Module 1 assignment: AI solution implementation

Introduction

This report outlines the proposed implementation of an AI-based solution for a small fintech consulting start-up. Their business model is to identify potentially successful start-ups, and then help them build their financial models and progress through successful fundraising rounds.

The problem to be addressed is the prediction of start-up growth and successful future acquisition to improve targeting of suitable customers (Dellermann et al., 2021; Potanin et al., 2023). By improving customer acquisition and resource allocation, such an approach could greatly increase return-on-investment for the company and allow it to provide its services at lower costs.

Development framework

Development of the proposed solution followed the Cross-Industry Standard Process for Data-Mining (CRISP-DM) framework, the *de facto* standard for developing and deploying data-mining projects (Schröer et al., 2021). The standard includes 6 stages, addressed as outlined below:

1. Business understanding – the company needs an accurate method to predict start-up success, as this will determine whether the time invested in helping them grow will lead to future returns. The model itself can be also used as a selling point to attract customers (Buchanan, 2019), potentially providing a competitive advantage on many levels.

2. Data understanding – the next stage involves identifying and exploring a suitable dataset containing data relevant to the business case and modelling problem. This includes developing an understanding of each attribute (i.e. variable or column) in the data and of relationships between them, and general descriptive analyses. Ideally, the dataset would be collated for purpose and using proprietary data (Bessen et al., 2022), but for this illustration a publicly-available dataset will be used.

3. Data preparation – after exploratory data analysis, relevant variables will be selected to train the prediction model, along with any transformations required to extract useful information from the data available (a process known as feature engineering; Duboue, 2020)
4. Modelling – using the resulting dataset, a number of different candidate models will be developed and fine-tuned in order to identify the optimal underlying parameters to be used each model (i.e. hyperparameter tuning; Russel and Norvig, 2021).

5. Evaluation – the performance of the resulting models will then be described and compared using a range of metrics; this includes developing an understanding of errors made by the model, and if possible of how predictions are made.

6. Deployment – the development process terminates with deployment of the model within existing workflows. This requires a thoughtful implementation and maintenance strategies, including building streamlined user interfaces, integration of real-time data feeds, user training and support, and monitoring of model performance.

For the purpose of this report, the free software WEKA (Waikato Environment for Knowledge Analysis, v3.8.6) will be used for a preliminary demonstration of the possibilities of the proposed solution (Frank et al., 2016). WEKA allows the development of machine learning (ML) models with a point-and-click approach (running on a Java backend), which facilitates early development and exploration (Bell, 2020).

Data source description, exploratory data analysis, and feature engineering

A publicly-, freely-available Kaggle dataset was used for this use-case. The dataset ("Startup Success Prediction") contains information on 923 real-world US-based start-ups, and can be accessed at https://www.kaggle.com/datasets/manishkc06/startup-success-prediction/data.

This dataset was chosen as it includes information on a reasonably large number of companies, including 49 attributes relating to location, sector, and previous funding rounds and milestones, as well as a variable for "status" (acquired or closed) which can be readily used as target class for prediction (Figure S1).

The data included 4 identifier attributes, 12 attributes associated with geographical location, 12 associated with business sector, 18 for fundraising and milestones, and 3 for outcome (i.e. acquired or closed) (Table 1). Companies included were located across 221 distinct US cities and 35 states, founded between 1984 and 2013, and with funding rounds and outcomes collected from 2001 to 2013 (Table 1).

After exploratory data analysis, 32 attributes were identified as potentially relevant and selected for modelling, after excluding of repetitive or highly-correlated attributes (based on their description, e.g. coordinates and city) and focusing on aggregated attributes where relevant (e.g. focusing on state-level location, and with one-hot encoding for particular states; Figure S2). Of note, many of the attributes included in the raw data were duplicates from one another (e.g. several copies of company identifier, or different expressions of geographical location), one-hot encoded attributes for particular US states or business sectors, or computed attributes (e.g. age of company at first successful funding round or milestone, based on founding and first funding dates). The selected attributes were further investigated visually to exclude the possibility of co-linearity (data not shown). Data transformations were applied as required in order to convert attributes to the correct data type (e.g. numeric to nominal for outcome labels), as outlined in Table 1. Distributions were assessed visually for numerical attributes (Figures S3-S10), after which an additional mathematical transformation was applied to log-transform total amount of funding received (Figure S10). The dataset was provided without any missing values, i.e. all cells have a value except for cases where one should not exist (e.g. date of closure for companies that did not close).

Target class imbalance was found, with most companies observed to achieve success (i.e. acquisition; 597/923 or 64.7%). Class rebalancing was undertaken using Synthetic Minority Oversampling Technique (SMOTE), which yielded a new total number of instances of 1249 (652 fails, 597 successes).

Problem conceptualisation and identification of candidate algorithms

The solution under development represents a classification problem (i.e. predicting a binary label) for a known label (the success label), and can therefore be tackled using supervised ML approaches. While other ML paradigms could be considered (e.g. unsupervised ML with clustering to identify companies which stand out from others in some dimension), the availability of a well-coded target variable of interest for all observations renders supervised ML a more useful and interpretable framework.

Myriad candidate algorithms could be selected for assessment. For this proof-of-concept, commonly-used and well-established algorithms were chosen to keep the proposed solution streamlined and focused on the potential capabilities of ML in this scenario, rather than the technical or computational aspects required for an industry-grade solution. The algorithms chosen were:

1) logistic regression (LR);
2) naïve Bayes (NB);
3) decision tree (DT);
4) random forests (RF);
5) k-nearest neighbours (KNN); and
6) support vector machines (SVM).

All of these are standard supervised ML algorithms, representing a range of fundamentally distinct mathematical classification approaches, therefore multiplying the likelihood of identifying an algorithm with adequate performance. The models selected also include highly-explainable and relatively simples modes (e.g. LR, DT, NB) and more complex ones (RF, KNN, SVM).

Performance evaluation

Model performance was evaluated with three aims: 1) identify the optimal hyperparameter settings for each model, 2) compare model performance across different models, 3) estimate the generalisation accuracy of the selected model on unseen data (Raschka, 2018).

Model performance was assessed via 10-fold cross-validation (Russel and Norvig, 2021). Alternative methods such as holdout and bootstrapping could also be used. However, cross validation is better suited for small-to-medium datasets than holdout, and is less computationally intensive than bootstrapping (Raschka, 2018; Russel and Norvig, 2021). A fold number of 10 was chosen as this is considered the standard approach when using cross-validation, and is supported by empirical evidence (Raschka, 2018; Russel and Norvig, 2021).

For the purpose of hyperparameter tuning, model performance was estimated before class rebalancing. Once optimal hyperparameter settings were identified for each model, the impact of class imbalance was estimated by comparing model performance before and after class rebalancing.

Multiple metrics may be used to assess model performance. In the interest of simplicity, the following commonly-used metrics were chosen: accuracy, recall, precision, F1-score and area-under-the-Receiver-Operator-Curve (AUROC). However, other metrics have been suggested (Foody, 2023). For hyperparameter tuning, accuracy, F1-score, and AUROC were used as they provide more holistic measures of model performance (vs precision/recall), with accuracy prioritised for hyperparameter selection as a more simple and interpretable metric (F1-sore and AUROC used as complements).

Tables 2-5 show the hyperparameter tuning steps applied to each model (excluding logistic regression and naïve Bayes, as hyperparameter tuning does not apply to these). For DTs, model accuracy was improved from a baseline of 72.3% to 76.1% by lowering the confidence factor for tree pruning from 0.25 to 0.05, and increasing the minimum number of objects per leaf from 2 to 10. For RFs, none of the alternative settings improved default model accuracy (79.3%). For KNN, model accuracy improved from 61.8% to 67.5% by increasing the number of neighbours from 1 to either 7 or 10, with the later yielding higher F1-score and AUROC. For SVM, model accuracy was improved from 74.5% to 74.9% by allowing construction of calibration models and increasing the complexity parameter from 1 to 2. Of note, prioritising a different performance metric could lead to selection of different hyperparameter settings, but leading to small differences in performance.

Table 7 depicts a comparative assessment of model performance across all candidate models using the best performing hypeparameter setting in each, both before and after class rebalancing. Figures S11-S21 show WEKA screenshots for the underlying performance evaluation and attribute weighting/selection outputs. Baseline accuracy for this assessment was 64.7% and 52.2% before and after class rebalancing. RFs were the most accurate model in both settings (79.3% and 82.1% accuracy, respectively), outperforming other models across all metrics. Of note, precision, recall, and F1-score for the target class (1, i.e. success) were higher before class rebalancing. The next best performing algorithms were SVMs (74.9% and 79.7% accuracy) and LR (74.0% and 79.6%). Analysis of RF attribute importance suggests the most informative attributes were those related to total amount of funding, number of milestones and relationships established, and company age at different milestones, with location and sector having less importance (Figure S18). Interestingly, relationship number was also the attribute used in the first DT node (Figure S16) and the one with the highest weight in SVM (Figure S21), but the relative importance of each attribute varied widely across models. Of note, performance varied more widely across different models than with alternative hyperparameter tuning settings within each model.

Table 7 shows the resulting RF confusion matrices. After class rebalance, the model correctly predicts company success in 82.1%, with a false-positive rate of 10.4% (i.e. companies predicted to succeed, but which fail), and a false-negative rate of 7.5% (companies predicted to fail, but which succeed). In this business context, this would translate into a precision for success predictions of 79.5%, meaning that on average 1 out of 5 companies approached as considered potentially successful in the future would represent failed investments. This compares with 64.7% if no classification model was employed (i.e. baseline model precision for class 1). Although imperfect, a similar approach could be used to target customer acquisition efforts to more suitable companies, potentially leading to important improvements in resource allocation and return-on-investment.

Solution deployment and limitations

Successful deployment of this solution would require integrating the model into user-friendly applications to be used by company employees without direct input from ML programmers/engineers (by developing bespoke programming code, or using API interfaces to connect to WEKA or other off-the-shelf modelling solutions). This could include the possibility of filtering for companies at specific stages or in specific sectors, with the best possible accuracy presented after retraining of candidate models in each specific data split. Deployment should also allow integration of real or near real-time data feeds given the highly dynamic nature of this sector. Finally, continuous model performance monitoring should be undertaken to account for the impact of changes in the external landscape on likely customer success, namely new regulation, legislation, fundraising environment, or market trends.

Some limitations should be discussed. First, the dataset used only provides a proof-of-concept as it is focused on US companies only, is not recent, and included very limited information on how it was assembled or the expected meaning of some attributes. Deployment of this solution would first require collecting relevant data and developing a model trained on that data, which can be achieved via web-scraping from open online sources (and eventually collection of proprietary data). The data used had high class imbalanced, and skewed towards the class of interest, but this was addressed by applying SMOTE to the underlying data and comparing model performance before and after (leading to accuracy improvements of approximately 1-5%).

Second, model accuracy could have been further improved by more extensive or targeted data collection, and more detailed or exhaustive exploratory data analysis and feature engineering techniques (including formal assessments of collinearity, and further attribute selection refinement). However, this means that the accuracy found here is an underestimation rather than overestimation of the maximum possible model performance. Likewise, other more advanced ML models could also have been employed, such as artificial neural networks, but these were outside the scope of this proof-of-concept.

Conclusion

This proof-of-concept exercise outlined the steps required for successful development and deployment of an AI-based solution for classification within a business context. The model trained using publicly-available data yielded high accuracy for predicting future start-up success, highlighting the potential added value for company returns if a similar solution were developed using bespoke data collection procedures, further refined with more advanced feature engineer and modelling techniques, and successfully integrated within existing business workflows.

Tables and figures

Table 1 – Dataset structure and descriptive summary

Attribute name	Description	Attribute group	Retain in model	Summary statistics (for variables retained in the model)	Transformations applied (for variables retained in the model)
unnamed: 0	Unique identifier	Identifier			
state_code	US state code	Location		Number of distinct: 35	
latitude	Latitude	Location			
longitude	Longitude	Location			
zip_code	ZIP code	Location			
id	Unknown	Identifier			
city	City	Location		Number of distinct: 221	
unnamed: 6	City + ZIP code	Location			
name	Company name	Identifier			
labels	0-1 label (based on *status*)	Outcome	Yes	0: 326 (35.3%) 1: 597 (64.7%)	Numeric to nominal
founded_at	Date company founded	Fundraising/ milestones		Minimum: 01/01/1984 Maximum: 16/04/2013	
closed_at	Date company closed	Outcome		Minimum: 01/01/2001 Maximum: 30/10/2013	
first_funding_at	Date of first funding round	Fundraising/ milestones		Minimum: 01/01/2000 Maximum: 20/11/2013	
last_funding_at	Date of last funding round	Fundraising/ milestones		Minimum: 01/01/2001 Maximum: 20/11/2013	
age_first_funding_at	Age of company at first funding round (calculated from founding date)	Fundraising/ milestones	Yes	Minimum: -9.047 Maximum: 21.896 Mean: 2.236 SD: 2.51	Nominal to numeric
age_last_funding_at	Age of company at last funding round (calculated from founding date)	Fundraising/ milestones	Yes	Minimum: -9.047 Maximum: 21.896 Mean: 3.931 SD: 2.968	
age_first_milestone_year	Age of company at first milestone (calculated from founding date); NB definition of milestones is unknown	Fundraising/ milestones	Yes	Minimum: -14.17 Maximum: 24.685 Mean: 3.055 SD: 2.977	

Attribute name	Description	Attribute group	Retain in model	Summary statistics (for variables retained in the model)	Transformations applied (for variables retained in the model)
age_last_milestone_year	Age of company at last milestone (calculated from founding date); NB definition of milestones is unknown	Fundraising/ milestones	Yes	Minimum: -7.005 Maximum: 24.685 Mean: 4.754 SD: 3.212	
relationships	Number of relationships established with other businesses/investors	Fundraising/ milestones	Yes	Minimum: 0 Maximum: 63 Mean: 7.71 SD: 7.266	
funding_rounds	Number of funding rounds undertaken	Fundraising/ milestones	Yes	Minimum: 1 Maximum: 10 Mean: 2.311 SD: 1.391	Ordinal to numeric
funding_total_usd	Total funding secured (in USD)	Fundraising/ milestones	Yes	Minimum: 11,000 Maximum: 5,700,000,000 Mean: 25,419,749.092 SD: 189,634,364.489	Log transformed
milestones	Number of milestones achieved (NB definition of milestones is unknown)	Fundraising/ milestones	Yes	Minimum: 0 Maximum: 8 Mean: 1.842 SD: 1.323	
state_code.1	Repeat from state_code	Location			
is_CA	One-hot encoding for location in California	Location	Yes	1: 487 (52.8%)	Numeric to nominal
is_NY	One-hot encoding for location in New York	Location	Yes	1: 106 (11.5%)	Numeric to nominal
is_MA	One-hot encoding for location in Massachusetts	Location	Yes	1: 83 (9.0%)	Numeric to nominal
is_TX	One-hot encoding for location in Texas	Location	Yes	1: 42 (4.6%)	Numeric to nominal
is_otherstate	One-hot encoding for location in other states	Location	Yes	1: 204 (22.1%)	Numeric to nominal
category_code	Sector category	Sector			
is_software	One-hot encoding for software sector	Sector	Yes	1: 153 (16.6%)	Numeric to nominal
is_web	One-hot encoding for web sector	Sector	Yes	1: 144 (15.6%)	Numeric to nominal
is_mobile	One-hot encoding for mobile sector	Sector	Yes	1: 79 (8.6%)	Numeric to nominal

Attribute name	Description	Attribute group	Retain in model	Summary statistics (for variables retained in the model)	Transformations applied (for variables retained in the model)
is_enterprise	One-hot encoding for enterprise sector	Sector	Yes	1: 73 (7.9%)	Numeric to nominal
is_advertising	One-hot encoding for advertising sector	Sector	Yes	1: 62 (6.7%)	Numeric to nominal
is_gamesvideo	One-hot encoding for videogames sector	Sector	Yes	1: 52 (5.6%)	Numeric to nominal
is_ecommerce	One-hot encoding for e-commerce sector	Sector	Yes	1: 25 (2.7%)	Numeric to nominal
is_biotech	One-hot encoding for biotech sector	Sector	Yes	1: 34 (3.7%)	Numeric to nominal
is_consulting	One-hot encoding for consulting sector	Sector	Yes	1: 3 (0.3%)	Numeric to nominal
is_othercategory	One-hot encoding for other sectors	Sector	Yes	1: 298 (32.3%)	Numeric to nominal
object_id	Repeat from *id*	Identifier			
has_VC	One-hot encoding for VC funding	Fundraising/ milestones	Yes	1: 301 (32.6%)	Numeric to nominal
has_angel	One-hot encoding for angel funding	Fundraising/ milestones	Yes	1: 235 (25.5%)	Numeric to nominal
has_roundA	One-hot encoding for round A funding	Fundraising/ milestones	Yes	1: 469 (50.8%)	Numeric to nominal
has_roundB	One-hot encoding for round B funding	Fundraising/ milestones	Yes	1: 362 (39.2%)	Numeric to nominal
has_roundC	One-hot encoding for round C funding	Fundraising/ milestones	Yes	1: 215 (23.3%)	Numeric to nominal
has_roundD	One-hot encoding for round D funding	Fundraising/ milestones	Yes	1: 92 (10.0%)	Numeric to nominal
avg_participants	Average number of participating investors in each funding round	Fundraising/ milestones	Yes	Min: 1 Max: 16 Mean: 2.839 SD: 1.875	
is_top500	Is it a Top 500 company?	Sector	Yes	1: 747 (80.95)	Numeric to nominal
status	Current status (source for *label* and based on *closed_at*)	Outcome			

Table 2 – Decision tree hyperparameter tuning (before SMOTE)

Hyperparameter	Hyperparameter specification	Accuracy (%)	F-score (weighted average)	AUROC
Default model	Default model	72.3	0.715	0.675
Confidence factor	0.10	74.5	0.734	0.711
	0.05*	76.0	0.746	0.726
	0.01	75.8	0.750	0.725
Minimum number of objects per leaf	5	75.0	0.740	0.727
	10*	76.1	0.748	0.730
	15	74.8	0.736	0.735
	20	75.6	0.743	0.746
	30	75.8	0.745	0.744
Reduced error pruning	Yes	75.0	0.739	0.712

Legend: Tuning performed sequentially using the best specification identified for each hyperparameter. Asterisks identify altered hyperparameters versus the default model, and the specification chosen. Cells highlighted in bold show the maximum across each performance metric. Default model specifications are as follows: confidence factor 0.25, minimum number of objects 2, no reduced-error pruning. AUROC – Area-under-the-Receiver-Operator-Curve; SMOTE - Synthetic Minority Oversampling Technique

Table 3 – Random forest hyperparameter tuning (before SMOTE)

Hyperparameter	Hyperparameter specification	Accuracy (%)	F-score (weighted average)	AUROC
Default model	Default model	79.3	0.785	0.820
Break ties randomly	Yes	78.5	0.777	0.816
Maximum tree depth	2	75.5	0.720	0.814
	5	78.8	0.783	0.827
	100	78.5	0.777	0.816
	200	78.6	0.777	0.816
	500	78.6	0.777	0.816
Number of randomly chosen attributes	1	77.1	0.771	0.797
	10	78.6	0.777	0.817
	30	77.9	0.769	0.807
Number of random trees in forest	50	78.2	0.775	0.820
	200	78.7	0.778	0.823

Legend: No alternative hyperparameter configurations were selected. Cells highlighted in green show the maximum across each performance metric. Default model specifications are as follows: ties not broken randomly, unlimited maximum tree depth, 0 randomly chosen attributes, 100 random trees. AUROC – Area-under-the-Receiver-Operator-Curve; SMOTE - Synthetic Minority Oversampling Technique

Table 4 – k-nearest neighbours hyperparameter tuning (before SMOTE)

Hyperparameter	Hyperparameter specification	Accuracy (%)	F-score (weighted average)	AUROC
Default model	Default model	61.8	0.612	0.581
Number of neighbours (k)	2	56.3	0.573	0.596
	3	62.9	0.605	0.586
	4	59.8	0.599	0.599
	5	66.5	0.630	0.605
	6	65.5	0.640	0.613
	7	67.5	0.638	0.610
	8	66.2	0.640	0.618
	9	67.2	0.672	0.627
	10*	67.5	0.648	0.631
	15	67.0	0.621	0.649
Distance weighting	1/distance	66.5	0.631	0.631
	1-distance	67.0	0.629	0.631

Legend: Tuning performed sequentially using the best specification identified for each hyperparameter. Asterisks identify altered hyperparameters versus the default model, and the specification chosen. Cells highlighted in bold show the maximum across each performance metric. Default model specifications are as follows: 1 neighbour, no distance weighting. AUROC – Area-under-the-Receiver-Operator-Curve; SMOTE - Synthetic Minority Oversampling Technique

Table 5 – Support vector machine hyperparameter tuning (before SMOTE)

Hyperparameter	Hyperparameter specification	Accuracy (%)	F-score (weighted average)	AUROC
Default model	Default model	74.5	0.733	0.689
Build calibration models	Yes*	74.6	0.738	0.785
Complexity parameter	2*	74.9	0.741	0.786
	3	74.2	0.735	0.788
	5	74.1	0.735	0.788
Training data filter	Standardise	74.1	0.735	0.785
	No normalisation/ standardisation	74.1	0.735	0.786
Kernel used	Normalised polykernel	73.2	0.718	0.777
	Puk	66.7	0.666	0.683
	RBF	70.7	0.680	0.757

Legend: Tuning performed sequentially using the best specification identified for each hyperparameter. Asterisks identify altered hyperparameters versus the default model, and the specification chosen. Cells highlighted in green show the maximum across each performance metric. Default model specifications are as follows: no calibration models built, complexity parameter 1.0, training data normalised, polykernel. AUROC – Area-under-the-Receiver-Operator-Curve; SMOTE - Synthetic Minority Oversampling Technique

Table 6 – Comparative summary of performance metrics across candidate algorithms

Algorithm	SMOTE	Accuracy (%)	Precision		Recall		F1-score		AUROC
			Target class (1)	Weighted average	Target class (1)	Weighted average	Target class (1)	Weighted average	
Baseline accuracy *(rules.ZeroR)*	No	64.7	0.647	N/A	1.00	0.647	N/A	0.786	0.495
	Yes	52.2	N/A	N/A	0	0.522	N/A	N/A	0.497
Logistic regression *(functions.logistic)*	No	74.0	0.773	0.773	0.846	0.740	0.808	0.734	0.786
	Yes	79.6	0.761	0.799	0.836	0.796	0.796	0.796	0.889
Naïve Bayes *(bayes.NaiveBayes)*	No	72.7	0.795	0.729	0.779	0.727	0.787	0.728	0.790
	Yes	74.5	0.732	0.745	0.745	0.745	0.733	0.745	0.824
Decision tree *(trees.J48)*	No	76.1	0.770	0.756	0.898	0.761	0.829	0.748	0.730
	Yes	77.1	0.754	0.771	0.774	0.771	0.764	0.771	0.789
Random Forest *(trees.RandomForest)*	No	79.3	0.801	0.791	0.905	0.793	0.850	0.785	0.820
	Yes	82.1	0.795	0.822	0.843	0.821	0.818	0.821	0.899
K-Nearest Neighbours *(lazy.IBk)*	No	67.5	0.701	0.655	0.866	0.675	0.775	0.648	0.631
	Yes	71.2	0.736	0.715	0.620	0.712	0.673	0.709	0.804
Support Vector Machine *(functions.SMO)*	No	74.9	0.774	0.742	0.863	0.749	0.816	0.741	0.786
	Yes	79.7	0.771	0.798	0.817	0.797	0.793	0.797	0.890

Legend: The WEKA model implementation used to run each algorithm is outlined in italic. The target class (label 1) represents successful acquisition. Cells highlighted in green show the maximum for each performance metric. AUROC – Area-under-the-Receiver-Operator-Curve; SMOTE - Synthetic Minority Oversampling Technique

Table 7 – Confusion matrix for the optimal model (random forest)

A - Before SMOTE

		Observed		
		Success	Fail	Total
Predicted	Success	540 (58.5%)	134 (14.5%)	674 (73.0%)
	Fail	57 (6.2%)	192 (20.8%)	249 (27.0%)
	Total	597 (64.7%)	326 (35.3%)	923 (100%)

Total accuracy: 79.3%

B - After SMOTE

		Observed		
		Success	Fail	Total
Predicted	Success	503 (40.3%)	130 (10.4%)	633 (50.7%)
	Fail	94 (7.5%)	522 (41.8%)	616 (49.3%)
	Total	597 (47.8%)	652 (52.2%)	1249 (100%)

Total accuracy: 82.1%

Legend: Cells highlighted in green show correct predictions, those highlighted in orange show false-positives (i.e. model predicts success but company failed, or "failed hunches"), and those in yellow show false-negatives (i.e. model predicts failure but company succeeded, or "missed opportunities"). SMOTE - Synthetic Minority Oversampling Technique

References

Bell, J. (2020) *Machine Learning: Hands-On for Developers and Technical Professionals*. 2nd edn. Chichester: Wiley.

Bessen, J., Impink, S.M., Reichensperger, L. & Seamans, R. (2022) 'The role of data for AI startup growth', *Research Policy*, 51(5), p. 104513. Available from: https://doi.org/10.1016/j.respol.2022.104513.

Buchanan, B.G. (2019) *Artificial intelligence in finance*. The Alan Turing Institute. Available from: https://www.turing.ac.uk/sites/default/files/2019-04/artificial_intelligence_in_finance_-_turing_report_1.pdf (Accessed: 27 June 2024).

Dellermann, D., Lipusch, N., Ebel, P., Popp, K.M. & Leimeister, J.M. (2021) 'Finding the unicorn: Predicting early stage startup success through a hybrid intelligence method'. arXiv. Available from: https://doi.org/10.48550/ARXIV.2105.03360.

Duboue, P. (2020) 'The Art of Feature Engineering', in. Cambridge University Press.

Foody, G.M. (2023) 'Challenges in the real world use of classification accuracy metrics: From recall and precision to the Matthews correlation coefficient', *PLOS ONE*. Edited by S. Huang, 18(10), p. e0291908. Available from: https://doi.org/10.1371/journal.pone.0291908.

Frank, E., Hall, M.A. & Witten, I.H. (2016) *The WEKA Workbench*. 4th edn. Morgan Kaufmann.

Potanin, M., Chertok, A., Zorin, K. & Shtabtsovsky, C. (2023) 'Startup success prediction and VC portfolio simulation using CrunchBase data'. arXiv. Available from: https://doi.org/10.48550/ARXIV.2309.15552.

Raschka, S. (2018) 'Model Evaluation, Model Selection, and Algorithm Selection in Machine Learning'. arXiv. Available from: https://doi.org/10.48550/ARXIV.1811.12808.

Russel, S. & Norvig, P. (2021) *Artificial intelligence: A modern approach*. Global Edition. Pearson Higher Education.

Schröer, C., Kruse, F. & Gómez, J.M. (2021) 'A Systematic Literature Review on Applying CRISP-DM Process Model', *Procedia Computer Science*, 181, pp. 526–534. Available from: https://doi.org/10.1016/j.procs.2021.01.199.

Supplement: WEKA screenshots

Figure S1 – Initial data load

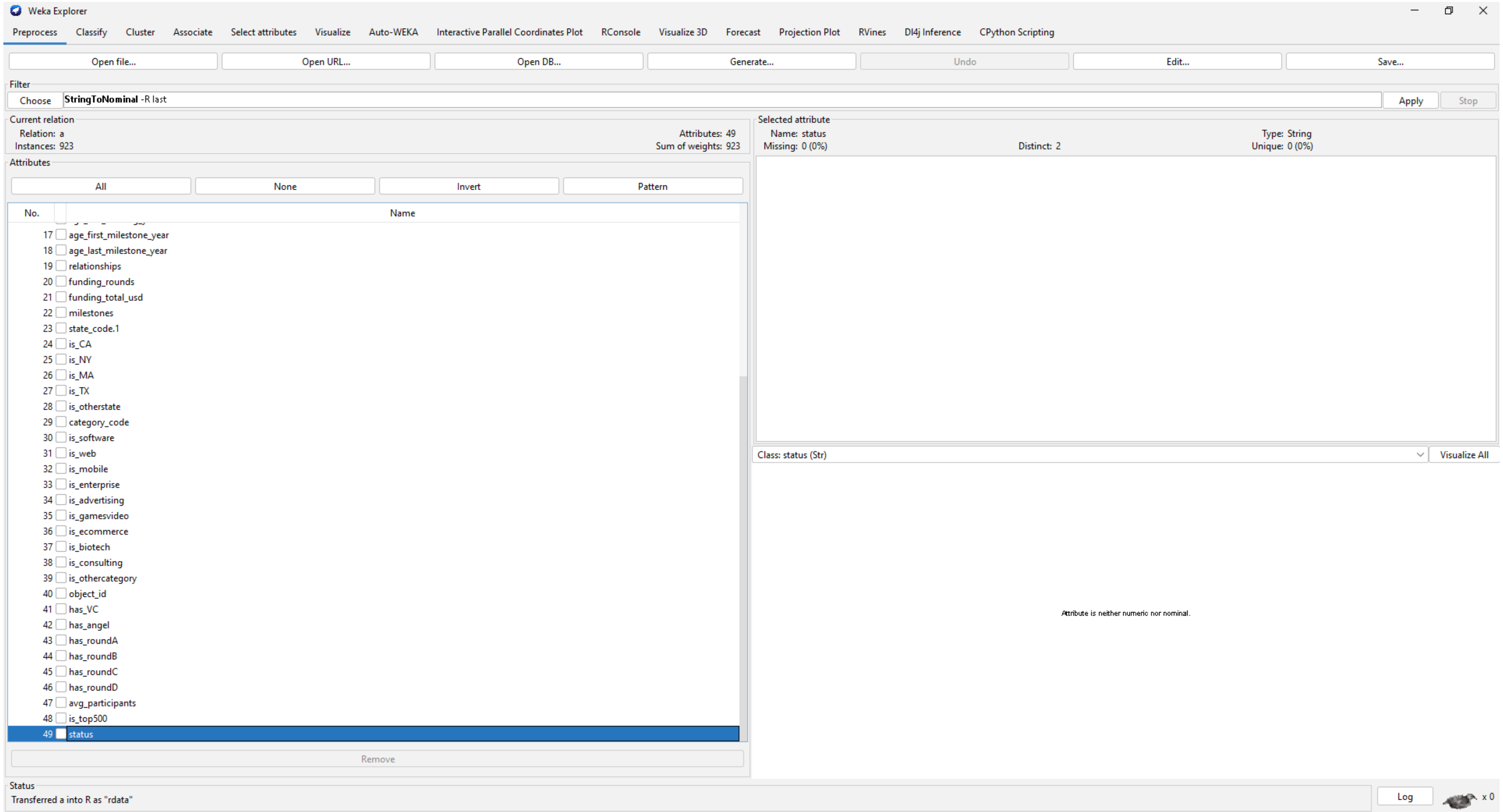


Figure S2 – Final set of selected attributes and target class overview

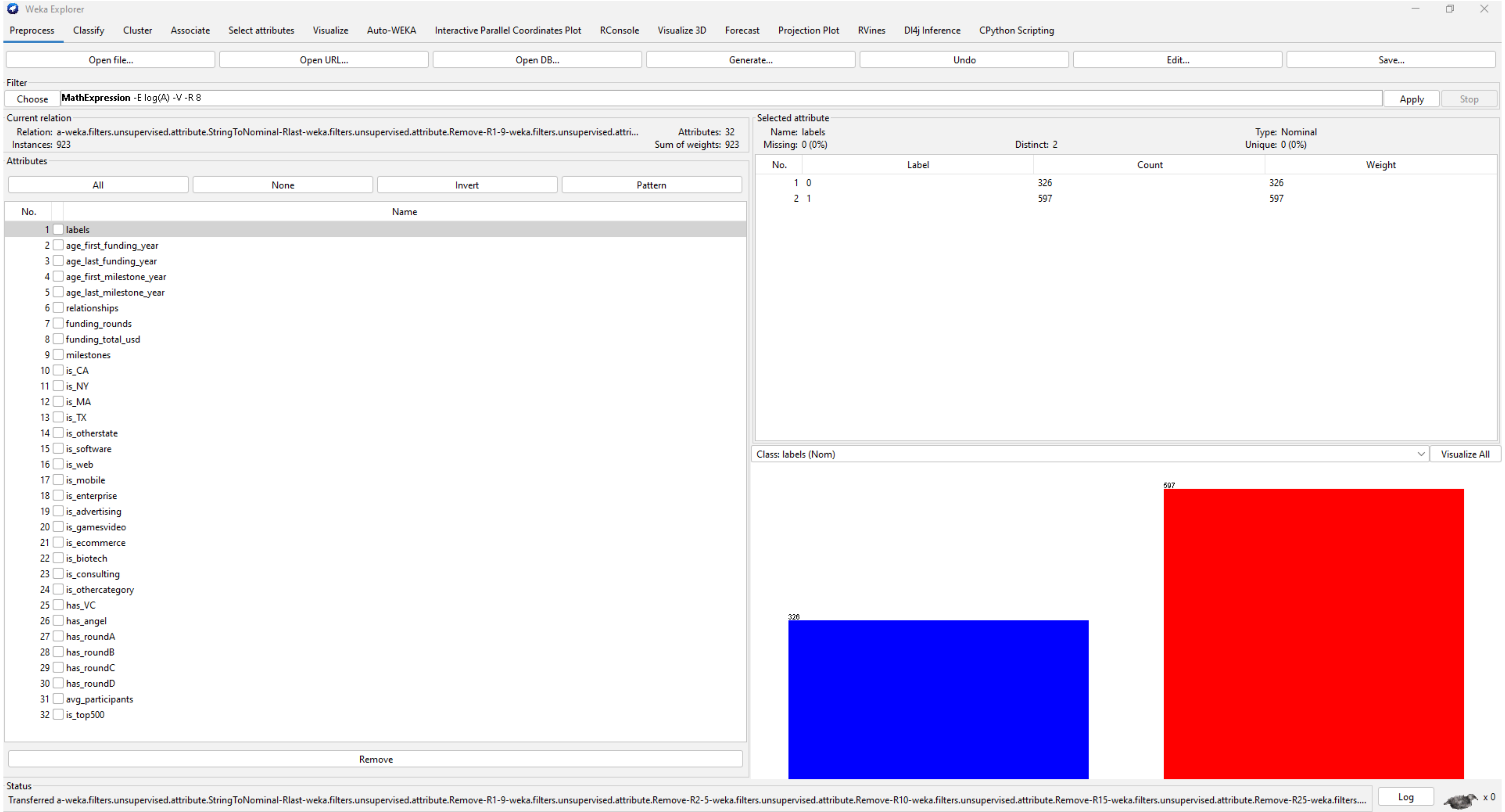


Figure S3 – Exploratory data analysis: age at first funding round

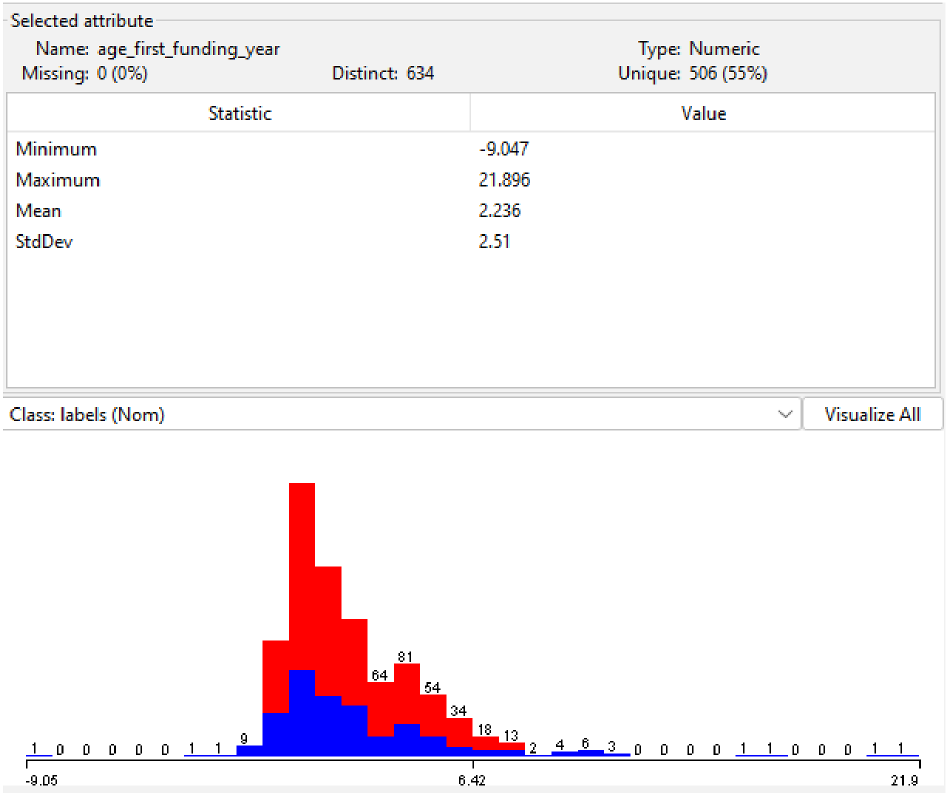


Figure S4 - Exploratory data analysis: age at last funding round

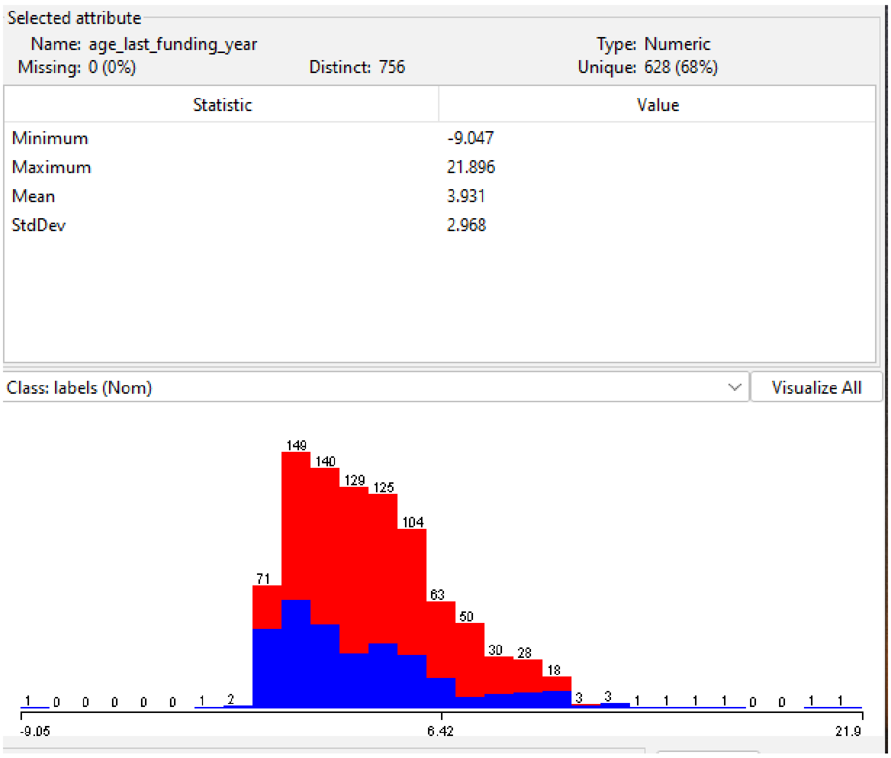


Figure S5 - Exploratory data analysis: age at first milestone

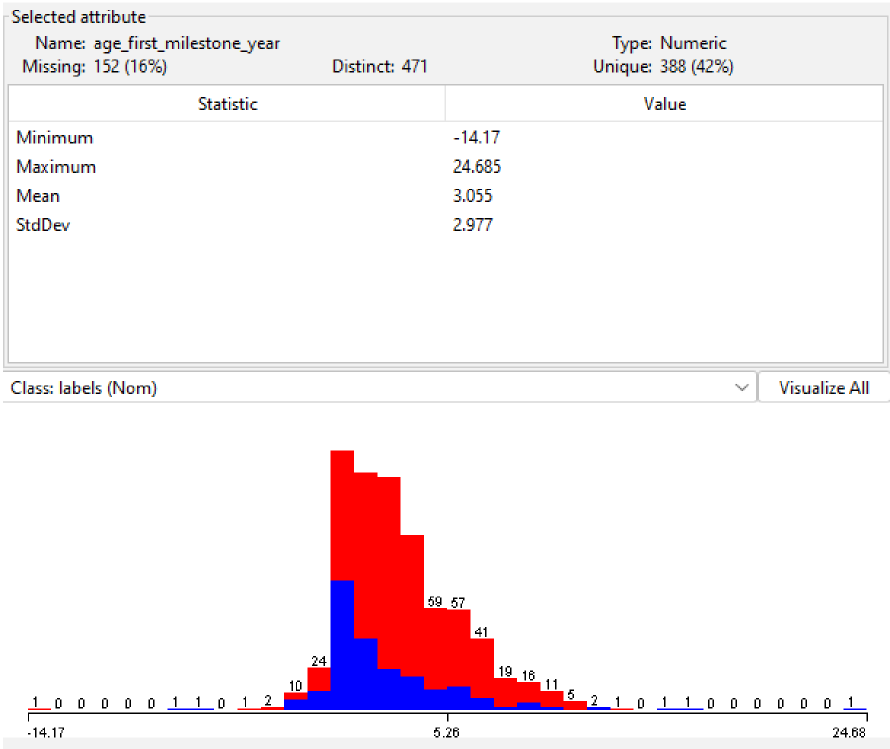


Figure S6 - Exploratory data analysis: age at last milestone

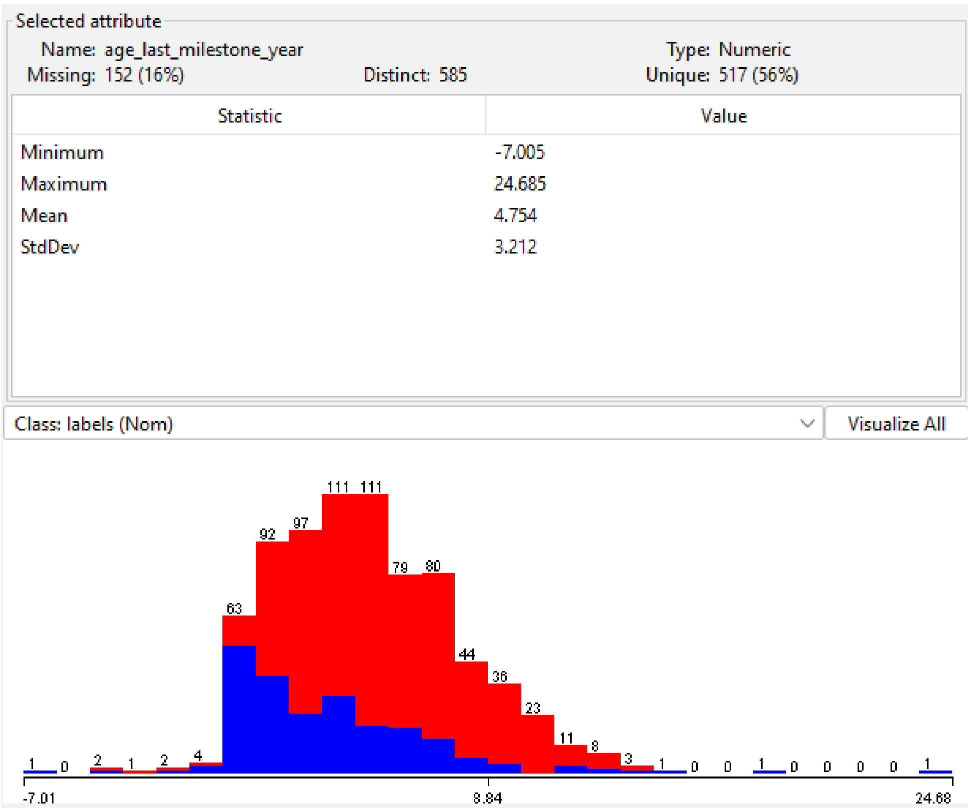


Figure S7 - Exploratory data analysis: number of relationships

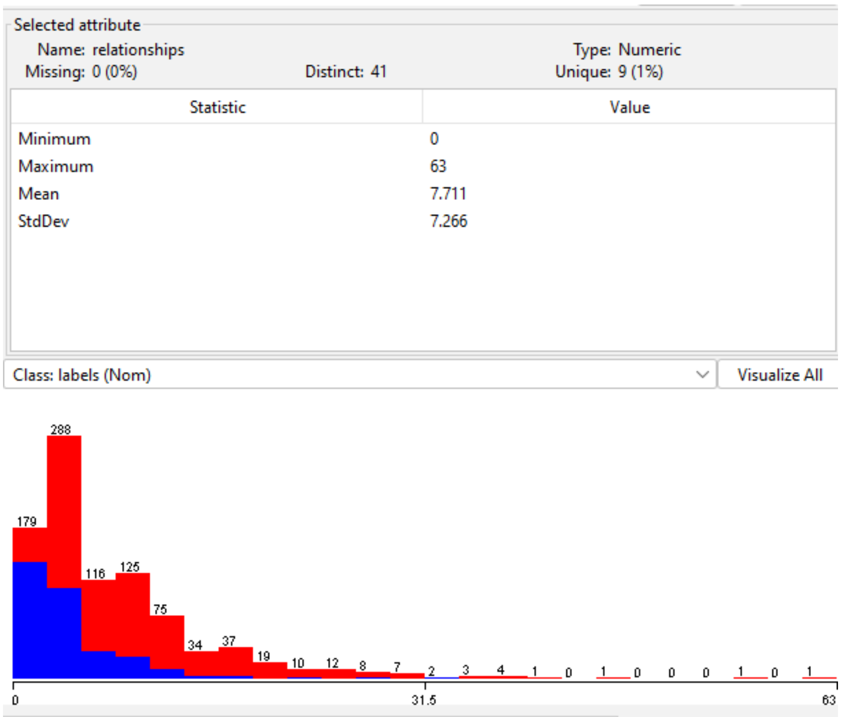


Figure S8 - Exploratory data analysis: number of milestones achieved

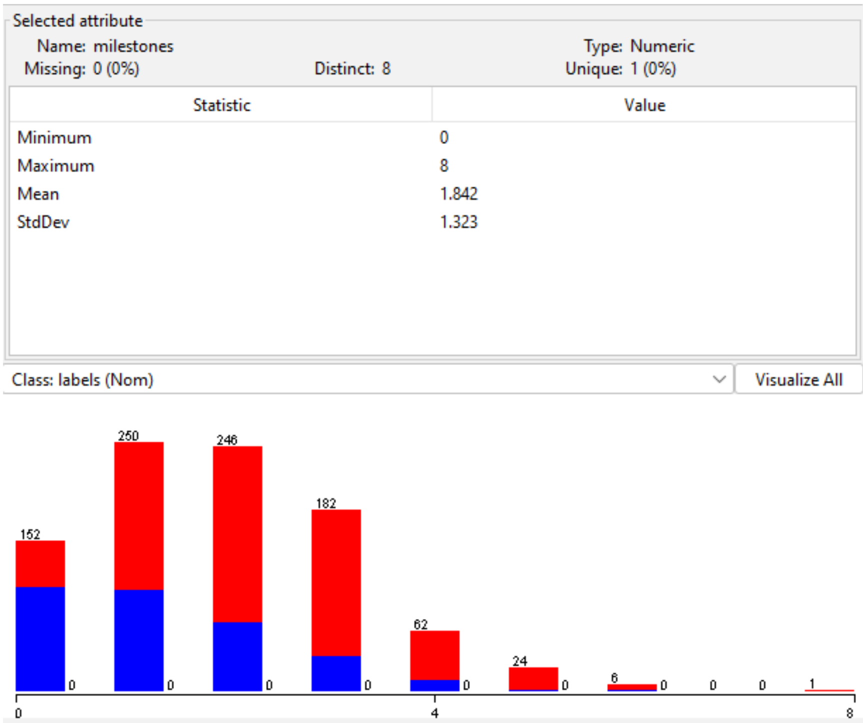


Figure S9 - Exploratory data analysis: average number of participants in funding rounds

Selected attribute

Name: avg_participants | Type: Numeric

Missing: 0 (0%) | Distinct: 59 | Unique: 25 (3%)

Statistic	Value
Minimum	1
Maximum	16
Mean	2.839
StdDev	1.875

Class: labels (Nom) | Visualize All

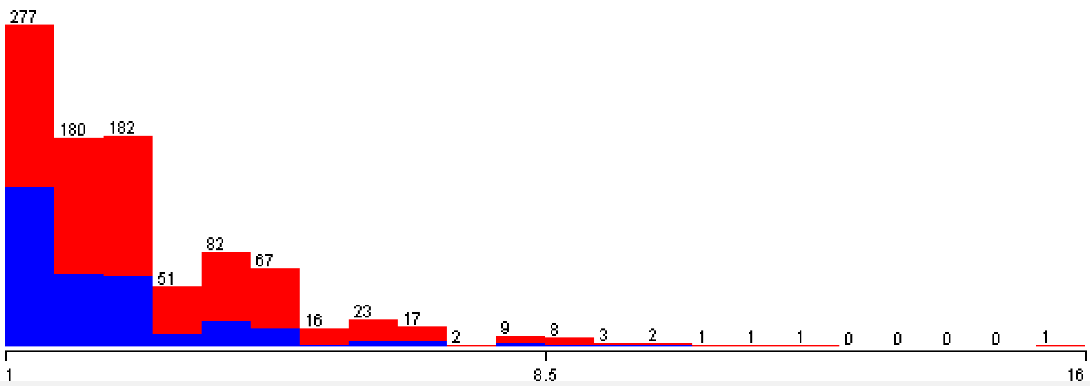
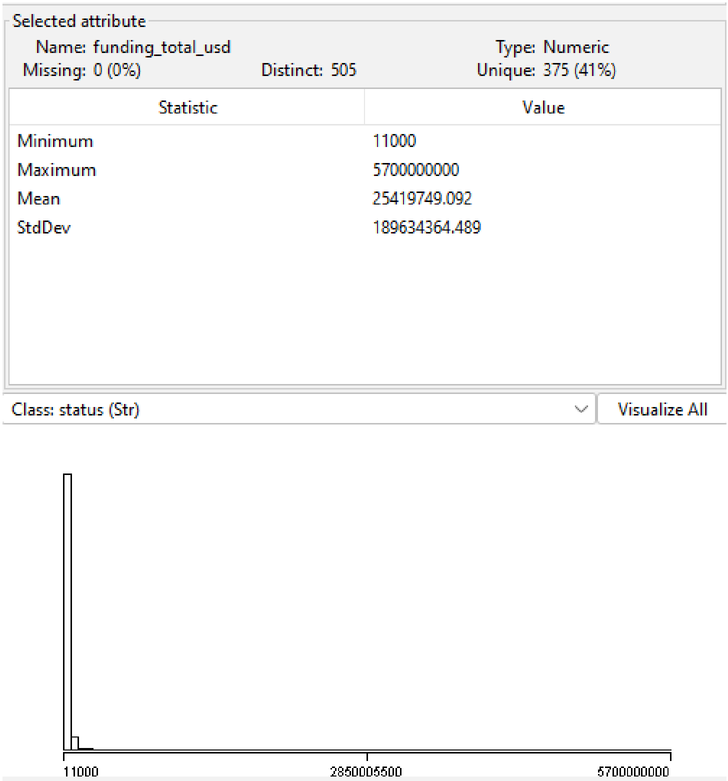


Figure S10 - Exploratory data analysis: total funding obtained

A – raw data



B – after log10 transformation

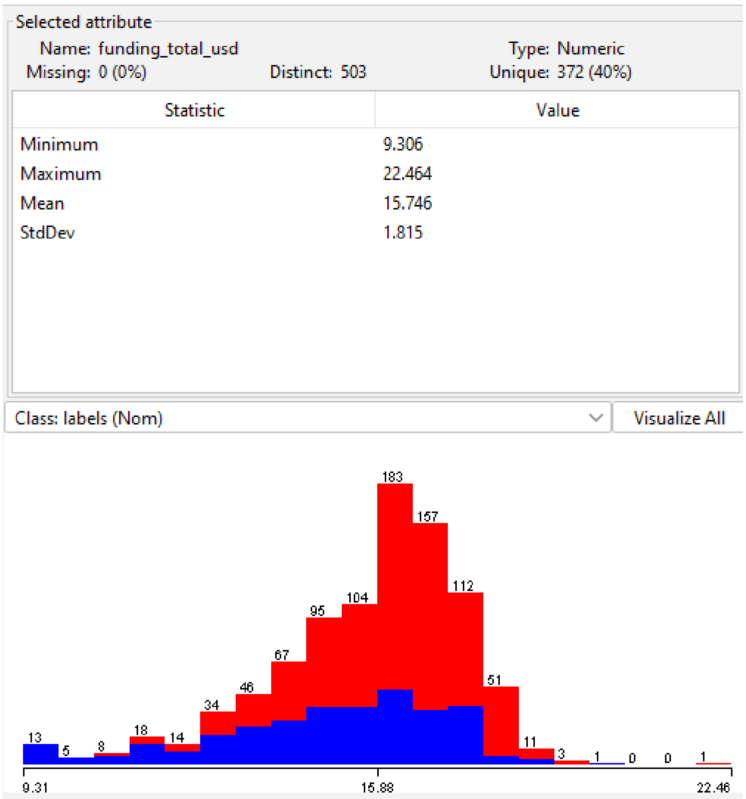


Figure S11 – Baseline accuracy performance

A – before SMOTE

```
=== Classifier model (full training set) ===

ZeroR predicts class value: 1

Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         597               64.6804 %
Incorrectly Classified Instances       326               35.3196 %
Kappa statistic                          0
Mean absolute error                      0.457
Root mean squared error                  0.478
Relative absolute error                100      %
Root relative squared error            100      %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.000    0.000    ?          0.000    ?          ?        0.495     0.350     0
                 1.000    1.000    0.647      1.000    0.786      ?        0.495     0.644     1
Weighted Avg.    0.647    0.647    ?          0.647    ?          ?        0.495     0.540

=== Confusion Matrix ===

   a   b   <-- classified as
   0 326 |   a = 0
   0 597 |   b = 1
```

B- after SMOTE

```
=== Classifier model (full training set) ===

ZeroR predicts class value: 1

Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         597               64.6804 %
Incorrectly Classified Instances       326               35.3196 %
Kappa statistic                          0
Mean absolute error                      0.457
Root mean squared error                  0.478
Relative absolute error                100      %
Root relative squared error            100      %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.000    0.000    ?          0.000    ?          ?        0.495     0.350     0
                 1.000    1.000    0.647      1.000    0.786      ?        0.495     0.644     1
Weighted Avg.    0.647    0.647    ?          0.647    ?          ?        0.495     0.540

=== Confusion Matrix ===

   a   b   <-- classified as
   0 326 |   a = 0
   0 597 |   b = 1
```

Figure S12 – Logistic regression performance

A – before SMOTE

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         684               74.1062 %
Incorrectly Classified Instances       239               25.8938 %
Kappa statistic                          0.4107
Mean absolute error                      0.3376
Root mean squared error                  0.4185
Relative absolute error                 73.8728 %
Root relative squared error             87.5494 %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.549    0.154    0.661      0.549    0.600      0.415    0.784     0.679     0
                 0.846    0.451    0.775      0.846    0.809      0.415    0.784     0.843     1
Weighted Avg.    0.741    0.346    0.734      0.741    0.735      0.415    0.784     0.785

=== Confusion Matrix ===

   a   b   <-- classified as
 179 147 |   a = 0
  92 505 |   b = 1
```

B – after SMOTE

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         994               79.5837 %
Incorrectly Classified Instances       255               20.4163 %
Kappa statistic                          0.5926
Mean absolute error                      0.2543
Root mean squared error                  0.3622
Relative absolute error                 50.9652 %
Root relative squared error             72.5022 %
Total Number of Instances             1249

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.759    0.164    0.835      0.759    0.795      0.595    0.889     0.918     0
                 0.836    0.241    0.761      0.836    0.796      0.595    0.889     0.843     1
Weighted Avg.    0.796    0.201    0.799      0.796    0.796      0.595    0.889     0.882

=== Confusion Matrix ===

   a   b   <-- classified as
 495 157 |   a = 0
  98 499 |   b = 1
```

Figure S13 – Logistic regression parameters (after SMOTE)

```
Logistic Regression with ridge parameter of 1.0E-8
Coefficients...
                                Class
Variable                            0
=====================================
age_first_funding_year         0.0506
age_last_funding_year          0.0278
age_first_milestone_year       0.0067
age_last_milestone_year       -0.0819
relationships                 -0.1268
funding_rounds                 0.0076
funding_total_usd             -0.1946
milestones                    -0.3415
is_CA=1                      -17.7439
is_NY=1                      -18.1646
is_MA=1                      -18.3144
is_TX=1                      -17.3227
is_otherstate=1               -17.623
is_software=1                -32.2063
is_web=1                     -31.8098
is_mobile=1                  -31.6948
is_enterprise=1              -32.4333
is_advertising=1             -32.0502
is_gamesvideo=1              -31.6007
is_ecommerce=1               -31.3152
is_biotech=1                 -32.3446
is_consulting=1              -31.7014
is_othercategory=1           -31.8123
has_VC=1                       0.4301
has_angel=1                   -0.1312
has_roundA=1                   0.0381
has_roundB=1                   0.0177
has_roundC=1                  -0.0787
has_roundD=1                  -0.4684
avg_participants              -0.0747
is_top500=1                   -0.7896
Intercept                     54.3873
```

Figure S14 – Naïve Bayes performance

A – before SMOTE

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         612               66.3055 %
Incorrectly Classified Instances       311               33.6945 %
Kappa statistic                          0.3443
Mean absolute error                      0.3516
Root mean squared error                  0.5123
Relative absolute error                 76.9389 %
Root relative squared error            107.1849 %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.798    0.410    0.515      0.798    0.626      0.372    0.783     0.707     0
                 0.590    0.202    0.842      0.590    0.694      0.372    0.783     0.839     1
Weighted Avg.    0.663    0.276    0.727      0.663    0.670      0.372    0.783     0.793

=== Confusion Matrix ===

   a   b   <-- classified as
 260  66 |   a = 0
 245 352 |   b = 1
```

B – after SMOTE

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         930               74.4596 %
Incorrectly Classified Instances       319               25.5404 %
Kappa statistic                          0.4882
Mean absolute error                      0.2734
Root mean squared error                  0.4455
Relative absolute error                 54.7868 %
Root relative squared error             89.1914 %
Total Number of Instances             1249

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.755    0.266    0.756      0.755    0.755      0.488    0.824     0.843     0
                 0.734    0.245    0.732      0.734    0.733      0.488    0.824     0.790     1
Weighted Avg.    0.745    0.256    0.745      0.745    0.745      0.488    0.824     0.818

=== Confusion Matrix ===

   a   b   <-- classified as
 492 160 |   a = 0
 159 438 |   b = 1
```

Figure S15 – Decision tree performance

A – before SMOTE

```
Time taken to build model: 0.01 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         702               76.0563 %
Incorrectly Classified Instances       221               23.9437 %
Kappa statistic                          0.4372
Mean absolute error                      0.3365
Root mean squared error                  0.4245
Relative absolute error                 73.6338 %
Root relative squared error             88.816  %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.509    0.102    0.731      0.509    0.600      0.452    0.730     0.630     0
                 0.898    0.491    0.770      0.898    0.829      0.452    0.730     0.773     1
Weighted Avg.    0.761    0.354    0.756      0.761    0.748      0.452    0.730     0.722

=== Confusion Matrix ===

   a   b   <-- classified as
 166 160 |   a = 0
  61 536 |   b = 1
```

B – after SMOTE

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         963               77.1017 %
Incorrectly Classified Instances       286               22.8983 %
Kappa statistic                          0.5417
Mean absolute error                      0.3273
Root mean squared error                  0.4196
Relative absolute error                 65.5868 %
Root relative squared error             84.0069 %
Total Number of Instances             1249

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.768    0.226    0.788      0.768    0.778      0.542    0.789     0.781     0
                 0.774    0.232    0.754      0.774    0.764      0.542    0.789     0.731     1
Weighted Avg.    0.771    0.229    0.771      0.771    0.771      0.542    0.789     0.757

=== Confusion Matrix ===

   a   b   <-- classified as
 501 151 |   a = 0
 135 462 |   b = 1
```

Figure S16 – Decision tree architecture (after SMOTE)

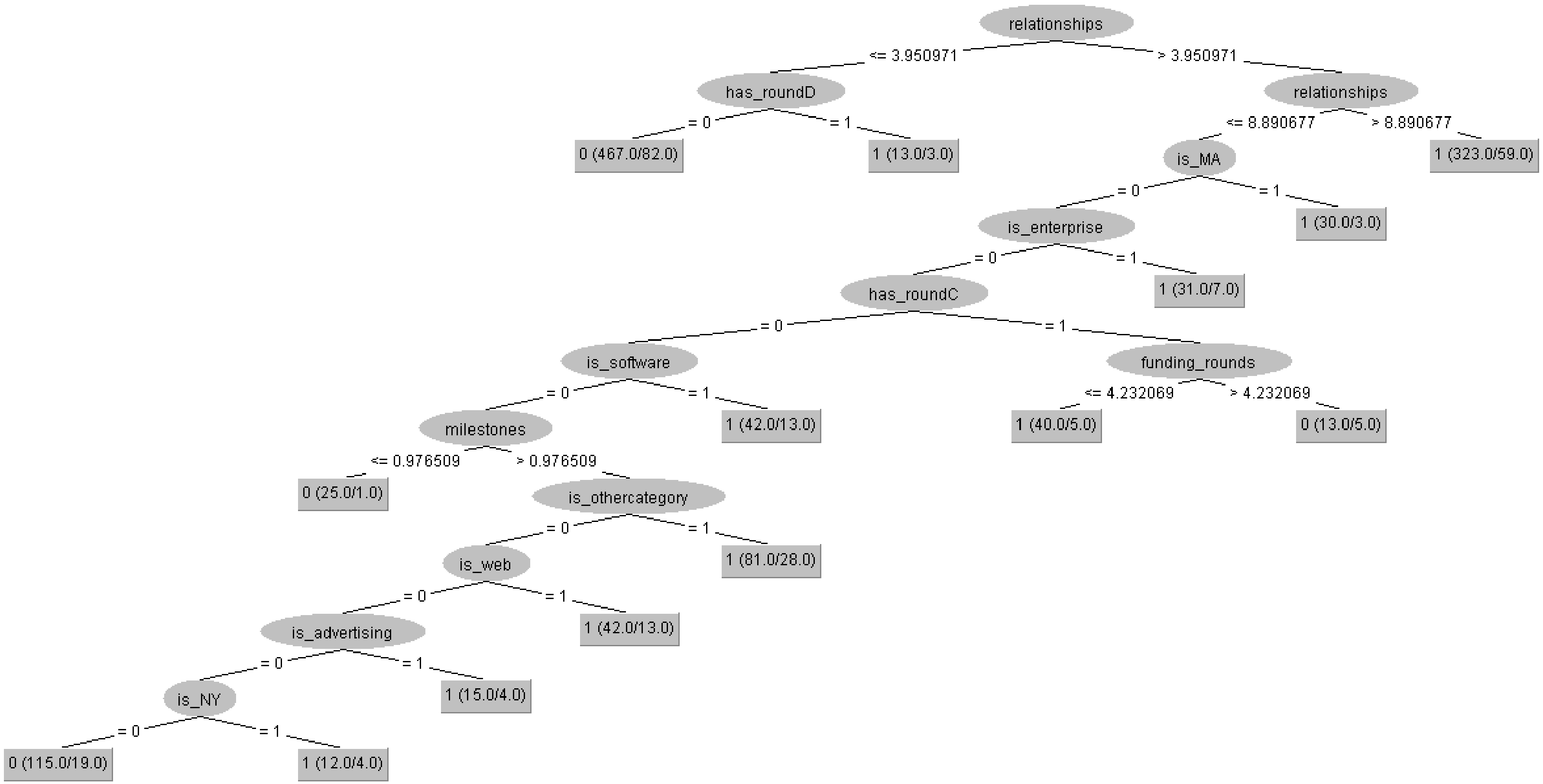


Figure S17 – Random forest performance

A – before SMOTE

```
=== Classifier model (full training set) ===

RandomForest

Bagging with 100 iterations and base learner

weka.classifiers.trees.RandomTree -K 0 -M 1.0 -V 0.001 -S 1 -do-not-check-capabilities

Time taken to build model: 0.12 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         732               79.3066 %
Incorrectly Classified Instances       191               20.6934 %
Kappa statistic                          0.5214
Mean absolute error                      0.3153
Root mean squared error                  0.3907
Relative absolute error                 68.9884 %
Root relative squared error             81.739  %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.589    0.095    0.771      0.589    0.668      0.531    0.820     0.775     0
                 0.905    0.411    0.801      0.905    0.850      0.531    0.820     0.863     1
Weighted Avg.    0.793    0.300    0.791      0.793    0.785      0.531    0.820     0.832

=== Confusion Matrix ===

   a   b   <-- classified as
 192 134 |   a = 0
  57 540 |   b = 1
```

B – after SMOTE

```
=== Classifier model (full training set) ===

RandomForest

Bagging with 100 iterations and base learner

weka.classifiers.trees.RandomTree -K 0 -M 1.0 -V 0.001 -S 1 -do-not-check-capabilities

Time taken to build model: 0.18 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances        1025               82.0657 %
Incorrectly Classified Instances       224               17.9343 %
Kappa statistic                          0.6415
Mean absolute error                      0.2951
Root mean squared error                  0.3626
Relative absolute error                 59.1428 %
Root relative squared error             72.5969 %
Total Number of Instances             1249

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.801    0.157    0.847      0.801    0.823      0.643    0.899     0.920     0
                 0.843    0.199    0.795      0.843    0.818      0.643    0.899     0.862     1
Weighted Avg.    0.821    0.177    0.822      0.821    0.821      0.643    0.899     0.893

=== Confusion Matrix ===

   a   b   <-- classified as
 522 130 |   a = 0
  94 503 |   b = 1
```

Figure S18 - Random forest attribute importance (after SMOTE)

```
Attribute importance based on average impurity decrease (and number of nodes using that attribute)

      0.36 (  2208)  funding_total_usd
      0.36 (  2190)  age_last_funding_year
      0.34 (  2109)  age_first_funding_year
      0.33 (  1741)  avg_participants
      0.33 (  1381)  age_first_milestone_year
      0.32 (  2035)  relationships
      0.31 (  1541)  age_last_milestone_year
      0.31 (  1588)  milestones
      0.28 (   479)  is_otherstate
      0.28 (   631)  is_CA
      0.28 (  1401)  funding_rounds
      0.27 (   570)  has_VC
      0.26 (   434)  has_roundB
      0.26 (   185)  is_TX
      0.26 (   512)  has_roundA
      0.25 (   603)  is_othercategory
      0.24 (   276)  is_mobile
      0.24 (   448)  is_software
      0.24 (   353)  has_angel
      0.24 (   407)  is_web
      0.24 (   122)  is_ecommerce
      0.23 (   391)  is_top500
      0.23 (   424)  has_roundC
      0.22 (   180)  is_gamesvideo
      0.21 (   319)  is_NY
      0.2  (   262)  is_enterprise
      0.2  (   267)  has_roundD
      0.19 (   316)  is_MA
      0.19 (   187)  is_biotech
      0.18 (   219)  is_advertising
      0.11 (     9)  is_consulting
```

Figure S19 – K-Nearest Neighbours performance

A – before SMOTE

```
=== Classifier model (full training set) ===

IB1 instance-based classifier
using 10 nearest neighbour(s) for classification


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         623               67.4973 %
Incorrectly Classified Instances       300               32.5027 %
Kappa statistic                          0.2118
Mean absolute error                      0.4023
Root mean squared error                  0.4737
Relative absolute error                 88.0229 %
Root relative squared error             99.1159 %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.325    0.134    0.570      0.325    0.414      0.228    0.631     0.482     0
                 0.866    0.675    0.701      0.866    0.775      0.228    0.631     0.734     1
Weighted Avg.    0.675    0.484    0.655      0.675    0.648      0.228    0.631     0.645

=== Confusion Matrix ===

   a   b   <-- classified as
 106 220 |   a = 0
  80 517 |   b = 1
```

B – after SMOTE

```
=== Classifier model (full training set) ===

IB1 instance-based classifier
using 10 nearest neighbour(s) for classification


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         889               71.1769 %
Incorrectly Classified Instances       360               28.8231 %
Kappa statistic                          0.4186
Mean absolute error                      0.3336
Root mean squared error                  0.4253
Relative absolute error                 66.8458 %
Root relative squared error             85.1394 %
Total Number of Instances             1249

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.796    0.380    0.696      0.796    0.742      0.423    0.804     0.835     0
                 0.620    0.204    0.736      0.620    0.673      0.423    0.804     0.717     1
Weighted Avg.    0.712    0.296    0.715      0.712    0.709      0.423    0.804     0.779

=== Confusion Matrix ===

   a   b   <-- classified as
 519 133 |   a = 0
 227 370 |   b = 1
```

Figure S20 – Support Vector Machine performance

A – before SMOTE

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         691               74.8646 %
Incorrectly Classified Instances       232               25.1354 %
Kappa statistic                          0.4225
Mean absolute error                      0.3362
Root mean squared error                  0.4149
Relative absolute error                 73.5607 %
Root relative squared error             86.8109 %
Total Number of Instances              923

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.540    0.137    0.682      0.540    0.603      0.429    0.786     0.707     0
                 0.863    0.460    0.774      0.863    0.816      0.429    0.786     0.850     1
Weighted Avg.    0.749    0.346    0.742      0.749    0.741      0.429    0.786     0.800

=== Confusion Matrix ===

   a   b   <-- classified as
 176 150 |   a = 0
  82 515 |   b = 1
```

B – before SMOTE

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         995               79.6637 %
Incorrectly Classified Instances       254               20.3363 %
Kappa statistic                          0.5935
Mean absolute error                      0.2592
Root mean squared error                  0.3648
Relative absolute error                 51.9344 %
Root relative squared error             73.0271 %
Total Number of Instances             1249

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.778    0.183    0.823      0.778    0.800      0.595    0.890     0.916     0
                 0.817    0.222    0.771      0.817    0.793      0.595    0.890     0.853     1
Weighted Avg.    0.797    0.202    0.798      0.797    0.797      0.595    0.890     0.886

=== Confusion Matrix ===

   a   b   <-- classified as
 507 145 |   a = 0
 109 488 |   b = 1
```

Figure S21 – Support Vector Machine weights (after SMOTE)

```
Machine linear: showing attribute weights, not support vectors.

        -1.0455 * (normalized) age_first_funding_year
 +      -0.7633 * (normalized) age_last_funding_year
 +       0.3585 * (normalized) age_first_milestone_year
 +       1.5272 * (normalized) age_last_milestone_year
 +       3.9039 * (normalized) relationships
 +       0.0423 * (normalized) funding_rounds
 +       1.2804 * (normalized) funding_total_usd
 +       2.2214 * (normalized) milestones
 +       1.7063 * (normalized) is_CA=1
 +       2.153  * (normalized) is_NY=1
 +       1.9767 * (normalized) is_MA=1
 +       1.5208 * (normalized) is_TX=1
 +       1.4328 * (normalized) is_otherstate=1
 +       2.3706 * (normalized) is_software=1
 +       2.0692 * (normalized) is_web=1
 +       2.0197 * (normalized) is_mobile=1
 +       2.5745 * (normalized) is_enterprise=1
 +       2.2464 * (normalized) is_advertising=1
 +       1.8179 * (normalized) is_gamesvideo=1
 +       1.3378 * (normalized) is_ecommerce=1
 +       2.4975 * (normalized) is_biotech=1
 +       1.7863 * (normalized) is_consulting=1
 +       2.0628 * (normalized) is_othercategory=1
 +      -0.2906 * (normalized) has_VC=1
 +       0.0418 * (normalized) has_angel=1
 +       0.0098 * (normalized) has_roundA=1
 +       0.1226 * (normalized) has_roundB=1
 +       0.2805 * (normalized) has_roundC=1
 +       0.5259 * (normalized) has_roundD=1
 +       0.8543 * (normalized) avg_participants
 +       0.7622 * (normalized) is_top500=1
 -       5.5905
```