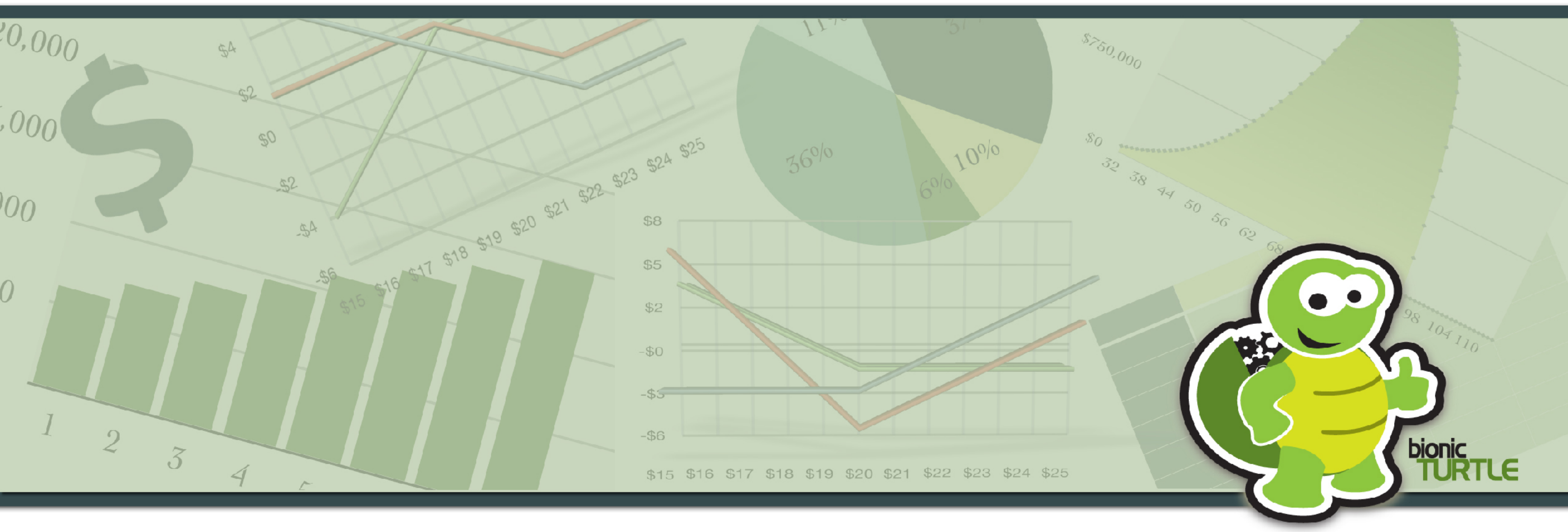

P2.T6. Credit Risk Measurement & Management

Giacomo De Laurentis, Renato Maino, and Luca Molteni: Developing, Validating and Using Internal Ratings

Bionic Turtle FRM Study Notes

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Chapter 2: Classifications and Key Concepts of Credit Risk

Chapter 3: Ratings Assignment Methodologies

Chapter 2: Classifications and Key Concepts of Credit Risk

Describe the role of ratings in credit risk management.

Describe classifications of credit risk and their correlation with other financial risks.

Define default risk, recovery risk, exposure risk and calculate exposure at default.

Explain expected loss, unexpected loss, VaR, and concentration risk, and describe the differences among them.

Evaluate the marginal contribution to portfolio unexpected loss.

Define risk-adjusted pricing and determine risk-adjusted return on risk-adjusted capital (RARORAC).

Describe the role of ratings in credit risk management.

The ratings system lies at the foundation of every modern credit risk management system. Basel II (the capital adequacy regulations) defines a ratings system as **"the [system] which comprises all of the methods, processes, controls, and data collection and IT systems that support the assessment of credit risk, the assignment of internal risk ratings, and the quantification of default and loss estimates."**

Rating are important tools for measuring and assessing the credit risk. The actual notion of risk **lies in unexpected loss rather than expected loss**. Banks confront unexpected losses by holding adequate capital. Thus capital plays a vital role in credit risk management. Determining the appropriate level of capitalization requires rigorous analytical risk models and measures. From this perspective, ratings help to establish credit contributions to the bank's overall risk.

The credit risk management procedure involves **identifying the credit quality measure of the counterparty, specifically the probability of default.** Ratings directly measure the expected default rates and the expected loss given default, which influence the credit funding required to be maintained by the banks. Actual loss tends to vary with different exposures in different rating classes. Therefore, ratings help to discern exposures in terms of variability of default and loss given default measures and their influence on the capital requirements of banks.

Ratings measure the borrower's creditworthiness; and such measures of creditworthiness enable:

- Capital markets to operate and function
- Investors and lenders to manage the critical forces underlying value creation
- Managers to differentiate the economic performance of business units (which empowers their coordination)

On all these accounts, the ratings system is contemplated as a good starting point for setting more risk-sensitive capital requirements for credit risk.

Describe classifications of credit risk and their correlation with other financial risks.

The **default-mode or loss based valuation** classifies credit risk into

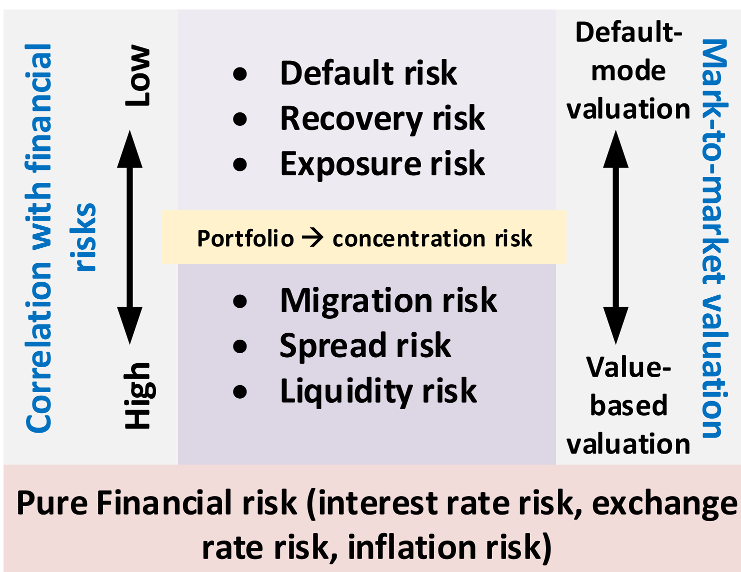
- **Default risk** – Also called as counterparty or borrower risk, it is the risk related to the event of a borrower's default.
- **Recovery risk** – This risk refers to the probability that the recovered amount is lower than the total amount due in case the default occurs.
- **Exposure risk** – This risk is associated with the likely increase in the exposure at the time of default compared to the current exposure.

The **value-based valuation** classifies credit risk into

- **Migration risk** – This is the risk linked to the change in credit quality and market value over time as denoted by rating migration from one class to another.
- **Spread risk** – This is the risk generated by the investors need for different risk premiums due to different market condition, based on the existing exposures.
- **Liquidity risk** – This risk is connected with the likelihood of less liquid market conditions in which credit exposures have to be sold at lower than their expected values.

Financial risks include interest rate risk, exchange rate risk and inflation risk.

Risks classified by default-mode valuation have low correlation with financial risks while risks classified by value based valuation have high correlation with financial risks.



Define default risk, recovery risk, exposure risk and calculate exposure at default.

- **Default risk**: probability of default by borrower (or counterparty) within a given time period, typically one year
- **Recovery risk**: possibility that recovered proceeds are less than obligation. Typically measured with loss given default (LGD) or recovery rate which is equal to (1-LGD).
- **Exposure risk**: the amount of risk in the event of default. Typically measured with exposure at default (EAD).

Default risk

Default risk measures the probability of the counterparty or borrower defaulting within a given time period, usually one year. If the period goes beyond a year, cumulative probabilities of the same are considered. In case of shorter time periods, like overnight lending, probabilities may be lower but certainly not nonexistent.

Default risk can be detected from the historical default frequencies of borrowers as observed by rating agencies. The agencies then segment the borrowers into different credit quality classes often by a **subjective or judgmental process**. Default risk can also be extracted from statistical methods using large databases where the default rates are forecast using models and scores are constructed to allocate borrowers to different risk categories. **This approach is mostly quantitative**.

A blend of subjective and systematical approaches may be used to determine default risk where statistical methods are deployed for objective classification while experts fine-tune the results to obtain a default probability associated to each rating class so as to combine both potentialities. Another technique uses the implicit probability of default inherent in market prices and is specifically applied to public listed entities on securities markets.

Recovery risk

The recovery risk measures the possibility that the proceeds recovered in case of a default are less than the actual obligation. It is measured by 'loss given default ratings' (or 'severity ratings') which refers to the loss estimated given that a default has already occurred.

Recovery rates normally vary with economic conditions, i.e., they are poor during economic downturns. They may also vary with different types of credit contracts subject to different legal systems and jurisdictions. This compromises their comparability. They also differ depending upon the borrowers' business sectors as asset values may be more or less volatile in different sectors. The recovery rates are also affected by covenants (agreements between borrower and lenders to limits borrower's actions, in order to benefit the creditors), such as those limiting the disposal of assets by the borrower which are used in estimating the loss given the default.

Recoveries are mostly calculated globally at the counterparty's position such that their reference to the original contracts, collaterals, and guarantees is mostly lost. Then, 'top down' procedures are normally used to outline the average loss given default rates for a related set of facilities and guarantees.

Exposure risk

Exposure risk is the amount of risk due to exposure in the event of default.

For term loans this amount is calculated easily in terms of the balance. For revolving credit lines which depend on external events and borrower's behavior, the amount due at default is detected by using the following equation:

$$\textbf{Exposure at default} = \textbf{drawn} + (\textbf{limit} - \textbf{drawn}) * \textbf{LEQ}$$

where

- drawn = amount currently used (it is zero for of back-up lines, letters of credit, performance bonds etc.),
- limit = the maximum amount granted by the bank to the borrower for this credit facility,
- LEQ (Loan Equivalency Factor) = the rate of usage of the available limit, beyond normal usage, in near-to-default situations.

In case of account receivables' financing, non-compliance in contractual terms and conditions can modify the amounts which are due from the debtor to the bank.

For derivative contracts, the amount due in the event of default depends on market conditions of the underlying asset.

The Exposure at Default (EAD) may thus be probabilistic in nature and calculated stochastically.

Explain expected loss, unexpected loss, VaR, and concentration risk, and describe the differences among them.

- **Expected loss (EL)** is the *average* long-term loss embedded in credit decisions. It is a "cost of doing business" that is generally expenses on the income statement
- **Unexpected loss (UL)** is the dispersion (or volatility) of the potential loss. UL is often measured as the standard deviation of the value at the horizon, but recognizing that credit risk is not symmetric.
- **Value at risk (VaR)** is the maximum loss at a given confidence level over a specified time horizon net of the expected loss; i.e., this VaR definition excludes expected loss.
- **Concentration risk** is a credit portfolio's high exposure—or higher than desired, at least—to a set of common risk factors such as a currency or an industry or even technological shifts

Expected loss

Expected loss is the average loss caused by a group of credit facilities in the long term. The 'expected loss rate' can be stated as the percentage of the exposure at default.

Where PD = default probability (aka, EDF), the expected loss is given by:

- **Expected loss (EL)** = PD * loss severity (LGD rate) * Exposure at default (EAD)
- **Expected loss rate** = EL / EAD = PD * severity of loss (LGD rate)

Expected loss can be expressed as a decline in market values resulting from any of the six credit risks (default risk, recovery risk, exposure risk, migration risk, spread risk, liquidity risk)

Expected loss may also be explained in an actuarial context considering only the default risk, recovery risk and exposure risk while ignoring migration risk, spread risk, and liquidity risk (default mode approach). For banks, the expected loss is an implicit cost in the bank business to cover losses over time that fluctuate with different economic cycles.

Unexpected loss and value at risk (VaR)

The actual loss encountered is likely to differ from the expected loss; in fact, the actual loss might be greater—or even much greater—than expected due to credit cycles and other events. Unexpected loss attempts to quantify this potential dispersion in the difference between a possible loss and the expected loss.

Adequate capital or funding is essential for protection against unexpected loss. Unexpected losses are often measured by standard deviation although it may not be appropriate tool for assessing credit risk. This is because, in case of credit risk, the distribution of losses, of default rates, and losses given default is asymmetric which cannot be explained by standard deviation. Their probability distributions are considered asymmetric as catastrophic events often have high impact on the losses but occur with small probability.

Specifically, for measuring credit risk, value at risk (**VaR)** is more suitable than standard deviation. **VaR can be described as the difference between the maximum loss rate at a certain confidence level and the expected loss rate, in a given time period.** It denotes the amount of capital (**called 'economic capital**') required by the bank as a cushion against failure at the stated level of confidence.

Let us say if the VaR is stated at a confidence level of 1.0%, then it shows the capital required for tackling the unexpected losses in 99.0% of the cases. With VaR being expressed as such, it limits the disastrous or worst case loss rates to probabilities of no more than one per cent. The VaR calculation involves evaluation of the credit portfolio's probability density function. Monte Carlo simulations, scenario analysis or parametric closed-form distributions may be used for VaR estimation.

In the aftermath of the financial crisis, however, a measure called expected shortfall is gaining traction. Expected shortfall (ES) is the average (conditional average) of the worst losses in the tail above some probability threshold.

Concentration risk

If a credit portfolio is particularly exposed to a set of common risk factors (e.g., interest rates, currencies, technological shifts, etc.), then the portfolio is said to be "concentrated" with respect to those external factors and thus concentration risk emerges. These risk factors affect the willingness and ability to repay outstanding debts of a large number of counterparties.

While expected losses and VAR measures (aka, "standalone VAR") are important and may explain individual risks, they do not take into consideration the risk of the entire portfolio.

According to Markowitz's principle, **only if and when the correlation coefficient is one does the portfolio risk equals to the sum of the individual borrowers' risks**; otherwise, the sum of the individual risks cannot be equated to the total portfolio risk. In fact, diversifying the portfolio and expanding the number of loans decreases portfolio risk because of the less than perfect correlation among different exposures.

Concentration risk takes into account the risk created from portfolio concentration. Thus, to handle the concentration risk, banks limit exposures by diversifying away from common external risk factors (granularity criterion). With respect to quantitative credit risk management, the granularity criterion is used along with and sometimes replaced by the correlation analysis of events of default and of changes in credit exposures values.

"Full portfolio credit risk models" calculate how much concentration is created by the individual borrowers' risk factors. The credit portfolio model helps to quantify the marginal risk attributable to different credit exposures. Estimating default co-dependencies become important then as they gauge the possibility of whether more counterparties in the same risk scenario can jointly default. Default co-dependencies can be modelled in the following ways:

- As 'asset value correlation' under the framework proposed by Merton. The event of joint default is linked to the possibility that two borrowers' assets values fall below their respective outstanding debt. The degree of diversification is determined by the correlation among assets values and by considering the outstanding debts of the two borrowers.
- As 'default correlation' in terms of historical correlations of data (business sector, size, location, etc.,) of similar groups of borrowers.

Differences among the various measures

- Expected loss is an expected mean, while unexpected loss is a dispersion (standard deviation).
- Expected loss is an income statement-based cost of doing business while unexpected loss is absorbed by the balance sheet. Unexpected loss has both a regulatory and economic perspective; i.e., regulatory capital versus economic capital
- Relative value at risk (rVaR) is a function of (i.e., depending on the confidence level, a multiple of) unexpected loss; for example, at some low level of confidence, rVaR = UL.

Evaluate the marginal contribution to portfolio unexpected loss.

Marginal VAR is required in order to measure how an individual exposure affects concentration risk, the overall portfolio risk, and the portfolio's economic capital. The marginal VAR calculates the additional risk created in the credit portfolio due to individual exposure.

Let	UL(portfolio)	= Unexpected loss of the portfolio
	w(i)	= weight of the i^{th} loan on the overall portfolio
	ρ(i, portfolio)	= default correlation between the i^{th} loan and overall portfolio

Then the marginal contribution of the i^{th} loan to portfolio unexpected loss is given by ULC(i):

$$ULC_i = \frac{\partial \text{ ULportfolio}}{\partial \text{ wi}} w_i$$

$$ULC_i = \rho_{i;\text{portfolio}} * \ w_i * UL_{\text{portfolio}}$$

β_i is the "i^{th} loan beta." This beta compares the marginal i^{th} loan risk with the average risk at portfolio level:

$$\beta_i = \frac{ULCi \ / \ wi}{\text{UL}_{\text{portfolio}}}$$

If β_i is larger than one, then the marginal risk adds more than the average risk to the portfolio (implying concentration) and if β is smaller than one, then the marginal risk adds less than the average risk to the portfolio (implying diversification).

At various levels of the portfolio (individual loan, individual counterparty, counterparties' segments, sectors and market level) correlation coefficients, ρ(I, portfolio), and β(i) can be calculated, for arriving at the quantitative measure of risk drivers.

Define risk-adjusted pricing and determine risk-adjusted return on risk-adjusted capital (RARORAC).

Risk-adjusted pricing is the practice of quantifying risk and then incorporating risk into product pricing. The value created by any business depends on its capability to produce returns higher than those needed to reward the market risk premium required for facing the risks. For banks, value creation happens when return for a bank's credit risk taking activities is greater than the cost of capital. Risk-adjusted pricing banks evaluates rules on how to combine risk and return of individual loans to set a price, which acts as a tool for developing the credit policies and credit portfolio risk profile.

Cost of capital multiplied by VAR is a lending cost, which has to be included in the credit spreads so as to determine the risk adjusted performance measures, i.e., the credit spread has to be in line with the market risk premium.

Banks use risk adjusted performance measures to support pricing models like RAROC (risk adjusted return on capital) or its alternative called RARORAC (risk adjusted return on risk adjusted capital).

For value creation, establishing a target return in terms of a target Return on Equity (accounting equivalent of the cost of equity) can be expressed as:

$$\text{RARORAC} > \text{ROE}_{\text{target}}$$

or in terms of EVA (Economic Value Added) as:

$$\text{EVA} = (\text{RARORAC} - \text{k}_\text{e}) \times \text{Economic Capital}$$

in which K_e is the cost of shareholders' capital.

Thus the risk adjusted pricing of credit products will include the cost of funding, the expected loss, the allocated economic capital, and extra return required by shareholders beyond the cost of funding.

Economic capital affects the credit process by the calculation of an interest rate that increases (or, at least, does not decrease) shareholders' value. Thus RARORAC is defined as:

$$RAROC = \frac{Spread + Fees - EL - CoC - CoO}{Economic\ capital}$$

where

EL = Expected Loss
CoC = Cost of Capital
CoO = Cost of Operations

By analyzing the relative risk adjusted profitability, economic capital can be used in optimizing the risk–return trade-off in bank portfolios.

Chapter 3: Ratings Assignment Methodologies

Explain the key features of a good rating system.

Describe the experts-based approaches, statistical-based models, and numerical approaches to predicting default.

Describe a rating migration matrix and calculate the probability of default, cumulative probability of default, marginal probability of default, and annualized default rate.

Describe rating agencies' assignment methodologies for issue and issuer ratings.

Describe the relationship between borrower rating and probability of default.

Compare agencies' ratings to internal experts-based rating systems.

Distinguish between the structural approaches and the reduced-form approaches to predicting default.

Apply the Merton model to calculate default probability and the distance to default and describe the limitations of using the Merton model.

Describe linear discriminant analysis (LDA), define the Z-score and its usage, and apply LDA to classify a sample of firms by credit quality.

Describe the application of logistic regression model to estimate default probability.

Define and interpret cluster analysis and principal component analysis.

Describe the use of cash flow simulation model in assigning rating and default probability, and explain the limitations of the model.

Describe the application of heuristic approaches, numeric approaches, and artificial neural network in modeling default risk and define their strengths and weaknesses.

Describe the role and management of qualitative information in assessing probability of default.

Explain the key features of a good rating system.

A good ratings system should possess the following attributes:

- **Measurability and verifiability**: Ratings should be quantifiable and produce correct expectations for default probabilities. They must be subjectable to frequent back testing.
- **Objectivity and homogeneity**: Objectivity refers to judgments based on credit risk considerations of the underlying data while avoiding subjective influences. Homogeneity relates to the property of being able to compare ratings among portfolios, market segments, and customer types.
- **Specificity**: Specificity is concerned with measuring only the distance from the specific default event, paying no attention to other events not directly related to it, such as short term fluctuations in stock prices.

Describe the experts-based approaches, statistical-based models, and numerical approaches to predicting default.

Expert based approaches

Under this approach, experts with vast experience in credit markets predict defaults based on their knowledge acquired over the years and the process is usually a matter of high subjectivity. They include:

- **Agencies ratings:** Ratings agencies functioning as external appraisers pronounce their expert judgement on the credit quality of issuers by researching the determinants of default risk.
- **Experts based internal rankings used by banks:** Instead of relying on external agencies ratings, banks internally develop classification methods for credit quality assessment.

Statistical based approaches

They use the formal (quantitative) models based on simplifying assumptions that reveal the relation among variables to explain about the phenomena they intend to predict. Quantitative financial models usually include statistics, behavioral psychology, and numerical methods. They are further categorized into:

- **Structural approaches -** They rely on theory to build relationships between the relevant variables and examine the causal effects in predicting the default. The default event is implicit in the model.
- **Reduced form approaches -** They use statistically suitable set of variables to arrive at the default prediction while ignoring the theoretical and conceptual relations among them. The default event is exogenously expressed.

Heuristic and Numeric approaches

- **Heuristic methods** try to replicate human decision making process by making use of properly calibrated rules to obtain solutions in complex environments. They intend to produce high frequency standardized decisions with high quality by adopting low cost processes. They function on a trial by error basis, with constant feedback systems to improve their efficiency and speed. They are also called ‘expert systems’ and are based on artificial intelligence techniques.
- **Numerical methods** try to attain optimal solutions by using ‘trained’ algorithms to take decisions in highly complex environments. One example of these approaches is ‘Neural networks’ which continuously auto-update themselves in order to adjust to environmental modifications. Efficiency criteria are externally given or endogenously defined by the system itself.

Describe a rating migration matrix and calculate the probability of default, cumulative probability of default, marginal probability of default, and annualized default rate.

From the observations of average actual frequencies per rating class, probabilities of default can be inferred. **The frequency of migration from one ratings class to another helps in detection of migration frequencies and in the estimation of migration risk**.

The numbers depicted at the intersection of the rows and columns in a rating migration matrix represent the relative frequencies of counterparties (as a percentage of the number of counterparties in the initial rating class) that have moved from the rating class denoted in each row to the rating class marked in each column. WR refers 'withdrawn ratings', which are the ratings that have been removed for reasons, other than default.

One-year Moody's migration matrix (1970-2007 average) [Giacomo's Table 3.3]

		Final Rating Class (%)									
		Aaa	**Aa**	**A**	**Baa**	**Ba**	**B**	**Caa**	**Ca-C**	**Def**	**WR**
Initial Rating Class	**Aaa**	89.1	7.1	0.6	0.0	0.0	0.0	0.0	0.0	0.0	3.2
	Aa	1.0	87.1	6.8	0.3	0.1	0.0	0.0	0.0	0.0	4.5
	A	0.1	2.7	87.5	4.9	0.5	0.1	0.0	0.0	0.0	4.1
	Baa	0.0	0.2	4.8	84.3	4.3	0.8	0.2	0.0	0.2	5.1
	Ba	0.0	0.1	0.4	5.7	75.7	7.7	0.5	0.0	1.1	8.8
	B	0.0	0.0	0.2	0.4	5.5	73.6	4.9	0.6	4.5	10.4
	Caa	0.0	0.0	0.0	0.2	0.7	9.9	58.1	3.6	14.7	12.8
	Ca-C	0.0	0.0	0.0	0.0	0.4	2.6	8.5	38.7	30.0	19.8

Probability of default

The default frequency in the time horizon (k), which is [t, (t+k)] is given by:

$$PD_k = \frac{Def_t^{t+k}}{Names_t}$$

Where names = the number of issuers,

Def = the number of names that have defaulted in the given time horizon
PD = probability of default.

Cumulative Probability of default:

The cumulative default frequency for the time horizon (k) is given by:

$$PD_k^{cumulated} = \frac{\sum_{i=t}^{i=t+k} Def_i}{Names_t}$$

Marginal Probability of default

The marginal default rate on the [t, (t+k)] time period is calculated as:

$$PD_k^{marg} = PD_{t+k}^{cumulated} - PD_t^{cumulated}$$

Forward Probability of default

The forward probability for the time period k, that is dependent on the survival rate at time t is calculated as:

$$PD_{t,t+k}^{forw} = \frac{Def_{t+k} - Def_t}{Names\ survived_t} = \frac{PD_{t+k}^{cumulated} - PD_t^{cumulated}}{1 - PD_t^{cumulated}}$$

The cumulated default rate ($PD^{cumulated}$) may be calculated using forward probabilities(PD^{forw}) by using the 'forward survival rates'($SR_{t,t+k}^{Forw}$).

$$PD_t^{cumulated} = 1 - \left[\left(1 - PD_1^{forw}\right) \times \left(1 - PD_2^{forw}\right) \times \left(1 - PD_3^{forw}\right) \times \left(1 - PD_4^{forw}\right) \times \ldots \times \left(1 - PD_n^{forw}\right)\right]$$

Let $SR_{t,t+k}^{Forw} = \left(1 - PD_{t;t+k}^{forw}\right)$

Then the cumulated default rate is stated as:

$$PD_t^{cumulated} = 1 - \prod_{i=1}^{t} SR_i^{forw}$$

So, $\left(1 - PD_t^{cumulated}\right) = \prod_{i=1}^{t} SR_i^{forw}$

Annualized default rate (ADR)

If the credit risk exposure continues for more than a year, it is useful to reduce the cumulated default rate to an annual basis. The annualized default rate can be calculated by solving for the following equation:

$$\left(1 - PD_t^{cumulated}\right) = \prod_{i=1}^{t} SR_i^{forw} = (1 - ADR_t)^t$$

Therefore, the **discrete annualized default rate, ADR(t,d)**, is given by:

$$ADR_{t,d} = 1 - \sqrt[t]{\prod_{i=1}^{t} SR_i^{forw}} = 1 - \sqrt[t]{\left(1 - PD_t^{cumulated}\right)}$$

The continuous annualized default rate can be solved from the following similar (to above) equation:

$$1 - PD_t^{cumulated} = e^{-ADR_t \times t}$$

Such that the **continuous annualized default rate, ADR(t,c)**, is given by

$$ADR_{t,c} = \frac{\ln(1 - PD_t^{cumulated})}{t}$$

The various measures of default can be illustrated with the below example:

Table 2: Example of default frequencies for a given rating class

	YEARS					
	1	**2**	**3**	**4**	**5**	**Formulas**
NAMES $_{T=0}$	1000					
NAMES $_T$	990	978	965	950	930	
DEFAULT $_{CUMULATED,\ T}$	10	22	35	50	70	
PD ^{CUMULATED,} **%**	1.00	2.20	3.50	5.00	7.00	$\frac{\sum_{i=t}^{i=t+k} Def_i}{Names_t}$
PD $^{MARGIN}{}_{K}$**, %**	1.00	1.20	1.30	1.50	2.00	$PD_{t+k}^{cumulated} - PD_t^{cumulated}$
PD $^{FORW}{}_{K}$**, %**	1.00	1.21	1.33	1.55	2.11	$\frac{Def_{t+k} - Def_t}{Names\ survived_t}$
SR $^{CUMUL}{}_{T}$**, %**	99.00	97.80	96.50	95.00	93.00	$1 - PD_t^{cumulated}$
SR $^{FORW}{}_{K}$**, %**	99.00	98.79	98.67	98.45	97.89	$1 - PD_k^{forw}$
ADR $_{T,DISCRETE\ TIME,}$ **%**	1.00	1.11	1.18	1.27	1.44	$1 - \sqrt[t]{(1 - PD_t^{cumulated})}$
ADR $_{T,\ CONTINUOUS\ TIME,\ \%}$	1.01	1.11	1.19	1.28	1.45	$\frac{\ln(1 - PD_t^{cumulated})}{t}$

Describe rating agencies' assignment methodologies for issue and issuer ratings.

Rating agencies' assignment methodologies vary based on the

- **counterparty's nature** - corporations, countries, public companies etc., and/or
- **nature of the products** - bonds, structured finances, etc.

The final ratings are derived from two parts which observe the classification as proposed by Modigliani and Miller:

- **Business risks**
    - Country risk
    - Industry characteristics
    - Company positon
    - Profitability, peer group comparison

- **Financial risks**
    - Accounting
    - Governance, risk tolerance, financial policy
    - Cash flow adequacy
    - Capital Structure
    - Liquidity/ Short term factors

Ratings are not directly dependent upon the financial ratios, but they help in the process of determination of ratings. Favorable ratios in some areas could be balanced by less favorable ratios in others, so ratios are not considered either as a barrier or a requirement for attaining a specific debt rating bit commonly used financial ratios are profitability ratios, coverage ratios quick and current liquidity ratios.

The general rule is that the borrower's credit rating is better when the financial structure is safer as depicted by larger cash flow margins from operations. This rule when consolidated with sovereign risk (country of incorporation and/or operations), the industry profile and the competitive environment, and the business sector helps with the determination of ratings.

The traditional areas of analysis were:

- management's reputation, reliability, experience, and past performance;
- coherence and consistency in the firm's strategy;
- organization adequacy to competitive needs;
- diversifications in profit and cash flow sources;
- firm's resilience to business volatility and uncertainty.

In recent times new analytical areas are being explored to take care of new sources of risk. They are:

- internal governance quality
- environmental risks, technology and production processes compliance and sustainability;
- potential exposure to legal or institutional risks, and to main political events;
- potential hidden liabilities as seen in workers' pension plans, health care, private assistance and insurance, bonuses, ESOP incentives etc.

Depending on all the criteria mentioned above the rating process is considered to be very complex. **In general, rating process consists of the following steps**:

- preliminary analysis,
- meetings with the counterparty,
- preparation of a rating report to be submitted by the Analytical Team to the Rating Committee,
- new detailed analysis if needed,
- final approval by the Rating Committee,
- official communication to and meeting with the counterparty, and, if required, a new approval process and rating submission to the Rating Committee.

Globally, the ratings industry has consolidated over time to form three main competitors each with a different definition for ratings for both issues and issuers. This complicates the ratings comparison among the three players, namely Moody's, S&P and FITCH. However, market pressure in recent times has evolved the usage of wider range of criteria to produce ratings that are more comparable.

Recent changes embraced in the ratings arena include the adoption of core earnings methodology, assessment of liquidity profiles, initiating new corporate governance rules and strengthening of monitoring activities and inspection of market signals.

Describe the relationship between borrower rating and probability of default.

Credit agencies predict the default rates of borrowers by way of ratings assignment. They are capable of collecting a vast amount of observable data about their assessment of forecasted default rates.

The actual default rates of borrowers can thus be observed and averaged over a period of time by the experience and established methodologies applied by the ratings agencies.

From these observations of average actual frequencies of default per ratings class, probabilities of default can be deduced. These probabilities can be used for future forecasting of default rates.

The borrower ratings can be effectively used to arrive at the default probabilities on the premise that:

- in the long run, given a homogenous population, actual frequencies approach the central probability estimated, as the average of the results attained from a large number of trials would be closer to the expected value;
- in the long run, given a homogenous population, actual frequencies are a good prediction of central probabilities.

However, in real world, actual observations convey that ratings are better than expected if the initial classes are low (bad) while they become worse than expected if the initial classes are very high (good). Migrations of ratings from one class to another over time are dependent and correlated and not a random occurrence. Issues such as these constitute a matter of concern and need to be taken into account while measuring the risk of a credit portfolio.

The actual default frequencies used to predict the default probabilities somehow face the following shortcomings:

- Different rating agencies define default in a different manner so frequencies may point to unlike events;
- The frequencies may come from different underlying populations (not homogenous)
- Amounts rated are different, so when summed using weighted averages, the weights are dissimilar;
- Initial rating for the same counterparties as rated by different rating agencies may not be always similar.

Since official rating classes just indicate the ranking, the difference between the ratings class cannot be measured objectively. Actual frequencies are only a proxy for default probability. Standard deviations of default rates observed over a long period is seen to be high with fat tail problem and large probability of overlapping classes. Despite these drawbacks, ratings are seen to be the best among the available measures of classifications for credit quality purposes.

Compare agencies' ratings to internal experts-based rating systems.

Internal classifications by banks normally tend to rely on a more formalized or quantitative model based approach based on statistical analysis. Though the process varies between the various banks, availability of information on credit risk market prices helps in the convergence of approaches adopted for ratings.

Although the internal ratings system of the banks follows a framework different from that of the agencies ratings processes, the underlying processes are considered similar when banks internally undertake judgmental approaches to credit quality assessment. The agency ratings then act like a frame of reference for developing the structure in internal ratings system. However, judgment based approach requires vast experience and repetitions, to reach a consistency in their methodologies. The convergence of judgements is increasingly difficult to achieve because of

- constantly changing organizational patterns;
- mergers and acquisitions that consolidate various credit portfolios, credit approval procedures, internal credit underwriting powers etc.;
- changes in company culture and experts' skills and analytical frameworks, over time.

Although the forecasts may be relevant in the current period their influence in the future periods could be uncertain. As such, this uncertainty weakens the systems that are based on internal rating systems.

Distinguish between the structural approaches and the reduced-form approaches to predicting default.

Structural approaches

- They construct models based on an economic or financial theory that help in building formal relationships between the relevant variables.
- They make use of theoretical assumptions to examine the cause and effect relationship between the variables which assist in predicting the default.
- The structural approach offers analytical insight into the default process.
- In the structural models, the default event is implicit in the model and the result is intrinsically probabilistic in a continuous space and determined stochastically.

To elaborate on the structural approach, let us consider the Merton's proposal on path to defaults. Accordingly, default occurs when the borrower is insolvent. Merton suggests that cash flows out of a credit contract have the same structure as a European call option. That is,

- the lender has the right to take ownership of the borrower's assets when borrower is unable to pay;
- the lender sells a call option on the borrower's assets to the borrower, which has the same maturity as debt, at the strike price equal to the face value of the debt;
- when the debt matures, if the value of borrower's assets is greater than the face value of debt, the borrower will pay the debt and the assets remain with him, else if the value of assets is lower than the face value of debt, the borrower tends to default and will lose his assets to the lender.

Thus default depends on financial variables and the Black Scholes Merton formula is used to calculate default probability in structural approaches. The relevant variables in this call option are 1) the face value of debt (option strike), 2) assets value (underlying option), 3) maturity (option expiration date), 4) assets value volatility (sigma), and 5) market risk interest rate. The probability of the option being exercised indicates the probability of borrower defaulting.

Reduced form approaches

- They use statistically suitable set of variables to arrive at the default prediction while ignoring the theoretical and conceptual relations among them.
- They make no assumptions about the casual relationship between the variables to predict the default.
- The model's relationships are estimated in order to improve their prediction power.
- The default event is exogenously expressed.
- The set of variables in the reduced form model can change their relevance in different stages of the economic cycle, in different sectors or for firms of different sizes. Consequently, due to model risk, the result of a reduced form model cannot be generalized, i.e., model estimated in a given environment may be totally ineffective in another.

Apply the Merton model to calculate default probability and the distance to default and describe the limitations of using the Merton model.

According to the Merton model, a firm's equity is comparable to an option contract wherein the default probabilities are embedded in the option values for debt and equity. As such, the market value of the firm (assets) is equal to the market value of debt(liability) plus the market value of the equity. While the objective of business management lies in maximizing the firm's value, the aim of financial structure management lies in maximizing of shareholders' value. The choice of the financial structure influences the equity value because of the default probability (possibility that shareholders will lose their investments).

Merton proposed that the firm's equity is a call option on the market value of the assets which can be evaluated from the market value of its assets, the volatility of the assets, and the book value of the liabilities. Alternatively, it can be said that the business risk and the financial risk are linked to one another at the same time by the volatility of the firm's assets. Highly volatile businesses point out to lower debt/equity ratios and conversely low volatility in firm's value imply higher debt/equity ratios.

Based on the Merton approach and using the Black Scholes Merton formula, the probability of default(PD) is given by:

$$PD = \left(\frac{\ln(F) - \ln(V_a) - \left(\mu - {}^{1}/_{2}\,\sigma_a^2\right)T}{\sigma_a\sqrt{T}}\right)$$

where

ln = the natural logarithm,
F = face value of debt,
V_a = the firm's asset value (market value of equity and net debt),
μ = is the 'risky world' expected return,
T = the remaining time to maturity,
σ_a = the instantaneous assets value volatility (standard deviation),
N = the cumulated normal distribution operator.

The practical application of Merton approach in the real world is complex and at the same time not directly applicable. This is because

- The asset value of the firm and its volatility are both unobservable
- the debt structure is usually complex, consisting of numerous contracts, maturities, guarantees, clauses and covenants.
- Also Black Scholes formula is highly simplified in terms of interest rates, volatilities, and probability density functions of future events.

As a solution to these, the default probability can be calculated starting with the distance to default formula and using econometric calibration on historical values of actual defaults. The portion in brackets of the Black Scholes Merton calculation represents a standardized measure of the distance to the debt barrier. It is the threshold beyond which the firm goes into financial distress and default. This expression is converted into a probability by using the cumulated normal distribution function.

Also the relation which connects the equity and asset value, based on their volatilities and the 'hedge ratio' of the Black Scholes formula is expressed as:

$$\sigma_{equity} E_0 = N(d_1)\sigma_{asset\ value} V_0$$

This expression is pertinent to publicly traded companies whose asset values and asset values' volatility can be observed from their market prices. From this equation and the Black Scholes Merton formula, the **distance to default (DtD)** can be calculated (assuming T = 1) as:

$$DtD = \frac{lnV_a - \ln F + (\mu_{risky} - \frac{\sigma_a^2}{2}) - \text{"}other\ payouts\text{"}}{\sigma_a} \cong \frac{lnV - \ln F}{\sigma_a}$$

Limitations of Merton model:

- The model is only relevant to companies which are liquid and trade in public.
- Their application to unlisted companies is restricted due to the following reasons
  - The prices of unlisted companies are not observable.
  - Using proxies or comparables may not give reliable results as it is very sensitive to some key parameters.
  - Also the use of comparables prices is not possible for medium sized companies.
- There is a need for constant calibration which means that some maintenance is required which may not be affordable for small issuers.
- Also since the results are highly sensitivity to parameters and input measures, unsophisticated approaches with regard to this model may not to be encouraged.
- Due to constant movements in market prices, volatility, and interest rates, this approach is unstable. As a result, long term institutional investors who are resistant to changing asset allocation often may not prefer this approach.

Describe linear discriminant analysis (LDA), define the Z-score and its usage, and apply LDA to classify a sample of firms by credit quality.

Linear Discriminant Analysis(LDA)

Linear discriminant analysis(LDA) is a linear function (called scoring function) of variables which are selected depending on their statistical significance or their contribution to the possibility of default. They are reduced form models as the variables are exogenously selected.

Z score

The coefficients of the variables in a LDA reflect the weight of each ratio to the overall score. The sum of all the coefficient times their corresponding variable values gives the overall score referred to as Z-score or simply Z.

Usage of Z score

The discriminant function is first estimated using past data of borrowers to discern between the performing and defaulting borrowers. Then new borrowers can be classified again into these two predefined groups based on the scores generated. **An optimal discriminant Z score thus enables us to differentiate between the two groups based on their default probability**. The scoring function can also be transformed into a probabilistic measure, pointing out to the distance from the average characteristics of the two groups.

The number of discriminant functions obtained in this analysis is (k–1), where k is the groups' number. For instance, in case of two groups, say performing and defaulting borrowers, one discriminant function can be generated.

The most commonly used LDA in practice is the Ordinary Least Square method, similar to the linear regression analysis. The method seeks to minimize variance inside the groups and maximize variance among groups.

Applying LDA to classify firms based on credit quality:

Consider a group of firms under observation for their credit quality. Over time, two groups become visible:

1. companies that default
2. companies that do not default(solvent) during the given time period.

The distinction is evident at the end of the time period(t) under observation. Let us say if the firms' profile is given some time before the default (say t–k). In this case, between the time period t-k and t, it is possible to predict the distinction between defaulting and performing firm based on LDA.

Based on the available information at time t-k, LDA assigns a Z-score to each firm. That is, the groups of firms that will be solvent or defaulting at time t are indicated at time t–k by their Z-scores distributions. Z scores of performing and defaulting firms may overlap during this time period t-k, and, for a given cut-off, some firms may be classified in the wrong section. These kind of model's errors can be taken care of by the statistical procedure used to estimate the scoring function.

Altman's Z score model is a widely applied one with five discriminant variables and given by

$$z = 1.21x_1 + 1.40x_2 + 3.30x_3 + 0.6x_4 + 0.999x_5$$

where x_1 is working capital/total assets, x_2 is accrued capital reserves/total assets, x_3 is EBIT/total assets, x_4 is equity market value/face value of term debt, x_5 is sales/total assets, and Z is a number representing the total score. Here the discriminant threshold or the Z cutoff used to differentiate predicted defaulting from predicted performing firms is 2.675. A number lower than this suggests classification in the group of defaulting companies and vice versa.

For instance, consider a firm having a particular score that classifies it in the performing group of companies. The variables' contribution to the final score can be calculated in percentage terms. We can perform stress tests by increasing or decreasing the variables by a certain percentage (say x_1 increased by 10%, x_2 decreased by 20%) which also changes the variables contribution to give a new Z-score. This new score may differ from the old one and if it is lower than 2.675, it could result in a change in classification of the firm from a performing to a defaulting one.

Describe the application of logistic regression model to estimate default probability.

Logistic regression models (or LOGIT models) link the expected value of the dependent variable to a linear combination of the independent variables, without any restrictive hypotheses like those in case of classic linear models.

For this reason, they come under Generalized Linear Models in which some fundamental assumption of classical linear models, like linear relations among independent and dependent variables or the constant variance of errors, are relaxed. As a result, any type of explanatory variables is accepted (both quantitative and qualitative, and both scale and categorical), with no constraints concerning their distribution.

Consider Y, a random binary variable, which takes the value of one when the borrower defaults, else, a value of zero when there is no default. By defining π as the probability that default occurs, Y has a Bernoulli distribution with the probability of default = π and the probability of no default =1− π. However, Y may not be linearly related to the independent variables for obtaining a meaningful prediction.

So, we consider a function g(·) with a set of p independent variables $x_1, x_2 \ldots x_p$ and coefficients $\beta_0, \beta_1 \ldots \beta_p$ which is explained by a linear combination such as:

$$g(\pi) = \beta_0 + \beta_1 \cdot x_{i1} + \beta_2 \cdot x_{i2} + \ldots + \beta_p \cdot x_{ip} = \beta_0 + \sum_{j=1}^{p} \beta_j \cdot x_{ij} \quad i = 1, \ldots, n$$

This linear combination, also called the linear predictor of the model is the systematic component of the model.

Thus the function $g(\pi_i)$ is a link function which associates the expected value of the dependent variable Y (the probability of default) with the systematic component of the model consisting of independent variables $x_1, x_2 \ldots x_p$ and their effects(β_i).

For a Bernoullian dependent variable, the following condition is true.

$$g(\pi_i) = \log \frac{\pi_i}{1-\pi_i} = \beta_0 + \sum_{j=1}^{p} \beta_j \cdot x_{ij} \quad i = 1, \ldots, n$$

Thus the link function can be stated as the logarithm of the ratio between the probability of default and the probability of no default. The ratio between the probability of default and the probability of no default is called as 'odds'.

$$\text{odds} = \frac{\pi}{1-\pi} \text{ and alternatively, } \pi = \frac{\text{odds}}{1+\text{odds}}$$

Therefore the link function g(·) is known as LOGIT (the logarithm of *odds*)

$$g(\pi_i) = \text{logit}(\pi_i) = \log \frac{\pi_i}{1-\pi_i}$$

Therefore, to arrive at the relationship between the probability of default (π) and independent variables which is nonlinear, we make use of the logit (π) function whose relation with its independent variables is linear.

The logit function can be otherwise written in terms of default probabilities as:

$$\pi_i = \frac{1}{1+e^{-(\beta_0 + \sum_{j=1}^{p} \beta_j \cdot x_{ij})}}$$

Thus logistic regression allows the calculation of estimates of the probability of default. However, this probability is based on samples and may require rescaling to the represent the actual population.

Define and interpret cluster analysis and principal component analysis.

Cluster analysis and principal component analysis fall under the category of 'unsupervised' techniques, as the dependent variable (default probability) may not be explicitly defined like in case of LDA or LOGIT methods. Specifically, these unsupervised analyses help in simplifying the available information and are useful for segmenting portfolios and in revealing borrowers' characteristics and variables' properties.

Cluster analysis

Cluster analysis sorts the population in to groups of similar borrowers' profiles, i.e., it segments the borrower's in to various groups. The observable default rate for each group can be taken as borrower' default probability for each segment. Clusters can be located in a dataset by observing groups with similar characteristics based on some specific criteria and by aggregating them. The groups so clustered based on the variables show similarities within the group and are distinct from those in the other groups or clusters.

Two approaches to cluster analysis include:

1. **Hierarchical clustering(aggregative):** In this type, a hierarchy of clusters are created with aggregation on a case-by-case basis, to form a tree structure, with the leaves as clusters and the roots representing the entire population. Nearby clusters can be aggregated to form a new unit until the root is reached. The distance between each cluster is measured to get meaningful results.

   One of the major applications of this type of cluster analysis lies in detecting anomalies (like outliers among borrowers), so that they can be separated from the remaining observations, to build models without biases.

2. **Divisive clustering (**partitional or divisive): It is opposite to hierarchical clustering, as it starts at the root and repeatedly splits into clusters based on algorithms. Typically, the number of clusters (k) is chosen based on certain rules. Then, k randomly generated clusters are determined such that each observation is assigned to the cluster whose center is the nearest. New cluster centers are repeatedly calculated until finally the intra-group variance is minimized and the inter-group variance is maximized, subject to the constraint of number of clusters chosen(k).

   This approach tends to force the population into fewer groups than in aggregative clusters but the calculation power required is very high. Hence such divisive approaches are often limited to preliminary explorative analyses.

Interpretation of cluster analysis:

From cluster analysis we can observe

- small number of large clusters with high homogeneity
- numerous but small clusters with specific properties
- single units not aggregated with others because of their high specificity.

Principal Component Analysis:

Given a dataset in a table form with n observations and described by q variables, we can say that cluster analysis deals by rows (observations), while the principal component analysis examines the columns (variables), so as to reduce the set of variables in to a smaller set which is statistically more significant.

We can say that principal component analysis confines q variables into a smaller number of say m variables to efficiently summarize most of the original total variance as measured by q variables.

The method consists of extracting the first component that reaches the maximum communality (i.e., variance explained divided by total original variance). Then another component is extracted from the residuals which is not explained by the previous component, until the entire original set of variables is transformed into a new principal components set.

This analysis reveals the latent variables that explain the concept in a better way by removing redundancy and at the same time maintaining the comprehensiveness.

Interpretation of principal component analysis:

The new variables(components) derived are orthogonal, that is, they are statistically independent. Also they explain the original variance in a descending order which implies that the first component extracted explains most of the variance, followed by the second component and so on.

The eigenvalue which is a measure of the communality associated with the extracted component, explains how much variance is accounted by each component.

- Given that all the original variables, standardized, have contribution of one to the final variance, if the eigenvalue is more than one, it means we are summarizing a part of the total variance that is more than that explained by an individual original variable
- If the eigenvalue is less than one, the component contributes less than an original variable to describe the original variability.

Consequently, only the principal component that has an eigenvalue of more than one is considered.

Describe the use of cash flow simulation model in assigning rating and default probability, and explain the limitations of the model.

Cash flow simulation model involves predicting the pro-forma financial reports of a company and examining the volatility of the its future performances. These models use the techniques of both the structural and reduced form approaches and fall in between these approaches.

Use in assigning rating and default probability

Cash flow simulation model produces a number of potential default circumstances. The event of default is well defined. Default probability can be measured by assessing the number of scenarios in the future in which the default takes place with reference to the total number of scenarios simulated.

To arrive at the probability of default, typically two approaches are used

- **Scenario approach** – Probability is applied to different pre-defined scenarios. Then a weighted expectation of future outcomes will yield the ratings.
- **Numerical simulation model** - A large number of model iterations, which describe different scenarios are used. The scenarios like default and no-default and those in between like near-to-default, stressed etc. are evaluated. Then the relative frequency of the different stages is calculated.

The model in particular is useful for specific conditions, such as in case of a startup where there is no past data. Also this model is used in analyzing special purpose entities, firms that have merged recently, LBOs etc., in which we have to do not have enough facts. Further, in these transactions, contractual clauses like covenants have to be modeled. In such cases no other alternatives exist other than modeling by means of cash flow simulations.

When there is a requirement for debt repayment, the primary source of cash flow is operational profits. Nevertheless, in case of adverse conditions, company assets with guarantee offered by third parties are seen as a source of cash flow. Such deals need to be assessed based only on future plans, as there will be no historical data on backing-up lenders. In such cases where individual analysis is needed and where cost is also high, to spread fixed costs on large amounts, cash flow simulation models are used in the estimation of ratings and consequently default probability.

Limitations of the model:

- Model risk is inherent in this approach. This is because a model is just a simplification of reality and may not be representative of possible future scenarios.
- Errors in specification of a cash flow generator affects the default probability.
- Default probability can be calculated effectively only when future events are weighed by their occurrence.
- The issue of defining the default event is another drawback. If the assumptions about the default threshold is
    - too early, we will have many potential defaults, suggesting higher risk but the corresponding LGD will be low,
    - too late, we will have low default probability pointing to lower risk but LGD is considered high.
- The model being company specific, it needs calibration and supervision. So the cost to build the model may be high, whereas if we try to reduce the costs, the model efficiency and accuracy will be poor.

Describe the application of heuristic approaches, numeric approaches, and artificial neural network in modeling default risk and define their strengths and weaknesses.

Application of Heuristic methods:

Heuristic methods try to emulate the human decision making procedures by working on a trial and error basis with continuous feedback loops to enhance the knowledge base. Their main application lies with 'expert systems' which are based on artificial intelligence techniques.

Expert systems are software solutions that intend to simulate the performance of an expert.

First a knowledge base or database (called long term memory) is developed with a set of rules which can be used for decision making later. For this process, the information is gathered from experts in the field.

Then the process of gathering knowledge and codifying it according to a specific framework takes place. For this purpose, a working memory (called short term memory) is used, in which rules are built to solve the problem and produce solutions. Rules can incorporate probability of events and their gain or cost (utility).

Then the solutions are allowed to pass through an inferential engine which uses the rules together in various combinations to draw conclusions. As inference rules closely mimic a human expert's behavior, when a conclusion is reached, it is possible to understand how it was reached. Two kinds of approaches used by an inferential engine are

1. **Forward chaining**: Here with the available data, inference rules are used until the solution is met. So it is also called data driven.
2. **Backward chaining**: This begins with a set of goals and by working backwards, the system searches for the rule which closely matches with the goal. So it is also called goal driven.

The chaining methods thus discover new paths required for optimizing solutions over time.

Expert systems may use fuzzy logic which deals with approximate rather than exact reasoning, thus broadening the range of rules which can be applied for default risk analysis in the real world.

In a nutshell, expert systems try to consolidate knowledge and refine it by frequent (complex and recursive) calculations based on well-defined decision rules, so as to explore all possible solutions in order to offer the best one.

Strengths:

- Expert based systems can act as a substitute for human based decision making processes. They give order and structure to the process, thereby allowing high frequency and replication in decision making processes.
- They help consolidate the decision making processes, connecting statistical and inferential systems, procedures, classifications, and human behavior, allowing us to choose the best from a wide range of solutions.

Weaknesses:

- The accuracy of the final result depends on the model inputs. If the model inputs are or flawed or not clear, that limits the opportunities of expert system since human interaction in arriving at the solution is very limited.
- Rating assessment depends more on models with in the expert system that are derived from statistical or numerical methods. Consequently, expert systems, while structuring the knowledge and processes, do not attempt to produce new knowledge as they are not models or inferential methods.

Applications of Numerical approaches:

Numerical approaches try to reach optimal solutions by applying algorithms to take decisions in highly complex environments. One of their major application lies in Neural networks.**Artificial neural networks** consist of interconnecting artificial neurons (mimicking that of a human nervous system) or hierarchical steps(nodes) in a network. They are connected by mathematical models that make use of and transform information at each node, mostly by adopting a fuzzy logic approach to provide solutions.

For assessing credit risk, 'supervised learning' is mostly applied. Default risk models are built with the help of a training set formed from borrowers' characteristics. The cost function is also set to define the utility of the outcomes. In this case, the costs imply misclassification costs. A back-propagation learning engine is used to train the neural network. Iteration process is tweaked to yield a solution that minimizes the classification errors by changing the weights and connections at different nodes. The training process renders the neural network to become more efficient and helps to make decisions for new borrowers in future.

Strengths:

- The complex network of nodes enables the system to assess different problems and also helps to flexibly describe nonlinear relationships. This explains their potential application in credit quality monitoring.
- The system can be trained so as to improve its adaptability based on experience
- They are easy to use and solutions are arrived at quickly. In particular, neural networks are very suitable when working with an extensive quantity of data.

Weaknesses:

- We only get the results, but how the results are arrived (step by step process) cannot be explained in case of neural networks.
- There is no way to gauge if the results are optimally estimated.
- They are sensitive to input quality like any other system.
- They are more suitable for continuous quantitative variables rather than qualitative variables
- There is always a risk of 'over-fitting' as the system is dependent on the specific training set. As a result, its application in out of sample populations is limited.
- When dealing with default risk of borrowers, the output from a neural network is not a probability of default but only a classification. To derive the probability, default frequency gathered from historical data has to be applied to each class.

Describe the role and management of qualitative information in assessing probability of default.

Qualitative information plays a huge role in judgment-based approaches to credit approval. They are classified into:

- efficiency and effectiveness of internal processes (production, administration, marketing, post-marketing, and control);
- investment, technology, and innovation;
- human resource management, enhancing talent, key resources retention, and motivation.

There are usually a plenty of qualitative variables, so they require ordering and structure to reduce complexity and redundant information. In order to manage them effectively, the following activities can be performed.

- Only the qualitative information that cannot be extracted from quantitative data found in financial statements needs to be collected.
- To manage qualitative information in quantitative models, a preliminary classification is needed for different categorical types like:
    - nominal information, such as regions of incorporation;
    - binary information (yes/no, presence/absence of an attribute);
    - ordinal classification, with some graduation (linear or nonlinear) in the levels (very low/low/medium/high/very high).
- Binary indicators can be transformed into the form of 0/1 '*dummy variables*' while ordinal indicators can be transformed into numbers and weights can be assigned.
- The data collected should be in closed form, that is, it should involve selecting some pre-defined answers.
- A multistage answer is preferred instead of yes/no as it is difficult to model binary variables due to their non-normal distribution.
- Weights can be set using optimization techniques, like '*bootstrap*' or a preliminary test on different solutions to select the most suited one.

Conducting a survey to collect qualitative information may be a costly option and a not very efficient practice to collect information about non-performing loans. As such, these problems can be managed by a two-way process:

- First stage involves constructing a quantitative model along with collection of systematic qualitative data, so that the qualitative data can be used for taking control over the results of quantitative model through a formal or informal procedure.
- Second stage includes forming a new model based on qualitative information gathered from the first stage after a period of time, finding the most relevant data and modifying the data collection form if required.