



Recommending Investors for Crowdfunding Projects

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CROWDFUNDING

A founder proposes a project (e.g., smart watch, documentary, video game) and **asks the Internet crowd for money.**

More than **450 sites**
Raised **\$2.8 billion** in 2012

KICKSTARTER



**What is
Kickstarter?**

Discover
great projects

Start
a project

🔍 Search projects


Help [Sign up](#) [Log in](#)

Bring creativity to life

Curious how Kickstarter works?

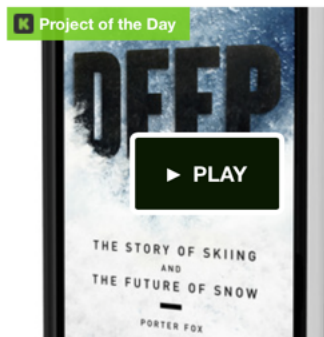
[Learn more >](#)

With the help of his 961 backers, Jack published his first novel.



Staff Picks: Publishing

See all **539** Publishing projects



DEEP: The Story of Skiing and the Future of Snow

by DEEP: The future of skiing and snow in Jackson, WY

Help publish a book about the culture of skiing, the miracle of snow and how climate change could wipe out both in 75 years.

77% funded	\$19,294 pledged	7 days to go
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- Art
- Comics
- Dance
- Design
- Fashion
- Film & Video
- Food
- Games
- Music
- Photography
- Publishing
- Technology
- Theater

KICKSTARTER

OMG

On March 3, 2014, Kickstarter passed \$1 BILLION in pledges.
That's \$1,000,000,000 pledged by 5.7 million people to creative projects.

More than half was pledged in the last 12 months alone.


PEBBLE WATCH

Pebble: E-Paper Watch for iPhone and Android

by Pebble Technology

Home
Updates **45**
Backers **68,929**
Comments **15,547**
Palo Alto, CA
Product Design

Funded! This project successfully raised its funding goal on May 19, 2012.



68,929
backers

\$10,266,845
pledged of \$100,000 goal

0
seconds to go

Funding period
Apr 11, 2012 - May 18, 2012 (37 days)

[Share](#) **20,418**

[Tweet](#) **<>** [Embed](#)

★

First created · 44 backed

Project by
Pebble Technology
Palo Alto, CA
[Contact me](#)

PEBBLE WATCH

↑ Check out the video ↑

Our Kickstarter campaign is over, but you can still get a Pebble. Head over to www.getpebble.com for more info and to place an order.

May 8 - Pebble now supports Bluetooth 4.0!

If you're an app developer, big or small, please keep Pebble in mind! Sign up for our Developer's mailing list [here](#).

High resolution photos for PRESS [download here](#). For press inquiries, please contact media@getinpulse.com. Follow Pebble on Twitter [@pebble](#) and on [Facebook](#).

April 12 pt 2 - Pebble is now even more water resistant! You can go swimming, run in the rain with Pebble.

April 12 update - We're absolutely blown away by your support, Kickstarter. \$1M in 28 hours!


[Daring Fireball](#) - "The watch itself is a very cool idea; I'm in as a backer"

[Forbes](#) - "Proven track record...Incredibly useful product"

[Engadget](#) - "Allerta intros Pebble smartwatch, inPulse's attractive younger sibling"

[Wired Gadget Lab](#) - "Smartwatches haven't really caught on with mainstream buyers -


Pledge \$1 or more

 2615 backers

Didn't get a chance to back Pebble before it sold out? Pledge \$1 and keep up-to-date on all things Pebble with exclusive updates, Pebble availability or more. You can also sign up for more updates at <http://eepurl.com/IG15L>

Estimated delivery: Sep 2012


Pledge \$99 or more

 200 backers **All gone!**

EARLY BIRDS Help us get started! One Jet Black Pebble watch. This watch will retail for more than \$150. Free shipping to USA. (Add \$10 for shipping to Canada, \$15 for international shipping.)

Estimated delivery: Sep 2012

Pledge \$115 or more

 40799 backers **All gone!**

One Jet Black Pebble watch. Free shipping to USA. (Add \$10 for shipping to Canada, \$15 for international shipping.)

Estimated delivery: Sep 2012

KICKSTARTER

Not all projects are successfully financed.

Success rate: **43.85%** (by Kickstarter)

A recent study has found that “the majority of failed project creators cited the inability to **successfully leverage an online audience** as a main reason for failing.”

OUR GOAL

To propose automatic ways of **matching**
Kickstarter founders with online investors

PROBLEM

We need to understand why people donate to which projects.

Founder cannot advertise through Kickstarter sites.

OUR GOAL

To propose automatic ways of matching
Kickstarter founders with **Twitter investors**

METHODOLOGY

Step 1. **Crawling** Kickstarter sites and Tweets

Project details, investors' profiles, tweets

Step 2. **Characterizing** pledging behavior

Step 3. **Recommending** Twitter users given a project

Predicting pledging behavior

Ranking investors

KICKSTARTER

DATASET



**PLEDGING
BEHAVIOR**



**RECOMMENDING
INVESTORS**

DATASET

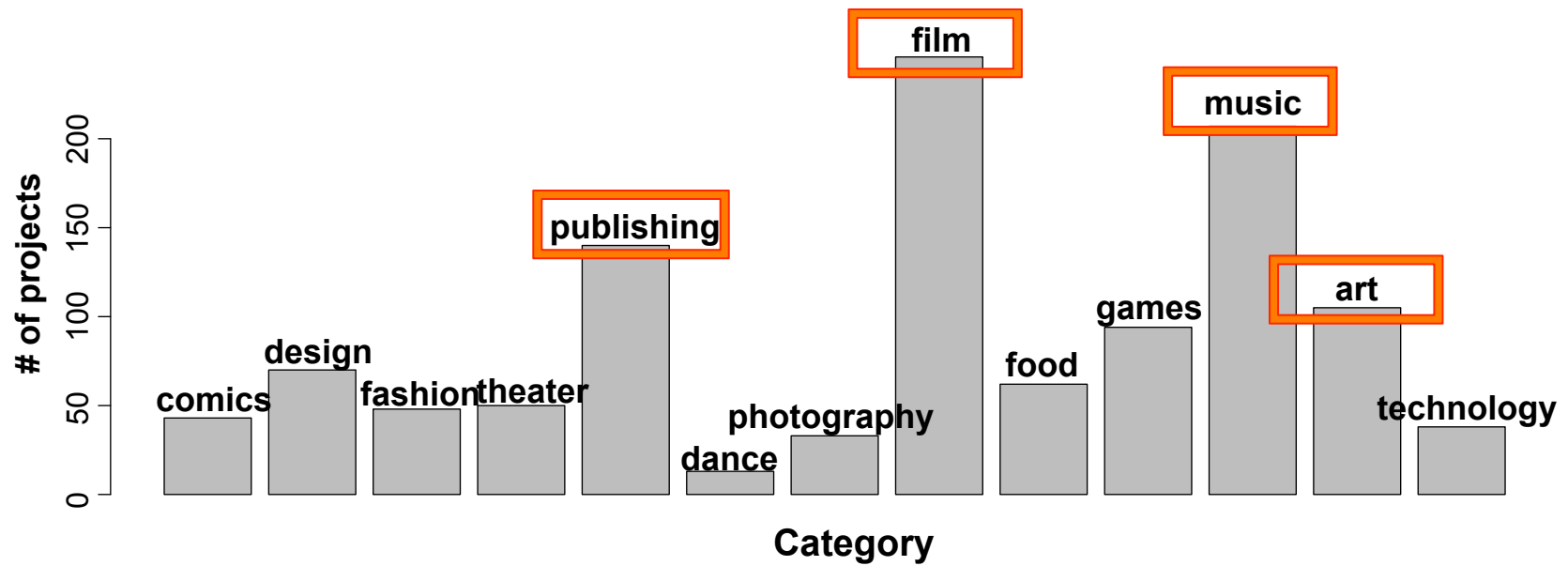
**PLEDGING
BEHAVIOR**

**RECOMMENDING
INVESTORS**

DATASET

- Data collection
 - Scraped all projects featured on 'Recently Launched Kickstarter page' between July - October 2013
 - Regularly checked each project for any changes in pledged money and investors
 - Collected all tweets containing "kickstarter" or project title/URL
- Focus on **1,149 USA based Kickstarter projects**
 - A total of **78,460 investors** and their pledges (177,882) raised a total of **\$12.3M**
 - 71,315 tweets relating to those project

KICKSTARTER



KICKSTARTER

	Successful	Failed	Total
Projects	520	629	1,149
Proportion	45.3%	54.7%	100%

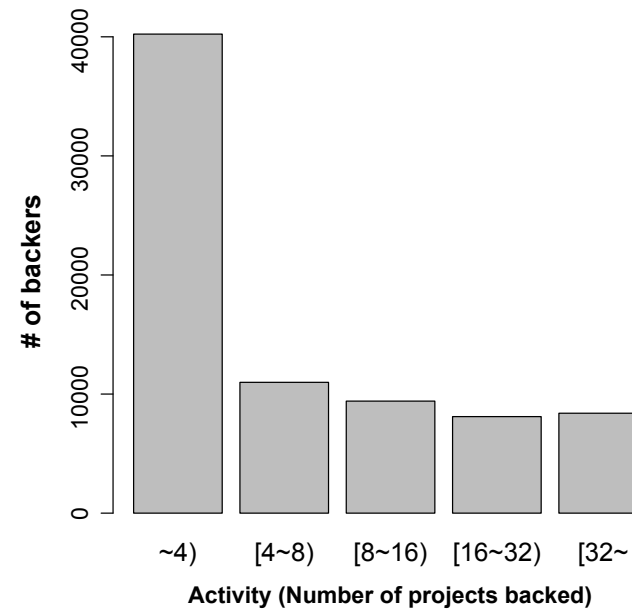


similar to success rate
published by **Kickstarter itself: 43.85%**

	Successful	Failed	Total
Goal (\$)	11,033.90 <	30,716.86	20,875.38
Duration (days)	28.56	29.25	28.91
Number of investors	285.11 >	47.09	166.10
Pledge (\$)	79.71	60.13	68.99
Final amount	168.93% >	19.51%	94.22%
Number of tweets	101.93 >	44.43	73.18

DATASET

78,460 investors
On average, investors supported three projects





DATASET



**PLEDGING
BEHAVIOR**



**RECOMMENDING
INVESTORS**

DATASET

**PLEDGING
BEHAVIOR**

RECOMMENDING
INVESTORS

INVESTORS VS. DONORS

“20-40% of initial fundings in Kickstarter come from **family and friends.**”

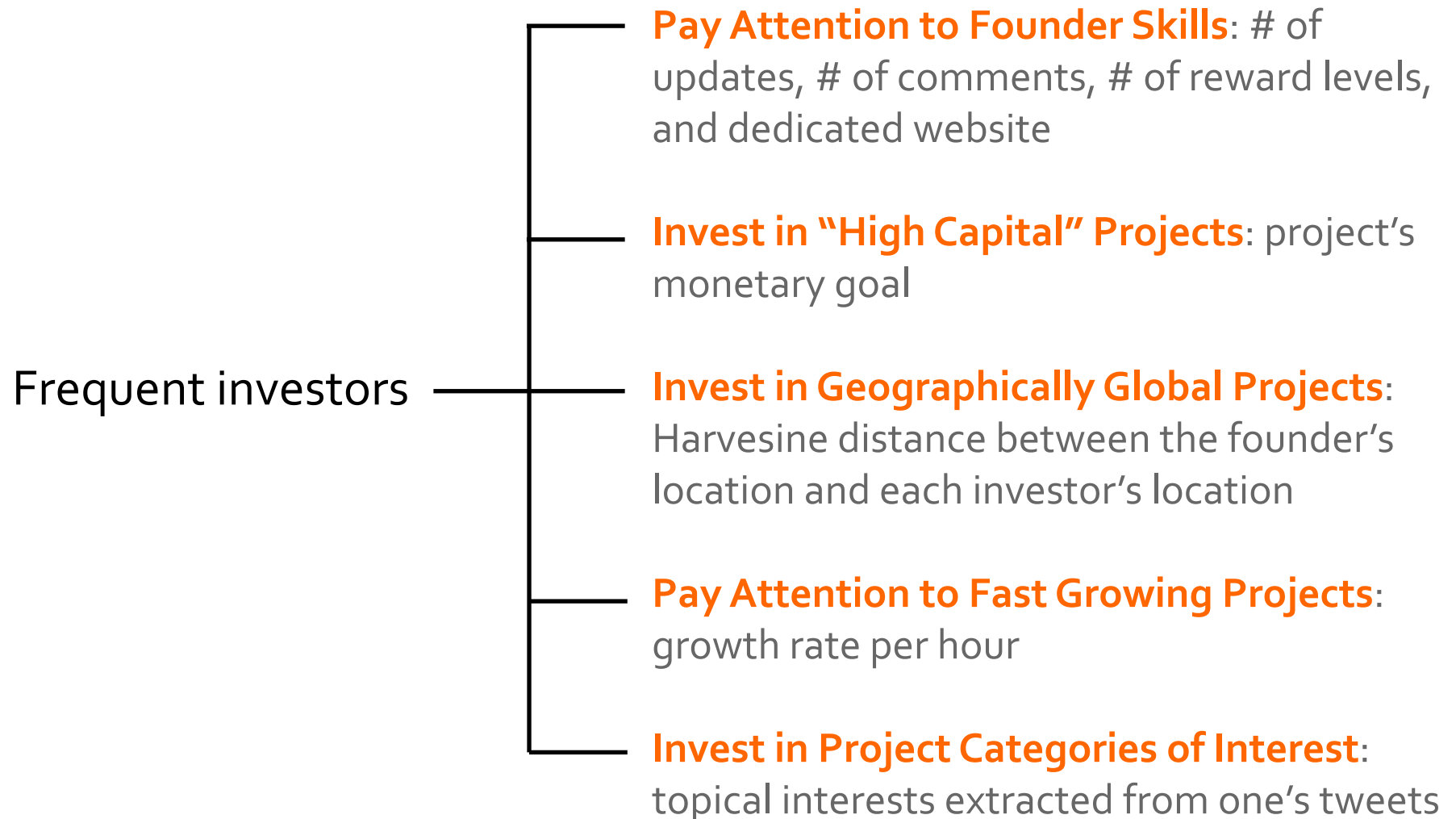
Frequent Investors



Occasional Investors



FEQUENT INVESTOR TENDS TO BEHAVE AS AN INVESTOR RATHER DONOR



PLEDGING BEHAVIOR

Hypotheses
<i>[H1] A project is likely to be financed by frequent investors if its founder: [H1.1] frequently updates the project after launching it. [H1.2] answers the potential investors' requests. [H1.3] allows for fine-grained funding levels. [H1.4] sets a dedicated web site.</i>
<i>[H2] A project with a high goal is likely to be financed by frequent investors.</i>
<i>[H3] A local project is likely to be supported by occasional investors.</i>
<i>[H4] A fast-growing project is likely to be financed by frequent investors.</i>
<i>[H5] Active investors tend to fund projects that match their own interests.</i>

PLEDGING BEHAVIOR

Probability that an investor of type B will fund a project of type P :

$$p(B|P) = \frac{p(B \cap P)}{p(P)}$$

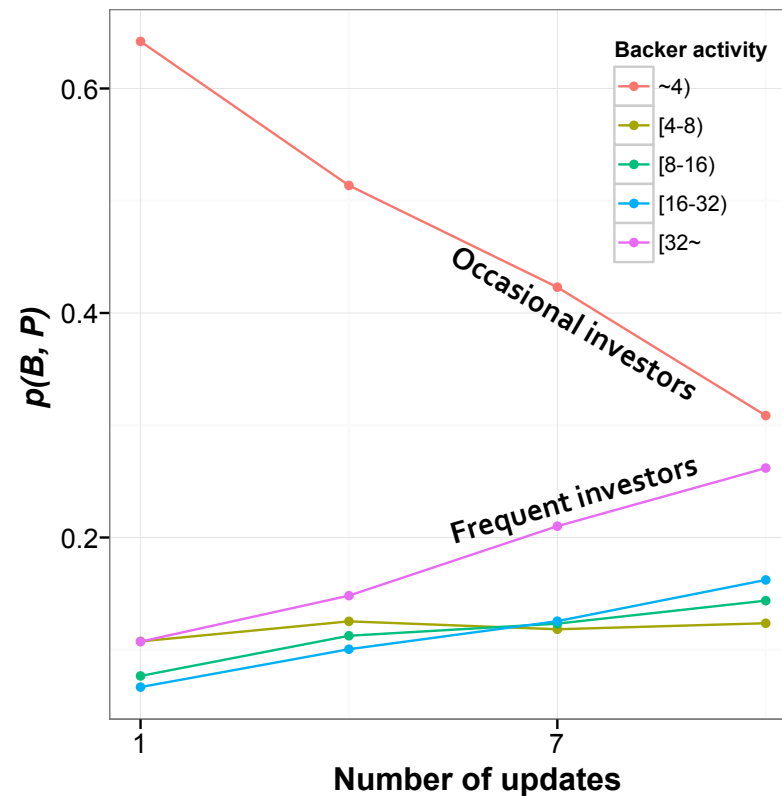
Investors of type B who funded projects of type P

All investors who backed projects of type P

PLEDGING BEHAVIOR

[H1] A project is likely to be financed by frequent investors if its founder:

[H1.1] frequently updates the project after launching it.



PLEDGING BEHAVIOR

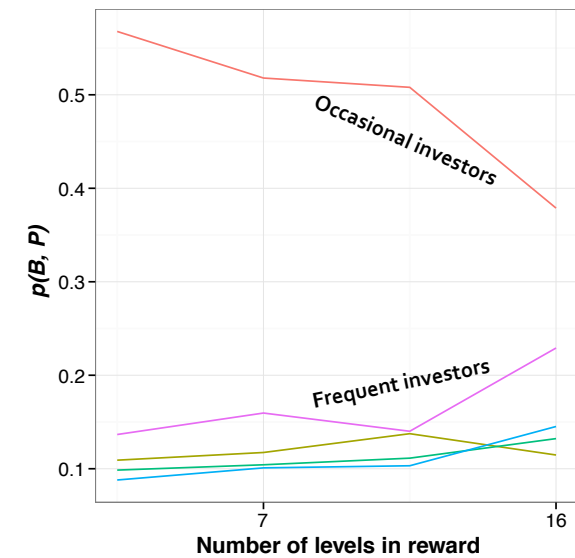
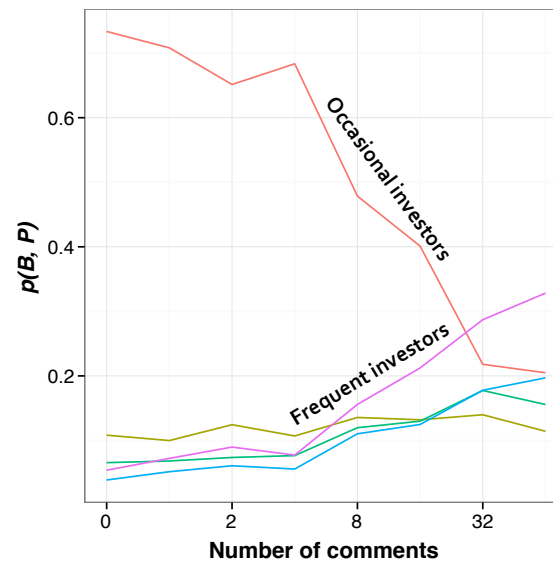
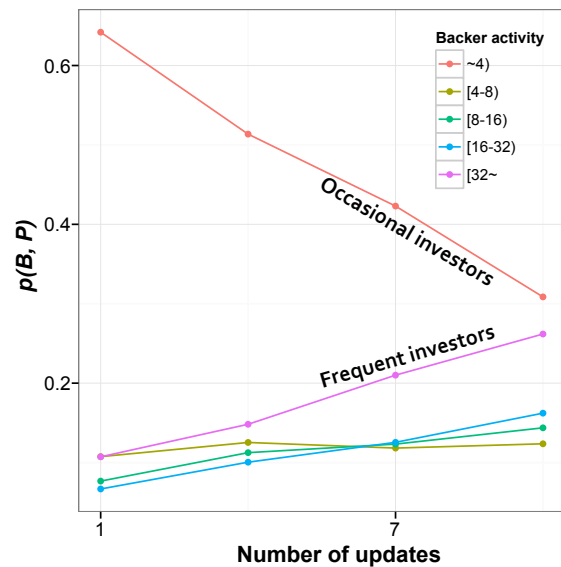
[H1] A project is likely to be financed by frequent investors if its founder:

[H1.1] frequently updates the project after launching it. $r=0.26$

[H1.2] answers the potential investors' requests. $r=0.19$

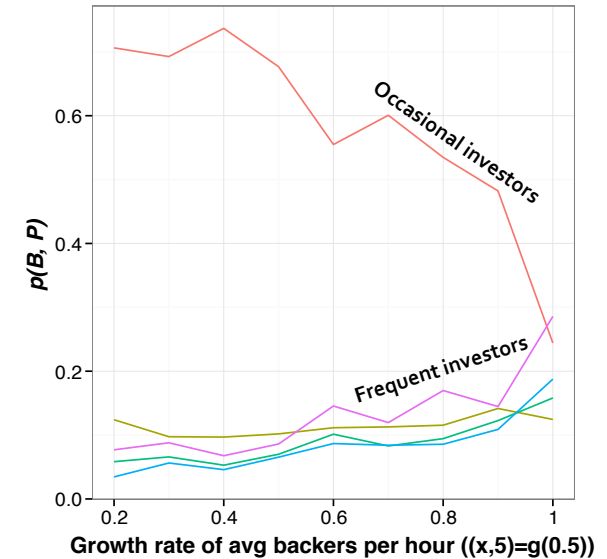
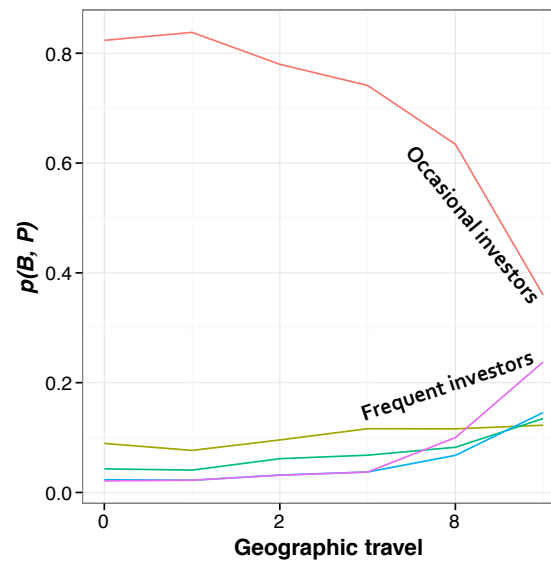
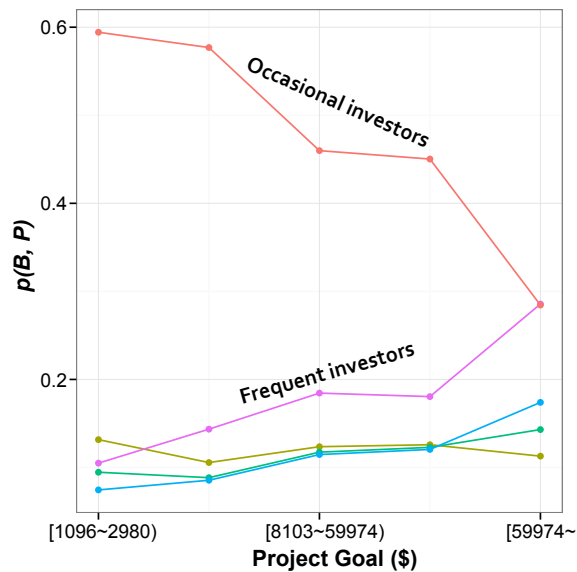
[H1.3] allows for fine-grained funding levels. $r=0.05$

[H1.4] sets a dedicated web site. $r=0.05$



PLEDGING BEHAVIOR

- [H2] A project with a high goal is likely to be financed by frequent investors. $r=0.21$
- [H3] A local project is likely to be supported by occasional investors. $r=0.32$
- [H4] A fast-growing project is likely to be financed by frequent investors. $r=0.17$
- [H5] Active investors tend to fund projects that match their own interests. $r=0.20$



PLEDGING BEHAVIOR

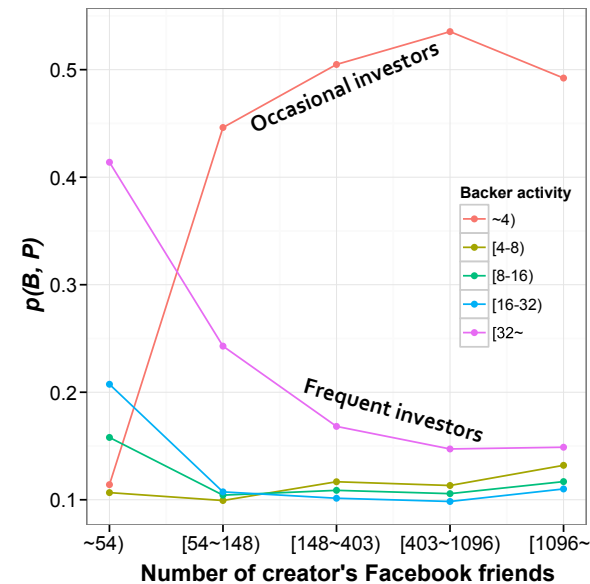
Those who have supported a considerable number of projects act in ways similar to how investors would do, while occasional supporters appear to be behaving as charitable donors.

well-managed;
have high pledging goals;
are global;
grow quickly;
and match their interests

Lured into Kickstareter by their own friends and family members who might happen to be on Facebook



Probability that an investor supports a project as a function of the number of the project founder's Facebook friends





DATASET



**PLEDGING
BEHAVIOR**



**RECOMMENDING
INVESTORS**

DATASET

PLEDGING
BEHAVIOR

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INVESTORS**

RECOMMENDING INVESTORS

1. **Linking** Kickstarter users to Twitter accounts

Matching the names of Kickstarter users interested in a project with Twitter users mentioning the project.

7,429 investors who are on **Twitter** with **891 projects** they funded

2. **Predicting** pledging behavior (who funds what)

Using Logistic Regression (**LR**) and Support Vector Machine (**SVM**) with three kernels: linear, polynomial, and RBF (Radial Basis Function)

3. **Ranking** investors

PREDICTING WHO FUNDS WHAT

Dependent variable

whether
the investor supports
the project
(prediction is 1)
or not
(prediction is 0)

Independent variable

- Static
 - Project feature: project's pledging goal, reward level, category.
 - Investor feature: Past supported project categories and his/her interests expressed on Twitter
- Dynamic
 - Project feature: growth rate, number of project updates, geographic dispersion of investors, and the number of comments exchanged

Problem

Our data **only** include **positive cases**—that is, the set of pledges that actually happened.

Solution

Augment our dataset with **negative cases**:
adding an equal number of negative cases (50-50 split)
(a set of random project-investor pairs)

PREDICTION WITH BALANCED DATASET

5-fold cross validation

SVM with polynomial and RBF kernels work best

82% of accuracy in predicting an unordered list of investors only by static features and 73% of accuracy by dynamic features.

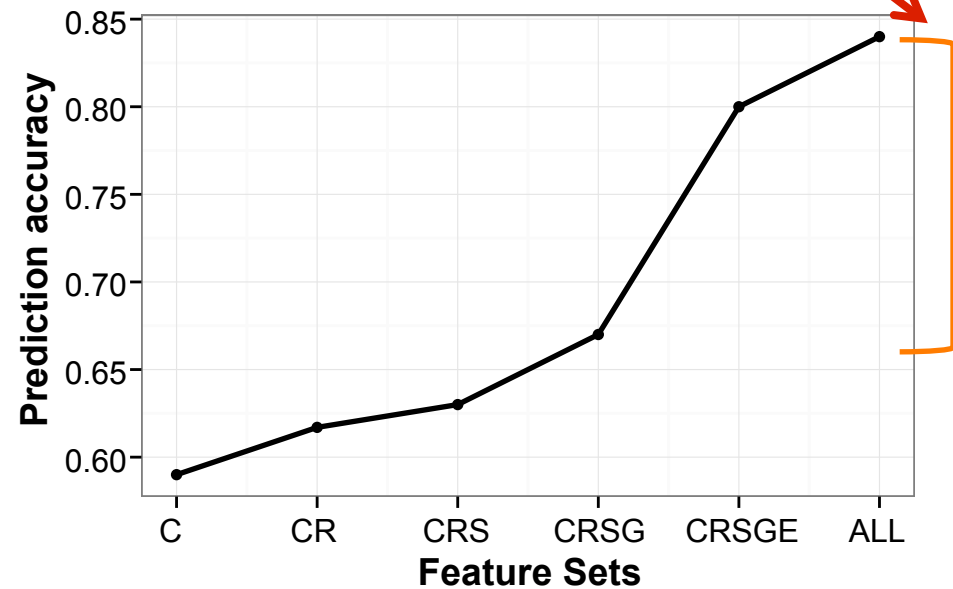
Model	Features	ACC	P	R	F_1	AUC
LR	Static	0.57	0.57	0.55	0.56	0.57
	Dynamic	0.57	0.58	0.55	0.56	0.57
SVM-linear	Static	0.58	0.60	0.51	0.55	0.58
	Dynamic	0.58	0.60	0.50	0.55	0.58
SVM-poly	Static	0.80	0.81	0.75	0.79	0.80
	Dynamic	0.68	0.76	0.54	0.63	0.68
SVM-RBF	Static	0.82	0.79	0.83	0.82	0.81
	Dynamic	0.73	0.75	0.68	0.71	0.73

PREDICTIVE POWER OF FEATURES

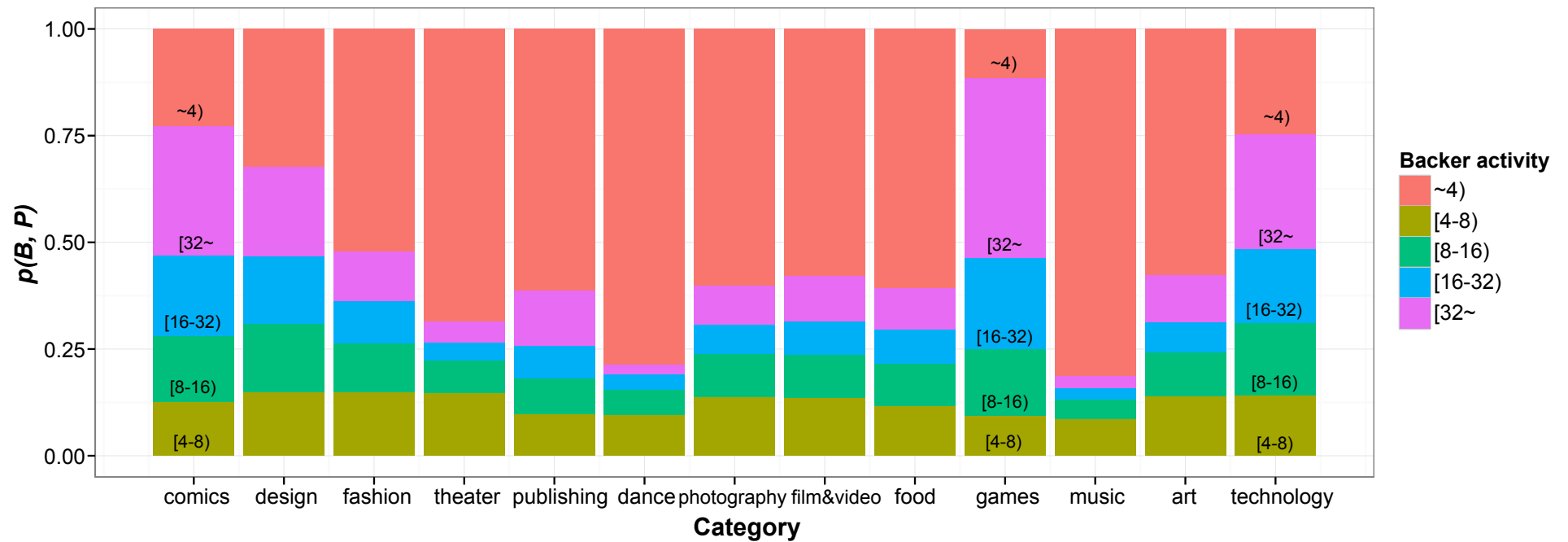
Run classifications on input of **different combinations of features**:

Number of comments (C),
Reward levels (R),
Geographic span (S),
Growth rate (G),
Category matching (E),
Topic similarity (TS)

Adding category matching and topical similarity results in considerable performance improvements.



Frequent investors: projects on technology, games, and comics
 <-> **Occasional** investors: art projects



PREDICTION WITH IMBALANCED DATASET

Creating an alternative test set:

20% positive cases and 80% negative cases (20/80 split)

Model	Features	ACC	AUC
LR	Static	0.56	0.57
	Dynamic	0.57	0.57
SVM-linear	Static	0.60	0.58
	Dynamic	0.61	0.59
SVM-poly	Static	0.81	0.80
	Dynamic	0.77	0.70
SVM-RBF	Static	0.82	0.81
	Dynamic	0.74	0.73

RANKING INVESTORS

Using our SVM-RBF,
Rank all Twitter users for each project

Probability that B will fund P
= SVM-RBF (investor B features, project P features)

For a given project,

All Twitter users	Probability	Funded
A	0.9	Yes
C	0.7	Yes
D	0.6	No
E	0.3	No
B	0.2	No

RANKING INVESTORS

Using our SVM-RBF,
Rank all Twitter users for each project

Then measure:

MeanRR (Mean Reciprocal Rank) and MaxRR (Maximum Reciprocal Rank)

a flag that reflects whether investor i has supported project P

the percentile-ranking of investor i within the ordered list of investors predicted for project P

$$\overline{rank} = \frac{\sum_{i,P} \text{funded}_{i,P} \text{rank}_{i,P}}{\sum_{i,P} \text{rank}_{i,P}}$$

RANKING INVESTORS

All Twitter users	Probability	Funded	<i>rank</i>	<i>funded</i>
A	0.9	Yes	0.1	1
C	0.7	Yes	0.3	1
D	0.6	No	0.5	0
E	0.3	No	0.7	0
B	0.2	No	0.9	0

$$\overline{rank} = \frac{\sum_{i,P} funded_{i,P} rank_{i,P}}{\sum_{i,P} rank_{i,P}} = 0.1 + 0.3 / 0.25 = \mathbf{0.16}$$

RANKING INVESTORS

33% gain over the random baseline in predicting an ordered list

Model	Features	MeanRR	MaxRR
Random	-	0.50	0.87
SVM-RBF	Static	0.34	0.39
	Dynamic	0.37	0.40
	All	0.32	0.38

COLD-START PROBLEM

Extend investor pool

The Twitter-derived features

1. **Activity**: the logarithm of the total number of tweets
2. **Status**: the logarithm of the total number of followers divided by the number of followees
3. **Influence**: the sum of the average number of retweets, favorites, and mentions of the account's tweets

Model	Features	ACC	P	R	F_1	AUC
SVM-RBF	Static	0.68	0.71	0.61	0.66	0.68
	Dynamic	0.67	0.72	0.58	0.64	0.67

model	Features	MeanRR	MaxRR
Random	-	0.50	0.87
SVM-RBF	Static	0.44	0.47
	Dynamic	0.44	0.46
	All	0.40	0.41

Prediction accuracy (69%)

Ranking performance (20% gain)

Recommending Investors for Crowdfunding Projects

Jisun An

(University of Cambridge, UK)

with Daniele Quercia

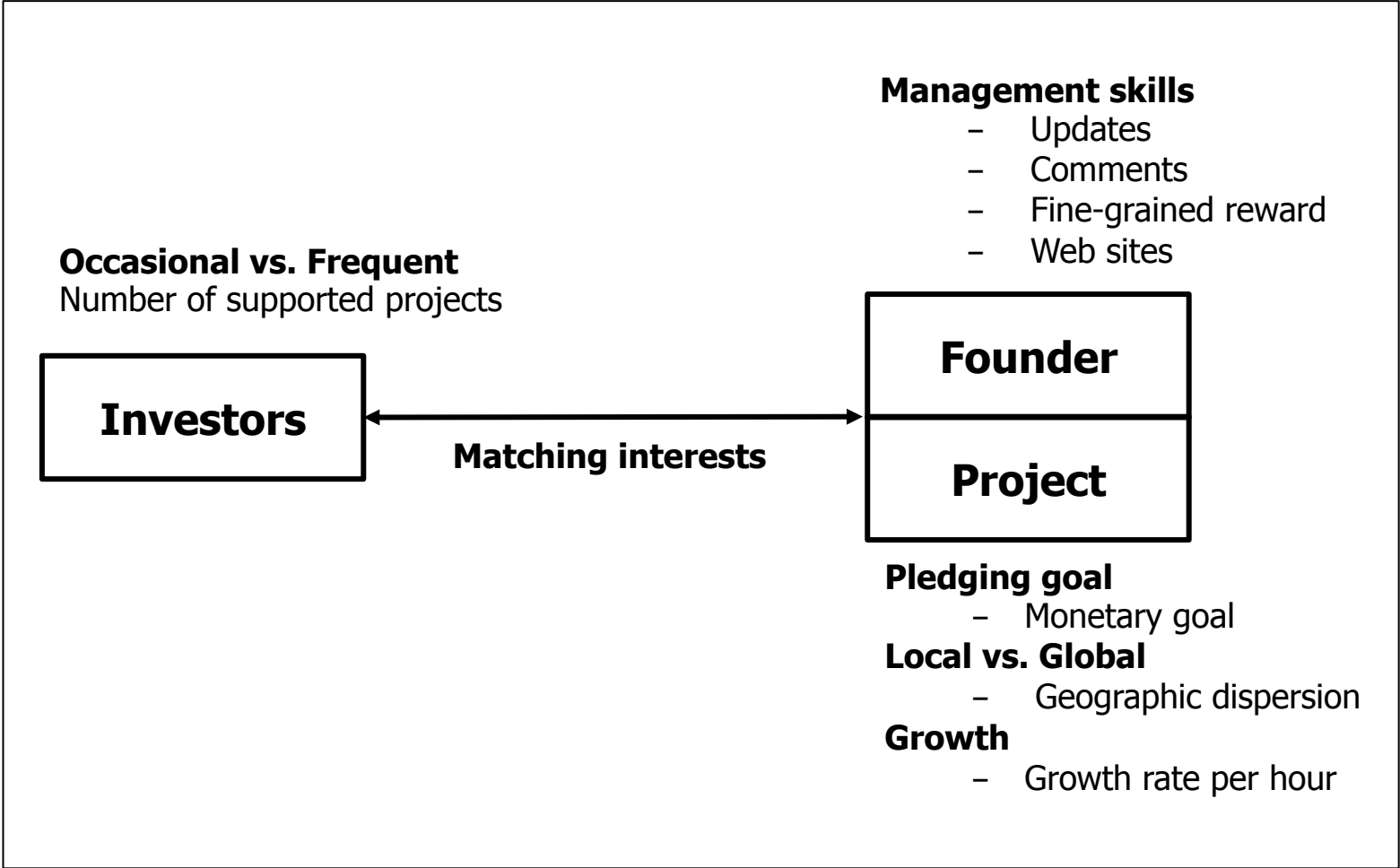
(Yahoo Labs, Barcelona)

Jon Crowcroft

(Univ. of Cambridge, UK)

- 1 Artistic projects should rely on the traditional 3Fs (friends, family, and fools), employing social media sites to efficiently reach them
- 2 Technology projects should broaden their search and look for active and frequent investors.

PLEDGING BEHAVIOR



Related work on predicting success of crowdfunding projects

Not all projects are successfully financed.
Success rate: **43.85%** (by Kickstarter)

	Min	Max	Mean	Distribution
#updates	0	42	3.5	
#comments	0	7298	22	
Reward level	1	52	10	
Web site				
Goal (\$)	47	3M	22K	
Geographic dispersion	0	76	12	
Growth rate	0	1.7	0.4	