Persuading Investors: A Video-Based Study

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2024 年 4 月 23 日

Motivation

- Persuasive communications mattes in economic decisions(e.g,.Pitches)
  - Prior persuasion models mostly focus on content(info or non-info).
  - Delivery also matters, yet researches on it remain scarce and meet challenges.
    - Hard to capture, represent, and quantify features in delivery(Video data).
    - Hard to observe investor decisions to quantify the impact.
- Startup pitch videos & ML Methods cloud overcome those challenges.
  - Startup pitch videos: Provide a real-word setting to observe complete persuasion deliveries, investor decisions and future startup performance.
  - ML Methods
    - Capture dynamic and complete information across multiple channels.
    - High scalability and replicability.

Why Video Data Hard to Process?

- Information intensive
  - 1s HD video equals over 2,000 text pages in size.
- Unstructured and high-dimensional
  - 1min video with a resolution of 1280×720 (720p) and two 48 kHz audio channels.
    - 1280×720=921,600 pixels in each image frame.
    - 48,000×2 dimensions per second audio
- Low signal-to-noise ratio(SNR) and low economic interpretability
  - Need to extract information that is useful and meaningful for economic research.

ML Methods could overcome those challenges!

Question

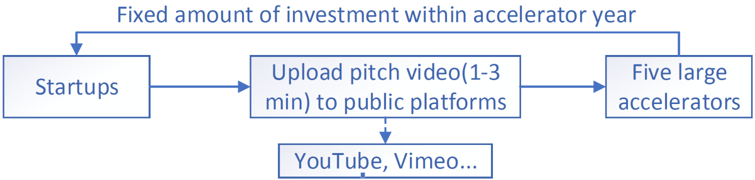
- Whether the pitch factor affects funding acquisition and improve?
  - Better pitch, more funding.
- Whether the pitch delivery features helps investors reach better decisions?
  - No, many positive pitch characteristics are associated with poorer performance.
- How can we economically explain the impact of delivery features on funding?
  - Inaccurate beliefs and preference-based channels contribute 82% and 18%.

Contribution

- Literature on interpersonal persuasions.
  - Prior studies:
    - Focus on content and framing.
    - Focus on marketing and advertising(Kim et al.,2023).
  - Extension:
    - Focus on the delivery features in interpersonal persuasions.
    - Present persuasion is important in startup pitches
- Literature on exploring video data.
  - Prior studies: Study features individually(Gorodnichenko et al.,2021).
  - Extension: Provide an ML method for exploring unstructured video data systematically.

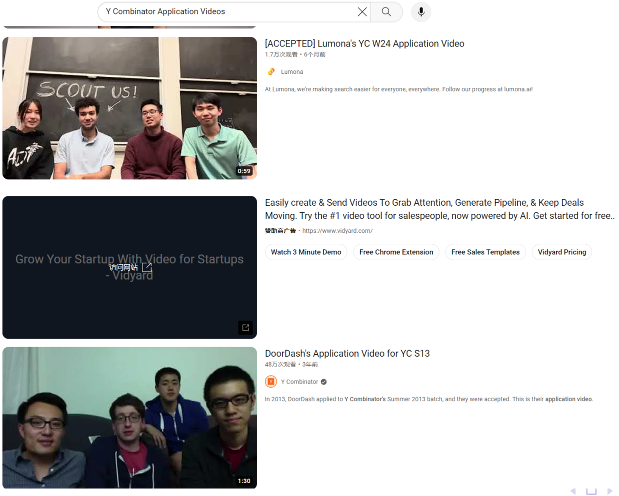
Data

- Video data: 1139 videos for 2010-2019



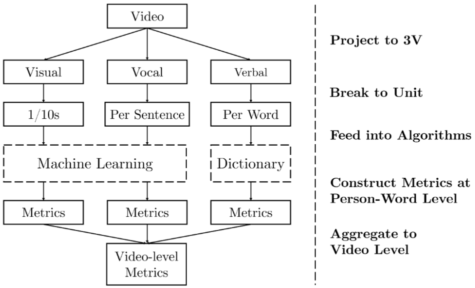
- Startup Information and Team Background:
  - Database: Crunchbase, PitchBook,LinkedIn
    - Startup-level: I(Invested), Employment, Raised VC, VC Amount, Startup Alive, Firm Age...
    - Team-level: education(<=5) and work(<=10) experiences, gender,team size...

Data: Video Data(Example)



Design: Processing Video Data

Illustration of the Data Processing Framework

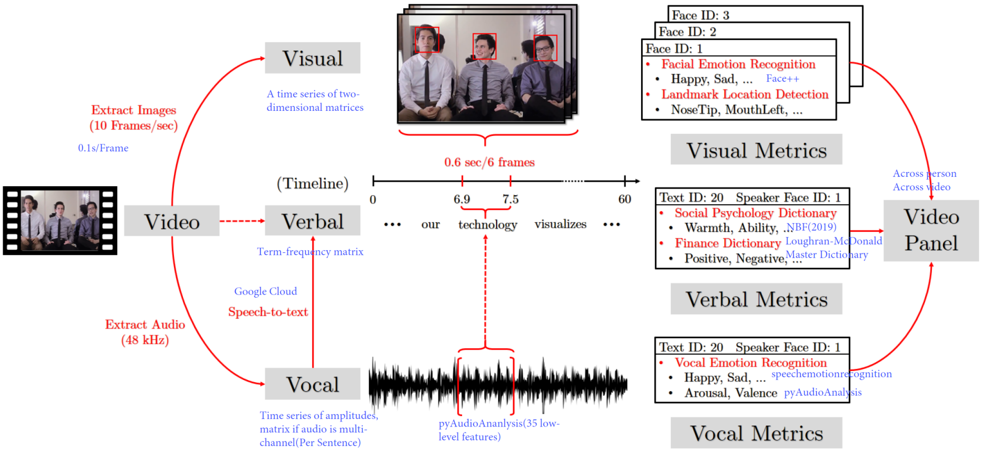


[a]

A. Visual Metrics	
Visual-Positive	Probability that the facial emotion is happiness by Face++ emotion recognition API
Visual-Negative	Sum of the probabilities that the facial emotion is sadness, anger, fear, and disgust by Face++ emotion recognition API
Visual-Beauty	Beauty scores for the faces in videos by Face++ beauty score API
B. Vocal Metrics	
Vocal-Positive	Probability that the vocal emotion is happiness by the LSTM model in `speechemotionrecognition`
Vocal-Negative	Probability that the vocal emotion is sadness by the LSTM model in `speechemotionrecognition`
Vocal-Arousal	Degree of vocal arousal by the SVM model in `pyAudioAnalysis`
Vocal-Valence	Degree of vocal valence by the SVM model in `pyAudioAnalysis`
C. Verbal Metrics	
Verbal-Positive	Whether a word is included in the positive category of the LM Master Dictionary (Loughran and McDonald, 2011)
Verbal-Negative	Whether a word is included in the negative category of the LM Master Dictionary (Loughran and McDonald, 2011)
Verbal-Ability	The direction (-1 or $+1$) of a word if it is included in the ability category of the NBF dictionary (Nicolas et al., 2019)
Verbal-Warmth	The direction (-1 or $+1$) of a word if it is included in the warmth category of the NBF dictionary (Nicolas et al., 2019)

[a] Pitch Factor: How well startup delivers pitch.

Design: Processing Video Data——Example



Design: Delivery Features

	(1)	(2)	(3)	(4)	(5)
(1) Visual-Positive	1.00				
(2) Visual-Negative	−0.12***	1.00			
(3) Visual-Beauty	−0.02	−0.20***	1.00		
(4) Vocal-Positive	0.16***	0.07**	−0.05*	1.00	
(5) Vocal-Negative	0.05*	0.06**	0.01	−0.07**	1.00
(6) Vocal-Arousal	0.02	−0.07**	0.05*	0.24***	−0.15***
(7) Vocal-Valence	−0.02	−0.07**	0.09***	0.13***	−0.12***
(8) Verbal-Positive	0.01	0.03	−0.01	0.02	−0.06*
(9) Verbal-Negative	−0.10***	0.04	−0.01	0.02	−0.04
(10) Verbal-Warmth	−0.05	0.00	0.01	−0.01	−0.01
(11) Verbal-Ability	0.00	0.02	−0.02	0.04	0.02
Continued	(6)	(7)	(8)	(9)	(10)
(6) Vocal-Arousal	1.00				
(7) Vocal-Valence	0.75***	1.00			
(8) Verbal-Positive	−0.01	0.01	1.00		
(9) Verbal-Negative	−0.08***	−0.07**	0.00	1.00	
(10) Verbal-Warmth	0.02	0.04	0.03	−0.05*	1.00
(11) Verbal-Ability	0.01	0.04	0.08***	−0.03	−0.02

- Vocal and visual expressions are correlated yet separate signals.
- Verbal information is uncorrelated with other features,as scripted text can be prepared independently of vocal and visual delivery.

Design: Experiment to explore mechanisms

- Conceptual Framework

$$I_{ij} = 1_{U_{ij} \geq \overline{U}}, \quad \textit{where} \quad U(\mu_{ij}, \sigma_{ij}, \theta_i) \equiv \gamma_\mu \mu_{ij} + \gamma_\sigma \sigma_{ij} + \kappa \theta_i \tag{1}$$

$$\mu_{ij} = \lambda_\mu Q_i + \psi_\mu \theta_i, \quad \sigma_{ij} = \lambda_\sigma Q_i + \psi_\sigma \theta_i \tag{2}$$

  - θ_i: delivery features
  - μ_{ij}: investor(j)'s belief of startup(i);
  - σ_{ij}: the precision or confidence level of the belief
- θ_i affects decisions in two ways: impact on beliefs(μ_{ij}, σ_{ij}) and direct utility($\kappa\theta_i$)

Design: Experiment to explore mechanisms

- How to get I_{ij}, μ_{ij}, σ_{ij}? (Experiment design)
  - whether she/he would invest in company i, denoted as I_{ij};
  - Her/his expectation of the company' s success probability, μ_{ij}, measured between 0 and 100%;
  - Her/his confidence level on her/his decision and expectation, σ_{ij}, measured on a scale of 1 to 5.

Baseline Result

- Whether the pitch factor affects funding acquisition?
  - $I(Invested)_{ijt} = \alpha + \beta \times X_{it} + \sigma_j + \epsilon_{ijt}$

Dependent Var: I(*Invested*)	Logit without Controls			Logit with Startup/Team Controls		
	Marginal Effect	S.E.	Pseudo R^2	Marginal Effect	S.E.	Pseudo R^2
Pitch Factor	0.030***	(0.007)	0.193	0.026***	(0.007)	0.253
Visual (Facial)						
Visual-Positive	0.015***	(0.005)	0.178	0.012**	(0.006)	0.240
Visual-Negative	−0.027***	(0.007)	0.187	−0.029***	(0.007)	0.253
Visual-Beauty	0.015**	(0.006)	0.178	0.015**	(0.007)	0.242
Vocal (Audio)						
Vocal-Positive	0.009**	(0.005)	0.174	0.011*	(0.006)	0.239
Vocal-Negative	−0.045***	(0.016)	0.183	−0.047***	(0.017)	0.248
Vocal-Arousal	0.023***	(0.009)	0.184	0.019**	(0.008)	0.245
Vocal-Valence	0.023***	(0.006)	0.185	0.020***	(0.007)	0.246
Verbal (Text)						
Verbal-Positive	−0.010	(0.009)	0.174	−0.011	(0.009)	0.239
Verbal-Negative	−0.026***	(0.007)	0.186	−0.022***	(0.008)	0.246
Verbal-Warmth	0.026***	(0.008)	0.190	0.028***	(0.008)	0.256
Verbal-Ability	−0.049***	(0.009)	0.243	−0.043***	(0.007)	0.298

- Delivery features matter for financial investment decision-making.

Performance of startups

- Whether the pitch delivery features helps investors reach better decisions?
  - $Performance_i = \alpha + \gamma \times X_i + \sigma \times Controls_i + \sigma_{FE} + \epsilon_i$
  - Sample: Startups received investment in or prior to 2017

	(1) Employment	(2) Raised VC	(3) VC Amount	(4) Startup Alive
Pitch Factor	-0.166^{**}	-0.089^{***}	-0.168^{*}	-0.043^{**}
	(0.050)	(0.018)	(0.086)	(0.021)
Observations	150	132	132	174
(Pseudo) R^2	0.267	0.257	0.306	0.290

- Startups with a high Pitch Factor underperform in the long run.

Experiment to explore mechanisms

- Interaction Features and Inaccurate Beliefs

	(1)	(2)	(3)	(4)	(5)
	P($alive \mid invested$)		P($success \mid invested$)		$alive \mid invested$
	μ	σ	μ	σ	Realized
Pitch Factor (θ)	0.020**	−0.020	0.016**	−0.030	−0.117**
	(0.009)	(0.027)	(0.007)	(0.028)	(0.053)
Observations	952	952	952	952	495
R^2	0.569	0.545	0.565	0.519	0.673
Startup/Team Controls	Y	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y	Y

- The beliefs channel exists.
- The miscalibration of beliefs has a magnitude of 0.137 (= 0.020 − (−0.117)).

Experiment to explore mechanisms

- Decomposing Inaccurate Beliefs and Preferences

$$I_{ij} = \kappa \times \theta_i + \gamma_\mu \times \mu_{ij} + \gamma_\sigma \times \sigma_{ij} + \sigma_j + \epsilon_{ij} \quad (3)$$

	(1)	(2)	(3)	(4)
	Dependent Var: I(*Invested*)			
Pitch Factor (θ)	0.125***			0.067***
	(0.037)			(0.022)
$\mu(alive\|invested)$		2.309***		2.208***
		(0.120)		(0.132)
$\sigma(alive\|invested)$			−0.171***	−0.054**
			(0.041)	(0.026)
Observations	952	952	952	952
Pseudo R^2	0.157	0.423	0.135	0.436

- The preference channel exist(θ).
- Inaccurate beliefs channel is more important than the taste-based channel.

Heterogeneous Effects Across Gender

- Does this impact of delivery features on funding differ between genders?
  - $I(Invested)_{ijt} = \alpha + \beta \times X_{it} + \sigma_j + \epsilon_{ijt}$

	(1)	(2)	(3)	(4)
	Dependent Var: I(*Invested*)			
	Single-Gender Teams			Mixed-Gender Teams
	Men	Women	Pooled	Pooled
Pitch Factor (Men)	0.018**		0.018**	0.048*
	(0.008)		(0.008)	(0.026)
Pitch Factor (Women)		0.170***	0.077**	0.019
		(0.051)	(0.031)	(0.042)
p-value of Men vs. Women Test			0.079*	0.661
Observations	559	310	869	270
Pseudo R2	0.194	0.334	0.217	0.653

- Investors reward women who fit their stereotypes(warmer...)
- Women are ignored in the pitches when they co-present with a man.

Conclusion

- Non-content delivery features in persuasion significantly affect investors' decisions, yet don't improve investors' decisions.
- These features bias investors by particularly leading them to form inaccurate beliefs.
- Impact of delivery features on funding differ between genders in a direction consistent with gender biases.

New ideas

- Explore further the root of the inaccurate beliefs:
  - Categorical and coarse thinking
  - Failure to account for repeated information
  - Emotions
- Other video data via the three-V dimensions
- Other behaviors: gestures...