The Future of Banking: Credit Risk Seminar

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FMO
Entrepreneurial Development Bank

Credit Scoring Done Right
18 September 2015 in Amsterdam

EDUCATION MADE IN GERMANY

AACSB ACCREDITED

EFMD EQUIS ACCREDITED

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Agenda

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Friday, 18 September 2015 - Credit Scoring Done Right

Part 1: **What is Scoring ?**

Part 2: **Statistical Credit Scoring - It is really that easy**

Part 3: **Other Scoring Methods: Credit Bureau Scoring, Expert Scoring etc.**

Part 4: **Scoring Implementation: It's a process not a project.**

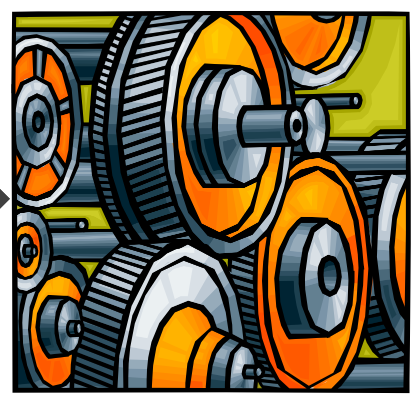
Statistical Credit Scoring

- Scorecards use predictive statistical models (discriminant analysis or logistic regression) applied to the behavior of previous customers: i.e. a database of descriptors / demographics combined with a subsequent performance record.
- With credit scoring, lenders obtain ex-ante visibility of the Probability of Default.
- Together with LGD & EAD estimates, banks now have a basis for risk-based pricing of individual clients, particular products or client groups.

Database

- Loan Contract
- Socioeconomic descriptors
- Default (yes/no)

Statistical Model



Score Result

Score Value

High Risk: Reject
Medium Risk: Review
Low Risk: Accept

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Scoring versus Rating versus Expert Scoring

- When we say "credit scoring" we generally refer to the more common approach of **statistical credit scoring**, not the lesser known **expert scoring** variant, which is essentially a **simplified rating** method.
- **Statistical scoring and credit rating are often confused** because both methods share the objective of developing a ranking of existing or potential borrowers in respect to their credit risk. Both methods should tell us whether or not Client A is more likely to default than Client B over the next year, given everything that we know about the borrowers' financial circumstances, activities and the overall macroeconomic environment.
- **In statistical scoring** we assess the credit risk by measuring correlations of borrower performance with proxy indicators of risk using statistical tools on a large number of prior observations. We would like to assess the risk factor of "stability of personal life", but instead we score observable proxies such as home ownership, marital status or even "fixed line telephone at the home yes/no".

Scoring versus Rating versus Expert Scoring

- In **rating models**, we go directly for the underlying risk factors and capture structured expert judgments on their relevance for the particular client.
- For example, we ask the loan officer to rate on a scale from 1 to 5, the exposure of the borrower's business model to a small number of large clients. The risk being, of course, that if one of the large clients stops buying from the small business, our loan will default.
- Generally, we opt for the rating approach and the structured judgments out of necessity, because we **don't have a database of thousands of prior observations** with hundreds of data points for each. The number of medium-sized business clients will often only be in the hundreds and not in the tens of thousands like in retail or microcredit. So, building a statistically relevant reference population for scoring SMEs is generally out of the question.
- The range of industries, the **diversity of small business models** and the types of credit products offered to them translates into a much higher complexity than in standardized retail credit. A "blind" statistical credit scoring on proxy risk factors really would not do justice to this complexity.

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Is scoring right for (micro-) enterprise finance?

- Well, absolutely!
- Scoring works well whenever we have a large number of relatively standardized loans made to clients in comparable economic circumstances, exposed to similar risk factors.
- Consumer Credit including housing loans and microenterprise finance are the obvious candidates for standardized scoring approaches.

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Step 1: We need lots of data - all nicely lined up, coded and complete

- Correlation Matrix (excerpt) - standard Excel function

	A	B	D	F	G	I	J	S	T	AA	AB	AD	AG
1	LoanID	DisburseDate	TenorMonths	Male=1	AgeYears	Single=1	Divorced=1	YearsInBusiness	Branch1=1	Agriculture=1	RetailTrade=1	Construction=1	Bad61d+=1
2	OH1	23-Oct-2012	41	1	52	0	0	9.5	0	0	1	0	0
3	AW2	26-Feb-2012	20	0	23	0	0	0.5	0	0	0	1	0
45	TL46	25-Mar-2012	18	1	39	0	1	3.5	0	0	0	1	1
46	GA47	18-Jun-2013	17	0	59	1	0	3.5	1	0	1	0	0
47	KK48	23-Feb-2012	8	0	31	0	0	1	0	0	0	0	0
48	UJ49	1-Jun-2012	26	0	40	0	0	6.5	0	0	1	0	0
49	RG50	10-Oct-2012	19	0	64	0	0	8	0	0	1	0	0
50	CQ51	24-Mar-2013	6	0	37	0	0	0.5	0	0	1	0	0
51	LW52	31-May-2012	21	0	58	0	0	6.5	0	0	0	0	0
52	SC53	24-Jul-2013	20	0	31	1	0	0.5	0	0	0	0	0
53	MI56	30-Nov-2012	12	0	59	0	0	3	0	0	1	0	0
54	CJ57	10-Jul-2013	19	1	37	1	0	2.5	0	0	1	0	0
55	AX58	26-Jul-2012	9	1	64	0	0	1	0	0	0	0	0
56	YO59	8-May-2012	33	0	50	1	0	1	0	0	1	0	0
57	HD60	2-May-2013	6	0	25	0	0	0	0	0	0	0	0
58	GH61	28-Mar-2013	38	0	22	0	0	1	1	0	0	0	0
59	ZC62	10-Oct-2012	6	1	46	0	0	0.5	0	0	0	0	1
60	ZQ63	3-Jan-2013	25	0	43	0	0	6.5	0	0	0	1	0

➤ SampleApplicationScoring.xlsx

2 Statistical Scoring – Data Sources

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What everybody has:

Contracts & Transactions

- Clients : Legal Identifiers
- Clients: Addresses & Contacts
- Loan Contracts
- Deposit Contracts
- Accounts and Transactions
- Collateral
- Client Revenues

What market leaders are adding right now:

Context & Descriptors

- Client Prospects
- Client Interactions (including collections)
- Client-Related Tasks & Workflow
- Supplementary Address and Contact Data
- Socio-demographics & Quality of Life
- Credit History & Scoring / Rating
- Client Financials & Household Budget
- Loan Applications & Credit Decisions
- Guarantors, Co-Signers, References
- Household & Family Relationships
- Employment & Business Activities

Step 2: Look for correlations with the default yes/no outcome

- Correlation Matrix (excerpt)

A	F	G	H	I	J	M	P	Q	S	W	X
	Male=1	*AgeYears*	*Married=1*	*Single=1*	*Divorced=1*	*SomeSecondary=1*	*YearsAtAddress*	*OwnHome=1*	*YearsInBusiness*	*Branch4=1*	*Branch5=1*
Male=1	1										
AgeYears	0.0044895	1									
Married=1	-0.0010763	0.0962571	1								
Single=1	0.0009653	-0.196623	-0.6919273	1							
Divorced=1	-0.0092882	0.077226	-0.4763086	-0.1728723	1						
SomeSecondary=1	-0.1936569	-0.1580594	-0.0341129	0.1084767	-0.06484321	1					
Secondary to 10=1	-0.237022	-0.0297692	0.0460116	0.094646	-0.14820047	-0.241942211					
CompletedVocational=1	0.6165323	-0.2574669	0.2756229	-0.1443877	-0.17593473	-0.131641908					
YearsAtAddress	0.0011284	0.4595061	0.0378632	-0.0844942	0.041175072	-0.069811789	1				
OwnHome=1	0.0074659	0.5694163	0.5531755	-0.4716878	-0.2868337	-0.215325405	0.257242664	1			
NumberDependents	0.0007051	0.5596	0.5031795	-0.5315729	-0.06329946	-0.277054529	0.244420379	0.6311007			
YearsInBusiness	0.0857176	0.4987866	0.1577337	-0.1708826	-0.04086032	-0.108174088	0.224476227	0.358542578	1		
Branch4=1	0.0006408	-0.0036737	0.0016098	-0.0018108	0.000897343	0.006072641	-0.003819585	0.005206196	-0.003522377	1	
Branch5=1	0.0010707	0.0108412	0.0041856	-0.0038352	-0.00275952	-8.3365E-05	0.000911593	0.007029315	0.008011528	-0.2784709	1
AvgArrearsDays per Month	0.004458	-0.0061262	0.0011698	0.0028667	-0.00296831	0.007246516	0.002761608	-0.002659807	-0.003800745	0.004355	0.0042632
NumberEmployeesFamily	-0.0033339	0.1330372	0.1146104	-0.1198123	-0.01226438	-0.059157946	0.058429336	0.145336065	0.459513999	-0.0069946	-6.905E-05
Agriculture=1	-0.0003751	-0.0033506	0.0054918	-0.0075485	0.002031729	0.002508523	0.004018927	-0.002697204	-0.060577254	0.000851	0.0035441
RetailTrade=1	0.0086076	-0.0039109	0.0005539	0.004477	-0.00244886	0.004243437	-0.008526602	0.002532566	-0.016308596	-0.0098067	-0.0106132
PersonalServices=1	-0.0093827	-0.0001942	-0.0011257	0.0032889	-0.0045022	-0.004955571	-0.00479236	0.001281253	-0.03399821	-0.0007635	0.0016167
Construction=1	-0.0061508	0.0009244	0.0003814	0.0019135	0.000477114	0.003064366	0.002649141	-0.004035396	0.098034932	-0.0001307	0.0037456
Artisan=1	-0.001489	0.0035905	-0.006506	0.0008211	0.00340271	-0.002021167	0.003441428	-0.002260906	-0.104469741	0.0006072	0.001596
MonthlySalesUSD	0.0043821	0.0015596	0.0009792	0.0044376	-0.00206081	0.006337326	-0.005906998	0.002024483	0.159131515	-0.012486	-0.0046287
Bad61d+=1 Final	0.0047134	-0.2006664	-0.1813075	0.121416	0.100949536	0.046781745	-0.109745115	-0.223742817	-0.139250965	-0.0491573	-0.0002919

➢ SampleApplicationScoring.xlsx

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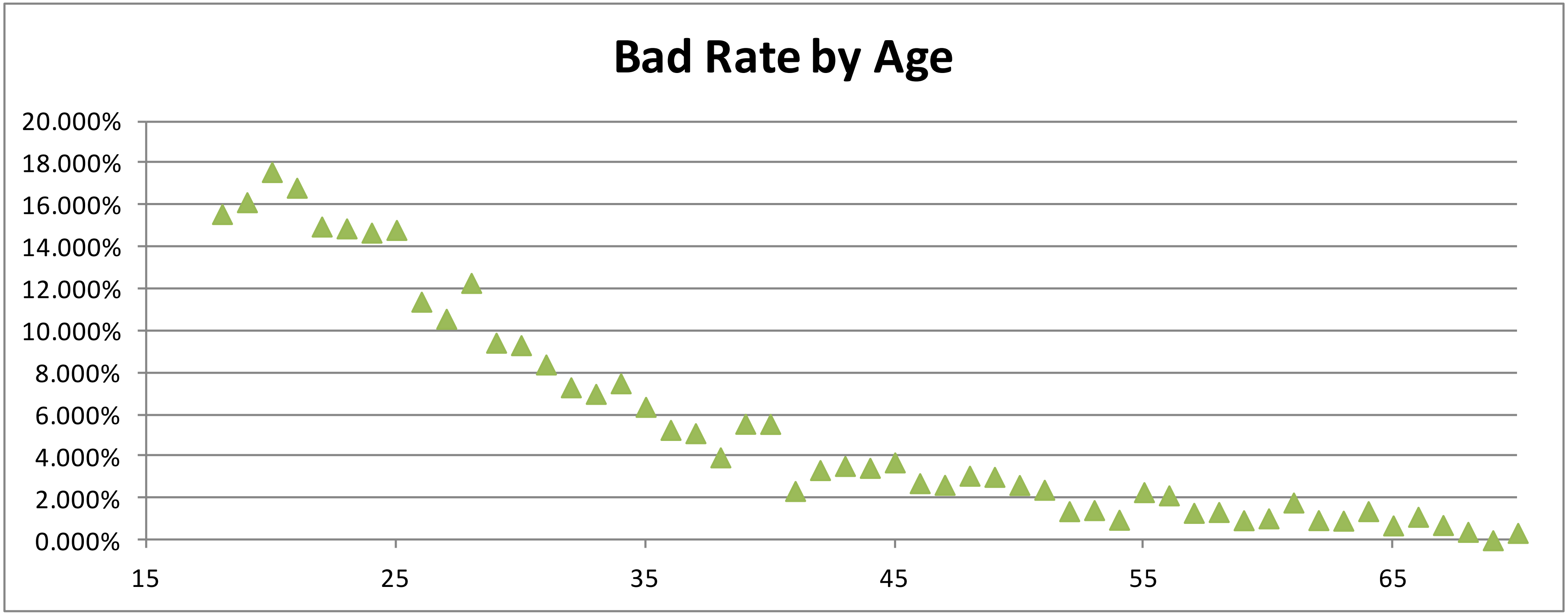
Step 2: Look for correlations with the default yes/no outcome

- Conditional default rates by age: a reasonably linear relationship.
- But a simple transformation =ln(Age) or 1/Age could still improve the correlation.



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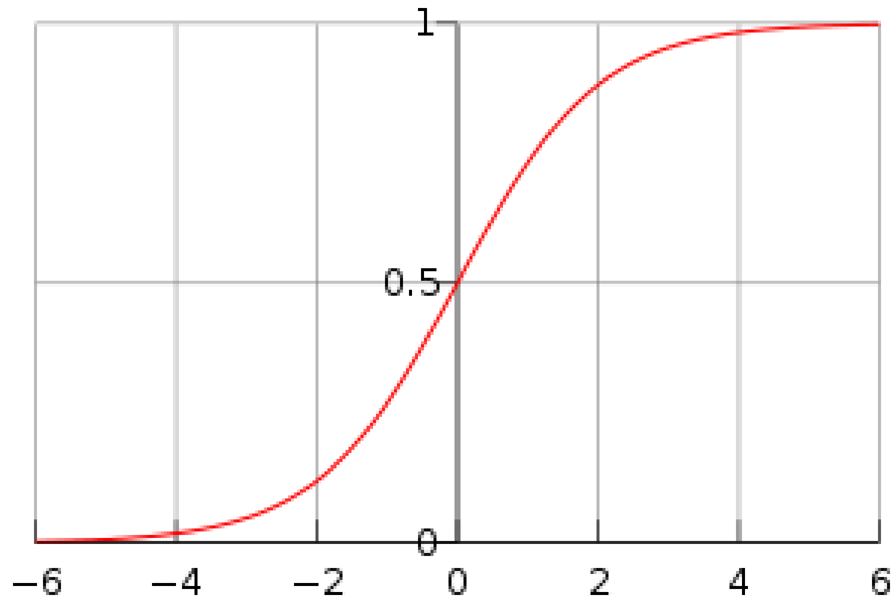
Step 3: Model Calculation using Logistic Regression

- Logit Function:

$$f(z) = \frac{1}{1 + e^{-z}}$$



$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k,$$

- Simple transformation of the linear multivariate regression onto the logit function
- Values range between zero and one, more suitable for modeling binary outcomes, such as “default or no default“.

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Step 3: Logistic Regression: the "model"

Model Variable	Coefficient Value
Intercept	-3.190
1/Age	32.787
Married=1	-0.936
Divorced=1	0.552
SomeSecondary=1	0.021
Secondary to 10=1	-0.099
YearsAtAddress	-0.044
OwnHome=1	-1.359
1/Dependents	0.031
LN(YearsinBusiness)	-0.436
Branch4=1	-0.726
AvgArrearsDays per Month	0.310
NumberEmployeesFamily	-0.074
Agriculture=1	1.113
RetailTrade=1	-0.376
Construction=1	0.691

- SampleApplicationScoring.xlsx

Step 3: Logistic Regression: classification table output & model performance

Classification table for the estimation sample (Variable Bad61d+=1 Final):

Actual \ Prediction	Good	Bad	Total	% correct
Good	31250	2888	34138	91.54%
Bad	1048	819	1867	43.87%
Total	32298	3707	36005	89.07%

Default rate if applying this model to reject likely defaulters:	3.24%
Default rate in underlying population:	5.19%
Reduction in Default Rate:	37.42%

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Step 3: Logistic Regression: classification tables for various cut points

- Results from an actual microcredit score (hybrid application / behavioral model)
- Read this like a menu of alternative business strategies in implementation

Score > x = reject (Cut-off Score)	5%	15%	25%	30%	40%	45%	50%	60%	65%	70%	75%	80%
Good predicted	32,871	74,994	100,541	110,484	124,648	129,532	133,817	140,417	143,176	145,657	147,901	150,038
Bad predicted	125,271	83,148	57,601	47,658	33,494	28,610	24,325	17,725	14,966	12,485	10,241	8,104
Actual bad predicted as good	22	216	525	722	1,103	1,289	1,504	1,934	2,135	2,436	2,733	3,073
Default rate = actual bad / predicted good	**0.07%**	**0.29%**	**0.52%**	**0.65%**	**0.88%**	**1.00%**	**1.12%**	**1.38%**	**1.49%**	**1.67%**	**1.85%**	**2.05%**
Good rejected	119,646	77,717	52,479	42,733	28,950	24,252	20,182	14,012	11,454	9,274	7,327	5,530
Bad eliminated	5,625	5,431	5,122	4,925	4,544	4,358	4,143	3,713	3,512	3,211	2,914	2,574
Good rejected / bad eliminated	**21.3**	**14.3**	**10.2**	**8.7**	**6.4**	**5.6**	**4.9**	**3.8**	**3.3**	**2.9**	**2.5**	**2.1**

Actual Good	152,495
Actual Bad	5,647
Total Population	**158,142**
Total Default Rate	**3.57%**

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Credit Bureau Score: FICO Scorecard

- FICO by Fair Isaac Corporation, distributed by Experian used in mortgage lending, vehicle finance and unsecured consumer credit.
- Exact factor combinations for calculating credit scores are proprietary and not public. However, Fair Isaac discloses the following general score components and approximate weights:
  - 35% — punctuality of payment in the past (only includes payments later than 30 days past due)
  - 30% — the amount of debt, expressed as the ratio of current revolving debt (credit card balances, etc.) to total available revolving credit (credit limits)
  - 15% — length of credit history
  - 10% — types of credit used (installment, revolving, bank loan)
  - 10% — recent search for credit and/or amount of credit obtained recently.

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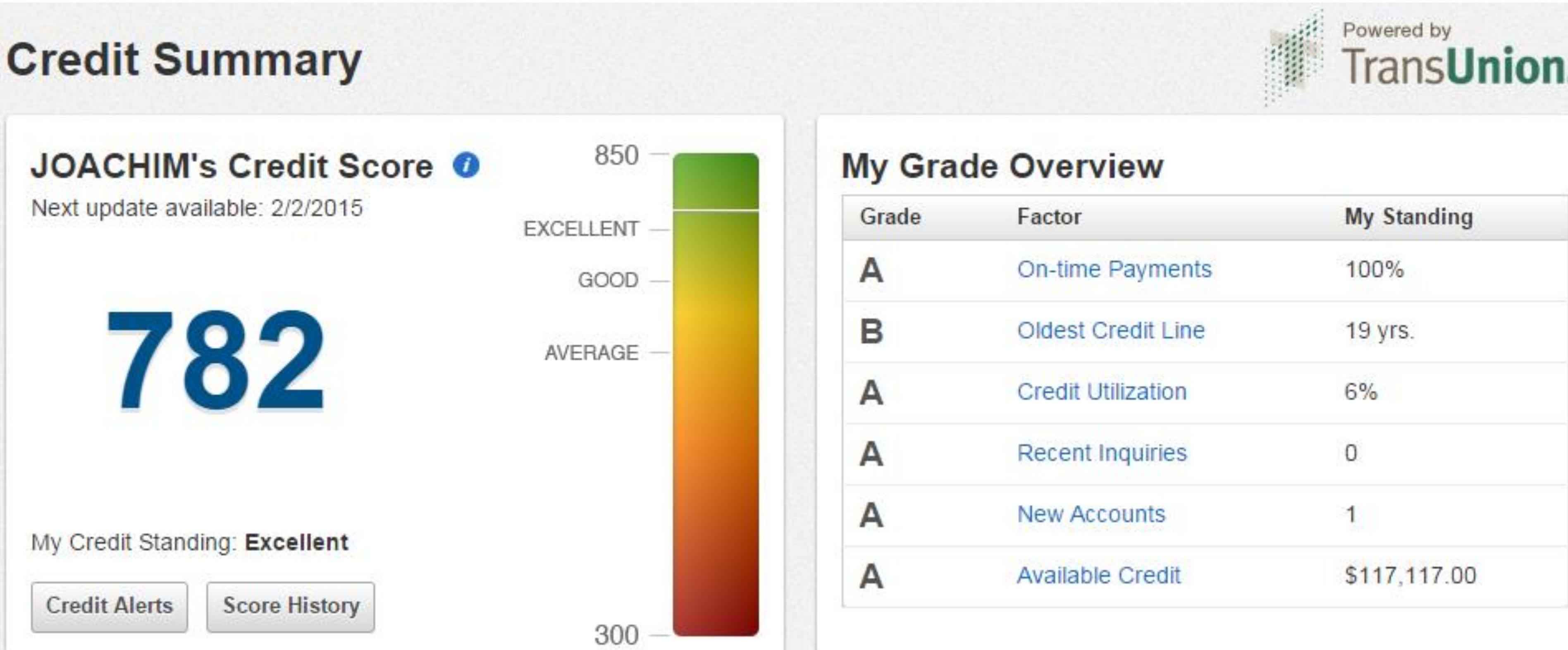
Credit Bureau Score: FICO Scorecard



Grade	Factor	My Standing
A	On-time Payments	100%
B	Oldest Credit Line	19 yrs.
A	Credit Utilization	6%
A	Recent Inquiries	0
A	New Accounts	1
A	Available Credit	$117,117.00

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Expert Scoring

- Expert scoring is essentially a **simplified credit rating** that is specifically tailored to small consumer credit or micro-enterprise loan products.
- An expert scoring also consists of a series of **closed-form judgments** about credit risk factors that are weighted and combined into a summary ranking of credit risk for a particular loan request.
- An expert scoring model typically assesses credit risk directly in terms of an all-in **expected loss**. (This means no explicit distinction of PD = Borrower Rating and LGD = Facility Rating).

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Generic Expert Scoring Example

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Sample Microenterprise Expert Score for Small Working Capital Loans												
2													
3	Reference Information												
4													
5		Borrower Name:	ClientName 1		Client ID Number:		45678956			Scoring Date:		14-Apr-14	
6		Responsible Loan Officer:	Name&Staff_ ID_2		Scoring Analyst:		Name&Staff_ ID_2			Scoring Approved by:		StaffSupervisor_ID_1	
7													
8	A.	Personal Borrower Characteristics		Global Weight:		35%							Values
9	1	Integrity & Moral Character		10.0%	4 Somewhat mixed reputation, limited experience with the lender.								4
10	2	Civil Status		5.0									3
11	3	Education Level		2.5									5
12	4	Years at Address		2.5									3
13	5	Own or Rent Home		2.5%	Rent								3
14	6	Loan Cycle		2.5%	3 1st loan								3
15	7	Prior Payment Discipline		10.0%	1 Arrears < 30 days max twice per year								1
16													
17	B.	Business Activity		Global Weight:		50%							
18	8	Competitive strength and client goodwill		5.0%	5 Unattractive location, undistinguished product or service, customers come for cheapest price								5
19	9	Volatility & resilience of business model		10.0%	0 Low overheads, steady patronage, business easily bounces back after an interruption.								0
20	10	Legality, licensing and permits		5.0%	4 Business operates illegally and is vulnerable to police intervention or criminal disruption.								4
21	11	Management skill		5.0%	3 Self-taught entrepreneur in reactive mode without clear strategy								3
22	12	Own or rent business premises		2.5%	0 Own								0
23	13	Reliability of financial information		2.5%	5 No written business records. Unreliable ad-hoc estimates. Client is flying blind.								5
24	14	Seasonality of revenues		2.5%	0 Steady cash flow. Low seasonal variation.								0
25	15	Profitability		5.0%	0 Above average margin on sales for this type of business								0
26	16	Debt service coverage ratio		10.0%	1 Free cash flow to installment > 150%								1
27	17	Sensitivity to currency induced credit risk		2.5%	0 Low sensitivity to forex risk								0
28													
29	C.	Facility Risk Factors		Global Weight:		15%							
30	17	Nature of primary collateral		5.0%	5 None								5
31	18	Collateral value to loan amount		5.0%	0 > 150%								0
32	19	Guarantors outside of household?		5.0%	2 No								2
33													
34	Totals		100%		Score Value:		2.175		Score Grade:		Accept with additional collateral		

1 Adheres to highest ethical standards, a moral authority in the community, high affinity to the lender.
2 Good reputation, longstanding relationship, proven ethical behavior.
3 Average reputation, some experience with the lender, relatively undistinguished in the community.
4 Somewhat mixed reputation, limited experience with the lender.
5 Has disappointed before, resorts to lying, is openly criticized as unreliable by others.

➢ SampleExpertScore.xlsx

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Expert Scoring versus Statistical Scoring

What is better: statistical scoring or judgment-based expert scoring?

- The proof that an expert scoring model works will be in the **accuracy of predicting default rates** and materialized loss numbers.
- Therefore, even if it is not a statistical credit score to begin with, the predictive performance of expert scoring will have to be **statistically validated**.
- Naturally, credit professionals and consultants tend to gravitate to the hard statistics. This is intellectually more satisfying because the statistical tools may discover complex multi-variable patterns of borrower behavior that are difficult to observe with the naked eye.
- The **statistical scoring** measures not how we think or wish that the borrowers might behave, but how they actually paid.
- A **statistical model** also has a built-in algorithm for determining the criteria weights that combine the various risk factors into a single score result. This summary score optimally discriminates between probable good and probable bad clients.

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Expert Scoring versus Statistical Scoring

What is better: statistical scoring or judgment-based expert scoring?

- The **central challenge in expert scoring**: It easy to come up with a short-list of risk factors that should be evaluated for each loan application. The problem is how to weigh and combine the scoring elements. This synthesis remains arbitrary and is always a source of debate in expert scoring.
- Most lenders opt for expert scoring out of necessity, because the data history for calculating a statistical credit scoring model just is not there:
  - Not enough past loans in a similar product definition, in a similar target market, in a similar macro-economic environment.
  - Not enough data captured in consistent, machine-readable format for the otherwise existing relevant loan history.
  - Not enough defaulted loans in the data history in order to establish stable correlations between the explanatory factors (borrower characteristics / activity / economic environment) and the good/bad credit outcome.

How to Assemble an Expert Scoring Model

Step 1: List the credit risk factors

- Capitalize on the experience of the loan officers and field staff in order to compile a concise list of risk drivers.
- These can be factors that increase or mitigate PD, LGD, or EAD.
- The list may also include elements that favor or discourage operational risk in the credit process, such as internal or external fraud and theft.
- These credit risk factors will mostly require expert judgment along a pre-defined ordinal scale, but they can also simply express the presence or absence of certain observable facts.

How to Assemble an Expert Scoring Model

Step 2: Define judgment scales or observable categories for each scoring element.

- Use closed form drop-box for each scoring element that contains the judgment scale or the observable status types for each.
- These scales should not just give numbered level, e.g. "Moral Integrity of the Borrower - select 1 through 5". Instead, one should place next to each number a descriptive definition of what a level 2 would look like in your market.
- Without concise definitions and examples of the scoring scales, staff will be tempted to collect the necessary points and click the levels that will get a passing score, so that the loan will be made and the disbursement target met.
- Expert scoring is always transparent in respect to the relationship between component judgments and the final score result. Therefore, the issue of "target scoring" is the most obvious problem of the method.
- Just like in rating, we must make expert scoring replicable, i.e. give enough guidance on the risk factor levels. Another loan officer or an internal auditor looking at the same applicant should come to roughly the same scoring result.

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How to Assemble an Expert Scoring Model

Step 3: Multiply the score levels with factor weights and add them up.

- This step is about **deriving the summary score** from the list of judgments and observations on the various elementary risk factors.
- The **weights** have been assigned during the model design and are part of the expert knowledge that goes into the system. The weights can be percentages that add up to 100%, or they can be any system of values where some factors get a bigger number and others a smaller number relative to their perceived importance for the overall credit outcome.
- If we do not assign explicit weights, then we either just assumed that all **factors will be equally weighted**, or the weights are implicit in the elementary scales, i.e. the range of achievable points per credit risk factor.
- By adding the (weighted) factor points up, one obtains an **ordinal scale that is assumed to rank the expected loss** such that a higher score number means either a higher expected loss or a lower expected loss, depending on the direction in which the scoring point system is set up.

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How to Assemble an Expert Scoring Model

Step 3: Multiply the score levels with factor weights and add them up.

- In addition to or instead of the score point value, lenders generally display a more intuitive classification by score value interval. This could be a numbered or lettered score grade, a color code (green/yellow/red) or an equivalent instruction for action: accept / accept with special conditions / review / reject etc.

Step 4: Back testing and statistical validation

- Before going into production, it is recommended to have several experienced loan officers apply the score to a substantial number of past loan applications.
- This will show whether the scoring factors are well balanced and relevant across most applications and whether the score level definitions are intuitive and can be applied consistently.
- More importantly even, one should verify by way of back test that the materialized loss rates for the higher risk scores are indeed higher and that the lower risk scores cost less in terms of actual write-offs.

How to Assemble an Expert Scoring Model

Step 4: Back testing and statistical validation

- Back testing is about comparing score predictions with actual loss rates.
- Most of this proof will have to be carried out on future loan generations made under the expert score model. It is simply too much effort to retro-score thousands of small loans from paper records. Moreover, the score outcome would be biased by the credit outcome that is already known at time of score assignment.
- For the purposes of subsequent statistical validation, it is essential to store the scores and the elementary judgments in a database alongside the scoring date and the staff codes of the persons who scored and approved the loan application. Machine-readable scoring history data is indispensable for evaluating the predictive performance of the expert score: Are materialized loss rates really lower for the predicted good clients versus the marginal clients versus the scoring overrides? Occasional overrides are important opportunities to observe the error rate of the scoring: How many good clients are unnecessarily rejected by the scoring model?

How to Assemble an Expert Scoring Model

Step 4: Back testing and statistical validation

- As an institution builds up the client data history for statistical credit scoring, the structured judgments in an expert score need not be abandoned.
- The expert score may become a powerful explanatory factor within a broad-based statistical credit scoring.
- The expert scoring must only be systematically applied to all loan applications and its component values stored in a database, so that one can mine for predictive correlations using the usual statistical tools such as logistic regression or linear discriminant analysis.

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How to Assemble an Expert Scoring Model

A few more words of wisdom on expert scoring

- Abstraction is the key to success in expert scoring. We see a tendency among practitioners to make scoring factors and level definitions specific to particular client groups, business activities or products. One quickly ends up with a dozen slightly different special purpose scoring models. This invites counterproductive arbitrage between the models: "In Model 2 the loan is rejected but with model 7, I can still get the application through ..."
- Too many scoring models also make statistical validation practically impossible. Hence, we recommend to keep the rating factors relatively abstract, so that they can be interpreted for many different types of clients and business models.
- It is acceptable to carry some special scoring factors through the general model, which will only apply to a subset of applications. Where the question obviously does not apply, one selects "not applicable" and the factor weight for this question is set to zero. This is preferable over creating an entirely separate scoring model, each time one requires a few special questions for a particular product or target market.

Practical Implementation Challenges

- Real-time score calculation: getting the data lined up and coded per the model
- Managing the field staff concerns: getting their buy-in.
- How to compensate for lost production (the good clients rejected)
- Improving loan application data quality
- Better visibility of client prospects and the branch level decision process
- Controlling for client elimination based on eligibility criteria and process filters
- Analyzing the scoring overrides and controlling the alpha and beta errors

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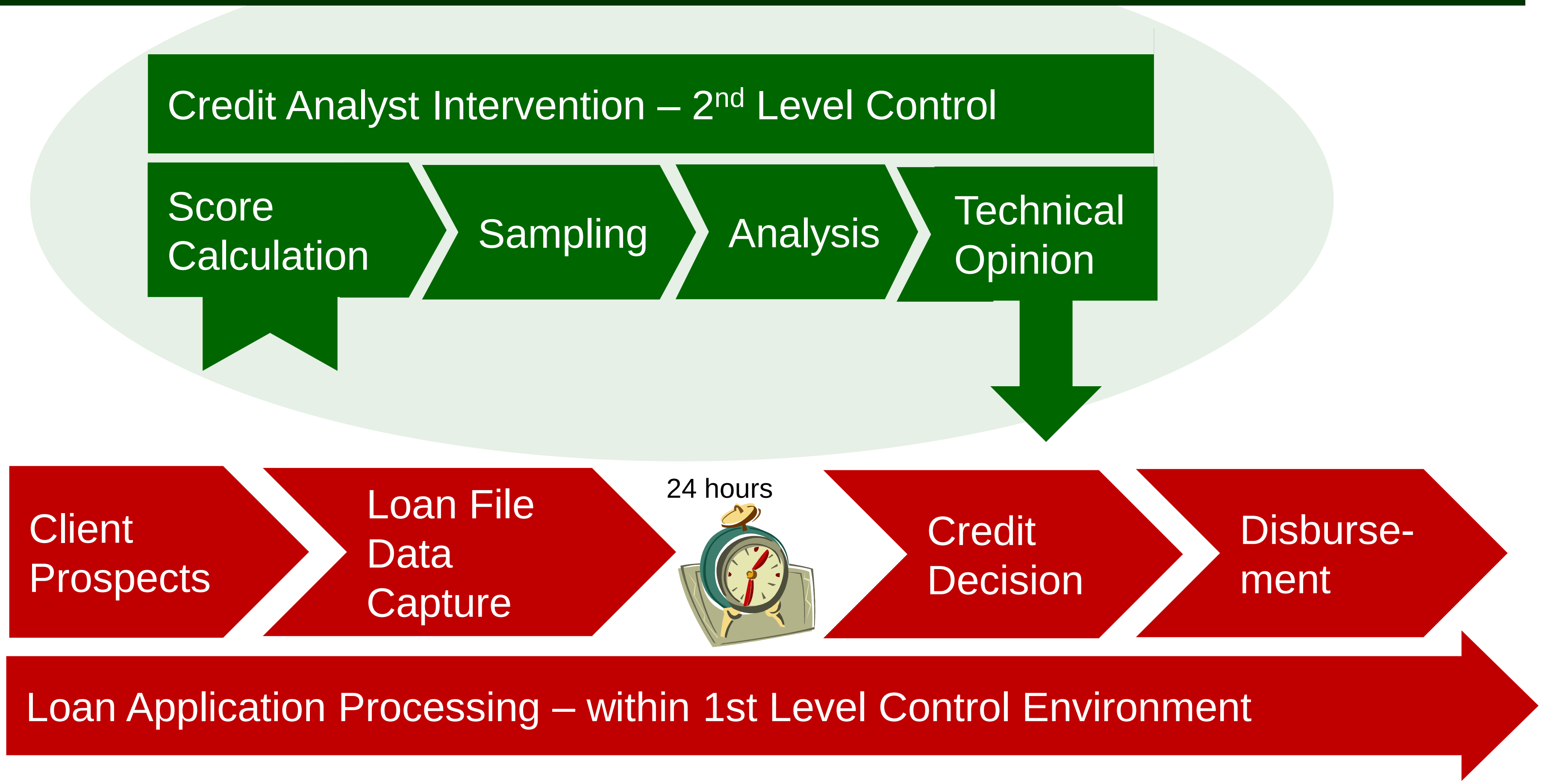
Scoring as a Decision Support Tool in Decentralized High-Volume Lending

Role of Risk Management in Credit Analysis



4 Scoring Implementation

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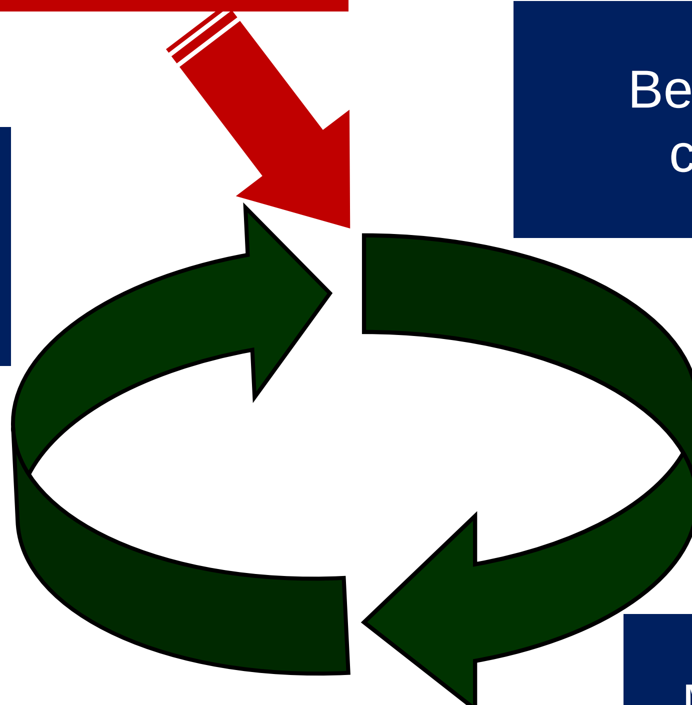
Scoring is a Process not a Project : don't outsource - internalize

Scoring Roll-Out



Better data capture

More predictive model

More visibility of the decision process

New risk factor identification

More consistent credit decisions

Better visibility of the client pipeline

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- www.linked.fs.de