Understanding the Australian D&B Failure Score

THIS DOCUMENT IS INTENDED TO ADDRESS THE FOLLOWING QUESTIONS:

- What is the D&B Failure Score?
- What does the D&B Failure Score predict?
- What is the availability of the D&B Failure Score?
- How is the D&B Failure Score calculated?
- How does the D&B Failure Score perform?
- What is the Relationship between the D&B Failure Score and Failure Rates?

INTRODUCTION

The Australian D&B Failure Score, also known in some markets as the D&B Financial Stress Score (FSS), predicts the likelihood that a business will seek legal relief from its creditors or cease business operations without paying all its creditors in full in the next 12 months based on the information in the Dun & Bradstreet Data Cloud.

To evaluate risks objectively and consistently, Dun & Bradstreet combines a large amount of business information with expert analysis and statistical techniques to determine the risk associated with a business.

The integrity of the information contained in the Dun & Bradstreet Data Cloud is driven by our proprietary DUNSRight™ Quality Process. DUNSRight™ is our process for collecting and enhancing information.

The Australian D&B Failure Score is highly effective in helping to predict the potential solvency of your existing and prospective customers. The solution allows you to:

- Automate decisions for increased efficiency
- Process large volumes of transactions more quickly
- Free up resources to look at time-intensive borderline decisions
- Enable more consistent decisions across the entire organization
- Reduce the costs associated with full-scale application and annual risk reviews
- Apply scores across an entire portfolio to quickly identify risk and opportunity
- Manage collection resources with prioritized actions for delinquent accounts
- Satisfy regulatory needs for timely, consistent and objective review of decisions at the account level

This document explains in greater detail how the Australian Failure Scoring System was developed

AUSTRALIAN D&B FAILURE SCORE

WHAT THE D&B FAILURE SCORE PREDICTS

The D&B Failure Score predicts the likelihood that a business will seek legal relief from its creditors or cease operations leaving unpaid debts in the next 12 months.

Dun & Bradstreet defines a business which seeks legal relief from its creditors or ceases operations without paying all its creditors in full as a Failed Business. The D&B Failure Score predicts the likelihood such Failure.

The legal events which constitute failure in Australia include:

- A business that enters into external administration/liquidation
- A business that involuntarily deregisters

Cases which have experienced one or more of the above events will receive a Raw Score of 0 (Zero) and a Percentile Ranking of 0 (zero).

Note: Voluntary discontinuance involving no loss to creditors is not defined as financially stressed.

AVAILABILITY OF THE FAILURE SCORE

The D&B Failure Score is available on approximately 2,200.000 Australian based businesses. This is known as the Scoreable Universe.

The following are not considered for scoring and are outside of the Scoreable Universe:

- Businesses which are Out of Business
- Foreign Registered Businesses
- Inoperative Entities
- Entities in Strike-Off Action
- Entities in non-scoreable industries

The D&B Failure Score will not be calculated for branches. Automatic trade-up to the headquarter location score will take place for branch locations.

A D&B Failure Score will only be generated where an ACN (Australian Company Number) is present.

SCORE DEVELOPMENT PROCESS

The Failure Scorecards were developed using rigorous statistical techniques for all stages of the modeling process. This ensures that the resulting model is stable and robust. Our process of checks and balances also includes validation of the models on separate samples from different time periods to ensure stability over time. As a result our Standard Scores are suitable for use in regulatory environments such as Basel and Solvency.

In the scorecard development process, data is extracted from two time periods designated as an observation point and a performance window. The observation point defines the sample used in the model and all identification and characteristic data are collected from the time period directly prior to that point. The predictive variables and segmentation are defined from this snapshot. The performance window defines the length of time the businesses in the sample are tracked to examine their behavior.

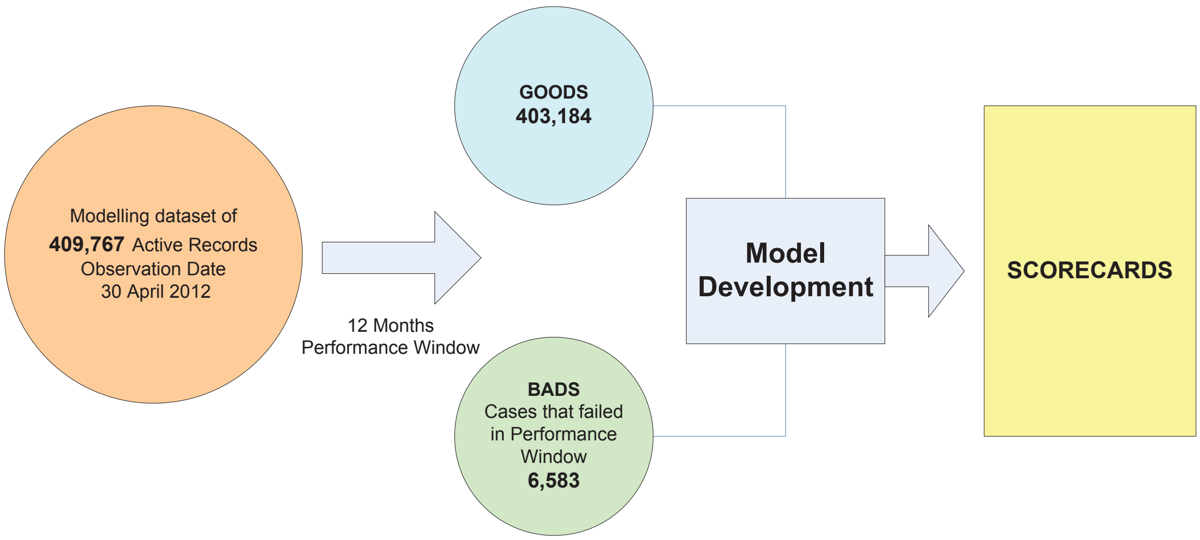
In the development of the Australian D&B Failure Score, the observation point was 30 April 2012 and the performance window was the twelve months from 1st May 2012 to 30th April 2013. A total of 409,767 businesses were used in model development. Of this population, 403,184 were considered “good” or non-financially stressed companies in the Dun & Bradstreet Data Cloud and 6,583 were considered “bad”, or financially stressed companies in the D&B database.

Sample data elements used in the model include:

- Demographic information such as industry size, corporate structure
- Financial information
- Dun & Bradstreet proprietary trade payment behavior information
- Legal events such as collections, liens and judgments

Appendix A contains a more comprehensive list of data elements which are used in calculating the score.

The following diagram shows the scorecard development steps:



Dun & Bradstreet's statistical model development process includes the following steps:

- Segmentation analysis for optimal representation of risk behavior of various sub-populations of the scoreable universe.
- Selection of optimal attributes (predictors) for each segment. The attributes selected by the statistical tool are also verified by the business experts to ensure suitability in the local market conditions.
- Optimal binning techniques to leverage data patterns observed in partition of the predictors
- Scoring algorithm calculation selected by the modeling technique used.

To ensure the model's robustness and stability of predictors, a test and validation approach for model estimation is used.

To ensure stability of the model over time, an additional validation is performed on samples from new time windows as well as on selected large customer portfolios.

The scoring algorithm formula calculates the probability of business failure. This predicted probability is then converted to a score using a scorecard which assigns points to each selected level of each predictor.

SCORING OUTPUTS – SCORE VALUES

The Failure Score assigns the following measurements of risk:

1. **A "Score" of 1001 - 1999** is the initial output (sum of assigned points) where 1001 represents businesses that have the highest probability of failure , and 1999 which represents businesses with the lowest probability of failure . This Score provides a direct relationship between the score and the level of risk. The marginal odds of being good doubles for each 40 point increase. For example, a score of 1200, on a marginal basis, represents twice the risk of Failure as a score of 1240. This score enables a customer to use more granular cutoffs to drive their automated decision-making process.

2. ***A* Percentile Ranking,** where 1 represents businesses that have the highest probability of failure and 100 which represents businesses with the lowest probability of failure. This Ranking shows you where a business falls among businesses in the Dun & Bradstreet Data Cloud, and is most effectively used by customers to rank order their portfolios from highest to lowest risk of business failure.

3. **A "Risk Indicator" of 1 - 4** which is a segmentation of the scorable universe into four distinct risk groups where a one (1) represents businesses that have the lowest probability of failure, and four(4) represents businesses with the highest probability of failure. This Risk Indicator enables a customer to quickly segment their new and existing accounts into various risk groups for high-level analysis and reporting.

SCORECARD PERFORMANCE

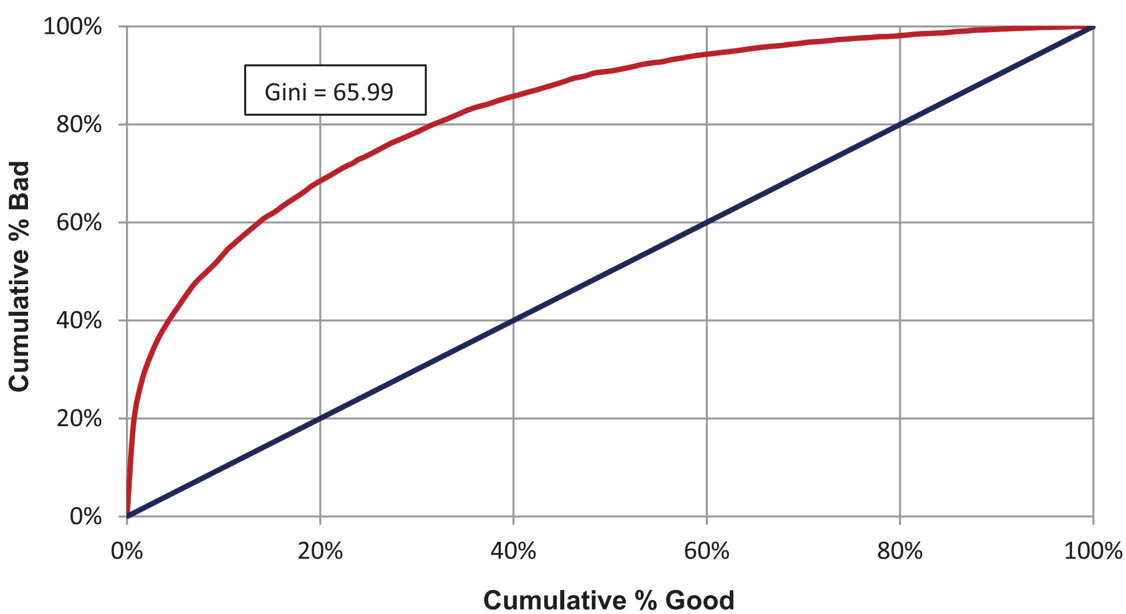
Dun & Bradstreet applies stringent rules to model performance to ensure that our scores meet the best in class performance standards. Measurements of model performance include an assessment of risk ranking, robustness and discriminate power. Metrics used are:

- Ranking accuracy by model, decile or quintile
- Close match between predicted and actual bad rates
- The Kolmogorov-Smirnoff (K-S) statistic distance between cumulated distribution of good and bad cases as rank ordered by the model
- Predictive Index (Gini Index) assessment of model gains compared to a perforce classifier
- The lift Gain chart with emphasis on showing the improvement in capturing Bads at the 10th and 20th scores

One of the typical ways to measure model effectiveness is by examining a trade-off curve. A trade-off curve is a plot of ascending accumulation of "good" businesses vs. "bad" businesses. It is useful for illustrating model performance both at a particular score and across the spectrum of score distribution.

The trade-off curve in Graph 1 illustrates the effectiveness of the Failure Score by identifying the failure captured within population groups. For example, at approximately 20% of the population, the Failure Score scores identified approximately 68% of the "bads". This means that if a business focused on the worst scoring 20% of their portfolio using the Failure Score, they would capture 68% of the "bads" in that group.

Graph 1: Failure Score Performance across All Size Segments



Scorecards are developed assuming that the relationships observed between past business characteristics and subsequent performance will hold true on future businesses. Because of this assumption development statistics should be viewed as estimates and not precise forecasts, of future performance at a given score.

SCORE PERFORMANCE MONITORING

Dun & Bradstreet is committed to delivering the highest quality scores to our Customers. Regular performance monitoring of the scorecards assures continual performance of the scores in identifying risk. Scores that lose their predictive power are scheduled for redevelopment or recalibration.

RELATIONSHIP BETWEEN THE D&B FAILURE SCORE AND PROJECTED FAILURE RATES

The national average failure rate, May 2012 to May 2013 failure statistics within the Dun & Bradstreet Data Cloud, is 1.61%.

Table 2 provides the national average failure rates and cumulative percent of failures identified, based on information in Dun & Bradstreet's database, for each Failure Risk Indicator.

Table 2: National Average Failure Rate by Risk Class (Based on 2008 Failure Statistics the Dun & Bradstreet Data Cloud)

FAILURE RISK CLASS	% OF D&B FILE REPRESENTED	PROJECTED FAILURE RATE WITHIN RISK INDICATOR	PROJECTED CUMULATIVE % OF FAILURES ELIMINATED
1	13%	0.11%	99.09%
2	62%	0.67%	72.93%
3	24%	3.62%	19.35%
4	1%	30.93%	0.00%

Each Failure Risk Indicator has a failure rate that can be compared with the national average of Failure. For example, the table above shows that 30.93% of all businesses scoring 4 failed. What this means is that businesses scoring in the Failure Risk Class of 4 are approximately 19 times more likely to fail than the national average. Similarly, businesses with a Risk Indicator of 1 are 14 times less likely to fail than the national average.

Table 3 provides the national average failure rates, based on information in the Dun & Bradstreet Data Cloud, by major industry group.

Table 3: National Average Failure Rate by Industry

MAJOR INDUSTRY GROUP	PROJECTED FAILURE RATE
Agriculture, Forestry, Fishing	0.88%
Mining	0.22%
Construction	1.55%
Manufacturing	1.09%
Transportation, Communications	1.41%
Wholesale Trade	1.21%
Retail Trade	1.71%
Finance, Insurance, Real Estate	1.15%
Services	1.21%

APPENDIX A

LIST OF DATA ELEMENTS USED IN THE FAILURE SCORING MODEL

Following is a list of some of the data elements used in the Failure Scoring Model:

Demographic/Public Records Information

FACTOR
Number of Employees
Geographic Location
Entity Age

Director Information

FACTOR
Number of Directors
Director Court Actions
Tenure of Directors

Financial Information

FACTOR
Quick Ratio

Payment Information

FACTOR
Number of Satisfactory Payment Experiences
Maximum Percentage of Overdue Payments
Average Percentage of Overdue Payments

APPENDIX B

The following Summary and Detailed Projected Performance Tables are based on the Country database. Actual performance for a customer portfolio may vary based on the account selection within that portfolio.

SUMMARY PROJECTED PERFORMANCE TABLES

Cumulative Failure Score Performance						
RISK CLASS	SCORE RANGE	PERCENTILE RANGE	% OF BUSINESSES	FAILURE RATE	% OF FAILURES ELIMINATED	GOOD-BAD RATIO
1	1501 - 1999	88 - 100	13%	0.11%	99.09%	876
2	1361 - 1999	26 - 100	75%	0.58%	72.93%	171
3	1232 - 1999	2 - 100	99%	1.31%	19.35%	75
4	1001 - 1999	1 - 100	100%	1.61%	0.00%	61

Failure Score Performance Within Range				
SCORE RANGE	PERCENTILE RANGE (APPROX)	% WITHIN RANGE (APPROX)	FAILURE RATE	% OF FAILURES IDENTIFIED
1501 - 1999	88 - 100	13%	0.11%	0.91%
1361 - 1500	26 - 87	62%	0.67%	26.16%
1232 - 1360	2 - 25	24%	3.62%	53.58%
1001 - 1231	1 - 1	1%	30.93%	19.35%

EXPLANATIONS

CUMULATIVE FAILURE SCORE PERFORMANCE:

- **% of Businesses:** To set an approval rate, select the appropriate score range that yields the desired approval rate. For example, to develop a credit policy that approves a projected 99% of all customers requires accepting businesses scoring at or above 1232 (or 2-100 percentiles). Businesses scoring below the cutoff score (1001 - 1231) are reviewed, declined, etc.

- **Failure Rate:** The failure rate represents those businesses that score between the lowest value in the score range (or score) and 1999 (or 100 percentile). For example, the failure rate for a credit policy which approves all businesses with a score at or above 1232 (or 2-100 percentile) is expected to be 1.31%.

- **% of Failures Eliminated:** The percentage of total failed businesses that score between 1,001 and the cutoff point for the approval rate. For example, approving businesses with a score at or above 1232 (or 2 - 100 percentiles) is expected to eliminate 19.35% of "bad" businesses.

- **Good-Bad Ratio (Odds):** The ratio of "Good" businesses to "Bad" businesses among those businesses that score between the lowest value in the score range and 1999 (or 100 percentile). For example, a credit policy that approves all businesses scoring at or above 1232 (or 2 - 100 percentiles) should result in a portfolio with 75 "Good" businesses for every "Bad" business in the portfolio.

FAILURE SCORE PERFORMANCE WITHIN RANGE:

- **Failure Rate within Range:** The failure rate for those businesses that score within the score range. For example, the failure rate for businesses scoring between 1001 - 1231 (or 1 - 1 percentile) is expected to be 30.93%.

- **% Of Failures Identified:** The percentage of total failed businesses within the score range. For example, 19.35% of failed businesses are expected to score between 1001 - 1231 (or 1 - 1 percentile).

DETAILED PROJECTED PERFORMANCE TABLE

Cumulative Failure Score Performance						Failure Score Performance Within Range			
SCORE RANGE	PERCENTILE RANGE	% OF BUSINESSES	FAILURE RATE	% OF FAILURES ELIMINATED	GOOD-BAD RATIO	SCORE RANGE	PERCENTILE RANGE (APPROX)	FAILURE RATE	% OF FAILURES IDENTIFIED
1532 - 1999	96 - 100	5%	0.07%	99.79%	1473	1532 - 1739	96 - 100	0.07%	0.21%
1508 - 1999	91 - 100	10%	0.09%	99.42%	1072	1508 - 1531	91 - 95	0.12%	0.36%
1491 - 1999	86 - 100	15%	0.13%	98.75%	747	1491 - 1507	86 - 90	0.21%	0.67%
1481 - 1999	81 - 100	20%	0.15%	98.09%	653	1481 - 1490	81 - 85	0.21%	0.67%
1470 - 1999	76 - 100	25%	0.16%	97.45%	614	1470 - 1480	76 - 80	0.20%	0.64%
1459 - 1999	71 - 100	30%	0.19%	96.49%	532	1459 - 1469	71 - 75	0.32%	0.96%
1451 - 1999	66 - 100	35%	0.21%	95.37%	469	1451 - 1458	66 - 70	0.37%	1.12%
1441 - 1999	61 - 100	40%	0.24%	94.14%	421	1441 - 1450	61 - 65	0.42%	1.23%
1430 - 1999	56 - 100	45%	0.27%	92.53%	373	1430 - 1440	56 - 60	0.49%	1.61%
1417 - 1999	51 - 100	50%	0.30%	90.72%	334	1417 - 1429	51 - 55	0.58%	1.81%
1404 - 1999	46 - 100	55%	0.34%	88.41%	294	1404 - 1416	46 - 50	0.75%	2.31%
1391 - 1999	41 - 100	60%	0.39%	85.42%	255	1391 - 1403	41 - 45	0.93%	2.99%
1381 - 1999	36 - 100	65%	0.44%	82.42%	228	1381 - 1390	36 - 40	1.05%	2.99%
1370 - 1999	31 - 100	70%	0.50%	78.13%	197	1370 - 1380	31 - 35	1.35%	4.30%
1361 - 1999	26 - 100	75%	0.58%	72.93%	172	1361 - 1369	26 - 30	1.52%	5.20%
1351 - 1999	21 - 100	80%	0.65%	67.52%	153	1351 - 1360	21 - 25	1.77%	5.41%
1341 - 1999	16 - 100	85%	0.74%	61.01%	135	1341 - 1350	16 - 20	2.19%	6.52%
1328 - 1999	11 - 100	90%	0.86%	52.10%	116	1328 - 1340	11 - 15	2.82%	8.90%
1302 - 1999	6 - 100	95%	1.01%	40.13%	98	1302 - 1327	6 - 10	3.81%	11.97%
1001 - 1999	1 - 100	100%	1.61%	0.00%	61	1001 - 1301	1 - 5	12.96%	40.13%

EXPLANATIONS

CUMULATIVE FAILURE SCORE PERFORMANCE:

- **Approval Rate:** To use, select the appropriate projected score or score cutoff that yields the desired approval rate. Approved businesses are companies scoring between the lowest value in the score range (or percentile) and 1999 (or 100 percentile). For example, a credit policy that approves 70% of all businesses requires accepting businesses between 1370 and 1999 (or 31 - 100 percentiles). Businesses scoring below the cutoff (1001 - 1369) are reviewed, declined, etc.

- **Failure Rate:** Represents those businesses that score between the lowest value in the score range and 1999. For example, the failure rate for a credit policy which approves all businesses with a score at or above 1370 (or 31 - 100 percentiles) is expected to be 0.50%.

- **% of Failures Eliminated:** The percentage of total failed businesses that score between 1001 and the cutoff point for the approval rate. For example, approving businesses with a score at or above 1370 (31 - 100 percentiles) is expected to eliminate 78.13% of the "bad" businesses.

- **Good-Bad Ratio (Odds):** The ratio of "Good" businesses to "Bad" businesses among those businesses that score between the lowest value in the score range and 1999 (or 100 score). For example, a credit policy which approves all businesses scoring at or above 1370 (or 31 - 100 percentiles) should result in a portfolio with 197 "Good" businesses for every "Bad" business in the portfolio.

FAILURE SCORE PERFORMANCE WITHIN RANGE:

- **Failure Rate:** The incidence of failure for those businesses that score within the score range. For example, the failure rate for companies scoring between 1361 and 1369 (or 26 - 30 percentiles) is expected to be 1.52%.

- **% Of Failures Identified:** The percentage of total failed businesses within the score range. For example, 5.2% of all failed companies are expected to score between 1361 and 1369 (or 26 - 30 percentiles).

APPENDIX C

GLOSSARY OF SCORING TERMS

TERM	EXPLANATION
D&B Financial Stress Score	D&B Standard Risk Score predicting likelihood of Failure and/or financial distress, also known as the D&B Failure Score
D&B Failure Score	D&B Standard Risk Score predicting likelihood of Failure and/or financial distress, also known as the D&B Financial Stress
Raw Score	Score with a direct relationship to Probability of Default (Failure). The Failure (FSS) form of the raw score is a 4 digit score
1-100 Score	Lesser granularity of the Failure Score: Value between 1 and 100 where 1 is the highest probability of default (failure)
Percentile Ranking	A ranking of the database where 1 is assigned to the highest risk 1% of a scoring universe and 2 is assigned to the next highest risk 1% of a scoring universe. 100 is assigned to the lowest risk 1% of a scoring universe.
Risk Class	Lowest granularity of Failure Score used in some markets (NA/Asia/AU/NZ); Segmentation of the Failure Score (FSS) into 5 risk segments where 1 is lowest probability of default (failure)
Risk Indicator	Lowest granularity of Failure Score used in EU markets; Segmentation of the Failure Score (FSS) into 4 risk segments, where 1 is lowest probability of risk
Scorable Universe	All cases which have a score assigned
Scored Universe	Period where the data sample is monitored to classify businesses as GOOD and BAD
Observation Point	Date, at which the data sample of active businesses is extracted and data elements observed at that point evaluated as potential predictors
Performance Window	Period where the data sample is monitored to classify businesses as GOOD and BAD
Financial Stress BAD definition	List of Legal Events that define targeted risk behavior
BAD	A business which meets the Bad definition
GOOD	A Business which does not have any information listed within the BAD definition
Out of Business	Business is no longer trading

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ABOUT DUN & BRADSTREET

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