Founder GPT

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Abstract

In assisting Vela Partners, the "Founder-GPT" project is an innovative venture capital initiative leveraging artificial intelligence to assess startup founders. Utilizing Large Language Models like GPT-4, the project aims to systematically evaluate founders' profiles, providing quantitative scores and qualitative pros and cons lists. The methodology encompasses several stages, starting with the extraction of similar founder profiles using a combination of embeddings generated from key profile dimensions and similarity measures. The subsequent phase involves leveraging GPT-4 to generate detailed rationales behind the success or failure of these profiles. This analysis forms the basis for a scoring system that quantifies the potential success of new founder profiles, along with generating insightful pros and cons lists. The results from the "Founder-GPT" project highlighted its strength in accurately identifying founders with high success potential, reflected in high scoring profiles. The system also successfully generated comprehensive pros and cons lists that provided nuanced insights into the founder profiles. However, our project faces challenges like a high false positive rate and significant computational demands. The project highlights the need for future enhancements, including refining false positive mitigation, computational efficiency, and the integration of broader data sources and advanced analytical methods. This work sets a foundation for AI-enhanced decision-making in venture capital, pointing towards areas for further development to fully realize AI's potential in founder evaluation.

Keywords: **venture capital investment, artificial intelligence, large language models, GPT-4, prompt engineering**

1 Introduction

1.1 Backgrounds

The landscape of venture capital investment is increasingly complex and competitive. In this environment, the ability to accurately assess the potential success of startup founders is invaluable for investment firms like Vela Partner. Traditionally, this assessment has relied on manual analysis, which is both time-consuming and subject to human bias. Recognizing the need for a more efficient and objective approach, this research paper presents a novel solution conducted in collaboration with Vela Partner. At the core of our approach is the understanding that a founder's background and the nature of their startup idea are critical indicators of potential success. Hence, effectively screening and analyzing founder details is paramount for making informed investment decisions.

1.2 Problem Statement and Objective

This research aims to address the challenge of evaluating startup founders in the context of venture capital investment decisions. Specifically, when provided with a founder's LinkedIn profile and a description of their startup idea, our goal is to develop a system capable of quantitatively assessing the likelihood of success. The system, "Founder-GPT," is designed to generate a score out of 10, indicating the potential for success, along with a detailed pros and cons analysis of the founder's profile. This analysis is grounded in a comparative approach, utilizing a dataset of both successful and unsuccessful founders as a benchmark for training and evaluation. The objective is to offer a nuanced and comprehensive assessment that aids investment firms in identifying promising entrepreneurial talent.

1.3 Methodology

The methodology of this research revolves around a multi-step pipeline, integrating advanced AI technologies and data analysis techniques. The process begins with the extraction of similar founder profiles from our extensive dataset, leveraging natural language processing (NLP) and similarity measures. Following this, Large Language Models (LLMs), specifically GPT-4, are employed to analyze these profiles and generate a detailed rationale for their success or failure. This rationale forms the basis for scoring a new founder's profile and constructing a list of pros and cons. The scoring system is carefully designed to quantify the founder's alignment with the identified success factors, while the pros and cons list offers qualitative insights. This combination of quantitative and qualitative analysis provides a well-rounded evaluation of the founder's potential.

2 Literature Review

In the domain of venture capital, the advent of artificial intelligence and machine learning has markedly refined the process of evaluating startup founders, as evidenced in seminal research works. The groundbreaking study of Lou et al[YL23], "Automating Startup Analysis: LLM-based Venture Capital Analyst", elucidate the efficacy of Large Language Models (LLMs) such as GPT-4 in the automation of startup analysis, with a particular emphasis on the intricate assessment of founder profiles. Concurrently, Research done by Marsden et al[Mar23] on the timeline analysis of founder details adopts a chronological approach in feature engineering, scrutinizing the trajectory of a founder's career to prognosticate their potential for success. These pivotal studies, along with the advent of AI's transformative role in entrepreneurship, collectively advocate for the integration of data-driven methodologies and AI algorithms. This burgeoning trend of employing AI for nuanced founder evaluations forms the crux of the "Founder-GPT" project, which seeks to amalgamate these innovative methodologies for a holistic assessment of entrepreneurial potential.

3 Methodology

The methodology underpinning the "Founder-GPT" project is anchored in an innovative multi-step pipeline. At its core, the methodology leverages the prowess of Natural Language Processing (NLP) and similarity measures to identify and analyze founder profiles from a comprehensive dataset. This is followed by the deployment of Large Language Models (LLMs), specifically GPT-4, to interpret these profiles and generate detailed rationales regarding their potential for success or failure. Subsequently, the methodology incorporates a scoring system designed to quantitatively evaluate the likelihood of a founder's success, complemented by a qualitative analysis in the form of a pros and cons list.

3.1 Feature Engineering on Founder's Data

The data collection process for the "Founder-GPT" project was meticulously designed to ensure a comprehensive and insightful analysis of startup founders. The process leveraged two distinct datasets: one comprising **2,180 successful companies** valued at over USD 500M, achieved through IPOs, mergers and acquisitions, or substantial funding rounds; and another featuring **3,901 unsuccessful companies** that raised between $4Mand10$M but could not match the growth pace of their successful counterparts.

The extraction of founder profiles was underpinned by the following steps:

1. Founder details were meticulously extracted from *success_enriched_linkedin_profiles.csv* and *fail_enriched_linkedin_profiles.csv* into individual JSON files. This step ensured a structured and accessible format for further analysis.

2. A specialized program read each founder's JSON file, extracting relevant information. This process was informed by the research of Marsden et al., ensuring that the extracted features were pertinent to assessing the founders' potential for startup success.

3. Relevant founder information include:

- **Name**: The founder's name (string).
- **Age**: The founder's age (float).
- **Startup Success Status**: A boolean indicating the success status of the startup (boolean).
- **Self-Descriptions**: Textual descriptions provided by the founders (string).
- **Education Backgrounds**: A list of 3-tuples for each educational history, including institution name (string), degree (string), and major (string).
- **Employment Backgrounds**: A list of 5-tuples for employment history, detailing company name (string), roles (list of strings), duration of employment (float), start date (datetime), and current employment status (boolean).
- **Startup Name** (string)
- **Startup Description** (string)
- **Startup Category**: The industry or sector category of the startup (string).

4. Each founder's details were assigned a unique ID, facilitating precise identification and referencing throughout the project.

5. The final step involved exporting all collated founder details into a comprehensive CSV file, *'Founder Features.csv'*, which served as the primary data source for the subsequent stages of the project.

3.2 Finding Similar Founder Profiles

The next phase of the "Founder-GPT" pipeline focuses on identifying similar founder profiles: on the input of a new founder's detail, we aim to extract the top 5 similar founder profiles in our existing database, and these top similar results will be crucial for the future stages of this pipeline. The similarity comparison process is grounded in a multi-dimensional approach, considering five key dimensions: **founder's self-description, education backgrounds, employment backgrounds, startup long description (startup idea), and startup category**.

To facilitate the comparison of these dimensions across different founder profiles, we employ a methodical process:

1. **Conversion to Embeddings**

   The string representations of the five dimensions for each founder are converted into separate embeddings. This transformation is achieved using OpenAI's embedding via the 'embed_text' function, which performs basic tokenization and then calls the OpenAI API to generate the corresponding embedding.

2. **Embedding Data Storage**

   The resultant embeddings for all founder details are meticulously stored in a file named *"Founder Features with Embeddings.csv"*, encompassing over 10,000 rows. This comprehensive dataset forms the backbone of our similarity comparison process.

3. **Data Splitting**

   The embedding data are split into training and testing datasets in a 9:1 ratio. The training data represent the existing database of founder details, while the testing data simulate "new" founder profiles for evaluating the program's accuracy.

4. **Extraction of Similar Profiles**

   The goal is to extract the top 5 similar founder profiles from the database upon input of a new founder's profile. This can be accomplished using two distinct methods:

   Method 1: Weighted Sum of Similarity Scores

   - Initially, 50 successful and 50 unsuccessful founder details are randomly selected from "Founder Features.csv".

- These samples are fed into GPT-4 to generate weights for each of the five dimensions, determining their importance in similarity comparison.
- The weights, standardized to sum to 10, are averaged over several trials using different random samples.
- The top 5 similar founders are identified based on the weighted sum of similarity scores across the dimensions, calculated using cosine similarity of their embeddings.

$$s_i = cosine\_similarity(new\_founder\_detail[i], existing\_founder\_detail[i])$$

$$aggregate\_similarityS = \sum_{i=1}^{5} w_i s_i$$

This method, while accurate, is time-intensive as it requires manual comparison with all embeddings in the training database.

Method 2: Using Pinecone Vector Database

- A Pinecone index "founder-profiles" is created to store the embeddings of all founder profiles, with each dimension stored in its respective namespace.
- For a new founder profile, the program first converts it to embeddings and then queries the Pinecone database to retrieve the top 5 similar results for a specific dimension.
- This method offers speed but potentially sacrifices accuracy as it does not amalgamate results from all five dimensions.

5. **Storing Similar Profiles**

   The top 5 similar founder profiles extracted are stored in "Top Similar Founders.csv," serving as a pivotal resource for subsequent stages of the pipeline.

This methodology underscores a balanced approach, leveraging both the depth of individual dimension analysis and the comprehensive overview provided by aggregated similarity scores. The dual methods cater to different needs, offering a choice between accuracy and time efficiency in the founder profile comparison process. The detailed procedures for deriving weights and further technical specifics are elaborated in the appendix section of this dissertation.

3.3 Using LLM for Rationale Generation

1. To facilitate the analysis of founder details using Large Language Models (LLMs) systematically, we create a Founder object. This object encapsulates a comprehensive set of attributes representing the key features of a founder, as identified in Section 3.1, including personal details, educational and employment backgrounds, startup descriptions, and other relevant data points. The Founder object also includes getter and setter methods, allowing for the efficient retrieval and updating of these attributes.

2. Upon the input of a new founder profile, the programme retrieves the top 5 similar founder profiles from "Top Similar Founders.csv", an output from Section 3.2. Each of these profiles is then used to create a Founder object, and all five of them are compiled into a list.

3. The next critical step involves generating a prompt for GPT-4 to analyze these founder profiles and produce a rationale. This is achieved through the generate_prompt_for_rationale() function, which takes the list of Founder objects as input. The function constructs a detailed prompt, incorporating information from each founder profile and framing specific queries for GPT-4. This prompt, as well as those in the subsequent subsections, are carefully constructed using techniques such as Chain of Thoughts(CoT) prompting and few-shot learning[htt]. The methodology and nuances of this prompt construction are detailed in the appendix of this paper.

4. Once the prompt is ready, it is passed to the get_rationale() function. This function interfaces with GPT-4, feeding it the constructed prompt and soliciting a comprehensive rationale. The rationale is restricted to a maximum of 500 tokens, ensuring conciseness while covering both Success and Failure Rationales, along with a synthesized conclusion. GPT-4's response provides an in-depth analysis of the similarities and differences between the founder profiles, offering insights into potential factors contributing to their success or failure. An example of such a rationale is included in the Result section.

3.4 Scoring and Pros/Cons List Generation

1. **Summarizing Key Factors for Success and Failure**

   The comprehensive rationale generated in the previous section serves as the foundation for extracting key factors of success and failure. Utilizing the extract_key_factors() function, this rationale is methodically fed into GPT-4, which then summarizes it into distinct lists of success and failure factors. Each factor is comprised of a name and a concise description, furnishing crucial insights for the subsequent scoring of new founder profiles. This step ensures that the analysis is grounded in factors directly relevant to startup success and failure, as discerned from the rationale.

2. **Scoring Founder Profiles**

   Building upon these extracted factors, the score_founder_profile() function is employed to evaluate the scores of the new founder's profile. This function orchestrates a prompt for GPT-4, requesting an evaluation of the founder against each success and failure factor listed. The response is a series of scores that reflect the founder's alignment with each factor. These scores are then aggregated to compute an overall score, calculated as the sum of success scores divided by the total of success and failure scores. This final score is normalized to a scale of 0 to 10, offering a quantifiable measure of the founder's potential for success.

$$overall\_score = \frac{\sum success\_scores}{\sum success\_scores + \sum failure\_scores} * 10$$

3. **Generating Pros and Cons List** The final step in the pipeline is the generation of a Pros and Cons list, executed through the generate_pros_and_cons() function. This function inputs the success and failure factors along with their respective scores and sets a threshold value. Factors scoring equal to or above this threshold are deemed significant and are included in the GPT-4 prompt. The AI then synthesizes this data into a list of Pros and Cons, highlighting the strengths and potential weaknesses of the founder's profile. This process not only identifies areas where the founder excels but also pinpoints aspects that might need attention or improvement.

   An example of scoring output and pros and cons list is provided in the Result section.

4 Results and Discussion

4.1 Analysis of Results: Case Studies

Given the computational constraints and the time-intensive nature of our methodology, a detailed case study is presented as a representative example to illustrate the efficacy of the "Founder-GPT" pipeline. This case study offers an in-depth look into the process of founder evaluation, encompassing similarity analysis, rationale generation, scoring, and the formulation of pros and cons lists.

In the following example, a successful new founder profile is randomly selected from the testing data set. Our model reads the input information without knowing if the founder's startup is successful or not, and make predictions about its chances of success based on the scoring and list of pros and cons.

Example of new founder details as input:

```
  Founder 1:
- Name:  Charles Vincent
```

- Age: 31.0
- Self Description: Charles is a Montreal-born Materials Engineer and holds a B.Eng. from McGill University. Prior to cofounding TemperPack, Charles worked in the EV industry, and led the design and development of a novel lithium-ion battery in collaboration with the Canadian Department of National Defense. Charles drives the design, execution, and scaling of revolutionary manufacturing processes across our operation to maintain our nimbleness and authority in the marketplace. When he is not thinking about the next big thing, Charles can be found repairing his '89 Wrangler, fly fishing in the Blue Ridge Mountains, or hiking with his fiancée Micah and his dog Molson.
- Education Backgrounds:
- Bachelor's (4 year program) in unknown from McGill University
- Employment Backgrounds:
- Worked in CrossChasm Technologies for 0.33 years, starting from 01/01/2013. His roles in the company include Intern, Engineering, IT and Software Development.
- Startup Name: TemperPack
- Startup Idea: TemperPack is seeking to solve the world's packaging problems through sustainable design. The company specializes in custom solutions for clients to scale in the perishable food and life sciences industries. TemperPack is also the first insulated packaging company to develop a certified fully curbside recyclable insulated shipping solution. TemperPack was founded in 2015 for the purpose of bringing sustainable packaging technology to companies that ship large volumes of perishable goods.

Upon this input, our programme first identify the top 5 matching existing founder details in our training data set, using similarity comparison techniques described in section 3.2. Due to space limitation, the following shows only the names and startup success status of the top 5 similar founders:

Founder 1: 'Benjamin Moore', status: 'Failed', aggregate similarity: 8.52
Founder 2: 'James Mcgoff', status: 'Successful', aggregate similarity: 8.44
Founder 3: 'Yoke Chung', status:'Successful', aggregate similarity: 8.31
Founder 4: 'Brian Powers', status: 'Successful', aggregate similarity: 8.29
Founder 5: 'Troy Swope', status: 'Successful', aggregate similarity: 8.25

Next, our programme generate a rationale based on these top 5 founder profiles. An example of the rationale generated is as followed:

Success Rationale:
- Successful founders presented robust educational backgrounds with qualifications in their startup's core domain or relevant fields. For example, Yoke Chung and Brian Powers possess degrees in fields closely related to their startups' main focus, enhancing their credibility and expertise.
- The successful founders have significant previous work experience, including leadership positions, which helped them acquire skills and competencies vital for their startups' navigation. For instance, James Mcgoff worked at Boeing Defense, and Yoke Chung had a tenure at Intel.
- Successful founders showed an ability to positively leverage their prior experiences, both career, and educational, in their current ventures. For instance, Footprint was established by Troy Swope and Yoke Chung, who applied their skills and experience from Intel to design new materials.
- Their startups centered around solving a significant problem or tapping into an emerging market demand, such as sustainable packaging in the case of TemperPack and Footprint.
- Recognitions such as being named to the Forbes 30 Under 30, EY Entrepreneur of the Year Winner, or Inc. 30 Under 30 were common among successful founders, indicating their exceptional contributions and achievements in the business

world.

Failure Rationale:
- The failed founder, Benjamin Moore, did not have a recorded educational background. This lack of demonstrated foundational or domain-specific expertise may have impacted the startup's ability to meet market expectations.
- While Benjamin has extensive experience as a Mechanical Engineer, his specific roles and responsibilities remain undefined, making it hard to ascertain whether his prior experience contributed helpful skillsets or connections for the startup.
- The startup idea, although innovative, might not have been economically viable or differentiated enough to succeed amidst competition. The lack of a clear competitive edge or unique selling proposition may have hindered success.

Synthesized Conclusion: Successful founders typically boast strong educational backgrounds in relevant fields, substantial prior professional experience often in leadership roles, and their ventures are commonly designed to address a significant problem or fulfill a market demand in innovative ways. Acknowledgements and recognitions on prestigious platforms demonstrate their skills and accomplishments. Failed startups, on the other hand, may be associated with founders lacking a proven educational track record, undefined professional experience, and startups without a distinctive competitive advantage. Thus, it appears that founders' education, experience, the nature of their ventures, and recognitions they received bear substantial implications for their startups' success or failure.

Based on the rationale, a list of factors for success and failure are generated respectively, and a score is rated for each of the factors against the new founder's profile. An example of the scoring output together with their list of success and failure factors is as followed:

Success 1) Relevant Educational Background: Successful founders have a robust education in their startup's domain or a closely connected field.
[Score: 6 / 10]
Success 2) Valuable Work Experience: Founders with substantial previous work experience, especially in leadership roles, often leverage these skills to navigate their startups successfully.
[Score: 5 / 10]
Success 3) Application of Prior Experience: The ability to leverage past experiences from career and education to the current venture can significantly contribute to success.
[Score: 8 / 10]
Success 4) Significant Problem-Solving: The startup focuses on solving a significant problem or taps into unmet market needs.
[Score: 6 / 10]
Success 5) Prevailing Recognition: Founders who have earned recognitions like Forbes 30 Under 30, EY Entrepreneur of the Year Winner, etc., are usually successful due to their exceptional contributions and abilities.
[Score: 0 / 10]
Success 6) Successful Entrepreneurship History: Founders who have successfully run or sold their previous startups are more likely to succeed again.
[Score: 0 / 10]
Success 7) High-Level Roles in Large Corporations: Founders with prior experience in VP/SVP/executive roles in big tech or other large companies are typically successful.
[Score: 2 / 10]
Success 8) Skills Mastery: Founders who exhibit mastery skills such as multilingualis leadership in sports teams, or championship in competitions may be more likely to lead their startups to success.
[Score: 4 / 10]

Success 9) Positive Personal Traits: Founders who are self-confident, perseverant, and articulate tend to drive their startups toward success.
[Score: 6 / 10]
Failure 1) Lack of Recorded Education: Founders without a proven educational background often struggle to meet the demands of startup leadership.
[Score: 1 / 10]
Failure 2) Undefined Work Experience: When past roles and responsibilities are indefinite, it becomes hard to determine if the founder's prior experience will be beneficial to the startup.
[Score: 2 / 10]
Failure 3) Lack of Unique Competitive Advantage: If a startup is not differentiated enough in its market or fails to propose a unique selling point, it may face failure.
[Score: 1 / 10]
Failure 4) History of Failed Startups: Founders who previously started and failed may be more prone to continue the failure trend.
[Score: 0 / 10]
Failure 5) Job Hopping: Founders who have frequently switched jobs may not provide the needed stability for a startup.
[Score: 1 / 10]
Failure 6) Incomplete Details: Unavailable information or incomplete details about a founder's background may suggest a likelihood of failure.
[Score: 1 / 10]
Failure 7) Mismatched Skills: When a founder's skills don't align with the market demands of the startup, there's a higher chance of failure.
[Score: 1 / 10]

Success Scores: [6.0, 5.0, 8.0, 6.0, 0.0, 0.0, 2.0, 4.0, 6.0]
Failure Scores: [1.0, 2.0, 1.0, 0.0, 1.0, 1.0, 1.0]
Overall Score: 8.40909090909091

A pros and cons list is then generated based on these factors and scores. An example of the list is as shown below:

Pros:
1. Relevant Experience and Background: Charles has an educational background in Materials Engineering, which aligns with his startup's field of specialization. Moreover, his past work experience in the Electric Vehicle (EV) industry demonstrates his ability to design, develop, and execute revolutionary manufacturing processes, potentially beneficial to his current startup.
2. Problem-solving Prowess: Charles's startup focuses on a significant market need: sustainable packaging. His background and his work in developing a novel lithium-ion battery suggest he is proficient at addressing complex problems, a valuable skill for leading a startup.
3. Positive Personal Traits: Charles self-describes as a proactive individual who enjoys taking on complex challenges. With his proven record of project management and innovation, his self-confidence and perseverance are assets that could drive his startup towards success.

Cons:
1. Undefined employment Background: Charles' previous roles at CrossChasm Technologies include a variety of functions such as Intern, Engineering, IT, and Software Development. However, specifics about his roles, contributions, and achievements during that period are missing, casting some doubts on whether his past experiences will be beneficial to his current venture.
2. No Unique Competitive Advantage: Although TemperPack addresses a significant market need, Charles has not uniquely differentiated it from other players

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in the sustainable packaging industry.  Without a clear unique selling proposition,
the startup could face stiff competition that could hinder its growth.
   3.  Incomplete Personal Details:  Many details about Charles' background,
such as his specific roles in previous employment or his particular skills
outside of managing manufacturing processes, are missing.  This lack of transparency
could lead to potential difficulties when making strategic decisions or forming
partnerships for the startup.
```

A detailed instruction on how to run the programme is shown in the Appendix. Morever, the Appendix provide another example on how a failed founder is predicted with scoring and pros and cons list.

4.2 Interpretation of Results: Strengths and Weaknesses

The case study reveals several key insights into the "Founder-GPT" system's capabilities and areas for improvement.

Strengths:

1. **Proficiency in Identifying True Positives**

   The Founder-GPT system demonstrates a notable strength in accurately identifying founders with high potential for success. Such profiles are consistently awarded high scores, reflecting the system's ability to align closely with the success factors prevalent among thriving startups.

2. **Comprehensive Pros and Cons Lists**

   The project excels in generating detailed pros and cons lists, providing a holistic view of each founder's profile. This comprehensive output offers valuable insights into both the strengths and areas for improvement, aiding in a more nuanced understanding of each founder's potential.

3. **Effective Utilization of LLM**

   The design of well-crafted prompts and logical structures to leverage the capabilities of Large Language Models (LLMs) is a key strength. This approach maximizes the potential of advanced AI technologies like GPT-4, enabling the extraction of meaningful and contextually relevant insights from complex founder data.

Limitations

1. **High Rate of False Positives**

   One significant drawback is the system's tendency to generate false positives, leading to overly optimistic predictions about certain founders' potential. This high Type I error rate necessitates caution and further refinement in the model's evaluative criteria.

2. **Computational Costs and Time**

   The computational intensity of the methodology presents a challenge. On average, querying a new founder profile incurs a cost of approximately 0.10 USD using GPT-4, with a computation time of around 10 minutes using the weighted aggregate similarity method. Although the Pinecone vector database offers a quicker alternative, the majority of time-intensive activity remains in querying GPT-4 for output, which can take up to 1-2 minutes.

3. **Limitations in AI Analysis**

   The AI's reliance on textual data poses limitations in its ability to accurately predict founder success. It lacks insight into actual market trends and may not effectively discern critical founder traits such as overconfidence or lack of confidence. The superficial textual evidence base may not always suffice for an accurate prediction, pointing to a need for incorporating more diverse data sources and analytical perspectives.

5 Conclusions and Future Work

The Founder-GPT project embarked on an ambitious goal to revolutionize the venture capital industry's approach to evaluating startup founders. By leveraging advanced AI technologies, specifically Large Language Models like GPT-4, the project aimed to provide a quantitative and qualitative assessment of founders' potential for success. The methodology employed a multi-step pipeline, involving the extraction of similar founder profiles, the generation of rationales using LLMs, and the creation of comprehensive scoring systems along with pros and cons lists.

The results of this project highlighted its proficiency in identifying true positives, as founders with higher chances of success were consistently given high scores. The comprehensive nature of the pros and cons lists generated by the system provided a nuanced understanding of each founder's profile. However, the project also encountered significant challenges, notably a high rate of false positives and substantial computational demands, both in terms of time and cost. Additionally, the reliance on textual data limited the AI's ability to fully grasp market trends and subtle founder traits, affecting the depth of its predictive accuracy.

In future iterations, the Founder-GPT project should prioritize enhancing its predictive accuracy, particularly by reducing false positives and increasing sensitivity to failure-prone characteristics. A critical focus will also be on optimizing computational efficiency, specifically in the process of comparing founder profiles' similarity, as well as reducing the times of querying sent to LLM or perform better prompt engineering. Moreover, more up-to-date and comprehensive datasets will be essential to ensure relevance and applicability in a rapidly evolving market. Additionally, the incorporation of advanced analytical techniques such as Retrieval-Augmented Generation (RAG), automatic prompt engineering and Reflexion[NS23] methods offers a promising path forward. These improvements aim to significantly bolster the system's analytical depth, enabling more nuanced and accurate evaluations, and positioning Founder-GPT as an indispensable tool in venture capital decision-making.

6 Appendix

6.1 Ethical Consideration in AI Analysis of Founder Details

Utilizing Large Language Models (LLMs) in the analysis of founder profiles raises several ethical concerns that warrant careful consideration:

Data Privacy: Ensuring the confidentiality and privacy of founder profiles is crucial. These profiles often contain sensitive personal information, necessitating adherence to data protection regulations like GDPR. Measures should include obtaining informed consent, anonymizing data, and implementing robust security protocols to prevent unauthorized access.

Intrinsic AI Bias: AI systems are prone to biases present in their training datasets. If the training data lacks diversity or contains historical biases, the AI might inadvertently perpetuate these biases in its analysis. Regular audits of AI outputs and using balanced, diverse datasets are essential to mitigate these biases.

Human Judgment Balance: Over-reliance on AI risks undervaluing human intuition and contextual understanding in evaluating founder profiles. Therefore, it is vital to maintain a balance between AI-driven analysis and human insight on founder profiles.

Addressing these ethical concerns involves implementing stringent data governance, striving for AI transparency and fairness, and balancing AI insights with human judgment. Such measures will uphold ethical standards and enhance the effectiveness and reliability of AI in venture capital decision-making.

6.2 Instructions on how to run the programme codes

The execution of the programme mainly takes place in the file *'Main Programme.ipynb'*. Make sure you run all the function blocks in the Preliminary sections, and replace the openAI API_KEYS with your own API keys (the original ones in the codes have been disabled). Then, execute one-by-one, the blocks in each of the 'Main Programme Execution' section. Some blocks may take longer to respond, as the computational time is high in some parts (particularly, the extraction of top similar founder profiles, and querying GPT-4).

Currently, all input are assumed to be taken from the testing set of our data (see the file 'Founder Features with Embeddings_Testing.csv'). Feel free to alter the code to accept input in your own

favourable ways. Also, feel free to update any methods more efficient – such as, replacing the aggregate similarity comparison in section 3.2 with Pinecone vector database.

6.3 Prompts used in Analysing Founder Profiles

For more detailed prompt, go to the sub-folder "prompt" to view.

6.3.1 Prompt used for Rationale Generation

```
I am analyzing the profiles of several startup founders to understand the key
factors contributing to their success or failure.  Below are the profiles of
5 founders:
   Founder 1:
- Name:  Peter Abrams
- Startup Status:  Successful
- Age:  31.0
- Self Description:
...

   Founder 5:
- Name:  Wendi Burkhardt
- Startup Status:  Failed
- Age:  Not Available
- Self Description:
...

   Based on these profiles, please analyze and provide a rationale explaining
the likely reasons for each founder's success or failure.  Possible ways of
thinking include:  What are the common factors among the successful founders
(if exist)?  What are the negative signals among the failed founders (if exist)?
Are there any discernible patterns or lessons that can be learned from their
educational and employment backgrounds, the nature of their startups, the way
they describe themselves (self-centered or team-oriented, confident or exaggerating
personal achievement) or other aspects of their profiles?
   Please provide a detailed rationale and a synthesized conclusion drawing
from these examples.  Present the rationale in the following format:
   Success Rationale:
   - Bullet points of factors / reasons / signals that contribute to successful
founders
   Failure Rationale:
   - Bullet points of factors / reasons / signals that contribute to failed
founders
   Synthesized conclusion:  <a summary of what factors is likely to make a successful
founder, and what signals is likely to lead to failure>
```

6.3.2 Prompt to Generate Factors for Scoring

```
I am a venture capital analyst who wants to make predictions about whether
a new startup founder will be successful or not.  Firstly, I need a list of
factors acting as the criteria for a founder's success or failure.  I will
give you the following contexualized rationale summarised from previously successful
or unsuccessful founders for your analysis:
...
   Furthermore, there are some general guidelines on the signals about success
and failure:
Positive signals
- Founder has had entrepreneurship that has been a success (M and A or going
```

public) before
- Founder's education includes top universities and technical majors (such as STEM subjects)
...

Negative signals
- Founder has started startups but failed in seed stage
- Founder jumped from one job to another frequently
...

Based on the above rationale and guideines, please identify and list all key factors stricly in the following bullet-point format:
A. Success Factors:
Success 1) [name of factor]: <brief explanation>
Success 2) [name of factor]: <brief explanation>
...

B. Failure Factors:
Failure 1) [name of factor]: <brief explanation>
Failure 2) [name of factor]: <brief explanation>
...

Note that you should list as many meaningful factors but only those that are relevant to the content in rationale, and be concise in the name of factor while be specific in the explanation of the factors. Ensure that name of factor and their explanations don't contain colons. Keep the length of your response under 500 tokens.

6.3.3 Prompt for Scoring

You are given the profile details of a new startup founder, as well as a list of factors that signals successful or unsuccessful founders. Your task is to give this founder a relevance score on each of the factors given. The founder's profile details is given as such:
Founder 1:
- Name: Olivier Brion
- Age: 48.0
- Self Description:
...

Could you analyse the founder's profile and score how well they align with a factor? Score between 0 to 10, where 10 is for a perfect match and 0 for no match. You should be very stringent, and would not usually give a score higher than 6 for success factor, or a score lower than 4 for failure factor. I will give you the list of factors for success or failure, and let's evaluate them one-by-one.

6.3.4 Prompt for Pros and Cons List Generation

I am analyzing the potential of a startup founder and need to summarize their strengths and weaknesses. Below are the details of the founder and the key success and failure factors with their respective scores (out of 10). Higher scores meas the founder has a higher alignment with the factor. Please summarize these into exactly 3 bullet points each for Pros and Cons.
//Founder details
Based on these factors and scores, please summarize the following in detail:
- Pros: What are the 3 (combined) strengths of this founder based on the success

factors?
- Cons: What are the 3 (combined) areas of improvement or potential weaknesses for this founder based on the failure factors?
In your summary, do not include the scores; rather, provides a detail explanation for each point of strength and weakness relating to the context of the new founder profile details given.

6.4 Another Case Study on the prediction of a Failed Founder

The input new founder profile (who is unsuccessful):
- Name: Jon Kalaugher
- Age: Not Available
- Self Description: Jon Kalaugher is the current Founder and CEO of Flowingly. He previously worked at Cin7 as a Director and Investor.
- Education Backgrounds:
- No Education Records
- Employment Backgrounds:
- Worked in Cin7 for 4.34 years, starting from 07/01/2015. His roles in the company include Management, Executive, Director, Shareholder.
- Worked in SecureCom for 6.76 years, starting from 04/01/2002. His roles in the company include Management, Executive, Director.

- Startup Name: Flowingly
- Startup Idea: Unshackle your business from the burden of manually run business processes and paper based systems. Quickly and easily transform staff and customer experiences with digital automation.

The scoring of the new founder:
Success 1) Relevant Employment History: Founders with a long-term employment in similar fields, especially in managerial roles, indicate acquisition of vital skills necessary for the startup's functioning.
[Score: 6 / 10]
Success 2) Industry Specific Experience: Founders who have direct experience working in similar technology segments which offer them insights and networking for their startup.
[Score: 6 / 10]
Success 3) Addressing Widespread Problem: Successful ideas often revolve around a solution to a common problem, demonstrating market keenness and clear understanding of the target audience.
[Score: 6 / 10]
Success 4) Team-Oriented Approach: Successful founders often demonstrate a clear team-oriented mindset, which indicates a focus towards collaborative efforts and shared success.
[Score: 4 / 10]
Success 5) Previous Entrepreneurial Success: Founders who have led their past ventures to success (through MA or IPO) are more likely to recreate their accomplishment.
[Score: 0 / 10]
Success 6) Top-Notch Education in Relevant Fields: Founders with educational backgrounds from top universities, especially in technical majors relevant to the startup's sector, exhibit their competency.
[Score: 0 / 10]
Success 7) Demonstrable Skills Mastery: Founders who possess superior skill sets, such as multilingual abilities or leadership in competitive fields, often indicate their potential to excel in a startup environment.
[Score: 5 / 10]

Success 8) Positive Personal Traits: Successful founders are often self-confident, perseverant, and articulate, striving for clarity in their vision and showing determination in their ventures.
[Score: 4 / 10]
Failure 1) Undefined Employment History: Lack of a defined employment history could suggest deficiencies in necessary skills and limited industry experience.
[Score: 0 / 10]
Failure 2) Vague Business Concept: A broadly defined business model may cause underspecified plans, making the venture less appealing to investors.
[Score: 2 / 10]
Failure 3) Individualistic Mindset: A lack of team-oriented descriptions indicates a potential overemphasis on individual roles, potentially detrimental to tiered growth strategies involved in a startup.
[Score: 2 / 10]
Failure 4) Prior Startup Failures: If a founder has previously led startups that failed early on, it can signal potential issues in executing the venture's initial stages.
[Score: 0 / 10]
Failure 5) Incomplete or Unknown Details: Unprovided details about a founder's background, skills or education can raise doubts about their competency or reliability.
[Score: 7 / 10]
Failure 6) Misaligned Skillsets: If a founder's skills don't match up with their startup's market demand, it can allude to potential difficulties in driving the venture to success.
[Score: 2 / 10]
Failure 7) Overly Ambitious or Misguided Ideas: Startup concepts that are overly ambitious or
[Score: 2 / 10]
Success Scores: [6.0, 6.0, 6.0, 4.0, 0.0, 0.0, 5.0, 4.0]
Failure Scores: [0.0, 2.0, 2.0, 0.0, 7.0, 2.0, 2.0]
Overall Score: 6.739130434782608

The pros and cons list generated is:

Pros:
1. Relevant Employment and Industry Experience: Jon has substantial experience in roles of responsibility and decision-making within the industry, which bestows him valuable insights and networks. This relevant employment history brings a strong backbone of expertise and knowledge to the new startup.
2. Issue Identification and Solution Proposal: Jon's idea demonstrates an understanding of the market, as it aims to innovate within a commonplace issue for businesses - manual processes and paper-based systems. His solution seems poised to offer valuable utilities to prospective clients.
3. Proven Leadership Positions: Jon has demonstrated leadership skills. His positions in management, directorship and executive roles at previous companies attest to his capability to lead, steer and make strategic moves in a company setting.
Cons:
1. Lack of Educational Background: Jon's unspecified educational background raises questions about his foundational knowledge and formal education, which could impact the perceived credibility and competency.
2. Vague Business Concept: A particularly unidentified or underspecified business idea may result in ambiguity while translating the concept into actionable plans, possibly making the task of accruing investments more difficult.

3. Potential Overemphasis on Individuality: The descriptions don't indicate a strong team orientation which could imply a lean towards individualism. This might create issues in startup environments that require increased collaboration and could hamper growth.

References

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