

Startup-O Expert Analysis

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A: Expert Curation

A1. Objective

The goal of 'Expert Curation' is to effectively determine, as a whole, which experts best predict the ranking(s) of companies, or are otherwise accurate in their evaluation.

A2: Methodology

There was a multi-step process to determining the most accurate experts. In order to simplify our analysis, only data from the Chaperone Evaluation Pitch Round and Judge Evaluation Pitch Round was utilized, each done independently.

The original pitch round survey data consisted of columns with various types of data. In the first step, the key idea was to normalize all columns to contain only numerical values between $[0,1]$ inclusive, with expert and startup name as columns, effectively creating a purely numerical representation of that same data. This would make the task of finding the best experts, against the ranking of the companies (explained later), slightly easier.

A2.1: Chaperone Data

A2.1.1: Numerical Ordinal Data

This data column was basically 1-4 rating data. In order to normalize it, all column entries were simply divided by 4, yielding a column of values between $[0,1]$. (see Figure 1)

A2.1.2: Categorical Ordinal Data

This column basically consisted of categorical data with implicit order (i.e High, Medium, and Low). The categorical code-words were first converted to numerical values (i.e High \rightarrow 2, Medium \rightarrow 1, Low \rightarrow 0), after which all the values were divided by the max, which was 2 in most cases... (see Figure 2)

A2.1.3: Binary Positive

This column type effectively already consisted of 0's and 1's, or otherwise 'Yes'/'No', which was mapped to its respective binary representation. (see Figure 4)

How well	What is th	What is th
4	3	2
2	2	1
4	4	2
3	1	1

(a) Sample Numerical Ordinal Data

How well i	What is th	What is th
1	0.75	0.5
0.5	0.5	0.25
1	1	0.5
0.75	0.25	0.25

(b) Sample Processed Numerical Ordinal Data

A2.1.4: Commentary Data

Finally, our last type of data was commentary data, in which each cell had commentary. In order to convert this data to the numerical described above, we used VADER, a sentiment analysis package, to convert the comment into a sentiment score, again with a $[0,1]$ inclusive value denoting the sentiment. (Figure 5)

What is the	What is the
Medium	Low
Medium	High
Medium	High
Medium	High
Medium	Medium

(a) Sample Categorical Ordinal Data

What is the	What is the
0.5	0
0.5	1
0.5	1
0.5	1
0.5	0.5

(b) Sample Processed Categorical Ordinal Data

Are the bu	Are the bu
1	Yes
0	No
1	Yes
1	Yes
0	Yes
1	Yes
1	Yes
1	Yes
1	Yes

(a) Sample Binary Positive Data

Are the bu	Are the bu
1	1
0	0
1	1
1	1
0	1
1	1
1	1
1	1
1	1

(b) Sample Processed Binary Positive Data

Additional
I think Wa
They are c
Although t
Google is c
It's a very
CRM is a g
if no mista
Exciting pr
I am not s

(a) Sample Commentary Data

Additional Comments	
0.998	
0.65395	
0.93125	
0.84205	
0.9841	
0.96005	
0.2249	
0.901	
0.749	

(b) Sample Processed Commentary Data

STARTUP-Q55 FASTTRACK ONLINE PROGRAM - RITCH ROUND																																			
expert_name	startup_name	How well	What is it	What is it	How high	What is it	What is it	Low Price	Superior	Distribut	Geograph	Other	What is it	What is it	No Tracts	Some Fre	Lots of Fre	Some Pals	Growing	Other	Are the b	Are the b	Other	Please rat	How feasi	What is it	Does the	How do y	What wou	How wou	Lack of co	No Tech	Quality of		
Madhulika Sachde Waitrr	4	3	2	1	Medium	Low				Distribut	Geograph		Medium	2-3 Count				Some Pals		Yes			DCA	3	3	Medium	Medium	Business	4			No Tech	L		
Madhulika Sachde BYKO	2	2	1	1	Medium	High			Superior	Distribut	Geograph		Low	<12 F Home Coi				Some Pals		No			DC	1	2	Medium	Low	none	1			No Tech	L		
Madhulika Sachde FINZZ	4	4	2	2	Medium	High				Distribut	Geograph		Low	<12 F Home Coi				Some Pals		Yes			DCA	2	2	Medium	Medium	Early mov	2						
Madhulika Sachde AyoSlide	3	1	1	1	Medium	High				Distribut	Geograph		Low	<12 F Home Coi					Growing		Yes		DBCA	2	1	Medium	Low	Investme	3						
Madhulika Sachde University Livin	4	4	2	1	Medium	Medium				Distribut	Geograph		Low	<12 F Global				Some Pals		Yes			DCA	2	2	High	Medium	First mov	2			No Tech	L		
Madhulika Sachde GetFly	4	3	2	1	Medium	Medium			Low Price				Medium	Home Coi					Growing		Yes		DCA	3	3	Medium	Medium	early mov	3						
Marc Nicolet Into23	3	2	2	3	Medium	High							Medium	Pan Asia			Lots of Fre		Growing		Yes		d	2	2	High	High	into23 is	2		Lack of co	No Tech	L	Quality of	
Marc Nicolet Stones2Milestc	4	3	4	3	High Like	Low				Distribut			High	>24 F Pan Asia					Growing		Yes		A	4	3	High	High	arriving fi	4						
Marc Nicolet Alakazam	3	2	2	2	Medium	High			Superior				Low	<12 F SEA		No Tracts	Some Fre			Yes			DCA	2	2	3	High	High	more eng	3					
Marc Nicolet Woolly Fed Fan	3	2	3	2	Medium	Low							12000 ex	Medium	Home Coi			Some Fre		Yes		not easy	18	3	2	Medium	Medium	existing	1	2		No Tech	L		
Marc Nicolet AIRPORTELS	4	3	3	2	Medium	Medium			Superior		Geograph		Medium	Pan Asia					Growing		Yes		C-their c	3	3	High	High	Have the	4						
Marc Nicolet NayaGaadi	3	2	2	2	Medium	High						niche for	Low	<12 F Home Coi				Some Pals		Yes			CD&A	3	3	Medium	Medium	new in th	3			No Tech	L		
Fred Then carmen automc	4	3	4	4	High Like	Low				Distribut	Geograph		High	>24 F Pan Asia				Some Pals		Yes			A, B, C, D	4	3	High	Medium	First mov	3						
Fred Then BotFactor	3	3	3	2	Medium	Medium			Superior			Easy of us	Medium	Global				Some Pals		Yes			C, D, A, B	3	3	Medium	Medium	Easy of us	3						
Fred Then GamerHours	2	2	2	2	Low	Unlik	High		Low Price	Distribut			Low	<12 F Global		Some Fre			Growing		No		D, C, B, A	2	2	Medium	Medium	Linking Ac	2						
Fred Then gisComm	4	4	3	4	High Like	High			Low Price Superior		Geograph		High	>24 F Pan Asia						Yes			C, D, A, B	3	3	High	High	Good test	3						
Fred Then Brill Technolog	4	4	4	3	Medium	Medium				Distribut	Geograph		Medium	SEA				Some Pals		Yes			C, D, A, B	3	3	High	Medium	They hort	3						
Fred Then Go Plus	4	3	3	2	Medium	High			Low Price	Distribut	Geograph		Medium	SEA				Some Pals		No			cdab	2	1	Low	Medium	They have	3						
Fred Then Quicksorum	1	2	2	1	Low	Unlik	High		Low Price	Distribut			Low	<12 F Home Coi					Growing		No		C, D, A, B	1	1	Low	Low	None	1						
Fred Then Sepio Products	4	4	3	3	High Like	Medium				Distribut	Geograph		Medium	Pan Asia				Some Pals	Growing		Yes		cdab	4	3	High	High	End to an	4						
Fred Then Air Freight Base	4	4	3	3	Medium	Medium			Superior	Distribut			Medium	Global				Some Pals		Yes			CD&A	3	3	Medium	Medium	Deep und	4						
Fred Then Got It	4	4	3	3	Medium	High				Distribut	Geograph		Medium	2-3 Count					Growing		Yes		cdab	4	3	High	High	Experienc	4						
Fred Then MIFON	4	3	2	2	Medium	Medium			Low Price				Low	<12 F Pan Asia				Some Pals		No			cdab	3	2	Medium	Low	preload	3						
Fred Then PHI	4	4	4	4	High Like	Medium				Distribut	Geograph		Medium	Global					Growing		Yes		cdab	3	3	High	High	Good pro	4						
Fred Then Hyperkchange	4	3	3	2	Medium	High			Low Price Superior	Distribut			Medium	SEA				Some Pals		No			cdab	3	3	Medium	Medium	No comm	3						

(a) Original Tabular Data Screenshot

expert_name	startup_name	How well	What is it	What is it	How high	What is it	What is it	Low Price	Superior	Distribut	Geograph	Other	What is it	What is it	No Tracts	Some Fre	Lots of Fre	Some Pals	Growing	Other	Are the b	Are the b	Other	Please rat	How feasi	What is it	Does the	How do y	What wou	How wou	Quality of	How did y	How wou
1	Madhulika Waitrr	1	0.75	0.5	0.25	0.5	1	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0.75	0.75	0.5	0	0.5	1	0	0.75	0.75			
2	Madhulika BYKO	0.5	0.5	0.25	0.25	0.5	1	0	0	0	1	1	0	0	0	0	1	0	1	0	1	0.25	0.5	0.5	0.5	0.625	0.25	0	0.5	0.25			
3	Madhulika FINZZ	1	1	0.5	0.5	0.5	1	0	0	0	1	1	0	0	0	0	1	1	1	1	1	0.5	0.5	0.5	0	0.5	0.5	0	0.75	0.75			
4	Madhulika AyoSlide	0.75	0.25	0.25	0.25	0.5	0.5	0	0	0	1	1	0	0	0	0	1	0	0	1	0.5	0.25	1	0.5	0.625	0.75	0	0.75	0.5				
5	Madhulika University	1	1	0.5	0.25	0.5	0.5	1	0	1	1	1	0.5	0	0	0	1	1	1	1	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	0.75				
6	Madhulika GetFly	1	0.75	0.5	0.25	0.5	1	0	0	0	0	0	0.5	0	1	0	0	0	1	1	0.75	0.75	1	1	0.5	0.75	1	0.5	0.75				
7	Marc Nico Into23	0.75	0.5	0.5	0.75	1	0	0	0	0	1	0	0	1	0	0	0	1	1	1	0.5	0.5	1	1	0.5	0.5	1	0.5	0.5				
8	Marc Nico Stones2M	1	0.75	1	0.75	0.5	1	0	1	0	0	0	0	1	0	0	0	1	0	1	1	0.75	1	1	0.70025	1	0	1	0.75				
9	Marc Nico Alakazam	0.75	0.5	0.5	0.5	0.5	0	0	0	0	0	0	0.5	1	0	0	0	0	1	0	0.5	0.75	0.5	0.5	0.5	0.75	0	0.75	0.75				
10	Marc Nico Woolfy Pi	0.75	0.5	0.75	0.5	0.5	0.5	0	1	0	0	1	0.5	0	0	0	0	1	1	1	0.75	0.5	1	1	0.7202	0.5	0	0.5	0.75				
11	Marc Nico AIRPORTE	1	0.75	0.75	0.5	0.5	1	0	0	0	0	0	0	0	0	0	1	0	1	1	0.75	0.75	0.5	0.5	0.5	1	0	1	1				
12	Marc Nico NayaGaadi	0.75	0.5	0.5	0.5	1	0	0	0	0	1	1	1	0	0	0	1	0	1	1	0.75	0.75	1	0.5	0.625	0.75	0	0.75	0.5				
13	Fred Then carmen au	1	0.75	1	1	0.5	0.5	0	1	0	0	0	0.5	0	0	1	0	1	1	1	1	0.75	0.5	0.5	0.7202	0.75	0	0.75	0.75				
14	Fred Then BotFactor	0.75	0.75	0.75	0.5	0	1	1	0	1	0	1	0	0	1	0	0	0	0	0	0.75	0.75	0.5	0.5	0.5	0.75	0	0.75	0.75				
15	Fred Then GamerHoi	0.5	0.5	0.5	0.5	1	1	1	1	0	1	1	0	0	0	0	1	1	1	1	0.5	0.5	1	1	0.85015	0.5	0	0.5	0.5				
16	Fred Then gridComm	1	1	0.75	1	0.5	0.5	0	0	1	1	0.5	0	0	0	1	0	1	1	0.75	0.75	1	0.5	0.44865	0.75	0	1	0.75					
17	Fred Then Brill Tech	1	1	1	0.75	0.5	1	1	0	1	1	0.5	0	0	1	0	1	0	1	0	0.75	0.75	0	0.5	0.57655	0.75	0	0.75	0.5				
18	Fred Then Go Plus	1	0.75	0.75	0.5	0	1	1	0	1	0	0	0	0	0	0	1	0	0	1	0	0.5	0.25	0	0	0.5	0.75	0	0.5	0.5			
19	Fred Then Quicksoru	0.25	0.5	0.5	0.25	1	0.5	0	0	1	1	0.5	0	0	0	1	1	1	1	1	0.25	0.25	1	1	0.6591	0.25	0	0.25	0.25				
20	Fred Then Sepio Pro	1	1	0.75	0.75	0.5	0.5	0	1	1	0	0	0.5	0	0	1	0	1	1	1	1	0.75	0.5	0.5	0.5	1	0	0.75	0.75				
21	Fred Then Air Freight	1	1	0.75	0.75	0.5	1	0	0	1	1	0.5	0	0	0	0	1	1	1	1	0.75	0.75	1	1	0.5	1	0	0.75	0.5				
22	Fred Then Got It	1	1	0.75	0.75	0.5	0.5	1	0	1	1	0	0	0	0	1	0	1	0	1	0.75	0.5	0	0.5	1	0	0.75	0.75					
23	Fred Then MIFON	1	0.75	0.5	0.5	1	0.5	0	0	0	1	1	0.5	0	0	0	0	1	1	1	0.75	0.5	1	1	0.7202	0.75	0	0.5	0.25				
24	Fred Then PHI	1	1	1	1	0.5	1	1	1	1	0	0.5	0	0	1	0	1	0	1	0	0.75	0.75	0.5	0.5	0.352	1	0	1	0.75				
25	Fred Then Hyperkchi	1	0.75	0.75	0.5	1	0.5	1	1	0	0.5	1	0	0	0	0	1	0.75	0.75	0.5	0.5	0.625	0.75	0.5	0.5	0.5	0	0.75	0.25				
26	Fred Then PriceMap	1	1	1	0.5	0.5	1	0	1	0	0	0	0	0	1	0	0	0	1	1	0.75	0.75	0.5	0	0.5	1	0	0.5	0.5				
27	David Wai Tesseract	0.75	0.75	0.5	0.25	0.5	0	1	1	0	0	0	0.5	1	0	0	0	0	0	1	0.75	0.75	0	0.5	0.5	0.5	0	0.5	0.75				
28	David Wai Pilot Auto	1	0.5	1	0.25	0.5	0.5	0	1	1	0	0.5	0	0	0	1	0	1	1	1	0.25	0.5	0.5	0.5	0.5	0.5	0	0.5	0.5				
29	David Wai EmotionR	0.75	0.75	1	0.5	0.5	0	0	1	1	0	0.5	0	0	1	0	1	0	1	0	0.75	1	0	0.5	0.5	1	0	0.75	0.75				

(b) Normalized Numerical Data Screenshot

A2.1.5. 1-Indexed Borda-Score

Developed by 18th century French mathematician Jean-Charles de Borda, the 'Borda Score' converts the ranking of various to a numerical representation between $[0,1]$. A higher rank corresponds to a higher score (i.e closer to 1), whilst a lower one to a lower score (i.e closer to 0). In the second step of the process, all companies in both rankings were assigned their 1-Indexed 'Borda Score'. (see Figure 7)

```

101 career: 0.0606
PHI: 0.8515
AIRFOR: 0.6667
AIRPORTELS: 0.8485
FINIZZ: 0.3657
SVK100: 0.9848
BamerHours: 0.7879
Bank2grow.com: 0.3182
Canopy Power Pte. Ltd.: 0.4848
Techprep: 0.2223
Carmen automotive pte ltd: 0.8182
Haitrr: 1.0
Nayabadi: 0.8333
kenyt.ai: 0.2576
HeartSmart: 0.4545
SetPV Analytics: 0.4697
Medinfi Healthcare Pvt Ltd: 0.3939
Sepio Products: 0.7121
Reppu: 0.1515
Velox Network Pte Ltd: 0.5455
Tesseract Global Technologies Pvt Ltd: 0.6861
Setfly: 0.9242
Sherpa Funds Technology: 0.8152
WPHish Technologies Private Limited: 0.4394
Cheqme: 0.0758
Pingal Technologies Pvt Limited: 0.2424
Pilot Automotive Labs: 0.5989
Fitree: 0.197
Limless: 0.2727
Air Freight Bazaar: 0.697
Singapore E-Business Pte Ltd: 0.4891
Discount monkey: 0.1818
Bluelotus360: 0.1212
Blonk: 0.3636
Mobility, Inc: 0.303
Alakazam: 0.8788
SmartClean Technologies Pte Ltd: 0.3788
EmotionReader: 0.5758
Invento Robotics: 0.3333
University Living Accommodation Pvt Ltd: 0.9394
Inspoon: 0.1801
Intoz3: 0.9891
iOPD: 0.1364
Roofz Pet Services Pvt Ltd: 0.8636
ForBinary: 0.5
Popular chips: 0.0455
Botfactory: 0.803
Go Plus: 0.7424
Solarte Technologies Pte. Ltd.: 0.5606
Got It: 0.6818
PriceMap: 0.6212
GridCom: 0.7727
Bonnes Tech Lab: 0.2576

```

(a) First Ranking

```

101 career: 0.697
PHI: 0.9697
AIRPORTELS: 0.8788
AIRFOR: 0.2424
FINIZZ: 0.3788
SVK100: 0.8455
BamerHours: 0.197
Carmen automotive pte ltd: 0.8333
Canopy Power Pte. Ltd.: 0.4545
Bank2grow.com: 0.2121
Haitrr: 0.7424
Techprep: 0.4242
Nayabadi: 0.3939
HeartSmart: 0.0909
Setfly: 0.4394
Sepio Products: 0.9091
kenyt.ai: 0.8758
Reppu: 0.9394
SetPV Analytics: 0.3182
Medinfi Healthcare Pvt Ltd: 0.2273
Velox Network Pte Ltd: 0.5758
Tesseract Global Technologies Pvt Ltd: 0.2727
Sherpa Funds Technology: 0.3333
Cheqme: 0.5455
WPHish Technologies Private Limited: 0.6212
Singapore E-Business Pte Ltd: 1.0
Pingal Technologies Pvt Limited: 0.0303
Limless: 0.1515
Pilot Automotive Labs: 0.1818
Fitree: 0.2727
Air Freight Bazaar: 0.7879
Discount monkey: 0.3485
Mobility, Inc: 0.1667
Bluelotus360: 0.7727
Blonk: 0.5152
Alakazam: 0.6861
SmartClean Technologies Pte Ltd: 0.5606
EmotionReader: 0.2889
Invento Robotics: 0.5303
Inspoon: 0.7121
Intoz3: 0.5
University Living Accommodation Pvt Ltd: 0.4848
Roofz Pet Services Pvt Ltd: 0.303
Popular chips: 0.8448
Go Plus: 0.2576
Solarte Technologies Pte. Ltd.: 0.3636
ForBinary: 0.6515
Botfactory: 0.6818
Got It: 0.8939
Copro: 0.4697
PriceMap: 0.7576
GridCom: 0.1111

```

(b) Second Ranking

Figure 6: Two company rankings w.r.t 1-Indexed Borda Score

A2.1.6. Combining all the results

Once, we have the 'Borda Score' for all of our companies, as well as the normalized numerical representation of the data, we can simply find the average difference between each experts' average score across all parameters, and the respective 'Borda Score' of the company they are reviewing. For simplicity, we assumed that each parameter column the expert is reviewing has equal weight. Below denotes each expert's average difference for the top 3 in each.

```
David Wai Lun Ng: 0.0639
Kenya: 0.1011
Ramm: 0.1112
```

(a) First Ranking Top 3 Experts

```
David Wai Lun Ng: 0.1605
Dorit: 0.1696
Kenya: 0.2117
```

(b) Second Ranking Top 3 Experts

Figure 7: Top 3 export rankings w.r.t 1-Indexed Borda Score (Chaperone Data)

A2.2: Judge Round Analysis

A2.2.1: Original vs. Normalized Data

For our Judge Round, all data was of the form 'Numerical Ordinal Data' described above. However, each parameter had an assigned weight, which gave way for a 'weighted sum' of the normalized numerical data against the 'Borda Score' of the rankings in the Judge Round. Below are two screenshots, one of the original, and one of the normalized...

	Please key in What's the	Business strength					Management quality					staying power					Exit potential						
		Value Proposit on	Market Size & Growth rate	Operati ng leverage	Margin structur e	Revenue	Clarity of vision	Knowle dge of custom er	Team dynamic s	Key man risk	Humilit y / arroganc e of	Cultural values	Learnab ility of manage ment	Founder Reserve & Life-cycle	Funding Pipeline	Time Commitment	% net worth investe d	Motivati on	Potenti al vendor possibi lity	Potenti al trade/strategi	Attractiv e valuation for	News momentum to catch	Network
Weights		15%	30%	15%	15%	25%	10%	20%	10%	15%	10%	10%	25%	15%	30%	15%	20%	20%	20%	10%	30%	10%	30%
		30%					40%						10%					20%					
Madhav AIRPORT	2	2	1	2	2	2	2	3	3	2	3	3	2	2	2	3	2	3	2	2	3	3	3
Madhav Superfan	4	4	3	3	4	4	4	4	3	3	3	3	4	3	3	3	3	4	4	4	3	4	4
Madhav Emotion R	4	3	3	3	3	3	4	3	4	3	3	3	3	3	3	4	3	4	4	3	3	4	3
Madhav Limitless	2	2	3	3	2	3	3	4	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2
Lindsay (Juno Clinic)	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	2	3	2	2
Lindsay (University)	3	3	3	3	3	3	3	3	2	2	3	3	3	3	3	3	2	3	2	3	3	2	3
Lindsay (Popular Culture)	2	3	3	3	3	3	3	3	3	2	3	3	3	3	3	3	3	3	4	2	3	2	2
Lindsay (reputation.com)	3	3	3	3	3	3	3	3	3	2	2	2	3	4	4	4	3	3	4	2	3	3	2
Steve Da Limitless	3	4	4	3	3	3	3	4	3	4	4	4	4	2	4	4	2	3	2	2	3	3	3
Steve Da Go Plus	2	3	2	2	2	2	3	3	4	3	3	3	2	2	2	3	3	3	3	3	1	4	3
Steve Da Singapore	4	4	4	4	4	4	4	4	4	2	4	4	4	4	3	4	2	4	4	4	3	4	3
Steve Da University	2	3	3	3	3	3	2	4	3	3	2	3	3	4	4	4	2	4	2	2	4	4	2
Jeffrey N repup.com	3	3	3	3	2	2	3	3	2	2	2	2	3	3	2	2	1	2	4	3	2	2	2
Jeffrey N Got It	2	2	2	2	2	3	3	3	3	2	3	2	2	2	3	2	2	2	3	3	1	2	4
Jeffrey N FitThree	2	2	2	2	2	3	2	2	2	2	2	2	2	2	2	2	1	3	2	2	2	2	1
Jeffrey N Popular Culture	3	3	2	2	2	2	2	3	2	3	1	1	2	2	2	2	1	3	4	4	1	4	2
Yen-Lu C PHI	4	3	4	4	3	4	4	3	3	3	4	3	3	4	4	4	3	3	4	3	3	3	3
Yen-Lu C Canopy Project	3	4	3	3	2	4	4	3	3	2	4	3	3	3	3	3	3	3	2	3	3	2	3
Yen-Lu C Juno Clinic	3	4	4	3	4	4	4	3	3	3	4	2	3	3	3	3	3	3	2	2	3	2	2
Yen-Lu C GridComms	4	3	3	2	3	3	3	3	3	2	3	2	3	2	2	3	3	2	4	3	3	2	2
Satoshi I Go Plus	2	2	2	2	2	2	2	2	3	3	3	2	3	2	2	3	2	2	3	3	2	2	3
Satoshi I GridComms	3	3	2	2	2	3	3	3	3	3	2	3	3	3	3	4	3	3	2	2	2	3	2
Satoshi I Canopy Project	2	2	2	2	2	2	2	2	2	2	3	2	3	3	3	4	2	2	3	4	2	2	2
Satoshi I PHI	3	2	3	3	2	3	3	3	2	4	2	3	3	3	3	4	3	3	4	4	2	3	2
Jojo Azuri PriceMap	4	4	4	2	3	4	4	4	3	3	3	3	4	3	4	3	3	3	3	4	3	3	4
Jojo Azuri Sepio Pro	4	3	4	4	4	4	4	4	4	3	4	4	4	4	3	4	4	4	4	4	3	2	4
Jojo Azuri FitThree	3	3	3	3	3	4	4	4	3	3	3	3	3	3	4	3	3	4	3	3	3	2	2
Jojo Azuri Singapore	4	4	3	3	3	4	4	4	4	3	4	4	4	4	4	4	4	4	3	4	4	4	2
Parimal I Medinfinet	3	3	3	1	2	2	3	3	3	3	3	3	2	3	3	3	3	2	2	2	2	2	2
Parimal I Waitress	3	3	3	1	2	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2
Parimal I Stones2Market	2	3	3	3	2	3	2	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	3
Parimal I Eunimart	3	3	2	1	2	3	3	3	3	3	3	3	3	1	1	3	3	3	2	2	3	2	2
Tim Kobe Got It	4	3	4	3	3	4	3	3	4	4	4	4	4	4	4	4	3	4	3	4	4	3	3
Tim Kobe SuperFan	3	4	4	3	3	4	4	4	3	3	3	3	3	3	3	4	3	3	4	4	4	3	3
Tim Kobe AIRPORT	3	3	3	2	3	3	3	3	2	3	4	4	3	3	4	3	3	2	2	2	2	2	3
Tim Kobe Emotionless	3	4	3	3	2	3	2	2	3	3	3	3	2	2	2	3	2	4	4	3	3	3	3

(a) Original Tabular Data Screenshot Judge Round

Please key in What's the	Value Proposition	Market Size & Growth rate	Operating leverage	Margin structure	Revenue	Clarity of vision	Knowledge of customer	Team dynamics	Key man risk	Humility / arrogance of	Cultural values	Learnability of management	Founder Reserve & Life-cycle	Funding Pipeline	Time Commitment	% net worth invested	Motivation	Potential vendor possibilities	Potential trade/strategi	Attractive valuation for	News momentum to catch	Network
Madhav K AIRPORTE	0.5	0.5	0.25	0.5	0.5	0.5	0.75	0.75	0.5	0.75	0.75	0.5	0.5	0.5	0.75	0.5	0.75	0.5	0.5	0.5	0.75	0.75
Madhav K Superfan	1	1	0.75	0.75	1	1	1	0.75	0.75	0.75	0.75	1	0.75	0.75	0.75	0.75	1	1	1	0.75	1	1
Madhav K Emotion R	1	0.75	0.75	0.75	0.75	1	0.75	1	0.75	0.75	0.75	0.75	0.75	0.75	1	0.75	1	1	0.75	0.75	1	0.75
Madhav K Limitless	0.5	0.5	0.75	0.75	0.5	0.75	0.75	1	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.5	0.5	0.5
Lindsay C Juno Clin	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	1	1	0.5	0.75	0.5
Lindsay C University	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.5	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.75	0.5	0.75	0.5	0.75
Lindsay C Popular C	0.5	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	1	0.5	0.75	0.5
Lindsay C repup.co	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.5	0.5	0.75	1	1	1	0.75	0.75	1	1	0.5	0.75
Steve Dav Limitless	0.75	1	1	0.75	0.75	0.75	1	0.75	1	1	1	1	0.5	1	1	1	0.5	0.75	0.5	0.5	0.75	0.75
Steve Dav Go Plus	0.5	0.75	0.5	0.5	0.5	0.75	0.75	1	0.75	0.75	0.75	0.5	0.5	0.5	0.75	0.75	0.75	0.75	0.75	0.25	1	0.75
Steve Dav Singapore	1	1	1	1	1	1	1	1	0.5	1	1	1	1	0.75	1	0.5	1	1	1	0.75	1	0.75
Steve Dav University	0.5	0.75	0.75	0.75	0.75	0.5	1	0.75	0.75	0.5	0.75	0.75	1	1	1	0.5	1	0.5	0.5	1	1	0.5
Jeffrey Na repup.co	0.75	0.75	0.75	0.5	0.5	0.75	0.75	0.5	0.5	0.5	0.5	0.75	0.75	0.5	0.5	0.25	0.5	1	0.75	0.5	0.5	0.5
Jeffrey Na Got It	0.5	0.5	0.5	0.5	0.75	0.75	0.75	0.75	0.5	0.5	0.5	0.5	0.75	0.5	0.75	0.5	0.5	0.75	0.75	0.25	0.5	1
Jeffrey Na FitThree	0.5	0.5	0.5	0.5	0.75	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.25	0.75	0.5	0.5	0.5	0.5	0.25
Jeffrey Na Popular C	0.75	0.75	0.5	0.5	0.5	0.5	0.75	0.5	0.75	0.25	0.25	0.5	0.5	0.5	0.5	0.25	0.75	1	1	0.25	1	0.5
Yen-Lu Ch PHI	1	0.75	1	1	0.75	1	0.75	0.75	0.75	1	0.75	0.75	1	1	1	0.75	0.75	1	0.75	0.75	0.75	0.75
Yen-Lu Ch Canopy P	0.75	1	0.75	0.75	0.5	1	0.75	0.75	0.5	1	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.75	0.75	0.5	0.75
Yen-Lu Ch Juno Clin	0.75	1	1	0.75	1	1	0.75	0.75	0.75	1	0.5	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.5	0.75	0.5	0.5
Yen-Lu Ch GridComm	1	0.75	0.75	0.5	0.75	0.75	0.75	0.75	0.5	0.75	0.5	0.75	0.5	0.75	0.75	0.75	0.5	1	0.75	0.75	0.5	0.5
Satoshi Kc Go Plus	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.75	0.75	0.75	0.5	0.75	0.5	0.5	0.75	0.5	0.5	0.75	0.75	0.5	0.5	0.75
Satoshi Kc GridComm	0.75	0.75	0.5	0.5	0.5	0.75	0.75	0.75	0.75	0.75	0.5	0.75	0.75	0.75	1	0.75	0.75	0.5	0.5	0.5	0.75	0.5
Satoshi Kc Canopy P	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.75	0.5	0.75	0.75	0.75	1	0.5	0.5	0.75	1	0.5	0.5	0.5
Satoshi Kc PHI	0.75	0.5	0.75	0.75	0.5	0.75	0.75	0.5	0.5	1	0.5	0.75	0.75	0.75	1	0.75	0.75	1	1	0.5	0.75	0.5
Jojo Azuri PriceMap	1	1	1	0.5	0.75	1	1	0.75	0.75	0.75	0.75	0.75	1	0.75	0.75	0.75	0.75	0.75	1	0.75	0.75	1
Jojo Azuri Sepio Pro	1	0.75	1	1	1	1	1	1	0.75	1	1	1	1	0.75	1	1	1	1	1	0.75	0.5	1
Jojo Azuri FitThree	0.75	0.75	0.75	0.75	0.75	1	1	0.75	0.75	0.75	0.75	0.75	0.75	1	0.75	0.75	1	0.75	0.75	0.75	0.5	0.5
Jojo Azuri Singapore	1	1	0.75	0.75	0.75	1	1	1	1	0.75	1	1	1	1	1	1	1	1	0.75	1	1	1
Parimal M Medinfi H	0.75	0.75	0.75	0.25	0.5	0.5	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.75	0.75	0.75	0.75	0.5	0.5	0.5	0.5	0.5
Parimal M Waitrr	0.75	0.75	0.75	0.25	0.5	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.5	0.5	0.5	0.5	0.5

(b) Normalized Numerical Data Screenshot Judge Round

A2.2.2: Judge Round 'Borda Score' Ranking and Top 3 Experts

Below is a screenshot of the Judge Round company to 'Borda Score' mapping, as well as a screenshot of the most accurate 3 experts, along with their respective average differences.

```
Go Plus: 0.0667
Popular Chips: 0.1333
FitThree: 0.2
AIRPORTELS: 0.2667
Canopy Power Pte. Ltd.: 0.3333
repup.co: 0.4
gridComm: 0.4667
University Living Accommodation Pvt Ltd: 0.5333
PHI: 0.6
Got It: 0.6667
Duno Clinic: 0.7333
Limitless: 0.8
EmotionReader: 0.8667
SuperFan.AI: 0.9333
Singapore E-Business Pte Ltd: 1.0
```

(a) Judge Round - Ranking

```
Madhav Kapadia: 0.2142
Yen-Lu Chow: 0.2289
Tim Kobe: 0.2291
```

(b) Judge Round - Top 3 Names

Figure 9: Judge Round Ranking with Top 3 Names

B: Predictive Power: S4 to S1 Funnel

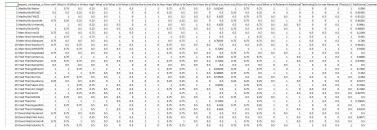
B1: Objective

In this section, we effectively wanted to determine which experts, in the previous rounds of the evaluation, best predicted success in the later corresponding rounds, from Chaperone to Expert to Judge...

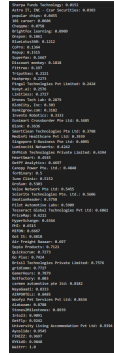
B2: Methodology

In order to perform this analysis, we looked at all drop-downs of the expert evaluation data from its higher level to the subsequent lower level, and compared an expert's accuracy in predicting a score of the company at that lower level. Below are the top 3 experts for each drop-down in the analysis, the normalized data and rankings for each of the three levels, and the respective average difference score.

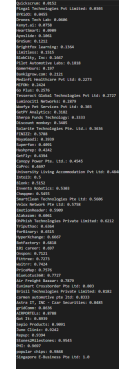
B3.1: Chaperone Normalized Data and Ranking



(a) Normalized Chaperone Ranking

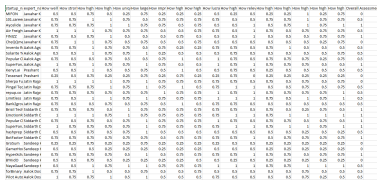


(b) First Chaperone Ranking

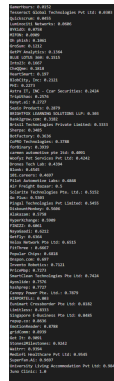


(c) Second Chaperone Ranking

B3.2: Expert Normalized Data and Ranking



(a) Normalized Expert Ranking



(b) First Expert Ranking



(c) Second Expert Ranking

B3.3: Judge Normalized Data and Ranking

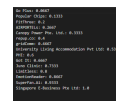
Judge	Category	Ranking
David Wai Lun Ng	0.1779	
Kenya	0.1536	
Marc Nicollet	0.1422	
David Wai Lun Ng	0.1309	
Kenya	0.1296	
Marc Nicollet	0.1283	
David Wai Lun Ng	0.1270	
Kenya	0.1257	
Marc Nicollet	0.1244	
David Wai Lun Ng	0.1231	
Kenya	0.1218	
Marc Nicollet	0.1205	
David Wai Lun Ng	0.1192	
Kenya	0.1179	
Marc Nicollet	0.1166	
David Wai Lun Ng	0.1153	
Kenya	0.1140	
Marc Nicollet	0.1127	
David Wai Lun Ng	0.1114	
Kenya	0.1101	
Marc Nicollet	0.1088	
David Wai Lun Ng	0.1075	
Kenya	0.1062	
Marc Nicollet	0.1049	
David Wai Lun Ng	0.1036	
Kenya	0.1023	
Marc Nicollet	0.1010	
David Wai Lun Ng	0.0997	
Kenya	0.0984	
Marc Nicollet	0.0971	
David Wai Lun Ng	0.0958	
Kenya	0.0945	
Marc Nicollet	0.0932	
David Wai Lun Ng	0.0919	
Kenya	0.0906	
Marc Nicollet	0.0893	
David Wai Lun Ng	0.0880	
Kenya	0.0867	
Marc Nicollet	0.0854	
David Wai Lun Ng	0.0841	
Kenya	0.0828	
Marc Nicollet	0.0815	
David Wai Lun Ng	0.0802	
Kenya	0.0789	
Marc Nicollet	0.0776	
David Wai Lun Ng	0.0763	
Kenya	0.0750	
Marc Nicollet	0.0737	
David Wai Lun Ng	0.0724	
Kenya	0.0711	
Marc Nicollet	0.0698	
David Wai Lun Ng	0.0685	
Kenya	0.0672	
Marc Nicollet	0.0659	
David Wai Lun Ng	0.0646	
Kenya	0.0633	
Marc Nicollet	0.0620	
David Wai Lun Ng	0.0607	
Kenya	0.0594	
Marc Nicollet	0.0581	
David Wai Lun Ng	0.0568	
Kenya	0.0555	
Marc Nicollet	0.0542	
David Wai Lun Ng	0.0529	
Kenya	0.0516	
Marc Nicollet	0.0503	
David Wai Lun Ng	0.0490	
Kenya	0.0477	
Marc Nicollet	0.0464	
David Wai Lun Ng	0.0451	
Kenya	0.0438	
Marc Nicollet	0.0425	
David Wai Lun Ng	0.0412	
Kenya	0.0399	
Marc Nicollet	0.0386	
David Wai Lun Ng	0.0373	
Kenya	0.0360	
Marc Nicollet	0.0347	
David Wai Lun Ng	0.0334	
Kenya	0.0321	
Marc Nicollet	0.0308	
David Wai Lun Ng	0.0295	
Kenya	0.0282	
Marc Nicollet	0.0269	
David Wai Lun Ng	0.0256	
Kenya	0.0243	
Marc Nicollet	0.0230	
David Wai Lun Ng	0.0217	
Kenya	0.0204	
Marc Nicollet	0.0191	
David Wai Lun Ng	0.0178	
Kenya	0.0165	
Marc Nicollet	0.0152	
David Wai Lun Ng	0.0139	
Kenya	0.0126	
Marc Nicollet	0.0113	
David Wai Lun Ng	0.0100	
Kenya	0.0087	
Marc Nicollet	0.0074	
David Wai Lun Ng	0.0061	
Kenya	0.0048	
Marc Nicollet	0.0035	
David Wai Lun Ng	0.0022	
Kenya	0.0009	
Marc Nicollet	0.0000	

(a) Normalized Judge Ranking



Judge	Ranking
David Wai Lun Ng	0.1779
Kenya	0.1536
Marc Nicollet	0.1422

(b) First Judge Ranking



Judge	Ranking
David Wai Lun Ng	0.1779
Kenya	0.1536
Marc Nicollet	0.1422

(c) Second Judge Ranking

B4.1: Chaperone to Expert

```
Marc Nicollet: 0.1422
Kenya: 0.1536
David Wai Lun Ng: 0.1779
```

B4.2: Chaperone to Judge

```
Madhulika Sachdeva: 0.0448
Ramm: 0.1855
Fred Then: 0.2074
```

B4.3: Expert to Judge

```
Shyam Ayengar: 0.0188
Nandini Das Ghoshal: 0.0479
Mustafa Kapasi: 0.0875
```


D: Question Predictive Power

D1: Objective

Finally, for our last section, the goal was to learn which questions, in the parameter section above, best determine the success of a given company, for the Chaperone and Judge rounds.

D2: Methodology

In order to best perform the above task, we effectively trained a Linear Regression Model that best determined the relative weights of a question parameter based on the normalized rating a given user gave to a company, and the corresponding 'Borda Score'(y) as described above. Since the experts came with their own respective biases (described above), it is important to note that each parameter was multiplied by the respective weight cell calculated earlier prior its input into the Linear Regression Model, in order to help mitigate bias. Once the weights of each of the parameters was calculated after the training of the Linear Regression Model, it was simply normalized by it being raised by e, and then being divided by the sum of all weights, each raised to the e.

D3: Relevant Output

Below is a figure denoting the respective weights of each question for both rounds based on the trained Linear Regression Model.

```
Addressable Market Size: 0.0384
Does the business model has high level of operating leverage & scalability potential?: 0.0428
What is the level of competition in terms of alternatives available?: 0.0365
How do you think is the ability of the team to manage risks with Plan B?: 0.0466
How well is the problem identified and defined?: 0.0481
Product Uniqueness: 0.0356
Are the business metrics clearly defined: 0.0428
What is the overall feasibility of the business going forward?: 0.0519
What is the level of uniqueness in the proposition for the venture?: 0.0386
Go to market plan strength: 0.0344
How would you rate the likability & connect with the Founder and his authenticity?: 0.0348
Additional Comments: 0.0382
Technology Barrier: 0.0356
What is the strength of the competitive advantage in the business model?: 0.0398
How would you rate the quality of presentation deck in terms of clarity, scope, visual impact & simplicity?: 0.0405
What is the level of sustainability of the competitive advantage in the next 24 months?: 0.0371
What would you say is your 'Unfair Advantage' that would add competitive advantage vs anyone who could start the same venture?: 0.0439
Are the business milestones for the next 24 months exciting?: 0.0404
How high are the defensible technology barriers in the business? (High being 4): 0.0416
What is the level of pain area felt / perceived by the target customers / consumers?: 0.0409
Relevant Industry/market background of team: 0.0392
How did you find the overall presentation quality in terms of clarity and impact through communication?: 0.0462
How feasible do you think is the Go To Market plan in next 12-18 month timeframe?: 0.0446
Revenue Stage: 0.0388
What is the level of understanding and clarity of the financial projections by the team?: 0.0305
```

(a) Relative Weights of Parameters Chaperone

```
Margin structure: 0.28790877593600234
Time Commitment: 0.11510182448916399
Knowledge of customer: 0.09987655189232056
Humility / arrogance of founders: 0.06726114776379409
Market Size & Growth rate: 0.06673334614505252
Key man risk: 0.052393189591581214
Potential trade/ strategic sales to corporates: 0.04900122284368937
Cultural values: 0.048067274871783146
Clarity of vision: 0.03441093034005964
Founder Reserve & Life-cycle: 0.030167139135916034
News momentum to catch investor attention: 0.029853176154953993
Revenue: 0.022896398009275575
```

(b) Relative Weights of Parameters Judge