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A Comprehensive Credit Assessment Framework: Overview and Implications for the Subprime Crisis

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ABSTRACT

Existing credit scoring approaches have put too much of an emphasis on past loan performance and historical market conditions and not enough on borrower capacity, new mortgage product risk characteristics, and economic cycles. This paper introduces a new comprehensive credit assessment framework (CCAF) that can provide early warnings and analyses of credit risk that do not rely on the premise that the past determines the future. We will show how CCAF addresses the credit scoring limitations imposed by insufficient credit and market information and sampling timeframes, and static data-driven factor selection and weightings. In particular we will explain how CCAF extends existing credit scoring to embrace all relevant factors and business context so that lenders can classify credit risk and decision all transactions in a more, effective, transparent, and forward-looking manner. A simple example is used to illustrate how this robust and flexible framework can be easily implemented with SAS products. CCAF's systematic segmentation approach has implications for both intervening in the mortgage crisis and preventing future financial disruption.

INTRODUCTION

The magnitude and scope of the subprime crisis makes it abundantly clear of the need for significant improvement in current credit assessment approaches. Two fundamental problems contributed to the weakened underwriting standards and degraded loan quality. First, credit scoring has not done an adequate job of assessing risk in the subprime mortgage market. The majority of underwriting systems for the subprime mortgages are unable to capture the full range of risk factors in the market. This is particularly true when their conventional risk models are applied to non-conventional loan products, which are associated with different payment terms and behavior. Lenders who depend on these credit scoring systems measured credit risk inaccurately and incompletely. Second, a blind spot exists in today's underwriting practices. That is, current practices over-rely on quantitative models and automated underwriting systems. Technology has a vital role to play to boost efficiency and to help measure and monitor credit risk. The models have their place and role to play. However, models must be controlled instead of the other way around so that loans are properly classified before risk is rated. Today's process has that backwards.

As the accuracy and power of the FICO[®] score is debated, methods that address limitations of credit scoring systems and improve how to evaluate credit risk will be in demand. You cannot simply re-calibrate the existing models and throw technology at the problem. A comprehensive new credit risk framework should use a hybrid approach. The best technological practices should be coupled with expert human judgment. Such an approach can help deal with the current crisis and might lessen the extent of, or even prevent, the next one.

SAS has pioneered a framework called a Comprehensive Credit Assessment Framework (CCAF) provides a consistent approach based on advanced computing technology, and proven model development and validation processes. CCAF naturally affords a sustainable and sensible segmentation based on all primary credit factors. Then a systematic means is offered for taking appropriate actions relative to those identified segments. Ongoing monitoring of the impact of those actions can occur in a comprehensive and efficient manner. Simply put, CCAF accomplishes this by

- expanding the boundaries of information
- segmenting appropriately loan applicants based on primary factors
- layering needed secondary qualification factors
- assigning actions for each identified segment
- executing an adaptable policy mechanism that is responsive to the evolving economic climate.

This paper explains how the CCAF system improves loan quality and overcomes the limitations of existing credit scoring methods. You learn about the underwriting gap and its components in current lending practice and what contributes to unrealistic loan decisioning. You are shown how CCAF can address each of the underwriting gap components, improve credit assessment accuracy, and simplify model validation process. A specific example of purchase mortgage fixed rate versus adjustable rate mortgage (ARM) is provided. The paper concludes with CCAF's policy implications for both crisis intervention and prevention relative to future loan underwriting.

THE UNDERWRITING GAP

To develop an effective, comprehensive credit assessment framework, you must understand the underwriting gap and its components. The underwriting gap refers to the difference between the underwriting decisioning model and the borrower, business, and market realities. Narrowing the gap translates to more accurate loss predictions, fairer treatment of the customer, and less reliance on the assumption that the past determines future outcomes.

Typically, the underwriting gap consists of the following components:

- Information gap
- Model factor gap
- Sampling gap
- Model formulation gap
- Process validation gap

INFORMATION GAP

This component refers to the data used to define and derive underwriting factors and to identify good versus bad loans. The information gap occurs because the current underwriting systems are based on insufficient data coverage (the individual fields of information that are input to the system). This differs from a lack of inclusiveness (records that are dropped or included), which is discussed in the sampling gap. Factor weights are improperly constructed when working with incomplete information. Their information value relative to predicting loan default can be significantly reduced by considering factors missing in the model.

For example, credit bureau scoring systems are developed based on performance definitions that stress payment history. Other information such as five Cs is not included in the model. Credit scores have a one-to-one correspondence with the odds that a loan goes bad. The lower the score is, the higher the likelihood of a bad outcome. Credit bureau scores place substantial weight on payment history for credit accounts (35%) and on how much a consumer owes relative to how much credit is available (30%). They also take into account the average age of the aggregate trade lines and the types of debt carried. As a result, a credit score is lowered by:

- mild, infrequent delinquency
- closing older, less used accounts which lowers the average age of aggregate trade lines and increases the aggregate utilization rate
- opening new accounts which lower the average age of aggregate trade lines
- the lack of installment credit by paying with cash or quickly paying for cars or major appliances

A borrower might have sufficient liquid capital reserves (such as funds in checking or savings accounts, short-term certificates of deposit, Treasury-bills) or the capacity to repay the loan through sources of income (base salary, commissions, bonuses, or investment earnings). However, these factors carry little weight, if any, relative to the likelihood of loan default. Yet the bureau credit score has a significant impact on how much consumers pay for financing. Conversely, if a consumer has little capital or capacity, then the risk of loan default is greater than the credit score might indicate. This occurs because the score is based on a population of consumers that have the full range of capital and capacity resources.

MODEL FACTOR GAP

This component is closely related to the data component. Maximizing the breadth of potential model factors makes for a more inclusive and accurate model. Also, the ability to tailor factor definitions helps maximize the information value of the data. An example of an alternative data-based capacity factor is an *obligation to income ratio* that combines a proposed loan payment with the sum of all payments of any kind in the numerator of the ratio (Abrahams and Zhang, 2008, page 225).

Especially relative to the subprime crisis, examining both future and current financial ratios are of key importance for ARM and Option-Based mortgages. Behavioral and historical variables capture more than a snapshot. Current income and income from the previous 12 and 24 months are averaged to calculate the average annual increase in the denominator for debt-to-income (DTI) ratio. For the numerator of the DTI ratio, the maximum rate on the next ARM reset date can gauge the borrower's future ability to repay the loan. Property valuations that use both best case and worst case provide a better estimate of the range of property values. This enables borrowers and lenders to view the future range of possible loan-to-value (LTV) ratios, and predict how borrower equity might grow or evaporate.

SAMPLING GAP

This component determines which observations to include in a model. Missing, or too little, data can cause observations to be disproportionately excluded for certain population segments. This can result in a biased sample and unintended results. Time intervals over which samples are drawn might, or might not, reflect current conditions. Hence models based on data from non-representative time periods can also be misleading. To illustrate, an observation window based only on years with a prolonged housing boom, strong economic growth, and falling interest rates produces data-driven factor weightings that are poor indicators of how future loans will perform. This is especially true when the future reality includes a recession, declining housing values, and rising interest rates.

Another aspect of sample selection is how to classify observations based on loan performance by defining what constitutes a good or bad loan. This is discussed in the next section on model formulation, but it also has implications for sample construction. Inclusion of loans in various stages of delinquency in the bad loan category can pose problems that carry over to the model's predictive power overall, and individual factor weightings. Another hurdle is whether to define a good loan as any loan that is not a bad loan, or to define a third category that corresponds to indeterminate performance. Indeterminate loans have insufficient performance so they cannot be classified as either good or bad. In credit scoring models, samples are "factored up" to reflect the true proportion of good and bad credit applicants in the general, or through-the-door, applicant pool. At the end of that process, only good and bad loans are in the reconstructed loan population. Exclusion of indeterminate loans can cause a gap in representation that is magnified when the sample is scaled up.

For example, in credit card scorecard development up to 40 percent of the sample can be lost to the inactive category of performance (for example insufficient account activity), 35 percent can be lost to the indeterminate category, and 5 percent to other exclusions. The scorecard that is purported to have reconstructed the total through-the-door applicant population ignores eighty percent of the observations. The result is an overstatement of the system's ability to decide which loans turn out to be either good or bad. Granted that the resulting systems might still rank-order loans by default risk, but the associated estimated default probabilities might lack precision. Scoring system developers have legitimate reasons for restricting samples but might be possible consequences of those restrictions.

MODEL FORMULATION GAP

In model building the dilemma is which factors to include and how much weight to put on them individually. This is complicated because many credit factors are correlated with one another. Primary underwriting factors have deep interrelationships and, as such, their interactions and conditional nature should be reflected in the model formulation. Failure to comply contributes to the gap. Typical credit scoring systems are considered discriminant analysis problems. The objective function is to maximize the separation between observations that are classified as *defaulter* and *non-defaulter* loan applicant groups. This approach makes assumptions about the form of the statistical distribution of the sample and general population of credit seekers, and the properties of the score distribution, such as equal variance of defaulter (bad) and non-defaulter (good) groups. Other approaches have modeled default risk as a propensity and include expected profit as the outcome to be predicted. These models produce different outcomes than those in standard use today and take into account a greater portion of the true business reality (Green, 2008). CCAF is not dependent on distributional assumptions or properties of the sampled data. This approach can consider multiple objectives, including profitability, prepayment likelihood, spending propensity, and default probability.

At any stage of variable selection, the marginal contribution with previously selected model factors determines which factor is selected. Debt ratio might be omitted from the model, even though it is a key indicator of borrower capacity, which occurs with many underwriting scoring models. This highlights the problem of letting the data drive the model selection, versus proven principles that far surpass the timeframes from which the model data are drawn. Alternatively, if correlations are high, then some of the more predictive factors might be withheld from selection until the end of the process because their early inclusion will result in only two or three factors being selected. As a consequence, if the factors that are highly predictive on their own are included in the model at a late stage, then their weight is substantially less than if they were allowed to enter the model without restriction. Unfortunately, factors that qualify as key credit indicators might be precluded from consideration for various technical reasons. For example, despite its obvious relevance, income might not be used because its thresholds for the point intervals can become less accurate due to inflation. Anecdotal evidence shows that a currently used major mortgage underwriting system omits debt ratio as a factor because reportedly other model variables capture all of its predictive content. Other factors are abandoned by model developers due to the incidence of missing data, despite their relevance.

PROCESS VALIDATION GAP

Constant redevelopment of scoring models is very resource-intensive. For most lenders, this translates to a constant burden of scorecard redevelopment about every two years. When the sample is drawn during economic change or transition, the scorecard's future results can significantly vary from the holdout sample that is used to validate and

back-test the system. This is because correlations for bad credit payment behavior change relative to the scorecard factors when new economic and demographic circumstances occur. In these cases, scorecard validation might not immediately surface the problem. When the issues become apparent, replacement of the scorecard will happen earlier than expected. Even then, the same sample issue can persist, and the cycle might repeat itself.

Many choices can be, and are being, made in model development. Weights might not be optimal, especially when you start varying certain assumptions, or drop into certain population segments. For example, there might be regional differences, product differences, or differences in customer culture or lifecycle. Perhaps consumers that use credit more sparingly tend to live within their immediate means and are more risk averse. Models developed on a more mainstream population might over-estimate risk in this segment. Furthermore, should the question be “Is the object of the exercise purely to predict default risk, or should fair credit access also be part of the objective?” Families of scorecards perform very similarly relative to credit default prediction, but differ significantly relative to acceptance rates for specific borrower population segments. This is often the case in underserved markets.

A COMPREHENSIVE CREDIT ASSESSMENT FRAMEWORK

FRAMEWORK OVERVIEW

The CCAF system is designed to address the underwriting gap components that are previously described. It offers a comprehensive rating system that enables lenders to classify credit risk and decision all transactions in the most fair, effective, and transparent manner. CCAF development involves four milestones that address different gap components. Figure 1 describes the overall CCAF process:

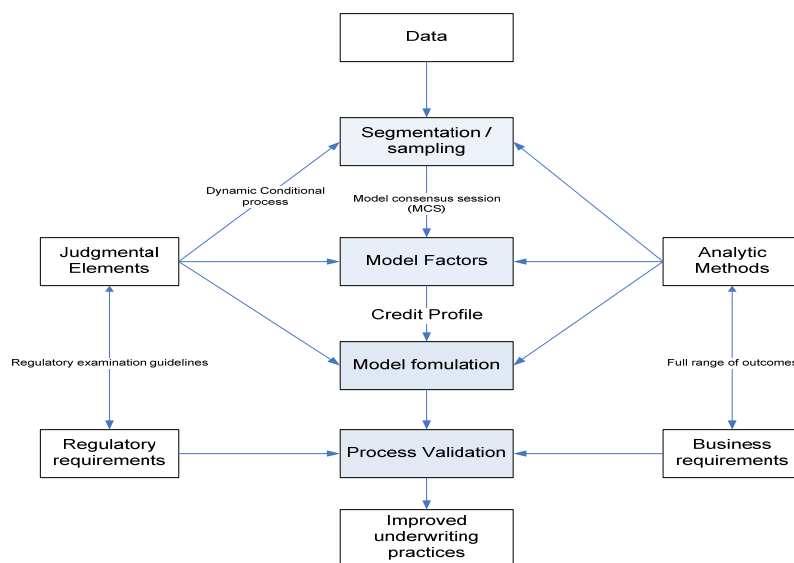


Figure 1. Overall Process of CCAF

As is the case with typical loan approval system development that uses the standard credit scoring approach, requisite loan data, product data, policies, and business requirements must be sourced and pre-processed to create a base of information that is sufficient for system construction.

The model consensus session (MCS) is the core mechanism whereby CCAF ensures that classification of credit transactions is performed sensibly and comprehensively (Abrahams and Zhang, 2008, pp. 158-159). Expert judgment, proven credit principles, and product and loan policy information are used, in addition to the available historical loan application and performance data. The resulting categorization is called a Transaction Contour (TC). A later section discusses the TC and a Borrower Contour (BC), which transcends all financial transactions for a particular borrower.

Next, external factors relating to the economy, market states, and underlying asset valuation are combined. A variety of modeling methods are used to arrive at a loan decision model in the form of an action table, which specifies an

approve decline decision for all borrowers relative to the credit transaction contour. A series of additional tables are generated that allow for the maintenance and monitoring of the action table.

The next to last step in the process is a comprehensive and transparent validation process that fosters trust and confidence. You know exactly how loans are evaluated and how credit quality and credit access are maintained and improved. This step involves an examination and interpretation of underwriting model inputs, processing, and outputs.

The final step produces various loan underwriting operational reports, including multidimensional accepted population mix reports and multidimensional acceptance rates tables associated with the current action table. In addition, you can produce alternative action tables that are associated with specific credit policy and marketing strategies, along with their system maintenance and operational reports. These reports can be regenerated and compared at two points in time. Using the TC as a basic frame of reference, you can produce detailed multidimensional variance reports that identify issues early on. Several reports might be generated and visualized graphically to easily identify trends.

The CCAF system results is a more flexible, adaptable lending system that can accurately evaluate credits, quantify transaction risk, and maintain appropriate risk levels based on policy-dictated risk tolerances. More effective information improves the monitoring and management of loan portfolios. CCAF provides consumers fair access to credit and ensures suitable loan products. Lenders generate a more profitable, safe, and stable loan portfolio.

DEVELOPMENT PROCESS

You are now shown how the four milestones address the underwriting gap components.

1. *Define objectives and identify required data sources*

CCAF starts with identifying business requirements and source data. CCAF can be used for different purposes such as managing credit risk or fostering profitable growth. Preparation of data involves defining project scope, determining availability of information, and capturing current underwriting practices. The outputs from this step are used as inputs for sampling, segmentation, and model formulation.

Data that are important for estimating loan default for consumers include, but are not limited to the following:

- an inventory of all current obligation terms, balances and monthly payment amounts with all lenders, service providers, landlords, insurers, and counterparties
- current sources of income and time in profession and with current employer
- liquidity and value of personal assets and net worth
- nature, and value of collateral (or asset being financed) based on both current appraisal and future value ranges, and the amount or percent of loan down-payment (or loan-to-value ratio)
- payment and delinquency history for credit and non-credit obligations and any past loan defaults
- insurance coverage by type, including policy limits and cash values
- Loan conditions that include maturity, loan amount, pricing mechanism, payment schedule and terms, and other borrower elected or lender-specific transaction requirements.

2. *Determine segmentation and perform model consensus session*

Sampling is an area where missing or too little data can disproportionately excluded observations for certain population segments. This can result in a biased sample and unintended results. Time intervals over which samples are drawn might not adequately reflect current conditions. Hence models based on data from non-representative time periods can also be misleading. Sampling and segmentation go hand-in-hand. Segmentation can be used to account for a variety of structural differences in a sampled population, such as demographic differences, economic differences, product differences, channel differences, or differences in customer culture or lifestyles.

Credit scoring models are based on observed good or bad performance for a set period of time. If the observation window occurs when the economy is good and interest rates are falling, then the information weights of evidence might be a poor indicator of how future loans will perform based on their scores during a recession or rising interest rates. The weights of a hybrid model, in contrast, are tempered by logic and proven judgment. The argument that statistical credit model factor point assignments do not make sense, when viewed in isolation, can lead to the failure to detect the impact of shifting assumptions and givens. A common consumer complaint relative to credit scores is that length of time for their scores to improve. Typically, the performance window for past due payments is 24 months. CCAF, in contrast, immediately recognizes changes in creditworthiness. For example, if a consumer has an inheritance, a bonus, or a capital position that changes significantly, then their credit contour immediately changes.

The same occurs if they experienced a change in capacity. Also, with additional sources of information, their satisfactory trade line information can be bolstered, which are explained in the next section on alternative data.

By way of a MCS, the CCAF affords a complete credit categorization of borrowers before risk rating them. The prevailing approaches are piecemeal and only risk rate certain aspects of borrower creditworthiness. In contrast, the CCAF adopts a more holistic view, drawing upon the well known Five Cs of Credit. The primary factors to encompass the first three Cs of Credit can be extended to create a BC, a distinctive pattern of values relating to character, capacity, and capital for a consumer or business. The notion of a lending TC is introduced, which is based on all five Cs of Credit that pertain to a particular obligation. TC is a distinctive pattern of values relating to character, capacity, capital, collateral, and conditions for a consumer or business. TC can encompass BC, or it can operate across segments defined by BC. TC can also encompass channel and market factors.

Each loan application and origination record should include both LTC and BC indicators. This enables a comprehensive view of credit risk. As a result, lenders can evaluate and monitor lending practices to identify subprime credit deterioration, and potential predatory or discriminatory issues. In terms of financial disclosure, CCAF provides consumers with their categorization relative to all primary underwriting factors via a transaction contour identifier. With this single number, strengths and weaknesses relative to the primary qualification criteria are immediately apparent. In addition, a simplified 1 to 10 rating scale describes the overall credit rating when all factors are combined. This rating is the same for all consumers that share the identical transaction contour.

The example shown is based loosely upon the way that credit bureau scoring is segmented in the United States. This scheme includes a combination of the extensiveness of the credit record (no or thin file, moderate file, or thick file) and the payment performance (good, mild delinquency, severe delinquency). Borrowers are grouped into distinct combinations, each having a distinct credit scoring model. This segmentation, unfortunately, does not reflect comprehensively the borrower's ability to repay debts.

In contrast, the CCAF uses the borrower contour based on character, capacity, and capital to create a credit contour that has twelve possible patterns, shown in Figure 3, based on the following:

- Capacity (Income +Debt Ratio): (High/Low)
- Capital (Liquid Reserves + Percent Down-payment): (High/Low)
- Payment Performance (Credit + Non-Credit): (Good/Fair/Poor)

Each primary category is assigned specific rating classifications based on causally related factors. For example, factors that assess borrower capacity might include income, DTI, payment-to-income or ratio (PTI). In the simple case for only DTI. A threshold value is determined of perhaps 40%, to separate borrowers possessing high capacity from those having low capacity. This process is repeated for the character and capital categories. The final step assigns judgment-based, or empirically based, ratings to each of the 12 unique segments (that is 1-Low, 2-Moderate, 3-High, 4-Severe), as shown in Figure 2.

Segment Handle	Capacity	Capital	Payment Performance	Risk Rating
1	H	H	G	10
2	H	H	F	9
3	H	H	P	8
4	H	L	G	8
5	H	L	F	7
6	H	L	P	5
7	L	H	G	7
8	L	H	F	6
9	L	H	P	4
10	L	L	G	5
11	L	L	F	3
12	L	L	P	1

Figure 2. CCAF Segment Handle Specifications

Within each segment, borrowers are homogenous relative to primary credit strength. Lenders might regulate products or programs in the segments that are based on affordability concerns. Lenders can use the BC segments to determine which products are appropriate for certain groups of borrowers. For example, borrowers with little capital or capacity might not qualify for variable rate loans. Moreover, the management of portfolio risk concentration and

exposure limits at the segment level uses a referencing scheme known as a segment *handle* (Abrahams and Zhang, 2008, page 158). After a certain frequency threshold is achieved, offerings in a given segment could be restricted. Using this approach, vulnerability metrics are applied to rank-order the cells that will perform better under different economic scenarios such as a housing slump and rising interest rates.

In addition to current financial ratios, future financial ratios are of key importance for certain types of loans, such as ARM and Option-Based mortgages. You can use behavioral and historical variables to capture more than a snapshot. For example, the current income and income for the previous 12 and 24 months are averaged to calculate average annual increase in the denominator for DTI projection on an ARM reset date, where the maximum rate on the reset date is also assumed. Another example is property valuation using best case, worst case, most likely to come up with a future valuation of the asset's current price, less one standard deviation, and a conservative future value for the LTV calculation on an ARM.

3. *Integrate business scenarios into analytical models*

This addresses model construction and formulation components of the gap. In this stage, segmentation results including TC or BC are integrated with proper business context or external factors relating to the economy, market states, and underlying asset valuation to fine tune model specifications. As a result of segmentation performed in the previous stage, this modeling process is significantly simplified. For example, when modeling with logistic regressions, each TC or BC naturally corresponds to a unique covariate pattern associated with a probability of default. The TC can accommodate changes in economic or business factors, such as the value of the underlying asset being financed, or the collateral pledged, for a secured loan transaction. For example, in the case of a mortgage, property reappraisal might result in a different LTV that can change the TC value. Another example is a borrower's working capital position, which might change when assets are marked to market, or possibly longer term asset liquidations.

Specifically, this process is accomplished through a dynamic conditional process. The impact of business context or external factors is associated with each TC or BC to create conditional and interactive structure for model specifications. Two steps are used that are adaptive at different levels. The first step enumerates and separately considers all possible combinations of the primary variables. The actions taken in step two depend on how the borrower was initially classified according to the primary credit risk factors. For a mortgage example, consider how you might appropriately decide what weight to apply on a value for the factor DTI based on knowledge of LTV. Consider the following three scenarios:

- LTV is 20%, so that the customer has an 80% equity stake in the property being financed. How would you weigh the importance of DTI? How would you rate the following values of DTI, relative to risk in this case:

DTI = 20%?	DTI = 40%?	DTI=60%?
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- LTV is 70%, so that the customer has a 30% equity stake in the property being financed. How would you rate the following values of DTI, relative to risk in this case:

DTI = 20%?	DTI = 40%?	DTI=60%?
------------	------------	----------
- LTV is 100%, so that the customer has no equity stake in the property being financed. Again, how would you rate the following values of DTI:

DTI = 20%?	DTI = 40%?	DTI=60%?
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You can repeat these scenarios holding the value of DTI constant and then varying the values of LTV under different scenarios. The point is that if you have a different weighting of one variable based on the value of another, then the alternative approach should make business sense. This is achieved with a transparent model validation process as detailed in the next session.

4. *Process updating and validation*

It is critical for a lender to continuously improve model predictability over time. Information accumulates that helps to maintain or improve the accuracy of the risk measurement system. For most lenders, this translates to a constant burden of scorecard redevelopment about every two years, which is very resource-intensive. When the sample is drawn during economic change or transition, the future results of the scorecard can significantly vary from those of the holdout sample that is used to validate and back-test the system. The bad credit payment behavior correlations will change relative to the scorecard factors when new economic and demographic circumstances occur. In these cases, scorecard validation might not immediately surface the problem. When the issues are apparent, replacement of the scorecard needs to occur earlier than expected. Even then, the same sample issue can persist, repeating the cycle.

In CCAF, process validation is integrated into the entire framework as shown in Figure 1. The expected frequencies of credit applicants and the weights associated with CCAF factors, by primary factor segment, are updated dynamically as information becomes available. In-depth analysis of all possible multi-way primary factor comparisons relative to the mix of accepted applicants and acceptance rates can occur at any point in time. The credit segments are immediately interpretable and comparable to one another relative to credit risk. Thus, CCAF validation affords an additional measure of transparency and confidence. Non-intuitive patterns can be detected, investigated, and remedied early to prevent unwanted consequences. CCAF also provides a cost-effective approach to monitor and validate the consistency of risk rating systems for the banks that want to implement or already use Basel II's Internal Rating Based Approach.

EXAMPLE

In this section, a hypothetical example shows how underwriting factors are identified, analyzed, and classified in CCAF process. The underwriting decisions are compared based on the modeling results from both the CCAF and the typical credit scoring approach. The example uses home purchase mortgages that originated through a lender's branch retail channel. Models for re-financings or home improvement loans would have different sets of criteria, as would wholesale channel mortgages.

Identify Primary Factors

To show how the value assignments associated with primary factors can vary by loan product, Figures 3 and 4 provide for a home purchase mortgage example for both a 30-year fixed rate mortgage and a five-year ARM. The corresponding handle structure is shown in Figure 5, which implicitly embeds different thresholds assigned for different loan products with a single handle structure.

Primary Factors	Categories, Definitions, and Value Assignments		
Capital	G - High Net Worth and Liquidity	F - Moderate Net Worth and Sufficient Liquidity	P - Low Net Worth and Minimal Savings
Character: Payment History for All Credit and Cash Trade Lines	G - based on past due occurrence for <1r, 1-2 yrs, >2yr sep. by trade line	F - based on past due occurrence for <1r, 1-2 yrs, >2yr sep. by trade line	P - based on past due occurrence for <1r, 1-2 yrs, >2yr sep. by trade line
Capacity	H - DTI<45% or Discretionary Mo. Inc. > 2xMortgage Payment	L - DTI45% + and Discretionary Mo. Inc. < 2xMortgage Payment	
Collateral and Conditions Exposure	L - LTV 80% or less	H - LTV 81% +	

Figure 3. Home Purchase Mortgage Loan Primary Factors–30-Year Fixed Rate Mortgage

Primary Factors	Categories, Definitions, and Value Assignments		
Capital	G - High Net Worth and Liquidity	F - Moderate Net Worth and Sufficient Liquidity	P - Low Net Worth and Minimal Savings
Character: Payment History for All Credit and Cash Trade Lines	G - based on past due occurrence for <1r, 1-2 yrs, >2yr sep. by trade line	F - based on past due occurrence for <1r, 1-2 yrs, >2yr sep. by trade line	P - based on past due occurrence for <1r, 1-2 yrs, >2yr sep. by trade line
Capacity	H - DTI<40% or Discretionary Mo. Inc. > 3xMortgage Payment	L - DTI>40% + and Discretionary Mo. Inc. < 3xMortgage Payment	
Collateral and Conditions Exposure	L - LTV 75% or less	H - LTV 76% +	

Figure 4: Home Purchase Mortgage Loan Primary Factors–5-Year ARM

Handle	Capital	Character: Payment History	Capacity	Collateral/Conditions
1	G	G	H	L
2	G	G	L	L
3	G	F	H	L
4	G	F	L	L
5	G	P	H	L
6	G	P	L	L
7	F	G	H	L
8	F	G	L	L
9	F	F	H	L
10	F	F	L	L
11	F	P	H	L
12	F	P	L	L
13	P	G	H	L
14	P	G	L	L
15	P	F	H	L
16	P	F	L	L
17	P	P	H	L
18	P	P	L	L
19	G	G	H	H
20	G	G	L	H
21	G	F	H	H
22	G	F	L	H
23	G	P	H	H
24	G	P	L	H
25	F	G	H	H
26	F	G	L	H
27	F	F	H	H
28	F	F	L	H
29	F	P	H	H
30	F	P	L	H
31	P	G	H	H
32	P	G	L	H
33	P	F	H	H
34	P	F	L	H
35	P	P	H	H
36	P	P	L	H

Figure 5: Identical Handles for 30-Year Fixed Rate Mortgage and 5-Year ARM

Identify Secondary Factors

Examples of secondary factors are shown in Figure 6. The primary factors and secondary factors are combined to render a loan-underwriting decision. Figure 7 specifies the two-stage action table for this example. The 36 primary handle cells are based on the handle dimensions.

Note: For this example the primary (stage 1) factors are identical, with identical actions, but the stage 2 factors differ for a 30 year fixed rate mortgages versus the 5 year ARM.

Every handle cell relationship to secondary factors is always defined, even if the definition specifies approve or decline with no secondary factors required, or a general rule such as any two secondary factors with good (G) ratings. A more in-depth discussion of how to apply the secondary factors to the primary factor combinations (handle cells) for a similar example can be found in the literature.

Months of Reserves	G - 6 months +	F - 3-5 months	P - 2 months or less
Similar Housing Expense	G - 120% or less of previous payment	F - >120-135% of previous payment	P - >135% of previous payment
Time in Profession	G - 5 yrs +	F - 3-4 yrs	P - <3 yrs
Strong Liquid Assets	G - >10% Loan Amt.	F - 5 to 9% Loan Amt.	P - 4% or less Loan Amt
History of Handling Higher Debt	G - 3+yrs	F - 1-2 yrs	P - <1 yr
Discretionary Income	G - > \$2M/mo.	F - \$1 to 2M/mo.	P - <\$1M/mo.
Relationship	G - 2+ loan, deposit, investment accounts	F - 1 loan, deposit, or investment account	P - None
Mandatory Reserve or Principal Paydown W/Re-Amortization at Reset Date if Higher Payment Required	G - Additional 20% of monthly payment set in reserve or paid toward principal each month for first 30 months	F - Additional 10% of monthly payment set in reserve or paid toward principal each month for first 30 months	P - None

Figure 6. Secondary Factors—Weight in Final Decision of 5-15 Percent Each

Capital	Payment History	Capacity	Low Expo Coll/Cond	High Expo Coll/Cond	Low Expo Coll/Cond	High Expo Coll/Cond
Good	Good	Low	1 Accept	19 Accept	37 n/a	55 n/a
Good	Good	High	2 Accept	20 Stage 2	38 n/a	56 Denial
Good	Fair	Low	3 Accept	21 Stage 2	39 n/a	57 Denial
Good	Fair	High	4 Stage 2	22 Stage 2	40 Denial	58 Denial
Good	Poor	Low	5 Accept	23 Stage 2	41 n/a	59 Denial
Good	Poor	High	6 Stage 2	24 Denial	42 Denial	60 n/a
Fair	Good	Low	7 Accept	25 Accept	43 n/a	61 n/a
Fair	Good	High	8 Accept	26 Stage 2	44 n/a	62 Denial
Fair	Fair	Low	9 Accept	27 Stage 2	45 n/a	63 Denial
Fair	Fair	High	10 Stage 2	28 Stage 2	46 Denial	64 Denial
Fair	Poor	Low	11 Accept	29 Stage 2	47 n/a	65 Denial
Fair	Poor	High	12 Stage 2	30 Denial	48 Denial	66 n/a
Poor	Good	Low	13 Accept	31 Stage 2	49 n/a	67 Denial
Poor	Good	High	14 Accept	32 Stage 2	50 n/a	68 Denial

Poor	Fair	Low	15 Stage 2	33 Stage 2	51 Denial	69 Denial
Poor	Fair	High	16 Stage 2	34 Denial	52 Denial	70 n/a
Poor	Poor	Low	17 Stage 2	35 Decline	53 Denial	71 n/a
Poor	Poor	High	18 Stage 2	36 Decline	54 Denial	72 n/a

Figure 7. Two-Stage Action Table for Mortgage Loan Examples

The current subprime crisis has seen certain loan products blamed, such as low, or no, documentation loans, option-adjustable priced mortgages, interest only ARMs, or 40-year mortgages. In the case of some variations on adjustable rate mortgages, the issue is more with how those products were administered than the actual products. A five year ARM might make sense for borrowers that have a strong capital position and adequate reserves. Borrowers that lack strong capital, but who have strong capacity might still be good candidates. Borrowers should have a strong savings rate and agree to build an adequate reserve over time to immunize themselves against the imbedded interest rate risk in their ARM. (See last example listed in secondary factors.)

Comparison of Model Results

In general, the modeling results show that the CCAF approach produces better model goodness-of-fit, more model stability, and results in fewer false negative errors. As shown in Figures 8, the CCAF model can achieve a 50% lower misclassification rate, a much higher log-likelihood-based R^2 , and a much better Pearson Chi-Square statistic, compared with the main-effects model. The main reason that the DCP model achieves a better model goodness-of-fit is that a set number of interaction and conditional variables are used to capture the true relationships between response variable and covariate. The number of new model covariates is selected to minimize the deviance residual and also to represent distinctive decision scenarios.

Based on CCAF modeling results, Figure 9 summarizes the underwriting decisions for the typical borrowers that fall in to different handle segments. These results are relative to subprime classification and loan approval. The first four borrowers would be declined using CCAF while receiving favorite considerations from credit scoring. The reverse is true for the next four borrowers. If CCAF had been implemented, a significant number of currently troubled loans would not have been approved.

Model Number	Model Description	Misclassification Rate	Max-Rescaled R-Square	Chi-Square	DF	Pr > Chi-Square
1	The CCAF model	0.211	0.357	7.838	8	0.450
2	The credit scoring model	0.292	0.139	19.169	8	0.014

Figure 8. Model Evaluation: CCAF versus Credit Scoring

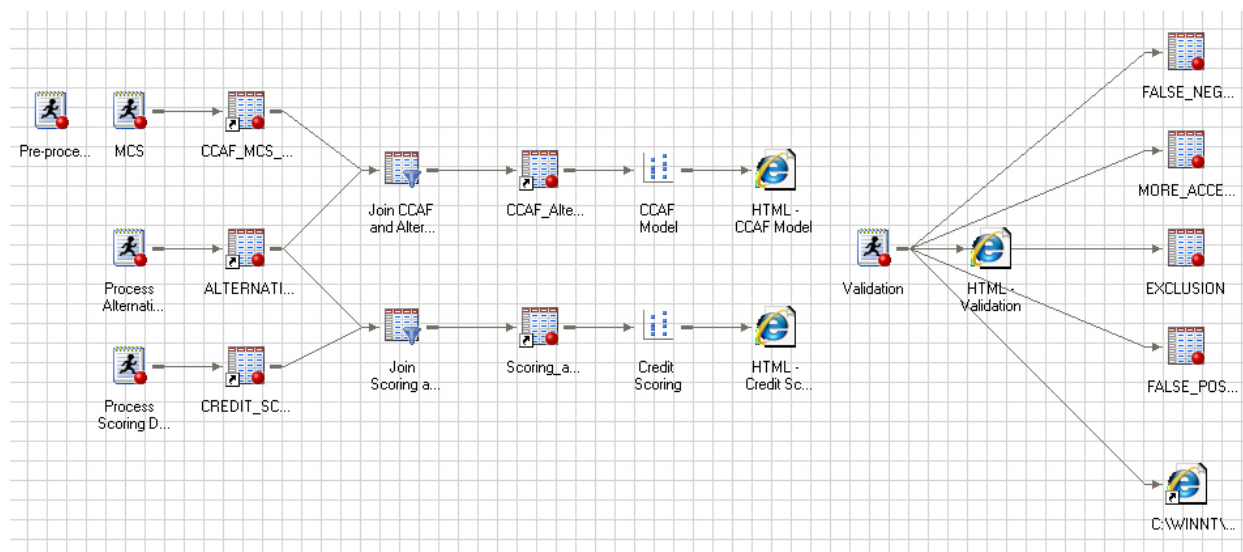
No.	Credit Score	Credit Score-Based Subprime?	CCAF-Based Subprime?	CCAF Score	Loan Decision
1	752	No	Yes	670	DECLINE
2	761	No	Yes	678	DECLINE
3	756	No	Yes	674	DECLINE
4	747	No	Yes	667	DECLINE
5	658	Yes	No	737	APPROVE
6	645	Yes	No	750	APPROVE
7	653	Yes	No	759	APPROVE
8	640	Yes	No	742	APPROVE
9	658	Yes	No	762	APPROVE

Figure 9. Underwriting Decision: CCAF versus Credit Scoring

SAS IMPLEMENTATION

CCAF is easily implemented with various SAS products that include Base SAS®, SAS® Enterprise Miner™, JMP® software, or SAS® Enterprise Guide®. This section briefly describes a simplified process that demonstrates how to implement CCAF with SAS Enterprise Guide.

1. **Prepare data.** Gather and process all relevant data so that the information is ready for the model consensus session. The data includes business rules, underwriting policies, application data, credit bureau data, performance data, as well as non-traditional data or alternative data.
2. **Conduct model consensus session (MCS).** Integrate policy thresholds and underwriting rules to define the primary or secondary factors. Policies and rules might be represented by using interaction and conditional variables.
3. **Perform predictive modeling.** Compare CCAF performance with other approaches. As discussed earlier, CCAF classifies the underwriting factors into either primary or secondary factors to jointly determine the credit risk or default probability of each borrower.
4. **Process validation and model maintenance.** Perform the validation process from two aspects: changes in borrower's classification as reflected in their credit contour.
5. **Produce reports.** Reports typically quantify changes in the borrower's profile, model specifications, and estimated probability of default; model performance such as adjusted R square and H-L Chi-square test; and statistics of modeling results such as cutoffs and classification matrix.



SUMMARY

CCAF's holistic classification affords transparency, assesses the borrower's qualifications, and risk rates credit transactions within that complete context. As a result, you avoid significant overstatement or understatement of risk on individual loan transactions. CCAF affords greater control of loan decisions through its ability to integrate expert judgment with statistically based criteria in the risk evaluation process by encompassing not only default risk, but also concentration risk, fair lending non-compliance risk, and a host of other important objectives. This enables for efficiency, transparency, and accuracy. CCAF transparency fosters financial education and literacy relative to the underwriting process and enables easy identification of loans that are truly affordable relative to every borrower segment. CCAF improves current credit scoring from following three perspectives:

1. CCAF ensures inclusion of primary predictive factors that cover the full spectrum of relevant qualification criteria, and determines and reveals how they combine to produce outcomes. Credit scoring, which relies on historical data, lacks this capability or a feedback mechanism to adjust factor weightings over time as experience accumulates.
2. CCAF determines the risk factors that pertain to the lending decision within the context of each borrower's situation and the loan product parameters. The factor weightings are appropriately adjusted to produce the right outcome. Credit scoring has a fixed number of factors that have a constant set of point weightings that are automatically applied to every credit applicant regardless of their qualifications. Furthermore, CCAF uses a forward-looking approach and simulates future economic conditions. Unlike credit scoring models, the adaptive nature of CCAF makes it more, not less, predictive over time.
3. CCAF systematically integrates judgmental components and proper context into the modeling process in a complete and transparent manner. Credit scoring systems lack context because they rely purely on the available data to determine what factors are considered. Credit scoring systems lack transparency because two individuals that have the identical credit score might vastly differ in their overall qualifications. The credit score is not readily interpretable, and industry credit scoring models are maintained as proprietary, as are their development processes.

To prevent future financial crises, it is absolutely necessary to improve the borrowers' financial literacy, the lenders' process of transparency. Better assessment of loan product affordability and suitability is necessary. CCAF achieves these goals through the following aspects:

- Comprehensive classification to convey the borrower's qualifications. This enables risk rating credit transactions within that complete context, including transaction and borrower contours. Financial education and literacy are fostered by informing the borrower about how he or she is classified and ranked according to relevant causally linked primary factors. Also a borrower knows how the proposed loan is classified versus other possible qualifying loans.

- Greater control of loan decisions. Expert judgment is integrated with statistically based criteria in the risk evaluation process to encompass not only default risk, but also concentration risk, fair lending non-compliance risk, and a host of other important objectives. Specific thresholds can be enforced at the segment level to limit risk exposure. This avoids significant overstatement or understatement of risk on individual loan transactions and unacceptable levels of risk across all portfolio segment levels.

RECOMMENDED READING

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