Score Complete

Customer Handbook

Prepared by:

Larry Macdonald, Sr. Product Manager

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Introducing Score Complete

Risk managers have a difficult task. Their companies are in the business of lending money or granting credit to ordinary Canadians who need credit cards for everyday purchases, loans to buy goods and services, lines of credit to optimize and bring flexibility to credit management, and mortgages so they will have a place to live. Unfortunately, it is not profitable for these companies if their customers don't pay them back. A credit file, supplemented with a credit score, gives a risk manager the ability to assess the likelihood that a customer will meet their financial obligations – to make regular payments on the credit that they use.

Credit scores are systematic and predictive, enabling the application of consistent business rules. Low risk customers may receive better product offerings, better terms, or higher limits, while high risk customers may be required to provide securitization or may not be offered credit at all.

Most Canadian consumers regularly pay their bills and have established good credit histories. These are profitable consumers for the lending institutions in the financial industry. Unfortunately, the consumers who are non-payers cause significant losses for the lenders, resulting in increased interest rates for all. Identifying these consumers and mitigating their losses in a timely manner makes the entire lending practice more efficient for the lender and borrower alike.

Score Complete is our most accurate solution in the prediction of consumer delinquency risk. Consumers or applicants with low scores have a high probability of going 90 days past due or worse on their debt obligations over the next 12 months. But Score Complete attempts to do something that no other score in the market does. It tries to score every Canadian consumer file or application for credit.

Score Complete uses such credit file characteristics as missed payments, utilization and balances, inquiries, public records, and the ages and types of credit products, to assess delinquency risk. For files with limited credit information and for applicants without credit files, aggregated credit data from the consumer's neighbourhood is used to augment the limited information available to assess credit risk.

1. Modeling Concepts

It is a relatively simple task to determine a consumer's behaviour when there is a long history with a lot of accounts and activity. One can assume that prior patterns will repeat. Someone who has paid their bills regularly for a number of years may be expected to continue to do so. When there is less information available, other considerations must be taken into account. Deriving the relationship between the information in a person's credit file and the future behaviour is a statistical exercise, creating the proper weighting for each factor, by determining the characteristics that distinguish the good payers from those who go delinquent. These relationships among the various factors may shift over time, due to different market conditions, so using a score that is up to date is key.

Score Complete is a predictive model offered by Equifax that risk managers use to help them determine which customers or applicants are creditworthy; that have credit characteristics that are associated with good payers.

In order to build a model, three key components are required: population, outcome, and data. The population is the collection of records used to build the model, and should be representative of the population where the model will be used. The outcome is the value to be modelled, and represents the unknown quantity that the model predicts. The data are the known attributes that are available at the time and used in the calculations.

1.1 Population of Interest / Minimum Scoring Criteria

There are two considerations necessary to define a population for a credit model. The first is to decide on the target population where the model is of interest. For a delinquency model, the ideal population may be any Canadian consumer or applicant for credit. Assessing the risk of every prospect or existing customer is the best case.

The second consideration is available information. It may be difficult or impossible to make an accurate assessment of risk given the sparcity of data in some cases. Among the common limitations:

- **Credit File Not Found.** Sometimes an applicant does not have a credit file. This includes young Canadians who apply for credit for the first time, or new immigrants. Some people may go for many years without building a credit history, preferring to pay cash for everything so as not to owe any money, or they use their family's credit (parents or spouse) for their own needs. A change in their family status, such as death or divorce, forces them to establish their own credit. Additionally, a credit file may not be found in cases where there are mismatches between the information in the credit file and the application. This could be due to typographical errors, information variants such as different name versions like Robert and Bob, revised information that hasn't been updated on the credit file like new address or change of name, or format errors, such as having the input data in the wrong fields, or supplying an address out of the country.
- **Death Notice on File.** Although the estate of a deceased individual may be responsible for the financial commitments in some cases, the information in the credit file may not be predictive of the future performance of the account.
- **Inactivity.** If a credit file has not been updated for a period of time, the information that it contains may be stale. In many cases, it may be more accurate for an institution to make lending decisions based on other information, such as income statements or wealth (including property equity), by providing collateral or security, or having a co-signer.

The combination of the target population and the available information to generate a score is known as the minimum scoring criteria.

For Score Complete, consideration was given to whether the credit file, by itself, contained enough information to calculate the credit score. It was determined that the criteria for this was to include all Canadian consumers with credit activity within the last 24 months and at least one valid trade line[1]. Activity is defined as a trade line updated (based on the date reported) or a hard inquiry[2].

For consumers with credit files that did not meet these criteria, aggregated credit data was used to augment the amount of available information about the consumer. If either a credit file is found, or aggregated credit data is found, Score Complete estimates the risk and calculates a score. Score Complete calculates and returns a score even when a credit file is not found.

[1] Trade lines are the accounts or credit products that financial institutions report to the credit bureau. They are the credit cards, loans, lines of credit, mortgages, etc. that show what responsibilities and history the consumers have with various reporting institutions.

[2] Inquiries are posted whenever somebody views or receives information contained in the credit report. Hard inquiries indicate that a consumer has applied for credit and granted permission for someone to see their credit report for the purpose of adjudicating that credit. Soft inquiries are posted whenever a company refreshes information about their customers, but are not motivated by consumer activity. Soft inquiries are only visible to the consumer, and do not affect any credit scores.

For credit files with death notices, the minimum possible score of 300 is returned. Many algorithms default to a no score result with a death notice. Since a no score implies that the institution must investigate further in order to assess the applicant, Score Complete suggests that no further investigation is required.

There are only two cases where Score Complete will not return a valid score. If there is no credit file, and there is no aggregated credit data from the address, there is no information available to the score. The other case is if a file has been flagged by Equifax as a manual file, or file under review. Manual files are rare; almost all instances of failure for Score Complete will be due to problems with the input address.

1.2 Response Variable

Credit scoring is done to help risk managers understand how likely it is that their customers are going to make the required payments on their credit products (loans, credit cards, lines of credit, mortgages, etc.). The model requires taking a representative sample from the target population from a recent archive period (known as the observation point), and then defining and calculating the response variable; consumer credit files are observed at a more recent period (12 months after the observation period for Score Complete; this is called the performance window) to determine whether there has been negative behaviour. For Score Complete, this response variable is defined as a serious delinquency (90 days or worse) or write-off of a trade line, or presence of a derogatory public record such as a bankruptcy, within the performance window.

For the development of Score Complete, three different time intervals were used to account for seasonality. Approximately 2 million records without death notices were chosen from time periods (observation and performance) spaced 12 months apart:

- June 2010 and June 2011
- September 2010 and September 2011
- December 2010 and December 2011

Special emphasis was placed on detecting characteristics of consumers at origination who opened accounts that went delinquent in the first year. Since Score Complete is particularly strong at predicting this behavior, it is an excellent score for risk managers to use at perhaps the most critical point of the consumer's life cycle – the point at which the consumer becomes a customer of the risk manager's lending institution.

In addition, approximately 900,000 files were used for consumers who opened a new account between July 2010 and March 2011, and did not meet the criteria to score based solely on the credit file, in order to build the additional scorecards.

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While Score Complete was developed as a score that predicts 90-day or worse delinquency of a consumer of any trade within 12 months, it is also very predictive of other similar outcomes, such as delinquency within 24 months rather than 12, or 60-day delinquencies rather than 90-days. Score Complete can be used to predict the likelihood of a consumer going delinquent on any individual account when being assessed for account management purposes, as well as predicting delinquency for a new account during acquisition / adjudication.

1.3 Available Data / Independent Variables

A model estimates an unknown quantity by developing the relationship between the known attributes and the required outcome (the performance as defined in the previous section). The known attributes have to be available at the time that the unknown quantity is to be estimated. The statistical term for these attributes is *independent variables*. For Score Complete, the attributes come from the credit file in most cases. When the credit file is not robust enough to return a score reliably, additional attributes are available from the aggregated data available within Neighbourhood View[3].

The credit file attributes are the Equifax Canada Risk Modelling Segments (RMS), consisting of over 400 proprietary credit file attributes covering a wide spectrum of credit file characteristics including delinquency, utilization and balances, inquiries, public records, and the make-up of the wallet. These segments include many industry-specific attributes as well as some that are aggregated for all trades or inquiries.

In order for Score Complete to accurately predict a delinquency rate for consumers with very limited credit file information, or no credit file at all, an additional data source must be used. Using the information that is there along with additional information that is relevant to the consumer and predictive of his behavior allows Score Complete to be a complete score for the Canadian credit-seeking population.

Augmenting the credit file in cases where there may not be enough information to calculate a reliable score is aggregated credit data from Neighbourhood View. Neighbourhood View is a tool originally designed for marketers who are looking for consumers that have desirable credit characteristics and are more likely to have a desire to consumer the company's products. Neighbourhood View is aggregated credit data, where the credit histories of consumers in each neighbourhood are combined to give a profile.

Information aggregated to a neighbourhood is representative, in a majority of cases, of the individuals within the neighbourhood. The average credit profile of a neighbourhood would be consistent with the credit profile of most of the residents in that neighbourhood. This consistency is enhanced by the fact that the consumer and all members of the same household contribute data to the neighbourhood. Therefore, it is reasonable that the aggregate information of the neighbourhood makes a good proxy for individual data, when individual data cannot be obtained.

The neighbourhood in which a person lives may be a defining characteristic. Whether they live in a rich or poor neighbourhood, a house, apartment, or condominium, a rural or urban community, these characteristics are shared with their closest neighbours. Knowing whether the other residents in a neighbourhood pay their bills on time or not, carry high or balances on their accounts, and whether or not they use different credit products reflects on the individuals for which little information is known. This aggregated data is helpful in predicting whether a consumer is likely to pay regularly their own bills on time.

With Score Complete, neighbourhoods are geographically defined at the Street Level. While privacy legislation prevents aggregating fewer than 15 credit files together, postal codes are sometimes very large, and one may wish to

[3] When files have a lot of information, predicting behavior is easy. With less information, a good model can provide an excellent estimate. When the credit file has very little information, other sources are required in order to build a model that distinguishes the consumers who are good payers from those who will go delinquent.

split a large postal code into smaller segments. This is what Street Level does. The credit files in each postal code are sorted by street, house (civic) number, and apartment (or suite) number. Along each street, credit files are counted by address until at least 15 credit files are found. Additional credit files may be included if they match the address of the 15th file. This segment is called a subdivision. Then the process continues from the next address. In this manner, large postal codes are segmented into a number of smaller subdivisions with at least 15 credit files, so these subdivisions are much more granular; perhaps only 7 or 8 households are used to define them. Consumers are aggregated with fewer neighbours, and likely those who are in closer proximity, and therefore likely share more common characteristics than those in a larger area. In addition, since fewer consumers are aggregated together, an individual's information contributes a larger proportion of data to the subdivision, making the subdivision data a much better proxy for the individual than the postal code as a whole.

2. The Score Complete Model

The Score Complete model returns a three-digit numerical score that corresponds to the delinquency risk for the individual consumer with the given credit file and address information. Consumers with high credit scores are less likely to have serious delinquencies than consumers with low scores. This section discusses properties of the score: how it is built and how the results can be interpreted.

2.1 Segmentation

The predictability of a model is often greatly enhanced by segmenting the population into a number of subgroups, and creating a different predictive formula in each segment. Different formulas may be needed because there may be differences in the availability of data for certain parts of the population. For example, there is no need to have attributes for public records in all formulas if there are different segments for consumers with and without public records. Another reason is that different business decisions may apply, such as if companies have different strategies for consumers who are new to credit. A third reason for segmentation is that there may be certain subgroups of the population for which there is a different relationship between the modeling attributes and the outcome.

Consumers with good but short payment histories may be considered low risk for continuing payment and obligations with the credit that they already have, but may not be as low risk for new credit granted. Identifying the segment for these consumers will help a risk manager deal with these two different cases.

Score Complete uses a segmentation scheme based on delinquency and public records, the age of the oldest trade, and the number of trades on file. A total of eleven segments are defined, of which eight are based entirely on credit file attributes, and three that are augmented with Neighbourhood View data. A different formula is to be applied to each, so that the attributes can predict the outcome over each segment. These distinct formulas are called scorecards. Since there is a direct relationship between the segment and scorecard, the two terms are commonly used interchangeably.

Some credit files have robust data, with a long credit history and a large number of trades, and the future performance of the consumer can be accurately assessed with great confidence. On the other hand, when the open date of the oldest trade is recent and/or the number of trades is few, the consumer doesn't have a robust credit history and there isn't a lot of information that can be used in identifying if these consumers are good credit risks. These files are often called thin files. Consumers with good but short payment histories may be considered low risk for continuing payment and obligations with the credit that they already have, but may not be as low risk for new credit granted. Identifying the segment for these consumers will help a risk manager deal with these two different cases.

In cases where aggregated data is used to augment the credit file, or is the only source of data when no file is found, it may be good practice to be cautious in granting credit. While these consumers live in areas which suggest that they may be good credit risks (and this has been demonstrated statistically), it may be wise to limit the exposure of credit to consumers who have not personally demonstrated the responsibility of managing their own credit. Applicants from the augmented scorecards can easily be identified and treated appropriately. This may depend on the financial product. The applicant may be approved for a cell phone based on his or her address, or a credit card with a moderate credit limit, but perhaps not for a large auto loan or a mortgage without a co-signer.

2.2 Modeling Technique

Eight of the eleven segments were built with individual credit file attributes (the RMS segments). The response for each of these segments was a 90-day delinquency or worse (including derogatory public record) within the 12-month performance window.

Within each segment, a logistic regression model was developed. Logistic regression is a modeling technique designed to model the relationship between a binary[4] outcome and the explanatory variables. For each variable, a weight is assigned, multiplying the weight by the value, or by giving a set number of points for each possible value of the variable.

In addition to the logistic regression models, there are two neural networks. Neural networks are statistical models that look at combinations of variables, and these combination variables are used to build the model. Neural networks can be highly predictive when the event that is being predicted is a rare event or when the amount of available information is limited.

With Score Complete, five of the eight segments enhance the predictability of the logistic regression models by combining the logistic regression result with the result of the neural networks. The two results are blended using a methodology called score fusion, transforming them into one estimate of the likelihood of serious delinquency. The results were fused in such a way as to maintain the logistic regression as the primary driver of the score.

After score fusion, the formulas applied to each credit file have derived a probability of delinquency. These formulas have been proven accurate, in the development dataset, by taking all of the records with similar probabilities and calculating the observed bad rates and comparing them to the expected bad rate.

Three additional scorecards were used to create the score in cases where there was limited credit file information. Recall from Section 1.1, all Canadian consumers with credit activity within the last 24 months and at least one valid trade line will score based on their own credit file information. Consumers who do not qualify are most likely new applicants for credit, and the response used in the development of these scorecards was a 90-day delinquency or

[4] Binary outcomes are those that can take two values. These are often denoted by "yes" and "no," or "true" and "false", or in this case, "good" or bad." They are represented in code as 0 and 1.

worse (including derogatory public record) within the 12-month performance window for any new account opened within the first quarter of the performance window; trade lines which already existed on the file were not used in the performance definition. In other words, the additional scorecards were built purely as an origination model.

Separate logistic regression scorecards were built for the consumers with limited credit file information and consumers without any credit file at all[5]. Consumers who have a credit file, but the credit file has been created within 30 days and there is no trade on file, are somewhat similar to consumers who do not have a credit file at all. In order to prevent a wild swing in score based on migration from the "no file" scorecard to the "thin file" scorecard, interpolation between the two scorecards was done, based on the age of the file. This "hybrid" calculation is presented as the eleventh scorecard.

Example: A consumer has a credit file that was created on March 1. At the time of an inquiry on March 1, without a credit file, this consumer (applicant) would have to be scored based on his address and the aggregated data from Neighbourhood View from his subdivision. He would be scored on the "No credit file found" scorecard, with a score of 640. The inquiry opens a thin file. With his next inquiry, since he has a credit file, he can be scored on the "Thin file augmented with aggregated data" scorecard. Using his address and thin file (with an inquiry on it), the calculation of his Score Complete would be 670 on the "Thin file augmented with aggregated credit data" scorecard. This consumer does not score 670 immediately after his file is created. His risk profile hasn't changed very much, so his score should not jump 30 points immediately. Instead, his score will increase by interpolation; 30 points in 30 days means a point per day. His score on March 18, for example, would be calculated as:

Score Complete = No-Hit Score + (No-Score Score – No-Hit Score) x (Current Date – File Creation Date) / 30
= 640 + (670 – 640) x (18 – 1) / 30
= 640 + 30 x 17 / 30
= 657

This interpolation only applies for consumers with no trades on file, and with files created within 30 days. After 30 days, this consumer will be scored solely on the "Thin file augmented with aggregated data" scorecard.

2.3 Scaling

Score Complete uses a 300 to 900 scale rather than a probability estimate, where a high score indicates a low delinquency risk. This is a convention that is standard to credit scoring. Most credit scores, regardless of bureau or country or score version, follow the same scale. It is not necessary that the scores do this, but professionals who work with different institutions that use different credit bureaus or scores, have gained experience in interpreting a score value, and redeveloped versions and other scores tend to follow the same convention.

The key is that scores should separate and rank order delinquency risk. This means that there should be a relationship between the score and the delinquency rate. Consumers with low scores have a high delinquency rate, while consumers with higher scores should have a lower delinquency rate. The relationship should be consistent,

[5] It may not be obvious how there can be records in the data where there is no credit file. The development data was selected by finding all trade lines opened between July 2010 and March 2011. The performance of these accounts was determined at the end of each of the three performance windows (June, September, and December 2011), giving each trade between 9 and 11 months of history. The observation dates of June, September, and December 2010 were used to pull information at origination. If a consumer opened a new account in July 2010, they may not have had a file in June 2010. This consumer's score would be based on the address, and Neighbourhood View Street Level data from June 2010.

and there should be a large difference in delinquency rates between consumers with the best and worst Score Complete.

Score Range	Interpretation
300-499	Very serious issues, difficult to get any credit
500-574	High risk customer, may be required to provide securitization. May be eligible in the Telco industry.
575-649	Above average risk profile. May be granted credit with high interest or low limits.
650-749	Fairly safe credit risk for most institutions
750-900	Safe credit risk, generally approved easily

Scores below 300 or above 900 are not possible with Score Complete at Equifax Canada.

This interpretation should be treated as a guideline only. Companies should validate scores on their own portfolio with their own definition of negative performance, in order that their risk managers can customize and optimize their strategy for their own business needs.

Over time, changes in lending policies, reporting policies, lending institutions, consumer behaviour, and the economy can change the relationship between scores and the expected bad rate. Score Complete will continue to perform in the future and continue to rank order delinquencies, but the bad rate at various scores may shift if the data or the economy changes significantly. Risk managers should monitor their portfolios regularly and determine if decisions should be implemented at a different score range or cut-off than has been used previously.

The eight scorecards built with credit file information only, using the definition of a 90-day delinquency on any trade in wallet were scaled identically; the same probability of delinquency in each scorecard was mapped to the same Score Complete result on the 300 to 900 scale.

The additional scorecards were built with a different performance definition: 90-day delinquency on new trades. To map to the same 300 to 900 scale and indicate the same degree of risk, two steps were taken.

First, new accounts opened between July 2010 and March 2011 for consumers for the development of the original eight scorecards were analysed, and the relationship between the Score Complete result of these consumers to the delinquency rate of these new accounts was determined. This was done to determine the relationship between the Score Complete calculated from the original eight scorecards with the performance definition applied to the augmented ones.

Second, an adjustment was made to the delinquency rate observed on the new open accounts used in the development of the augmented scorecards. The reason this was necessary is because the development data included all accounts for consumers who opened a new account, but is meant to apply to anyone who applies to open a new account. Consumers who were approved for accounts are likely to have qualified after some additional investigation by the lender, under criteria not accounted for in the data. It is likely that they are lower risks than average, and the delinquency rates observed was lower than would be expected on a typical application. The population used to build the model was not exactly representative of the population for which the model should apply, and this correction was made to account for that difference.

This adjusted delinquency rate was mapped to the delinquency of new accounts from the eight original scorecards and the associated Score Complete. In this way, the final Score Complete result, 300 to 900, indicates the same amount of risk regardless of which of the scorecards was used in the calculation.

Consumers with death notices on the file get a 300 score, the lowest possible score. The 300 score is reserved for files with death notices. Instead of returning no score, which implies that the lender should undergo an investigation of other sources to determine whether or not to approve credit, a death notice on file with a 300 score indicates that no further investigation is needed. The only way to get a 300 score is with a death notice. All other cases will be 301 or higher.

2.4 Attributes

The credit file attributes that are included in the final Score Complete model are those credit file characteristics that are found to be predictive of future delinquencies. These tend to be the same characteristics that risk managers consider when they look at a credit file. They can be classified into a number of categories:

Payment history. If you are trying to determine whether a consumer will be able to make regular payments in the future, the strongest predictor is to see if they have missed payments in the past. The number of accounts currently past due, the rating of the most seriously delinquent trade, the number of accounts past due previously, and the length of time since prior delinquency are considered here.

Utilization and balances. It is intuitively obvious that is it easier for consumers to pay their bills when they do not owe a lot of money and the required payments are small. In addition, carrying balances on revolving accounts suggests the inability to pay them off in full, which makes it more likely that the consumer will have problems continuing to pay their bills. Low utilization indicates a difference between the credit limit and the balance, sometimes called "open to buy." A large amount open to buy gives consumers flexibility, a way to pay bills for a short time that can't be covered by income, by tapping into their lines of credit. A small amount of open to buy reduces the incentive to make a payment on a credit card or line of credit since they won't be able to use much of it anyway. And once the credit cards are maxed out and the lines of credit are used up, they may not be able to cover their payments. Bankruptcy may become their only option.

Credit history. A consumer who has managed credit for many years is considered lower risk than someone new to credit. Over a long period of time, many people have significant life events, including moving, changing or losing job, marriage or divorce, having children, and serious illness or injury. Those who have experienced these events in the past and continued to pay their bills have a strong likelihood to continue doing so. They have shown responsibility and consistency over a long period of time and can be considered a good credit risk.

On the other hand, young Canadians or new residents, new to credit, who have managed a first credit card with a small credit limit have not demonstrated a history of managing large amounts of debt and haven't proven the ability to make regular payments over several years (such as a mortgage or auto loan). They are less likely to have dealt with significant life events, and if one occurs, they have not demonstrated the ability to deal with it and maintain their financial responsibilities.

Also in this category is the number and type of accounts. Consumers with many different accounts may be of higher risk, and the properties of some trades indicate a higher risk than they do in other industries. For example, high utilization in a line of credit may be a risk factor, while high utilization of a loan just means that it is a new account and the consumer hasn't had a chance to pay off much of the balance.

The presence of many new accounts may also be an indication of higher risk. For one thing, consumers in financial difficulty often try to open new accounts in order to extend their "open to buy" and continue to pay their bills through the tough times. Additionally, a number of new accounts may indicate that something has changed, and this brings uncertainly to the risk prediction, which in turn means higher risk to the lender.

Public records. Those who have a prior history of bankruptcy, or have had collection issues or other derogatory public records may be considered risky. The presence of these events, though relatively rare, has a significant negative impact on a credit score.

Inquiries. Consumers who are going through financial difficulties, whether through job loss, family or health situations, or general financial woes, often look for additional credit products to provide additional open to buy. They may apply for a loan to pay down the credit card they have maxed out, and try to get a new credit card. The inquiry may be the leading indicator, the first sign of danger that appears on the credit file. Of course not every inquiry is a sign of financial difficulty, and only a number of inquiries, in combination with other warning signals should lead to a significant decline in a credit score.

Consumers sometimes shop around when they are looking for certain products, and multiple inquiries over a short period of time can be considered as shopping for one product. Three mortgage inquiries in a week rarely means that a consumer is trying to buy three houses, while three credit card inquiries may mean that they are going to have three new credit cards. Mortgage inquiries, auto finance inquiries, and Telco inquiries are deduped, meaning that multiple inquiries within 30 days count as one inquiry in the calculation of the score. In addition, inquiries within the first 30 days do not count in the score calculation, allowing consumers a chance to shop at different places without there being an advantage to the first lender that pulls a file that receives a score with no inquiries counting.

The Neighbourhood View data elements that are used in Score Complete mimic the attributes for the individual. Attributes such as the average number of delinquent accounts, the number and recency of public records, inquiries, and high utilization are used, and have the same directional impact as they do at the individual level, although they are weighted differently, and appropriately, for estimating risk.

In the case where a score can be generated from the credit file information only, Telco trades are not used in the formulas. These scorecards use products including credit cards, loans, lines of credit, and mortgages from industries which include banks, credit unions, and finance companies. The additional scorecards use the Telco trades, any other trades in the file, inquiries, public records, and the aggregated data from the neighbourhood.

2.5 Account Management and Scorecard Migration

Score Complete is always calculated with the most up-to-date data available. Companies that want to monitor the behaviour of their consumers often refresh the scores of their portfolio on a regular basis, and store the historical scores in their databases. They may want to take action when consumers score differently.

When consumers are scored at different times, the information in the credit file will have changes, as new inquiries and trades are added to the files and existing trades are updated. Even if there hasn't been an update in the information, the data in the credit file ages. Increasing the length of time since the oldest trade has been opened is a positive factor, and negative behavior, such as missed payments and public records, move further into the past.

When Score Complete calculates a new score, it is based entirely on the current snapshot of the credit file (or the archive snapshot for scores on a historical file). The consumer may score on the same scorecard, or may have migrated to a different one.

When a consumer is scored on the same scorecard at two different points in time, the difference in the scores can be attributed to changes in the attributes used by that scorecard. If the consumer's attributes are similar from month to month (no new trades, few inquiries, no large change in balances), the score will change very little. When attributes change in a positive way (by paying down balances and keeping current on accounts and having delinquencies move further into the past), the score will increase in a predictable manner.

When a consumer's score is refreshed, and the consumer changes from one scorecard to another, the attributes used in calculating the score change as well. Using different attributes with different weights sometimes causes a change in the score that cannot be attributed to a single change in behavior. Moving from a thin file to thick (or to very thick), from young to old, or from the augmented scorecard to the regular one may cause score changes that can't be explained by looking at individual attributes. Of course, moving from the Clean to Delinquent scorecards will usually result in a much lower score.

Along with the score, companies may want to store the scorecard indicator in their databases. The scorecard indicator is returned as Score Complete's fourth reason code. When comparing the latest refresh to the saved historical data, they would be able to determine consumers who have significant changes in score. They can further understand these differences by comparing scorecard indicators. When the score change is based on scores from the same scorecard, it can be said that there has been improvement in the underlying attributes. The consumer has made positive changes in the characteristics of the credit file, and the score directly reflects that.

However, if the scorecard has changed, it is more complicated. There are two considerations. Sometimes a consumer will migrate from a clean scorecard (92 to 95) to a delinquent one (96 to 99) – see table below. This is a fundamental change in the file, and will usually be accompanied by a score decrease. However, changes between thin and thick, or moving to the mature scorecards mean that different elements of the credit files are used in evaluating risk, and so an increase or decrease in score is not necessarily attributed to improving or declining attributes; it may simply be that the consumer has better or worse characteristics on the attributes considered more important to the current segment than on the other scorecard. And movement from the augmented scorecards (89 to 91) to the established ones (92 to 99) indicates that the weight given to the neighbourhood transfers to the credit file itself. It is expected in these cases that the score may change as consumers attain more robust credit files, and are scored on different criteria. However, the scores should be correlated. For a population of consumers with scores based on thin files and neighbourhood data, high scores imply that the risk is low. Low risk implies that consumers are likely to make their payments on their new accounts. This positive behavior will lead them to have good credit scores when they migrate to the traditional scorecards, and these high scores also predict the same expectation of low risk.

Scorecard	Description
89	No credit file found
90	No trade on file and file age < 30 days

Scorecard	Description
91	Thin file augmented with aggregated credit data
92	Clean, mature and very thick
93	Clean, mature and thick
94	Clean and thick
95	Clean and thin
96	Prior delinquency thick
97	Prior delinquency thin
98	Delinquent thick
99	Delinquent thin

3. Output

While the score is the most important output from the scoring module, several other pieces of information are generated and returned with the output.

The first is a product identifier, "SC", which identifies the score as being a Score Complete. Following the three-digit score between 300 and 900 are four reason codes that help explain why a consumer file has the score that it does. Reason codes correspond to the attributes that have values that lower the score, such as delinquent accounts, high balances or utilization, or excessive inquiries. The first three reason codes correspond to the three attributes from the credit file whose values impact the score by the largest amount. The fourth reason code denotes the scorecard, or subpopulation, indicator.

The identification of the subpopulation used in the score may be a strong indication of the score. For example, the subpopulations defined by delinquency or public records tend to score lower than the subpopulations without them. In addition, the scorecard indicator highlights files with limited credit information, and the scorecards which are augmented with information from the credit files in the neighbourhood. In many cases, these "thin files" may be low risk for the accounts that they already have, but would be high risk if they were given a new and large loan, line of credit, or mortgage. Risk managers can use the scorecard indicator to automate different credit policies for consumers belonging to different subpopulations.

Score Complete: **657**
57 Too many auto inquiries
83 Too many derogatory public records in neighbourhood
35 High credit open telco trades is too high
91 Thin file augmented with aggregated credit data

There are only two cases where Score Complete will not return a valid score.
If there is no credit file, and there is no aggregated credit data from the address, there is no information available to the score. The other is if a file has been flagged by Equifax as a manual file, or file under review[6]. Reject codes are returned to account for these two cases.

See Appendix for a complete list of reason and reject codes for Score Complete.

[6] This is a very rare occurrence. In one recent month, less than one inquiry in 500,000 resulted in a manual file.

4. Using Score Complete – Alone or With Another Score

Score Complete is designed to score any credit file or application. It assesses the delinquency risk, either at origination or in batch for account management purposes, and returns a three-digit score which rank-orders delinquency risk. Score Complete returns a score virtually every time, unless there is problem with the input address, such as a format error (address elements are in the wrong fields, or the address is out of country) or an address in a new postal code that has just been created. Score complete rank-orders delinquency risk for all files, and can be used by itself as a complete delinquency score.

Some companies already use a delinquency score, such as BEACON, Equifax Risk Score (ERS), or Consumer Risk Predictor (CRP). These scores assess delinquency risk, but have minimum scoring criteria that do not score certain credit files, and they certainly do not return a score when no credit file is found. These companies may want to continue to use their choice of score, but have a waterfall process that uses Score Complete in cases where their primary score fails to return a score. This can be done.

To do this, the primary score must be activated for the inquiry, as well as Score Complete as a child score. If the primary score succeeds in scoring the file, the score identifier, three-digit score, and four reason codes are returned, as well as a blank reject code. The Score Complete algorithm does not run, and no result is returned.

If the primary score fails, the score identifier is still returned, along with a 0 score that indicates no score can be calculated. The reason codes will be blank. The reject code will be filled in, corresponding to the code for that particular score (reject codes do vary between the different generic scoring models).

Then the Score Complete algorithm runs, and generates a score. The SC score identifier, the three-digit score, and four reason codes are returned. The fourth reason code is the scorecard indicator. In the case of no data, neither a credit file nor aggregate data is available, the reject code will be returned.

Score Complete's 300 to 900 score range is similar to the range used by most versions of most of the generic delinquency scores available from Equifax. It may be appropriate in some cases to use the same strategies with a Score Complete result in the second bureau segment as would be used with a score in the primary segment, although companies would be wise to test this assumption on their own before relying on that assumption.

5. Evaluating a Model

What do we mean when we say that a model works? It means that a model can be used in predicting the unknown quantity that it is supposed to predict. There are a number of different ways to determine this. Formal methodologies include creating tables and graphs and calculating statistics.

Credit scores, especially with scaling, work if the scores **separate** and **rank order** credit risk. A population that is representative of the target population that has values for the required quantity are used to show how well the score predicts the outcome.

First, records are segmented by score. This may be done by fixed score ranges, like 20-point score bands, or by score distribution, such as deciles. The keys to looking at data expressed this way:

- **Separation.** Files with low scores should have a high percentage of records with the negative occurrence that was measured, while low risk scores should have a low percentage of bad outcomes. The more separation there is, the better the score is performing. It is better if the bad rate is 50% in the high risk section and 2% in the low risk, than if the differences vary between 15% and 10%.
- **Rank ordering.** As scores improve, the bad rate should improve in an orderly and predictable fashion. Score Complete scores increase when the risk decreases, so the observed bad rate should also decrease as scores increase.

Here is an example illustrating how scores separate and rank order risk:

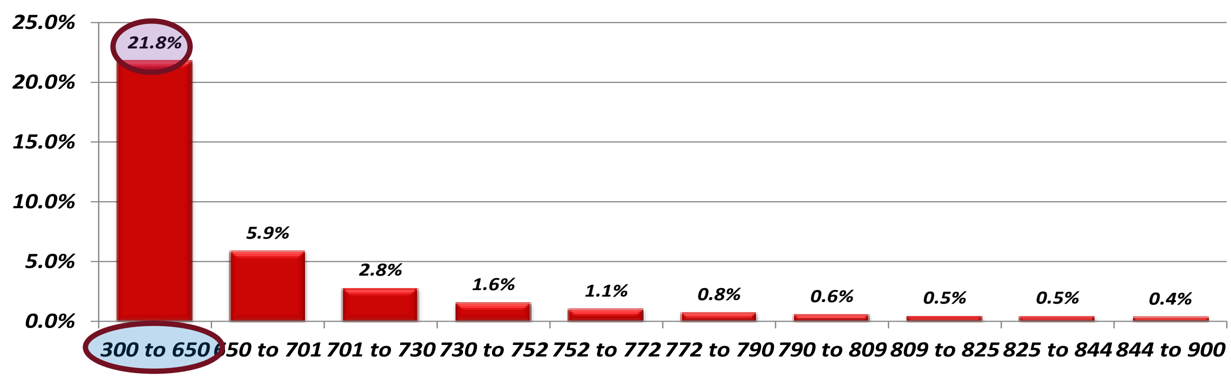
Separate and rank order

	All Accounts		Negative Performance Delinquency 90+ or bankruptcy			
	Consumers	**Cumulative %**	**Consumers**	**Cumulative %**	**Bad Rate**	**Goods to Bad**
300 to 650	2,209,742	10.0%	482,191	60.9%	21.8%	3.6
650 to 701	2,209,742	20.0%	130,614	77.3%	5.9%	15.9
701 to 730	2,209,742	30.0%	61,770	85.1%	2.8%	34.8
730 to 752	2,209,742	40.0%	35,120	89.6%	1.6%	61.9
752 to 772	2,209,742	50.0%	23,335	92.5%	1.1%	93.7
772 to 790	2,209,743	60.0%	16,740	94.6%	0.8%	131.0
790 to 809	2,209,742	70.0%	13,264	96.3%	0.6%	165.6
809 to 825	2,209,742	80.0%	10,570	97.6%	0.5%	208.1
825 to 844	2,209,742	90.0%	9,950	98.9%	0.5%	221.1
844 to 900	2,209,742	100.0%	8,807	100.0%	0.4%	249.9
Scorables	22,097,421		792,361		3.6%	26.9

In this example, the records are grouped in deciles, 10% in each row of the table. Within the entire population, only 3.6% of the records were classified with negative performance (792K out of 22M), having a 90+ day delinquency or bankruptcy within the performance window.

The lowest scores, 300 to 650, correspond to the 2.2M consumers (10% of the total) with the highest risk. They had a 21.8% bad rate, which is 6 times higher than the overall bad rate. The highest scores, 844 to 900, had a very low bad rate of 0.4%. The bad rates rank order through the score ranges, decreasing with every decile.

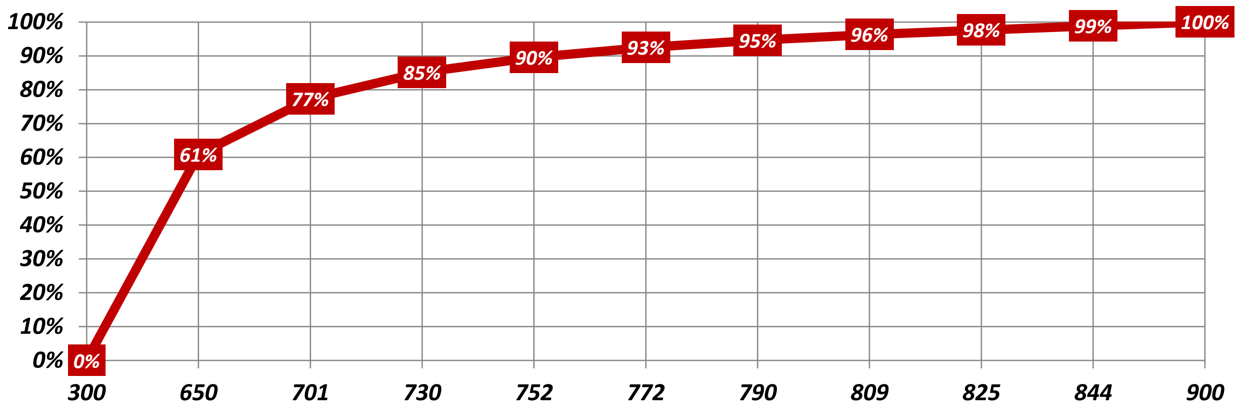
Bad rates are often shown graphically. This is a plot of the column represented in the table above by the red up arrow:



Companies will often set a score cut-off, with strategies to take adverse action to consumers with low scores, or will decline applicants with low scores that fall below the cut-off that has been set. Since they want to limit declines or adverse action to a small percentage of their consumers or applicants, it is crucial that most of the consumers who will, in the future, exhibit bad behaviour have scores that are below the cut-off now. Some good customers[7] have low scores for various reasons, and companies do not want to strain many of these relationships and lose good business.

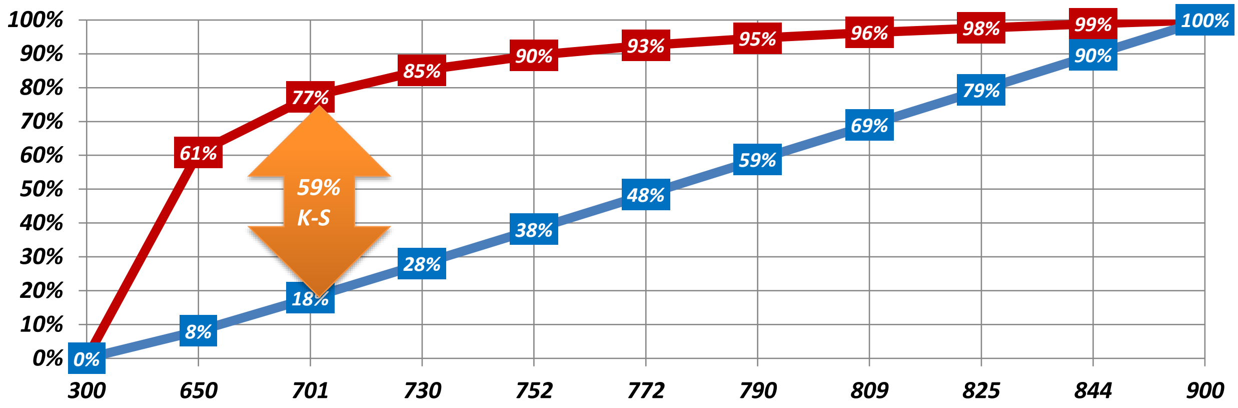
In the table above, of the 792,361 consumers with serious delinquency or bankruptcy, 482,191 scored in the bottom 10%. This represented 60.9% of all bads. It is often a key measure of the predictability of a credit score to determine the percentage of bad records identified in the highest risk scores, and the higher the better. This is the column in the table above highlighted by the purple down arrow.

Graphically, this is called a lift chart:



The better a score works, the higher the line will be in the lift chart. One way to measure how well the score works is called the Kolmogorov-Smirnov statistic, or K-S. The K-S looks at the lift chart, and calculates the percentage of good and bad records (represented by the blue line, below) scoring below each available score value. The maximum difference is the K-S[8]:

[7] Good means that they will be good customers in the future; they will meet their financial obligations, and not be classified as bad according to the definition that is used to test the score.
[8] Other metrics, such as the Gini and AUROC, measure the lift of a model differently, but K-S is often the standard metric in credit risk scoring.



Here, 77% of the bads (red line) score at 701 or below, but only 18% of the goods. The 59% difference is the largest difference at any point on the graph, so it is the K-S value. The higher the K-S, the better[9].

5.1 Score Complete Development Data

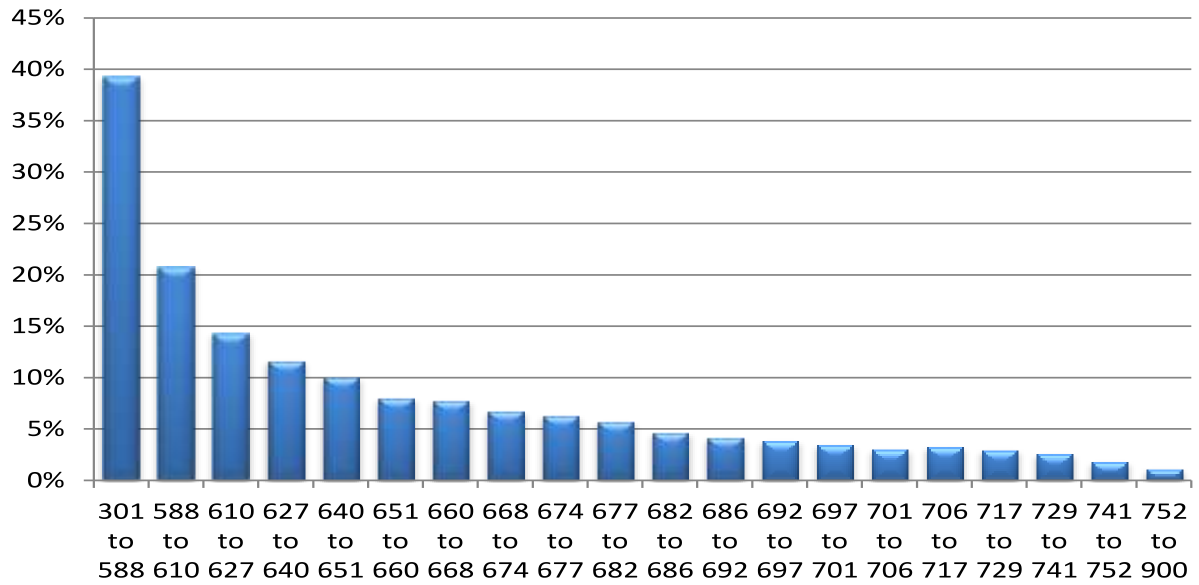
Score Complete is built in two pieces, the traditional credit score that is based on predicting delinquency from records with robust information, and a separate component for the no-hits and thin files. Traditional credit scores have been developed and redeveloped for many years by different modellers, and these scores have been accepted as valuable and predictive.

The concept of scoring every application, including no-hits and thin files may need some additional support. The results below are based on the data from the validation dataset from the score development data[10]. A bias correction, as described in section 2.3 to adjust the delinquency rate prior to the model scaling, is incorporated here as well.

The scorecards based on no-hits and thin files, applied to consumers who opened a new account between July 2010 and March 2011, show significant separation in the prediction of 90-day delinquencies:

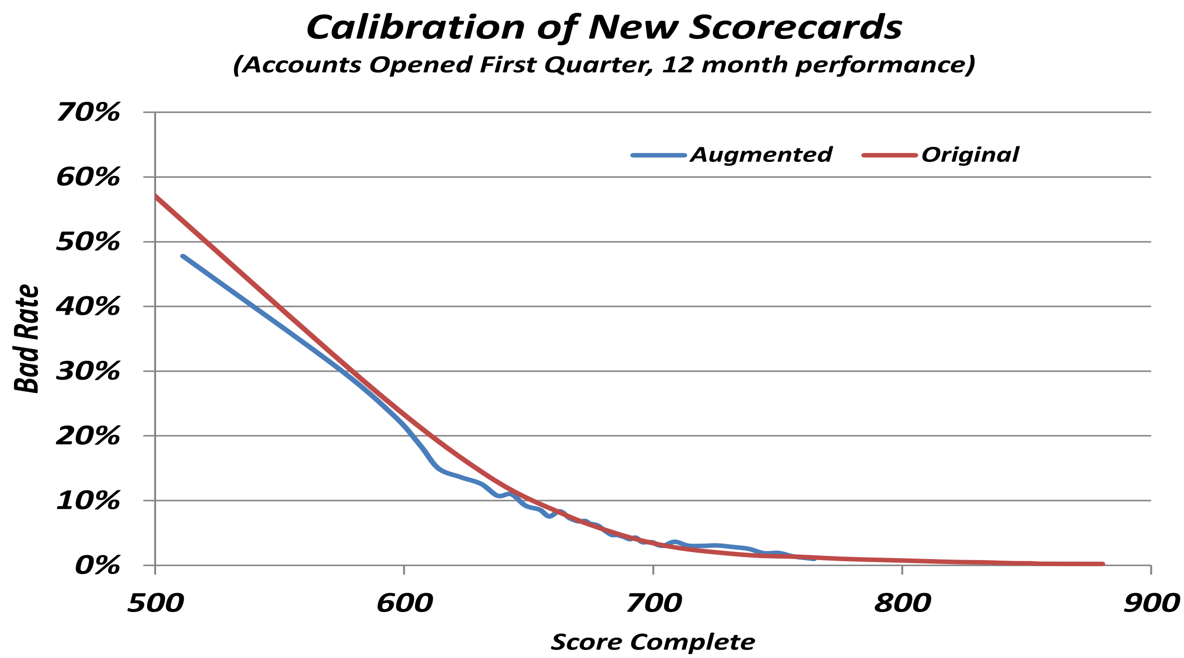
[9] What is a good K-S? It depends greatly on the use of the model and the available data. Sometimes a very small amount of lift can have tremendous benefit. One of the values of K-S is as a comparison tool between different models on the same data, as an evaluation of the models. Another is to evaluate how well a model performs over time as things change.

[10] Traditionally, when statisticians create a model, they separate the initial dataset into two parts, often with approximately the same number of records in each. The training dataset is the one used to build the model, and create the weights for each attribute. The formulas are optimized on the training dataset. The validation dataset is used to show that the formulas work on different data. It is fair to use the validation dataset to make inferences on how well the model would work in independent analyses.



The K-S is 37.2%. Given that there is limited, if any, credit file information, and the outcome is based on opening new accounts rather than managing existing ones, this K-S is very good.

While the traditional scorecards were developed with a negative performance definition of a 90-day delinquency or worse on any trade, not just new ones, the new accounts for consumers on these scorecards were analysed to estimate the relationship between the score and the probability of delinquency on a new account. As the following chart demonstrates, the bad rate by score range for the traditional scorecards and the augmented ones indicates the same expectation of a 90+ day delinquency on a new account.



These two charts show that the Score Complete augmented scorecards act the same as the original ones. They separate the high risk applications from the low risk applications and return a score that is consistent with the expectation of delinquency. Risk managers may be comfortable using the result of the Score Complete model to help assess the likelihood that a given applicant will make regular payments on their financial obligations, and will be pleased that so many applications are assessed where traditional credit scores fail.

Summary

Canadian consumers need credit cards for everyday purchases, loans to buy goods and services, lines of credit to optimize and bring flexibility to credit management, and mortgages so they will have a place to live. To finance these things, banks and other lending or credit granting institutions provide these credit products, but need to ensure that they can do so profitably. They send their data to Equifax, and Equifax builds credit files that contain the credit history of over 24 million active credit holders.

The information in these credit files allows risk managers the opportunity to evaluate the likelihood that the consumer or applicant is in a good financial position and will be able to repay the loan, or make regular payments on the revolving credit. A credit score, like Score, assists this process. Score Complete weighs the elements of the credit file properly, and provides consistency to the decision making process, allowing the risk manager the ability to optimize strategies to be as profitable and successful as possible.

The fact that Score Complete succeeds in returning a score on virtually every request makes it an outstanding risk management tool for any lender.

Additional Reading

The original eight scorecards used when a file is robust are the same as the Equifax Risk Score (ERS 2.0), with the only exception being that ERS 2.0 scores of 300 are bumped to 301 to free up the 300 score to account for death notices (Death notice files do not score with ERS 2.0). The reason is referred to the **Equifax Risk Score 2.0 Handbook**.

As the additional scorecards are somewhat based on Neighbourhood View, for a further understanding of that product, please see the **Neighbourhood View Handbook**.

Appendix – Reason Codes, Scorecard Indicator, Reject Codes

Reason Codes

Reason Code	Description
1	Average trade age too young
2	Too many trades currently 90+ DPD
3	Too many trades 60+DPD within the last 2 years
4	Too many trades opened within last 2 Years were 90+DPD
5	Too few satisfactory trades
6	Too few open trades
7	Too many trades past due
8	Too few trades on file
9	Length of time trades established
10	Percentage of trades satisfactory too low
11	Current delinquency
12	Delinquency on file
13	Too few auto trades
14	Too few satisfactory auto trades
15	Too many auto inquiries
16	Too few bank instalment trades
17	Too few satisfactory bank instalment trades
18	High ratio of balance to high credit on bank instalment trades
19	Current delinquency on bank instalment trades
20	Delinquency on bank instalment trades
21	Too many bank inquiries
22	Too few bank revolving trades
23	Too few bank revolving trades older than 6 months
24	Length of time bank revolving trades established
25	Too few satisfactory bank revolving trades
26	High ratio of balance to high credit on bank revolving trades
27	Current delinquency on bank revolving trades
28	Delinquency on bank revolving trades
29	Too many collection inquiries
30	Recent collection inquiry
31	High balance on collection items
32	Too many collection items within the last 3 years
33	Too few satisfactory credit union trades
34	Too many finance instalment trades
35	High credit open telco trades is too high
36	High ratio of balance to high credit on finance instalment trades
37	Too many personal finance inquiries in the last year
38	Too many personal finance inquiries
39	Too many finance revolving trades
40	High ratio of balance to high credit on finance revolving trades
41	Delinquency on instalment trades

Reason Code	Description
42	Too many national credit card inquiries
43	Average national credit card trade too young
44	High balance on national credit cards
45	Too many national credit cards
46	Too recent age of oldest trade in neighbourhood
47	Too many national credit cards with high utilization
48	Too many national credit cards with high utilization
49	Too many national credit cards with high utilization
50	High ratio of balance to high credit on national credit cards
51	High ratio of balance to high credit on new national credit cards
52	Current delinquency on National Card Trades
53	Delinquency on National Card Trades
54	Too many other inquiries
55	Recent public record
56	Public records within the last year
57	Public records within the last 3 years
58	High ratio of balance to high credit on personal finance trades
59	Too many revolving trades with balances
60	Too few revolving trades with $0 balance
61	Length of time revolving trades established
62	Too many revolving trades with high utilization
63	Too many revolving trades with high utilization
64	High ratio of balance to high credit on revolving trades
65	High ratio of balance to high credit on new revolving trades
66	Too many retail trades with balances
67	High ratio of balance to high credit on retail trades
68	High ratio of balance to high credit on sales finance trades
69	Current delinquency on sales finance trades
70	Too many telco inquiries in the last year
71	Too many telco inquiries
72	Too many inquiries in the last year
73	Too many recent auto, sales finance, national cards or other inquiries
74	Too many inquiries in the last 3 months
75	Too many inquiries
76	Too many auto, sales finance, national cards or other inquiries
77	Recent inquiry
78	Too many revolving trades with high utilization
79	Too many department stores inquiries on file
80	Current maximum rate in neighbourhood too high
81	Too few open trades in neighbourhood
82	Too many delinquent trades in neighbourhood
83	Too many derogatory public records in neighbourhood
84	Too many inquiries in neighbourhood
85	High utilization on open revolving trades in neighbourhood
86	Too few satisfactory trades in neighbourhood

Reason Code	Description
87	Too low high credit on open trades in neighbourhood
88	Death notice on file

Reject Codes

Reject Code	Description
G	No credit file or neighbourhood data available
F	Score Complete not available, file under review

Score Card Indicators

Scorecard	Description
89	No credit file found
90	No trade on file and file age < 30 days
91	Thin file augmented with aggregated credit data
92	Clean, mature and very thick
93	Clean, mature and thick
94	Clean and thick
95	Clean and thin
96	Prior delinquency thick
97	Prior delinquency thin
98	Delinquent thick
99	Delinquent thin