AN AUTOMATED STARTUP EVALUATION PIPELINE: STARTUP SUCCESS FORECASTING FRAMEWORK (SSFF) *

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ABSTRACT

Evaluating startups in their early stages is a complex task that requires detailed analysis by experts. Automating this process on a large scale can have a significant business impact, but the complexity involved makes it difficult. This paper addresses this challenge by introducing the Startup Success Forecasting Framework (SSFF), a new automated system that combines traditional machine learning with advanced language models. This intelligent agent-based architecture is uniquely comprehensive and designed to reason, act, synthesize and decide like a venture capitalist to perform the analysis end-to-end.

The SSFF is made up of three main parts:

- **Prediction Block:** Uses random forests and neural networks to make predictions.
- **Analyst Block:** Employs "Role-Play" and Chain of Thought (CoT) prompting techniques.
- **External Knowledge Block:** Gathers real-time information from external sources.

This framework requires minimal input data about the founder and startup description, enhances it with additional data from external resources, and performs a detailed analysis with high accuracy, all in an automated manner.

***K*eywords** LLM Agent · Random Forest · Neural Network · Venture Capital · natural language processing

1 Introduction

The evaluation of startups at their inception is an intricate endeavor that traditionally relies on the expertise of seasoned professionals. The inherent dynamism of startups, combined with the unpredictable nature of market reception, complicates the task of identifying ventures poised for success. Recent advancements in Large Language Models (LLMs) have opened new avenues for leveraging artificial intelligence in complex decision-making processes. However, challenges such as hallucination effects, generalizations, and the "fuzzy" semantics of LLMs limit their predictive reliability.

This paper introduces the Startup Success Forecasting Framework (SSFF), a pioneering approach that synergizes traditional machine learning methodologies with the capabilities of advanced LLMs to automate and enhance the assessment of early-stage startups. The SSFF harnesses external information retrieval to provide context, utilizes the predictive strengths of neural networks and random forests, and leverages the analytical prowess of LLMs. This multifaceted strategy aims to mitigate the aforementioned challenges, offering high-quality analysis and forecasting with minimal input data.

The SSFF marks a significant leap forward by broadening the analytical horizon through external data augmentation, crafting a thorough and autonomous evaluation tool poised to revolutionize the venture capital landscape. To our

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knowledge, the SSFF represents the first of its kind in the industry—a Startup Success Forecasting Agent integrating quantitative models and delivering unparalleled analysis quality. This innovation harbors profound implications for the venture capital sector and sets a new benchmark for future research in AI-driven analytical agents.

2 Literature Review

2.1 Startup Evaluation Pipeline

The evaluation of startups at their nascent stages is pivotal yet challenging, demanding a nuanced understanding of both the market and the innovative essence of the startup itself.

Historically, this process has been dominantly heuristic, relying on the intuition and experience of venture capitalists and angel investors (Fernandez, A., & Smith, B. J., 2018).

Recent trends, however, have seen a shift towards a more data-driven approach, utilizing advanced analytics and machine learning algorithms to quantify potential success factors (Liu, C., & Zhang, D. Q., 2020).

Despite these advancements, the integration of qualitative assessments—particularly the vision and drive of the founding team—remains a complex task (Greenwood, S., & Harris, P., 2019).

Recently, Xiong and Ihlamur (2023) introduced the Founder-GPT framework, which evaluates the "founder-idea" fit in early-stage startups using large language model techniques. The framework employs embeddings, self-play, tree-of-thought, and critique-based refinement techniques, demonstrating that the success patterns of each idea are unique and should be evaluated in the context of the founder's background. This research shows promising early results, highlighting the importance of personalized evaluation in predicting startup success.

2.2 LLM Agent

The advent of Large Language Models (LLMs) like GPT and BERT has revolutionized natural language understanding and generation, offering unprecedented capabilities in processing and producing human-like text.

With their incredible capabilities in understanding and answering, LLMs have recently shown transformative potential across different fields of research, from natural language processing to recommendation systems. [33, 34, 35], [36, 37, 38, 39]

As Large Language Models (LLMs) have become foundational platforms, the concept of Artificial Intelligence (AI) agents has expanded significantly. These systems are designed to perceive their environment, process information, and take actions to achieve specific goals. AI agents can operate autonomously or support human decision-making by analyzing large volumes of data and identifying complex patterns beyond human capabilities. Recent advancements in AI agents highlight their growing sophistication and applicability in various domains, demonstrating enhanced decision-making and interactive capabilities.

The ability of these models to interpret complex language patterns has opened new avenues for systematically evaluating qualitative aspects of startups, such as founder vision, market fit, and innovation level, which were previously difficult to assess. However, despite these advancements, a widely adopted AI agent specifically designed for analyzing startups has yet to emerge.

(Brown, T. B., et al., 2020; Lee, K., & Majumdar, S., 2021).

2.3 Prompting Techniques

The effectiveness of LLMs in various applications hinges significantly on the art of prompt engineering—crafting queries that guide the model to generate specific, useful outputs (Shin, R., et al., 2020).

This emerging field has shown that well-designed prompts can dramatically enhance the performance of LLMs in tasks with limited or ambiguous data, making it a crucial skill for applications within startup evaluation frameworks (Jiang, L., et al., 2021).

Useful prompting techniques include Chain-of-Thought, Tree-of-Thought, and Retrieval Augmented Generation. Chain-of-Thought involves guiding the AI through a step-by-step reasoning process to improve accuracy and clarity. Tree-of-Thought extends this by exploring multiple branches of reasoning simultaneously for complex decision-making. Retrieval Augmented Generation enhances responses by retrieving relevant information from external sources, grounding the AI's answers in factual data. In this paper, we use these techniques to enhance the AI's utility and reliability, from problem-solving and strategic planning to information retrieval and decision-making.

3 Founder Level Segmentation

3.1 Data Preparation

To embark on the analysis, we initially curated a dataset comprising founders' LinkedIn profiles, associated with startups classified as either successful or unsuccessful. This classification was based on the companies' market valuations, with successful ones having valuations over USD 500 million. The dataset was enriched with detailed profiles, including education and work backgrounds, extracted in JSON format from LinkedIn URLs. This preparation phase was crucial for ensuring a robust foundation for our segmentation analysis.

3.2 Segmentation Process

The segmentation of founders into levels L1 through L5 was guided by a combination of Large Language Models (LLMs) and manual review processes. Prompting techniques played a pivotal role in this phase, allowing for the nuanced extraction and categorization of founder experiences from their LinkedIn profiles. By crafting specific prompts, we directed the LLMs to identify key indicators of a founder's level, such as leadership roles, scale of business achievements, and educational background. These prompts were iteratively refined to improve accuracy and relevance, demonstrating the LLM's capacity to adapt to the subtleties of founder segmentation.

Our methodology involved a step-wise refinement process, where initial LLM outputs underwent a manual review to ensure alignment with the predefined segmentation criteria. This iterative loop, highlighted in Section 3.2, was essential in calibrating the model's understanding of the varied landscapes of founder experiences.

3.3 Segmentation Result

The segmentation results revealed a distinct correlation between the founders' levels and their startups' success rates. Founders at Level 5 (L5), characterized by their experience in building significant businesses or holding executive roles in notable technology companies, were markedly more likely to lead a startup to success. Specifically, L5 founders were found to be 3.79 times more likely to be successful compared to those at Level 1 (L1), who had minimal experience or were outside tech circles.

Founder Level	Success	Failure	Success Rate	X-Time Better than L1
L1	24	75	24.24%	1
L2	83	223	27.12%	1.12
L3	287	445	39.21%	1.62
L4	514	249	67.37%	2.78
L5	93	8	92.08%	3.79

Table 1: Success and failure rates by founder level, showcasing the predictive power of founder segmentation on startup success.

This segmentation not only underscores the influence of a founder's background on startup outcomes but also suggests that incorporating such a nuanced understanding into evaluation frameworks can significantly enhance predictive accuracies. Further, these insights open avenues for deeper explorations beyond the initial five levels, aiming for more granular segmentations that could offer even more precise predictive capabilities.

4 Prediction Block

To enhance the credibility of the AI Agent, a prediction block is designed to learn form past data and predict the success rate from startup and/or founder information.

The prediction block is separated as two parts: (1) LLM-Based Fuzzy Random Forest Model and (2) Founder-Idea Fit Network. These two sections are proposed to generate explainable and effective prediction results for startup founders. To the best of our knowledge, we are the first in the field to propose these two machine learning models. Apart from their use in the Startup Successs Forecasting Framework, the studies towards the models themselves could also shed light to our understanding of startup successes.

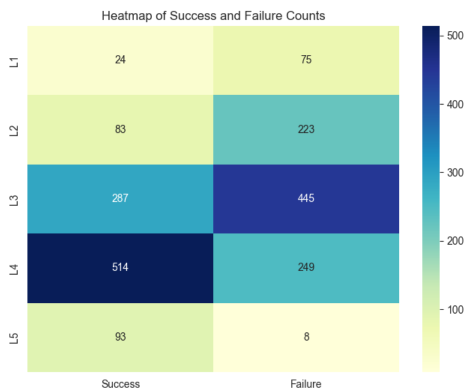

Figure 1: Heatmap showing the counts of successful and unsuccessful startups across different founder levels.

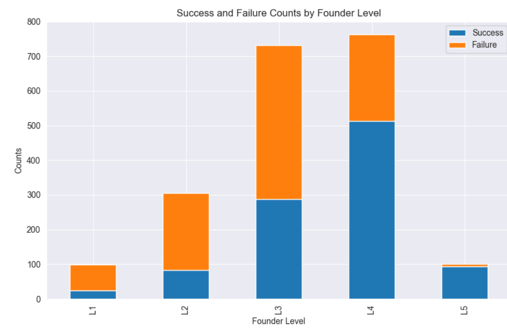

Figure 2: Stacked bar plot of success and failure counts, illustrating the distribution across founder levels.

4.1 LLM-Based Random Forest

4.1.1 Model Design

The conventional Random Forest algorithm, celebrated for its effectiveness and explainability, often faces challenges with categorical variables due to its inherent design constraints. To overcome these limitations, we introduce an LLM-based "Fuzzy" Random Forest model. This novel approach utilizes Large Language Models (LLMs), particularly GPT-3.5-turbo, for the extraction of features, thereby imbuing the model with the flexibility to handle a broad spectrum of categorical variables.

In our framework, startup and founder information is processed through an LLM to categorize data across 14 dimensions, including industry growth, market size, development pace, and product-market fit, among others. This method allows for a nuanced understanding of startup dynamics, which is critical for accurate prediction. The sample data analyzed through the LLM is structured as follows:

```
{
  "startup_analysis_responses": {
    "industry_growth": "Yes",
    "market_size": "Large",
    "development_pace": "Faster",
    ...
    "timing": "Just Right"
  }
}
```

The procedure for implementing this LLM-enhanced Random Forest model involves several key steps:

1. Encoding the categorical features into numerical values to facilitate machine learning processing.
2. Splitting the dataset into training and testing sets to ensure the model can be validated independently.
3. Training the Random Forest model on the encoded and segmented data.
4. Evaluating the model's performance to determine its predictive accuracy and utility.

This approach to leveraging LLMs for feature extraction and encoding provides a flexible and robust framework for startup success prediction, making full use of categorical variables without the constraints of traditional models.

The application of this model to a dataset comprising 200 startups—equally split between successful and unsuccessful cases—yielded promising results. The classification report and confusion matrix are put to present the results.

4.1.2 LLM-Based Categorical Data Extraction

A cornerstone of our LLM-based "Fuzzy" Random Forest model is the extraction of categorical data from startup and founder information. This process is guided by a Chain of Thought prompting technique, where the LLM is presented with a series of questions designed to elicit specific insights into various aspects of a startup's potential for success. These questions cover a wide range of topics, from industry growth and market size to innovation frequency and product-market fit.

The some of the questions used in this process includes:

1. "Is the startup operating in an industry experiencing growth? [Yes/No/N/A]"
2. "Is the target market size for the startup's product/service considered large? [Small/Medium/Large/N/A]"
3. "Does the startup demonstrate a fast pace of development compared to competitors? [Slower/Same/Faster/N/A]"
4. "Is the startup considered adaptable to market changes? [Not Adaptable/Somewhat Adaptable/Very Adaptable/N/A]"
5. "How would you rate the startup's execution capabilities? [Poor/Average/Excellent/N/A]"
6. ... omitted for sapce
7. "Are terms related to innovation frequently mentioned in the company's public communications? [Rarely/Sometimes/Often/N/A]"
8. "Does the startup mention cutting-edge technology in its descriptions? [No/Mentioned/Emphasized/N/A]"
9. "Considering the startup's industry and current market conditions, is the timing for the startup's product or service right? [Too Early/Just Right/Too Late/N/A]"

The corresponding encoding is presented in a table.

Table 2: Adjusted Category Mappings with "Mismatch" Included

Category	**Mappings**
Industry Growth	No, N/A, Yes, Mismatch
Market Size	Small, Medium, Large, N/A, Mismatch
Development Pace	Slower, Same, Faster, N/A, Mismatch
Market Adaptability	Not Adaptable, Somewhat Adaptable, Very Adaptable, N/A, Mismatch
Execution Capabilities	Poor, Average, Excellent, N/A, Mismatch
Funding Amount	Below Average, Average, Above Average, N/A, Mismatch
Valuation Change	Decreased, Remained Stable, Increased, N/A, Mismatch
Investor Backing	Unknown, Recognized, Highly Regarded, N/A, Mismatch
Reviews/Testimonials	Negative, Mixed, Positive, N/A, Mismatch
Product-Market Fit	Weak, Moderate, Strong, N/A, Mismatch
Sentiment Analysis	Negative, Neutral, Positive, N/A, Mismatch
Innovation Mentions	Rarely, Sometimes, Often, N/A, Mismatch
Cutting-edge Technology	No, Mentioned, Emphasized, N/A, Mismatch
Timing	Too Early, Just Right, Too Late, N/A, Mismatch

This structured approach to querying provides a rich dataset from which we can extract categorical variables with high relevance to startup success. The responses to these questions are then encoded into numerical values, forming the basis for training our LLM-based "Fuzzy" Random Forest model. This method ensures a comprehensive analysis by incorporating a wide array of factors influencing startup outcomes.

Note: The full prompt and methodology for this Chain of Thought technique, including question design and LLM interaction, are detailed in the Appendix of this paper.

4.1.3 Model Performance Evaluation

The performance of our LLM-based "Fuzzy" Random Forest model was rigorously evaluated to determine its predictive accuracy. The results are summarized in the classification report and confusion matrix below, showcasing the model's efficacy in startup success prediction.

Class	Precision	Recall	F1-Score	Support
0	0.83	1.00	0.90	19
1	1.00	0.81	0.89	21

Table 3: Classification report for the model.

		Predicted	
		0	1
Actual	0	19	0
	1	4	17

Table 4: Confusion matrix for the model.

These results indicate that the LLM-based "Fuzzy" Random Forest model is a highly effective tool for predicting startup success, demonstrating both high precision and recall. The model's ability to accurately classify startups into successful and unsuccessful categories underscores the potential of integrating advanced AI techniques with traditional machine learning models for enhanced predictive analysis.

4.2 Founder-Idea Fit Network

Evaluating Founder-Idea Fit has been crucial, and hence SSFF incorporates a novel network to assess it. The Founder-Idea Fit Model is designed to quantitatively assess the alignment between founders' expertise and characteristics and their startup's core idea and market positioning. This section outlines the methodology employed to develop and implement the model, leveraging advanced NLP techniques and neural network architectures.

4.2.1 Measuring Founder-Idea Fit

The previous sections show the strong correlation between founder's segmentation level and startup's outcome, as L5 founders are more than three times likely to succeed than L1 founders. However, looking into the data, one could also see that there are L5 founders who did not succeed, and there are L1 founders who succeeded. To account for these scenarios, we investigate the fit between founders and their ideas.

To assess quantitatively, we propose a metric called Founder-Idea Fit Score (FIFS). The Founder-Idea Fit Score quantitatively assesses the compatibility between a founder's experience level and the success of their startup idea. Given the revised Preliminary Fit Score (PFS) defined as:

$$PFS(F, O) = (6 - F) \times O - F \times (1 - O)$$

where F represents the founder's level (1 to 5) and O is the outcome (1 for success, 0 for failure), we aim to normalize this score to a range of $[-1, 1]$ to facilitate interpretation.

To achieve this, we note that the minimum PFS value is -5 (for a level 5 founder who fails), and the maximum value is 5 (for a level 1 founder who succeeds). The normalization formula to scale PFS to $[-1, 1]$ is:

$$Normalized\ PFS = \frac{PFS}{5}$$

This formula adjusts the PFS values directly into the desired range:

- A $Normalized\ PFS$ of 1 indicates the best possible founder-idea fit, achieved when a level 1 founder succeeds.
- A $Normalized\ PFS$ of -1 indicates the worst possible fit, observed when a level 5 founder fails.

This normalized score enables a straightforward comparison across startups, highlighting those with the most and least effective alignment between founder capabilities and startup ideas.

4.2.2 Preprocessing: Embedding & Cosine Similarity

The first step in the Founder-Idea Fit Model involves generating dense vector representations for both the startup descriptions and the founders' backgrounds. We utilize the *text-embedding-3-large* model from OpenAI to transform textual data into space of 100 dimensions, capturing the semantic essence of each description. This process includes:

- **Startup Description Embedding:** Converting startup descriptions into embeddings that encapsulate the startup's mission, technology, and market.

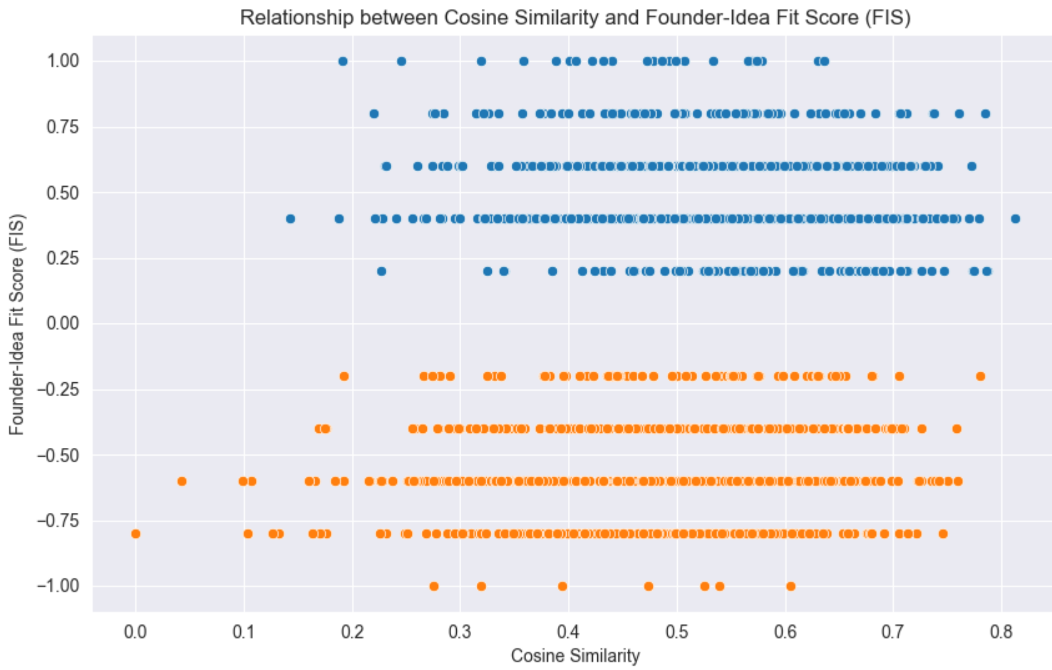

Figure 3: Relationship between cosine similarity and FIFS

- **Founder Description Embedding:** Generating embeddings from founders' professional backgrounds, including education and employment history, to capture their expertise and experience.

With embeddings for both startups and founders, we compute the cosine similarity between each founder's embedding and their startup's embedding. This metric serves as a proxy for the "fit" by measuring the semantic alignment between the founder's background and the startup's concept.

4.2.3 Statistical Analysis and Further Model Considerations

Our statistical analysis began with a calculation of the Pearson correlation coefficient between cosine similarity and the Founder-Idea Fit Score (FIFS), resulting in a coefficient of 0.173. While this indicates a positive relationship between the two variables confirming common-sense, the relatively low value suggests a weak linear association. The statistical significance of this relationship is bolstered by a p-value effectively at zero, indicating that the correlation is unlikely to be due to random chance.

Subsequently, an Ordinary Least Squares (OLS) regression was performed, which yielded an R^2 value of 0.030. This indicates that cosine similarity alone accounts for only 3% of the variability in FIFS. The regression model coefficients were statistically significant, but the small R^2 suggests the model's predictive power is limited. Additionally, the Durbin-Watson statistic points to the presence of positive autocorrelation, and the tests for normality of residuals (Omnibus and Jarque-Bera) indicate a deviation from the normal distribution.

Given these findings, we propose that a linear model may not be the best tool for predicting FIFS. The data might possess a non-linear structure that linear regression cannot capture, or there may be other important variables that we have not included in the model. Hence, we suggest exploring more sophisticated modeling techniques that can uncover complex relationships in the data.

```
Regression Analysis Summary:
Dep. Variable:                  FIFS    R-squared:                    0.030
Model:                           OLS    Adj. R-squared:               0.030
Method:                Least Squares    F-statistic:                  60.03
```

```
Date:                Fri, 22 Mar 2024   Prob (F-statistic):                1.50e-14
Time:                        15:46:09   Log-Likelihood:                     -1601.4
No. Observations:                1938   AIC:                                  3207.
Df Residuals:                    1936   BIC:                                  3218.
Df Model:                           1
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                -0.4562      0.056     -8.161      0.000      -0.566      -0.347
cosine_similarity     0.8228      0.106      7.748      0.000       0.615       1.031
=====================================================================================
Omnibus:                13439.810   Durbin-Watson:                            0.222
Prob(Omnibus):              0.000   Jarque-Bera (JB):                       177.673
Skew:                      -0.002   Prob(JB):                              2.62e-39
Kurtosis:                   1.517   Cond. No.                                  10.7
=====================================================================================
```

The search for a more appropriate model leads us towards neural networks, which are capable of capturing the non-linear relationships inherent in complex datasets. Moreover, neural networks can integrate a multitude of independent variables to develop a more holistic understanding of what influences FIFS. The next section will introduce how neural networks could be leveraged in this context to enhance the predictive accuracy of our model.

4.2.4 Model Architecture and Performance Analysis

Neural networks are known for their supreme capabilities in simulating complex relationships. The embeddings and their cosine similarities form the input features for a neural network designed to predict the founder-idea fit. This model is trained on the same dataset, learning to predict the fit score between a founder and their idea.

- Input Features: Embeddings and cosine similarity scores.
- Label: Founder-Idea Fit Score (FIFS)
- Training Process: Utilizing a training dataset with labeled examples of founder-startup pairs, the model learns to predict the degree of fit.

In particular, our model shines with its elegant simplicity and compelling numerical evidence. The neural network's architecture is purposefully uncomplicated, featuring a sequential array of dense layers augmented by dropout layers to mitigate overfitting. With the input layer accommodating 201 features, the network progresses through 128 neurons in the first hidden layer and then refines further through 64 neurons in the subsequent hidden layer. Each neuron is activated by the rectified linear unit (ReLU) function, which introduces non-linearity, allowing for the intricate modeling of founder-startup dynamics.

This straightforward design is fortified by dropout rates of 20% and 30%, respectively, which strategically silence a portion of the neurons during training to promote a robust and generalizable model. The output layer, comprised of a single neuron, is devoted to yielding the Founder-Idea Fit Score (FIFS)—a continuous value encapsulating the synergy between the founder's profile and the startup's ethos. In training, the model employs the Adam optimizer, a trusted choice for efficient stochastic gradient descent, along with a mean squared error loss function that hones in on precise FIFS prediction.

The numbers attest to the model's proficiency. Throughout the training phase, the model displayed a decisive drop in loss from 0.7182 to a mere 0.0407 in mean squared error, while the validation loss settled impressively at 0.0386. These metrics not only validate the model's accuracy but also reflect its reliable generalization from training to unseen data—a hallmark of a well-tuned model. Thus, this architecture, in its deliberate restraint, offers an insightful and scalable tool for investors and startup ecosystems, promising to elevate the art of early-stage startup evaluation.

4.2.5 Conclusion

The Founder-Idea Fit Model represents a novel approach to evaluating the synergy between startup founders and their business concepts. By leveraging state-of-the-art NLP techniques and neural network architectures, we aim to provide actionable insights that can guide investment decisions, team formation, and strategic planning in the startup ecosystem.

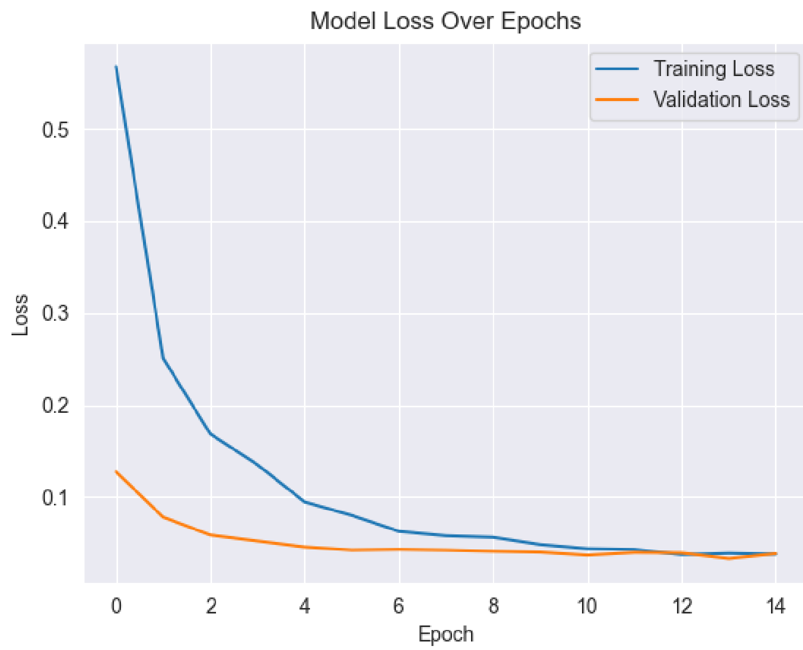

Figure 4: Training of the Founder-Idea-Fit Network

5 Analysis Block

The SSFF's Analysis Block represents a cornerstone in our comprehensive approach to evaluating startup ecosystems. By harnessing advanced NLP and machine learning technologies, we aim to distill complex, multi-dimensional data into actionable insights, assessing the potential success of startups within their respective markets. This section delves into the sophisticated methodologies and design strategies underpinning the Analysis Block.

5.1 Analytical Domains

The Analysis Block dissects each startup across four critical domains, thereby ensuring a complete evaluation:

1. **Market Analysis:** This segment appraises the startup's market alignment, growth potential, and strategic positioning within its target sector.
2. **Product Analysis:** Focuses on the startup's core offerings, evaluating innovation, scalability, and user engagement to ascertain product-market fit.
3. **Founder Analysis:** Assesses the founding team's background, expertise, and visionary alignment, recognizing the pivotal role of leadership in startup success.
4. **Comprehensive Integration:** Synthesizes findings across all domains to formulate a coherent investment insight, underpinning the SSFF's final recommendation.

5.2 Design and Implementation Techniques

The Design and Implementation Techniques of the Analysis Block within the SSFF harness state-of-the-art methodologies to ensure comprehensive and customized evaluations for each startup. Key strategies include:

- **Role-Play Simulation for Realistic Scenario Analysis:** The framework simulates a venture capital conference room scenario, positioning virtual analysts to read, dissect, and present findings to a supervisory entity. This role-play underpins the agent's operational backbone, emulating the collaborative and integrative analysis typical within professional investment settings. It embodies the dynamism and deliberative process of VC decision-making, enriching the SSFF's evaluative depth with scenarios that reflect real-world complexities.

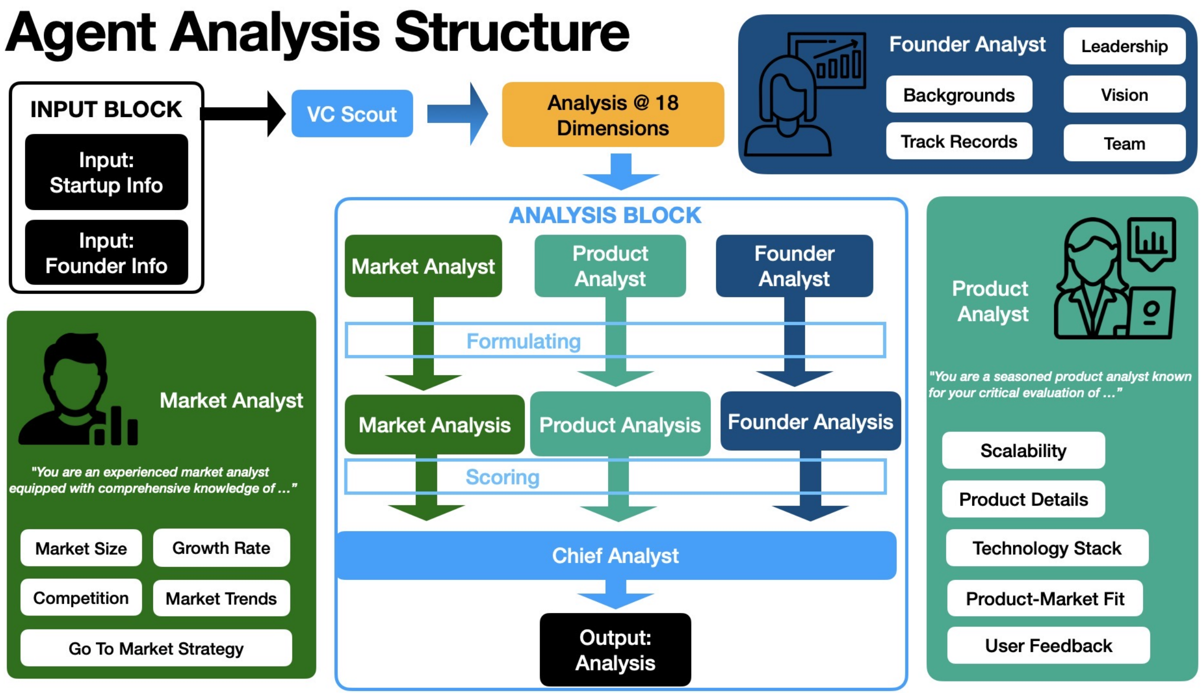

Figure 5: Analysis Block Framework

- **Few-Shot Prompting with Guided Examples:** The Analysis Block employs few-shot learning techniques, where prompts are designed with illustrative examples. This method instructs the AI to follow a similar analytical pattern, enhancing the relevance and accuracy of its output based on demonstrated instances.
- **Structured Analytical Output for Decision Support:** AI-generated analyses are meticulously formatted to ensure clarity and ease of integration. This structured output is critical for streamlining the assimilation of insights into the SSFF's decision-making processes, providing a cohesive and interpretable foundation for strategic evaluations.
- **Divide and Conquer Strategy for Comprehensive Analysis:** By segmenting the startup evaluation into distinct analytical domains, the Analysis Block adopts a divide and conquer approach. This strategy facilitates in-depth scrutiny by specialized virtual analysts, ensuring that each aspect of the startup's potential—market viability, product innovation, and founder dynamics—is thoroughly assessed. This methodological partitioning not only optimizes the analysis for depth and focus but also aligns with proven efficacy in complex problem-solving scenarios.
- **Chain of Thought Prompting for Enhanced Reasoning:** Each prompt is crafted to elicit a "chain of thought" reasoning from the AI, guiding it through a step-by-step analytical process. This approach encourages the generation of more reasoned, logical, and detailed insights, mirroring human analytical progression and supporting nuanced interpretation of startup ecosystems.

5.3 Framework Integration and Case Studies

Embedded within the SSFF, the Analysis Block significantly enhances our ability to forecast startup success with a high degree of confidence. Its integration not only elevates the framework's predictive accuracy but also enriches the strategic advisories provided to stakeholders, thereby shaping the future of venture investment strategies.

6 External Knowledge Block

The External Knowledge Block plays a pivotal role in the Startup Success Forecasting Framework (SSFF) by augmenting the analysis with real-time market insights and trends. A RAG-based module, this block leverages advanced data extraction and natural language processing technologies to provide a comprehensive understanding of the market landscape, critical for informing the decision-making process.

6.1 External Knowledge Generation: Market Knowledge

At the heart of the External Knowledge Block is the use of the web-scraing APIs like SERP (Search Engine Results Page) API to systematically gather current and relevant information about the market. This process involves:

1. **Keyword Generation:** Identifying pertinent keywords and search queries related to the startup's market, technology, and competition.
2. **Content Retrieval:** Utilizing the SERP API to execute search queries and retrieve a wide array of content, including news articles, blog posts, and reports that provide insights into market dynamics, trends, and consumer sentiment.
3. **Data Filtering:** Sifting through the retrieved content to focus on the most relevant and informative pieces, ensuring the analysis is based on high-quality data.

6.2 Insight Synthesis with GPT Models

Following the extraction of targeted information, the next step involves synthesizing this data into coherent and insightful market reports. This synthesis is accomplished through the use of Generative Pre-trained Transformer (GPT) models:

1. **Prompt Design:** Crafting detailed prompts that guide the GPT model to analyze the collected data, considering the startup's context and the specifics of its market.
2. **Report Generation:** Leveraging the GPT model's capabilities to integrate and interpret the data, generating comprehensive market reports that highlight key findings, opportunities, challenges, and trends.
3. **Integration and Feedback:** Incorporating the synthesized market reports into the SSFF's broader analytical framework, where they complement and enhance the insights provided by other blocks.

6.3 Strategic Value of External Knowledge

The incorporation of real-time, data-driven market insights significantly elevates the strategic value of the SSFF, offering:

- **Enhanced Market Understanding:** The detailed market reports provide a deep dive into the external factors that could impact a startup's success, offering a nuanced view of the market landscape.
- **Informed Decision-Making:** By integrating current market insights with internal analyses, the SSFF facilitates more informed and strategic decision-making, enabling stakeholders to identify and act on emerging opportunities and threats.
- **Dynamic Analysis:** The ability to continuously update and refine market reports ensures that the SSFF's evaluations remain relevant in the face of rapidly changing market conditions.

6.4 Case Study and Results

This case study illustrates the application of the Market External Module within the Startup Success Forecasting Framework (SSFF), particularly highlighting its use of the SERP API for extracting relevant content about the market, followed by synthesis through GPT models to generate comprehensive market reports. Complete prompting and responses are included in the appendix.

6.4.1 Preprocessing and Keyword Generation

The exploration begins with preprocessing inputs describing WeLight, a startup aiming to revolutionize the Chinese college application consulting market through AI-driven solutions. The initial step involves generating keywords using GPT-3.5-turbo to refine search queries:

> "WeLight aims to revolutionise China's $2.5 billion college application consulting market by increasing access for over a million Chinese students aspiring to study abroad. As an AI-powered platform, WeLight automates program selection, preparation guidance, and essay review using Large Language Models (LLM), the ANNOY Model, and an extensive database."

Keywords Generated: Chinese Education Consulting Market, Growth, Trend, Size, Revenue.

6.4.2 Market Analysis Through SERP API

Utilizing the SERP API with N = 3, we conducted a focused search on the generated keywords, yielding insights into the market's size, growth projections, and emerging trends. This process is scaled with N = 10 to deepen the exploration, uncovering nuances of market dynamics and consumer behavior.

6.4.3 Insights Synthesis and Report Generation

The synthesis phase leverages GPT models to integrate and analyze the search results, producing a nuanced market report that includes:

- The projected growth of China's education market, emphasizing an anticipated increase in market volume to US$2.32 billion by 2027 and highlighting the market's expected double growth from 2015 to 2020.
- An exploration of technology adoption within the education sector, identifying a significant surge in AI-driven personalized learning solutions.
- A segment-wise analysis revealing the adult learning industry's projected revenue growth and the K-12 sector's market dominance.
- A detailed look into market sentiment and timing for entry, suggesting a favorable climate for new ventures, given the market's expansive trajectory.

The report concludes with strategic recommendations for WeLight, emphasizing the importance of aligning with market growth areas, technological trends, and addressing credibility challenges within the education consulting sector.

6.4.4 Comparative Analysis and Findings

A comparative analysis reveals that the data depth, structured insights, and timeliness of information significantly improve as N increases from 3 to 10. The RAG-based Agent analyst, underpinned by GPT-4, showcases superior performance over traditional API-level Chain-of-Thought (CoT) prompting, particularly in terms of data sufficiency and relevance.

Key Findings:

1. Enhanced data richness and structured analysis with increased N, demonstrating the scalability and efficiency of the RAG-based exploration.
2. Superior performance of the RAG-based agent in synthesizing market insights compared to conventional CoT prompting methods, indicating a significant potential for business impact.
3. The analysis underscores the importance of comprehensive market studies, especially for startups like WeLight aiming to penetrate or expand within the dynamic Chinese education market.

6.5 Other & External Modules Within the Block

Another module is used to extract relevant news up-to-date information about the product, using relevant APIs.

6.6 Comprehensive Conclusion

The exploration of the Market External Module, as demonstrated in the preceding case study, and the overarching implementation of the External Knowledge Block within the Startup Success Forecasting Framework (SSFF), collectively underscore a pivotal advancement in startup ecosystem analysis. These components, through their advanced AI-driven methodologies and strategic integration of real-time market data, serve as cornerstone elements that significantly enhance the SSFF's analytical depth and strategic foresight.

The Market External Module, with its precise approach to data extraction and insight synthesis, exemplifies how targeted information retrieval and AI-powered analysis can yield profound understandings of market dynamics and opportunities. This case study, focusing on the Chinese education consulting market, illustrates the module's capability to distill complex datasets into actionable insights, facilitating nuanced decision-making that aligns with the current market landscape and future growth trajectories.

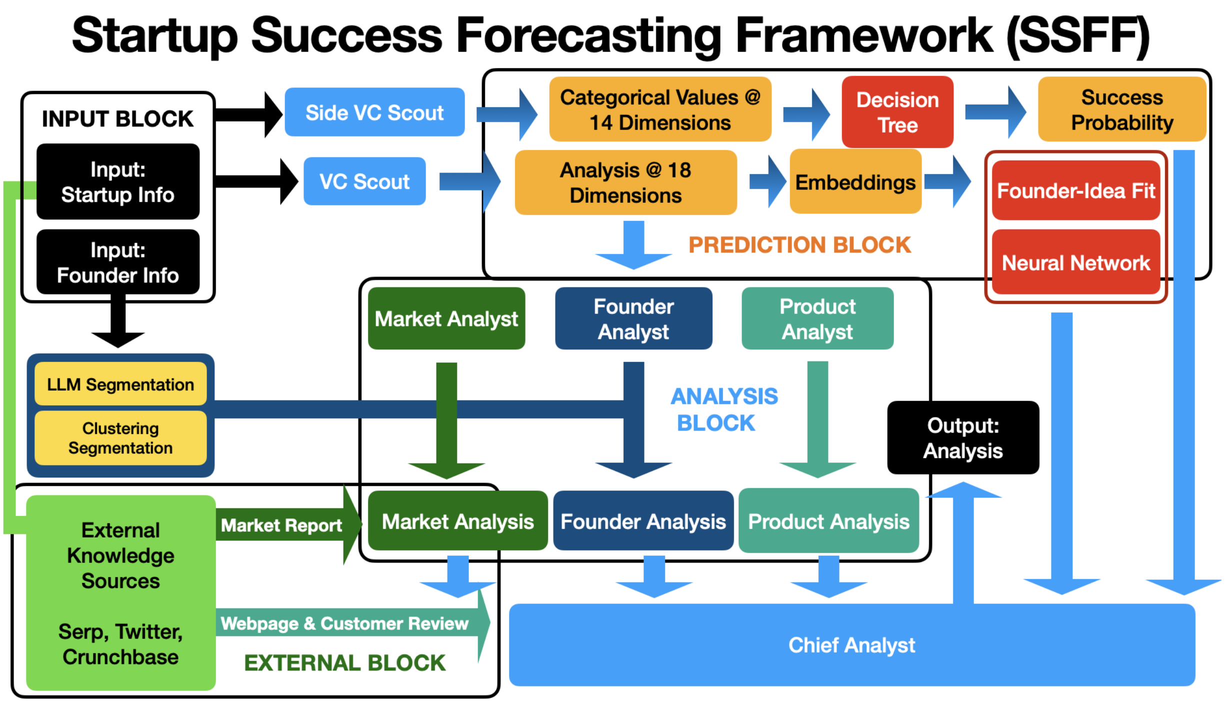

Figure 6: A schematic view of the Startup Success Forecasting Framework

Simultaneously, the broader External Knowledge Block's role within the SSFF highlights the essentiality of a real-time, data-driven perspective in startup evaluation processes. By systematically extracting, filtering, and synthesizing pertinent market data, this block significantly amplifies the SSFF's capacity to deliver grounded, comprehensive, and dynamic analyses. Such enriched assessments empower stakeholders with the foresight needed for strategic planning, market entry, and competitive positioning, ultimately reinforcing the SSFF's utility as an indispensable tool for informed decision-making in the venture capital ecosystem.

In synthesis, the integration of the Market External Module and the External Knowledge Block within the SSFF not only elevates the framework's analytic rigor but also ensures that evaluations are reflective of the evolving market conditions. This harmonized approach underscores the strategic value of leveraging advanced AI techniques and real-time market insights to navigate the complexities of startup success forecasting. The cumulative effect is a more robust, agile, and insightful framework capable of guiding stakeholders through the intricacies of strategic planning and market entry with confidence and precision.

7 Startup Success Forecasting Framework

7.1 Framework Design

The Startup Success Forecasting Framework (SSFF) integrates the three blocks in previous sessions seamlessly and dynamically, taking founder and startup information as input and generating multifaceted predictive analyses.

Initially, the data undergoes a preliminary review by a VC scout agent who synthesizes the information into 18 critical dimensions. Subsequently, the data is distributed to specialized analysts applying a divide-and-conquer approach. Simultaneously, a side VC poses fourteen tailored questions and harnesses a sophisticated, trained decision tree model to generate preliminary success predictions.

In parallel, a clustering segmentation process is employed to categorize founders, refining the analysis with granular founder information as outlined in the preceding discussion. In addition, the information goes through embedding and the Founder-Idea Fit model to generate a Founder-Idea Fit Score. Meanwhile, the External Block diligently compiles market intelligence and current news related to the product, enriching the data pool for both the market and product analysts.

Concluding the process, a chief analyst integrates the diverse strands of information, crafting a comprehensive report. This report embodies a cohesive synthesis of data-driven predictions and strategic insights, reflecting the intricate potentialities of the startup's trajectory towards success.

8 Conclusion and Discussion

In this section, we acknowledge the constraints of our current models and identify areas for future improvement. The Founder-Idea Fit Model, while robust, has been trained on datasets with relatively concise descriptions. In practical scenarios where web scraping is employed, the data collected could be significantly more extensive, potentially influencing the model's performance due to its reliance on the capacity of encoders used during training. Future iterations of the model could benefit from training on datasets with a wider range of description lengths to enhance its applicability in real-world scenarios.

Our architecture analyzes various dimensions of a startups, but it primarily relies on external datasets to make assessments faster and easier to reduce friction to request data from the startup founder. In the future, we plan to expand this model to include datasets like startup data rooms, product logs, and CRM data. This will allow for more thorough due diligence after analyzing publicly available information.

Regarding the Random Forest model, we recognize the limitations imposed by the size of our dataset, currently capped at 200 entries, all of which were synthesized using GPT-3.5-turbo. This restriction not only narrows the scope of our model's learning potential but also introduces a margin for error stemming from inaccuracies inherent in the GPT-3.5-turbo generated data, such as incorrect options among other issues. Future work will focus on expanding the dataset with more diverse and larger-scale data, as well as exploring the integration of more and recently released advanced language models such as gpt-4o that offer improved data generation capabilities. This two-pronged approach is anticipated to substantially mitigate current deficiencies and propel the efficacy of the Random Forest model forward.

References

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Appendix

The following section describes the output of our model.

XISEN to share more information about the input provided, and outputs for which examples. It is hard to understand the APPENDIX results.

A Appendix: Analysis Results, Final Decision, and Overall Investment Recommendation

A.1 Overall Investment Recommendation

Having considered the scores given and the detailed analysis, I recommend an 'Invest' decision. The overall scores for Market Viability, Product Viability, and Founder Competency are 8/10, 7/10, and 8.25/10, respectively. Here's a comprehensive rationale for this recommendation:

- **Market Viability:** The market conditions appear favorable with the rising demand for flexible credit alternatives. At a score of 8, the company shows promising indicators like considerable market size, strong growth trajectory, and robust customer acquisition strategies. Despite strong competition and some regulatory uncertainties, the company's positioning and go-to-market strategy should help navigate these challenges effectively.
- **Product Viability:** The product addresses a compelling market need and has demonstrated scalability across different markets. With a score of 7, uncertainties such as the level of innovation, specifics of technology used, and incomplete user feedback were noted. However, the product holds potential and fills a significant gap in the credit market.
- **Founder Competency:** The founder's broad industry experience, successful past ventures, demonstrated leadership skills, and clear vision make them highly capable of steering this startup. A score of 8.25 suggests strong founder competency, with room for improvement, particularly in team dynamics and specific strategies to realize the company's vision.

Given the balance of strengths and potential challenges, my recommendation is to 'Invest'. While there are points of caution, especially around product differentiators and team dynamics, the overall potential based on market demand and founder competency seems promising. The emerging market trend, along with experienced leadership, is likely to offer a significant competitive advantage while navigating the landscape. It's important, however, to encourage transparency on remaining unknowns and monitor the resolution of defined issues closely.

A.2 Market Info

A.2.1 Timing of Market Entry

Considering the shift towards flexible and responsible payment options, the company's entry into the market appears well-timed. The rising trend for more flexible payment options, which allow consumers to avoid incurring extended debt, has been expedited by recent economic uncertainties.

A.2.2 Market Size and Growth

The market size is large, with the company having over 50,000 retailers worldwide. The growth rate is also substantial, with 9 million active consumers observed as of 2020. These factors indicate healthy customer acquisition and marketplace traction.

A.2.3 Existing Competition

Though traditional credit and payment providers are the primary competition, other companies offering similar payment options pose significant challenges. However, the financial flexibility and lack of fees with on-time payments offer a competitive edge.

A.2.4 Go-to-Market Strategies

Partnering with global retailers provides a broad operational footprint, establishing brand recognition and credibility among consumers. This strategy ensures wider accessibility of the service.

A.3 Product Info

A.3.1 Market Fit

The payment service offering deferred payment in installments addresses a clear market need, appealing to a broad market including millennials and Generation Z.

A.3.2 Innovation Level

While the concept of deferred payment is not new, simplifying this concept within a fintech context is relatively innovative.

A.3.3 Scalability

The product's success in distinct markets indicates a high potential for scalability.

A.3.4 User Reception

Without specific user feedback, the product's success across multiple markets implies a generally positive reception.

A.4 Founder Info

A.4.1 Founders' Backgrounds

The founder, Anthony, has a robust background with an impressive span of 25 years, covering crucial areas such as investment and business development.

A.4.2 Track Records

Anthony's association with successful companies suggests a high level of proficiency and credibility.

A.4.3 Leadership Skills

Anthony's ability to design and execute strategic initiatives indicates strong leadership skills.

A.4.4 Vision and Alignment

The commitment to providing responsible payment alternatives showcases clarity of vision, although execution strategies and team alignment towards this vision are not detailed.

A.5 Advanced Result: Models & Predictions

Founder Segmentation: L5, indicating a high chance of success.

Founder Idea Fit: The score of 0.6147112 suggests the founder has a compatible background for the startup's success.

Categorical Prediction: Successful, with a 90% confidence level based on market viability, product viability, and founder competency scores.

The detailed analysis and predictions presented in this appendix form the basis for a strong 'Invest' recommendation. This venture shows promise across multiple critical areas, under

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B Appendix: Analysis Results, Final Decision, and Overall Investment Recommendation

B.1 Overall Investment Recommendation

Having considered the scores given and the detailed analysis, I recommend an 'Invest' decision. The overall scores for Market Viability, Product Viability, and Founder Competency are 8/10, 7/10, and 8.25/10, respectively. Here's a comprehensive rationale for this recommendation:

- **Market Viability:** The market conditions appear favorable with the rising demand for flexible credit alternatives. At a score of 8, the company shows promising indicators like considerable market size, strong growth trajectory, and robust customer acquisition strategies. Despite strong competition and some regulatory uncertainties, the company's positioning and go-to-market strategy should help navigate these challenges effectively.
- **Product Viability:** The product addresses a compelling market need and has demonstrated scalability across different markets. With a score of 7, uncertainties such as the level of innovation, specifics of technology used, and incomplete user feedback were noted. However, the product holds potential and fills a significant gap in the credit market.
- **Founder Competency:** The founder's broad industry experience, successful past ventures, demonstrated leadership skills, and clear vision make them highly capable of steering this startup. A score of 8.25 suggests strong founder competency, with room for improvement, particularly in team dynamics and specific strategies to realize the company's vision.

Given the balance of strengths and potential challenges, my recommendation is to 'Invest'. While there are points of caution, especially around product differentiators and team dynamics, the overall potential based on market demand and founder competency seems promising. The emerging market trend, along with experienced leadership, is likely to offer a significant competitive advantage while navigating the landscape. It's important, however, to encourage transparency on remaining unknowns and monitor the resolution of defined issues closely.

B.2 Models & Predictions

Founder Segmentation: L5

Founder Idea Fit: 0.6147112

Categorical Prediction: Successful

Numerical Prediction Summary: Successful, 90%. The Founder Segmentation of L5 indicates a high chance of success. The Founder-Idea Fit Score of 0.6147112 suggests the founder has a compatible background for the startup's success. The model's prediction favors the success of the startup. In the report, Market Viability, Product Viability fulfill the expectation with 8 out of 10 each. Furthermore, Founder Competency scores a high 9.75, strengthening the founder's potential. All these factors contribute towards the high probability of success.

B.3 Analysis Results and Final Decision

Based on the comprehensive analysis presented by the teams, the investment recommendation for this startup is as follows:

- **Market Viability:** 8/10 - The market for BNPL services is currently booming, and the company's strategy aligns well with this trend. There is potential regulatory risk due to the nature of BNPL services, however, their timely entry, execution strategy, and a shift in consumer spending behavior make the prospect favorable.
- **Product Viability:** 8/10 - The company has an excellent product-market fit with its offerings fitting into the current consumer behavior trend of responsibility and flexible spending. The product novelty isn't high given the existence of other competitors so the company needs to differentiate their offering continuously.
- **Founder Competency:** 9.75/10 - Co-founder, Anthony Eisen, has impressive industry experience and leadership capabilities. His strategy, shared vision with the Co-CEO, and proven ability to execute underline his strong competency, although the dynamics of co-CEOs may need further exploration.

The model's predictions further boost confidence in success with a likelihood of 65%. The startup also aligns well with the founder's background (score of 0.6147112), increasing the chances of success. However, predictions should be interpreted with caution as they're not infallible.