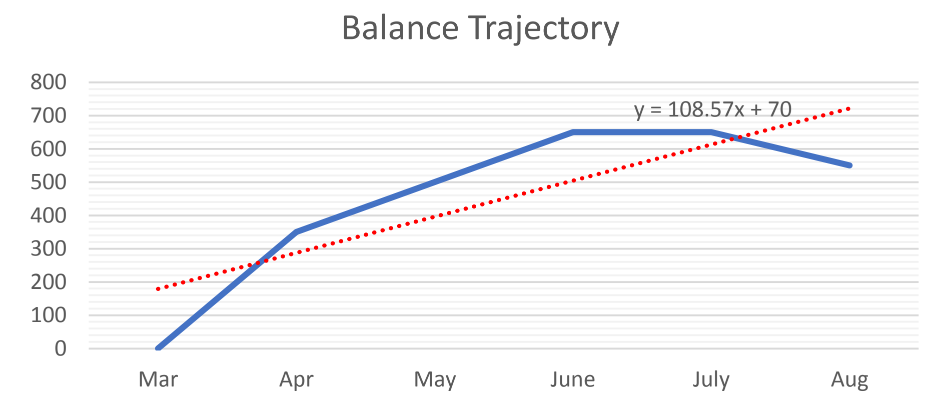
NEW-

Balance Trajectory on Accounts Last 12/24/36 months

Arrears Trajectory on Accounts Last 12/24/36 months

These new metrics can help to infer future balances, arrears status and will be used within the new Score Projection.

	Balance											
	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	July	Aug
Account 1 (opened in Jan)					100	250	0	350	300	500	550	500
Account 2 (opened in Apr)								0	200	150	100	50
Account 3 (closed in Nov)	400	300	0									
Total balance across all accounts	400	300	0		100	250	0	350	500	650	650	550



Rather than solely assessing a customers total current balance of £550, we instead can see that this customer is increasing spending at a rate of £109 per month as well.

Typical Scores shifts over time

As can be seen below, a sizeable proportion of applicants on a generic sample shift risk band between the point at which they apply for credit and 12 months later

		Credit Score 12 months on				
		Risk Band 1	Risk Band 2	Risk Band 3	Risk Band 4	Risk Band 5
Credit Score at Application Point	Risk Band 1	81%	15%	3%	1%	0%
	Risk Band 2	26%	46%	19%	6%	2%
	Risk Band 3	7%	19%	38%	26%	10%
	Risk Band 4	1%	6%	20%	42%	31%
	Risk Band 5	0%	2%	7%	26%	65%

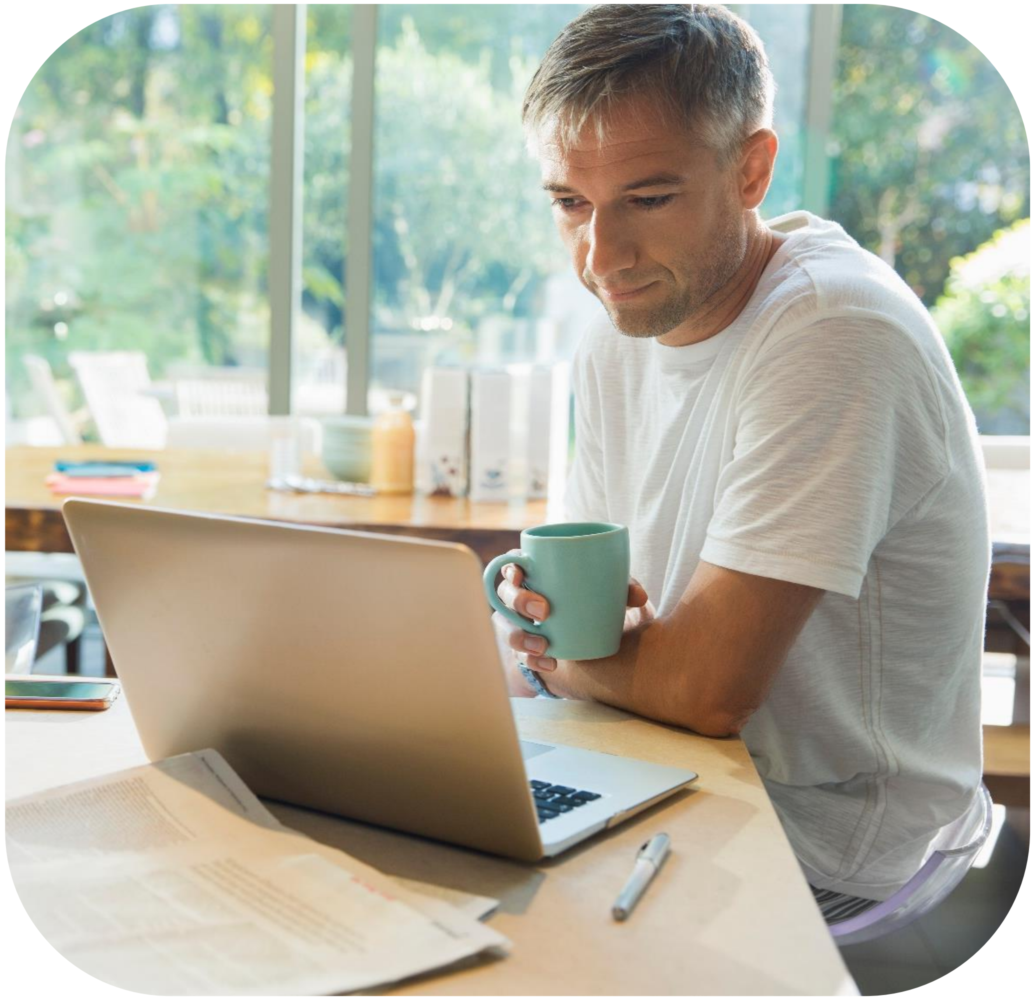
- At the application point, using new ‘Trended’ characteristics along with existing credit bureau references, can we accurately identify the customers which are likely to shift over the next 12 months?
- Is there any value over the traditional Credit Score in being able to pick out these customers?

The analysis has involved assessing the credit scores of consumers at the point of applying for credit and again 12 months later in order to derive performance (i.e. the score difference) and then modelling the profile at observation in order to predict the score difference.

Sample Composition

The Score projection sample is composed of a random selection of Credit Applications from Q3 2016 - Q2 2017. The applications were taken from Banking & Finance Products specifically Credit Cards, Loans, Mortgages, Motor Finance, Current Accounts. 300,000 records were taken for the analysis.

Two Outcome Flags have been appended to the data 12 months after the application point-



Difference in Credit Score-

Simply the customers credit score at outcome minus the score at observation

This will give us the dependant variable which we will try to predict using our score projection model

'Customer Level' Credit Risk Good/Bad Flag-

Bads- In summary this looks any Public Information(CCJs, IVAs etc) or Credit Defaults within the outcome window. It also includes customers which are in significant arrears (3 or more payments) or 'over-indebted'

Goods- Up-to-date on all Credit Products

Indeterminate-Any other accounts

This outcome flag is the dependant variable used to build the generic Snapshot credit score. Appending it here for reference allows us to assess 'Bad Rates' on different groups of customers and therefore the business value in identifying those customers which are likely shift score.

Subpopulations and Score Projection

A typical credit application scorecard may be built on a variety of segments in order to strengthen model performance on specific populations. Over the course of 12 months, the scorecard segment which a consumer falls into may change and therefore potentially change the variables which assess credit-worthiness.

Within typical risk models, the following segmentation is used:

Active- No Derogatory Data and Credit Balances >£100 with accounts opened for >12 months

Derogatory- Credit Defaults, Significant Arrears, County Court Judgements at the application point

Limited- Not Derogatory and Credit Accounts with Balances <£100

New To Credit (NTC) -No Credit Accounts or Oldest credit account < 12 months old

A different score projection model has been developed on each of the above segments in order to help refine the performance overall. The cross-tab below shows the shift in sub-pop over 12 months.

		Subpopulation 12 months on			
		Active	Derog	Limited	NTC
Subpopulation at Application Point	Active	90%	5%	5%	0%
	Derog	8%	91%	1%	0%
	Limited	44%	3%	53%	0%
	NTC	19%	13%	20%	47%

Modelling Methodology

Not as concerned with interpretability at this point and so a decision was made to assess ‘machine learning’ modelling techniques.

Three modelling methods have been used in order to derive the score projection:

Linear Regression

A standard model built using a linear combination of the features- used as a benchmark

Random Forests

A collection of Decision Trees each built on a different bootstrapped sample with a random selection of variables available at each node. The predictions of all trees are aggregated to give an overall score prediction for the applicant.

Gradient Boosting

Models built sequentially where each model attempts to minimise the error (difference between the actual and predicted scores) on each subsequent iteration

The data was split randomly into 80:20 populations for Development and Validation. All results are reported on the 20% Validation Sample

All models were built within Python.

Initial Results

The results assessing the actual score shift show that the models struggle to predict a credit score accurately 12 months from the application point.

The gradient boosting approach is the most promising but still, compared to the actual score difference, the projected score difference gives the following R-Square values-

	Gradient Boosting	Random Forest	Linear Regression
Combined	**0.2189**	**0.1928**	**0.1269**
Active	0.2034	0.1648	0.1072
Derog	0.2575	0.2219	0.1487
Limited	0.2324	0.1828	0.1702
NTC	0.1658	0.1405	0.0891

In terms of relative sub-pop performance, NTC struggles the most due to the lack of history to project a Future Score.

The Limited and Derog Subpopulations benefit the most from the projection and the Gradient Boosting model appears the most predictive

A credit score at any given point in time can be very sensitive to changes in Credit Balance, Credit Limit Utilisation and new credit accounts opened which is evidently difficult to predict 12 months in advance.

Given the results, potentially shifting to an approach of looking at the direction of score rather than trying to predict the exact value 12 months on may be more beneficial to lenders.

Actual vs Predicted Results

Note that the predicted score has been grouped into coarse bands to help give lenders a bit more clarity on the size of score shifts. 80 points has been chosen as Experian's Credit scores are generally calibrated so that the ratio of Goods to Bads double every 80 points.

The table shows the row percentage of the total predictions in each of the three coarse bands and how accurate they are

For all approaches, the models are more effective for predicting score increases in the Next 12 months rather than decreases or static customers.

		Actual score difference		
		[Low : -81]	[-80 : 80]	[81 : high]
Predicted score difference	[Low : -81]	50%	40%	10%
	[-80 : 80]	24%	54%	22%
	[81 : high]	11%	23%	67%

Gradient Boosting

This approach works best at predicting score increases as opposed to decreases.

		Actual score difference		
		[Low : -81]	[-80 : 80]	[81 : high]
Predicted score difference	[Low : -81]	52%	36%	12%
	[-80 : 80]	25%	52%	23%
	[81 : high]	12%	23%	65%

Random Forest

There is a slight improvement in predicting the score decreases although this is offset by the decrease in the percentage correct on the increases.

		Actual score difference		
		[Low : -81]	[-80 : 80]	[81 : high]
Predicted score difference	[Low : -81]	47%	42%	11%
	[-80 : 80]	25%	50%	24%
	[81 : high]	12%	27%	61%

Linear Model

The benchmark linear model is weakest across the board with both fewer increases and decreases predicted

Using the Projection alongside a Credit Score

Gradient Boosting Model

Note that all % figures are the proportion of 'Bads' in each cell. (i.e. the number of customers which default/enter significant arrears in the 12 months following the application point)

Risk Band 1 appears to show little value in using the score projection-there doesn't appear to be much misalignment between each cell and the overall Bad-Rate. Risk Band 2 is broken into more distinct groups (showing misalignment)

Due to the high Bad-Rates across the range, these are likely to be straight 'Rejects' anyway

		Future Score Projection					
		More than 160pt decrease (A)	Between 81-160pt decrease (B)	Within +/- 80pts (C)	Between 81-160pt increase (D)	More than 160pt increase (E)	Total Bad Rate
Credit Score	Risk Band 1	58.06%	52.35%	49.22%	61.14%	46.86%	**51.96%**
	Risk Band 2	28.50%	16.11%	10.72%	6.14%	3.74%	**11.79%**
	Risk Band 3	7.09%	3.91%	2.18%	1.22%	0.49%	**2.58%**
	Risk Band 4	1.23%	1.45%	0.53%	0.00%	0.00%	**0.63%**
	Risk Band 5	4.21%	0.47%	0.33%	0.00%	0.00%	**0.38%**

Potential Score Cut-off using Credit Score only

Cells highlighted in Risk Band 2 show misalignment for columns D and E compared to the overall Bad Rate (i.e. these groups have been identified by the Credit Score as Rejects. By overlaying with the Score Projection we can see that there are customers significantly less likely to go Bad than the average for that Risk Band)

Lenders may want to use the Score Projection in a positive manner-i.e. to Accept previously Rejected applicants rather than to Reject applicants which previously would have been Accepted

Projection vs Credit Score- Comparing Approaches

		Future Score Projection					
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Credit Score	Risk Band 1	58.06%	52.35%	49.22%	61.14%	46.86%	**51.96%**
	Risk Band 2	28.50%	16.11%	10.72%	6.14%	3.74%	**11.79%**
	Risk Band 3	7.09%	3.91%	2.18%	1.22%	0.49%	**2.58%**
	Risk Band 4	1.23%	1.45%	0.53%	0.00%	0.00%	**0.63%**
	Risk Band 5	4.21%	0.47%	0.33%	0.00%	0.00%	**0.38%**

Gradient Boosting

Note that all % figures are the proportion of 'Bads' in each cell. (i.e. the number of customer which default/enter significant arrears in the 12 months following the application point)

Risk Band 1 appears to show little value in using the score projection although Risk Band 2 is broken into more distinct groups

Using this Strategy gives 5.3% increase in Accepts

Random Forest

Again the Score Projection adds little value for Risk Band 1 potentially because even a large increase here still implies a low score to begin with. The RF model breaks up Risk Band 3 better than the gradient boosting approach

Using this Strategy gives 4.4% increase in Accepts

		Future Score Projection					
		More than 160pt decrease (A)	Between 81-160pt decrease (B)	Within +/- 80pts (C)	Between 81-160pt increase (D)	More than 160pt increase (E)	Total Bad Rate
Credit Score	Risk Band 1	66.13%	54.20%	47.84%	63.57%	48.32%	**51.96%**
	Risk Band 2	32.26%	17.13%	11.14%	6.00%	4.44%	**11.79%**
	Risk Band 3	10.47%	3.85%	2.38%	0.54%	1.28%	**2.58%**
	Risk Band 4	5.45%	2.14%	0.52%	0.00%	0.00%	**0.63%**
	Risk Band 5	2.86%	0.91%	0.34%	0.00%	0.00%	**0.38%**

		Future Score Projection					
		More than 160pt decrease (A)	Between 81-160pt decrease (B)	Within +/- 80pts (C)	Between 81-160pt increase (D)	More than 160pt increase (E)	Total Bad Rate
Credit Score	Risk Band 1	47.83%	51.86%	47.55%	65.10%	59.05%	**51.96%**
	Risk Band 2	18.07%	14.26%	11.79%	7.75%	7.26%	**11.79%**
	Risk Band 3	3.17%	3.50%	2.48%	1.74%	2.90%	**2.58%**
	Risk Band 4	3.45%	1.38%	0.54%	0.92%	0.00%	**0.63%**
	Risk Band 5	0.00%	1.02%	0.32%	0.00%	0.00%	**0.38%**

Linear Model

The general trends are flatter (cells are generally closer to the Total Bad Rate for the band) within each Risk Band which implies that the linear model does not add as much value as the two models above.

Using this Strategy gives 2.7% increase in Accepts

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Benefit to Consumers

- Using machine learning to only influence decisioning in a positive direction by accepting previously rejected ‘Good’ applicants and not used to decline previous accepts.

- This helps to ensure that GDPR regulation around a ‘right to an explanation’ can be fulfilled for all declines if needed (since for declines only the standard Credit Risk score is used- built using linear regression)

- Machine learning algorithms can therefore be utilised without complex variable Explanation tools/techniques such as LIME or Shapley values which aim to fit linear approximations to explain ML models

- With this increased predictive power of the combined Credit Score + Future Projection, more ‘Good’ customers are likely to be accepted for credit products which they are able to afford

Benefit to Lenders

- Using the power of machine learning techniques to enhance the decisioning process while still retaining the benefits of the linear, fully explainable scorecard for the vast majority of applicants

- More value comes from the coarse projection index taking values of indicating direction of future score (rather than given them the predicted score at outcome)

- Using the Gradient Boosting strategy outlined previously (Accepting customers in Risk Band 2 with a positive score projection), the Gradient Boosting model would have seen a ~**5%** increase in Accepts over the course of 12 months over and above the standard Risk Score while retaining comparable low Bad Rate of around 1%

- Due to this, more 'Good' customers on book for lenders, leading to a bigger market share for those that take the enhancement

Future Improvements

In terms of further work to improve the models in the future, some approaches include :

- Shorten the outcome window-Potentially 12 months is too long an outcome try to predict a future score especially given how much a credit profile can change within a year. Try using 6 or even 3 months
- Propensity scores are a potential option to improve the models going forwards. These scores assess the likelihood of a consumer applying for/taking out a range of credit products therefore may help to identify subpopulations likely to take action during the outcome window. These could be fed into the Score Projection in order to help determine customers who may be more likely to shift in score in the following year

- Product specific score projections-Tailor each future score projection to a corresponding credit score. (i.e. Retail, Mortgage, Subprime etc.) rather than one generic projection

Current Model is only a prototype-we are open to any suggestions as to how we might be able to add more value!

