WEPAY



Payments for platform businesses.

Leveraging Big Data For Payment Risk Management

John Canfield, VP Risk Management, WePay @JCRisk

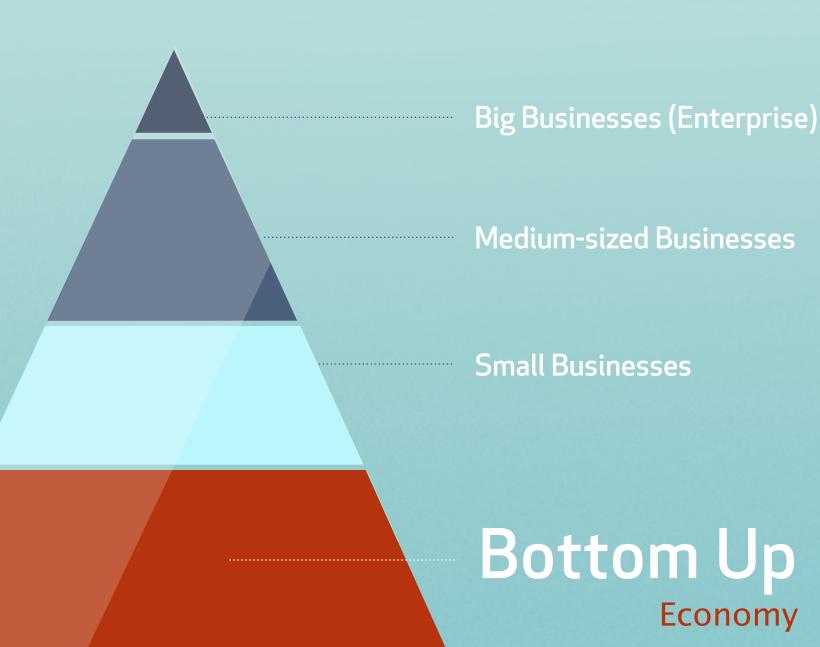
June 11, 2014

Outline

- 1. Payments opportunity for the bottoms-up economy
- 2. Requirements
- 3. Solution
 - a) Big data collection
 - b) Decisioning using machine learning, rules, and expert staff
 - c) Metrics and feedback

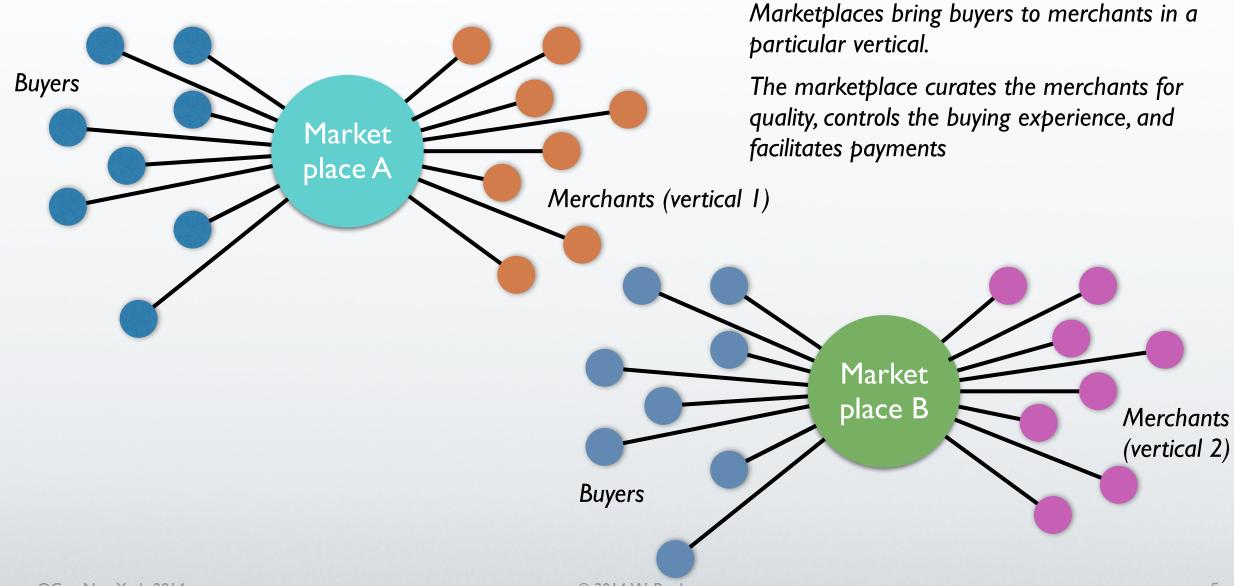


What is the "Bottom Up" Economy?



- According to IRS data, there are over 25 million businesses in the United States with less than 5 employees.
- They collectively take in over \$2 trillion annually - a tremendous opportunity for electronic payment conversion.
- ➤ Services (non-retail) is most of the market: 22m businesses & \$1.7 trillion in income.

Marketplaces



QCon New York, 2014 © 2014, WePay Inc. 5



Figor great Sitters and Mannies near you!

Try it FREE ▶









GROCERY PICK UPI

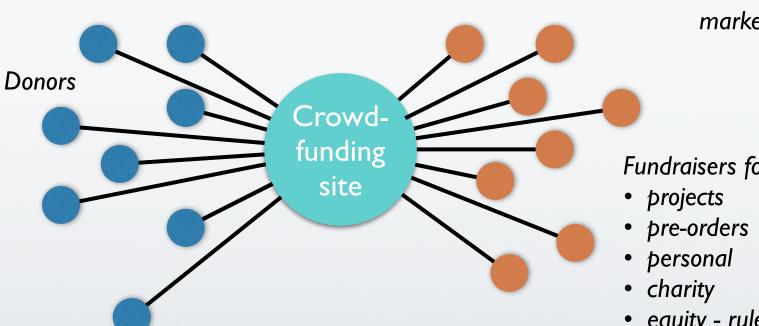








Crowdfunding sites



Crowdfunding sites are similar to marketplaces but instead of bringing buyers to sellers, they bring donors to fundraisers.

The crowdfunding site enables the fundraiser to market their campaign and accept payments

Fundraisers for

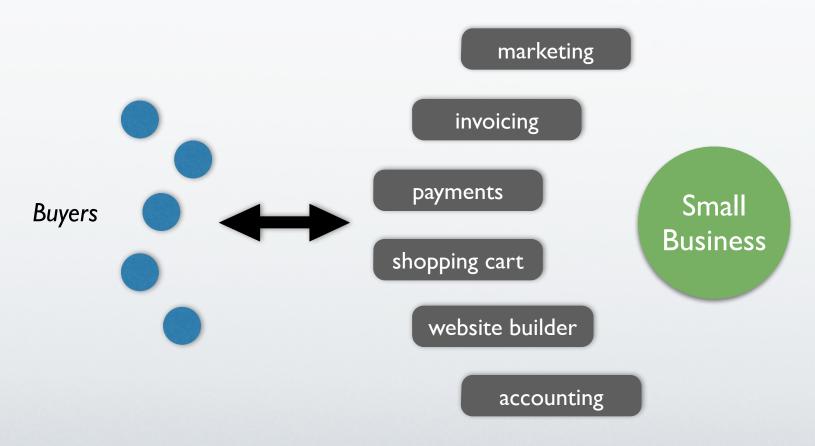
• equity - rule TBD

QCon New York, 2014 © 2014, WePay Inc.



Small Business Platforms

Small business platforms offer online services to small businesses like marketing, invoicing, shopping cart, accounting and payments



QCon New York, 2014



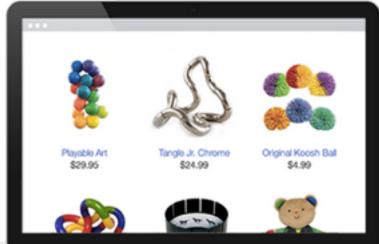




Manage Account

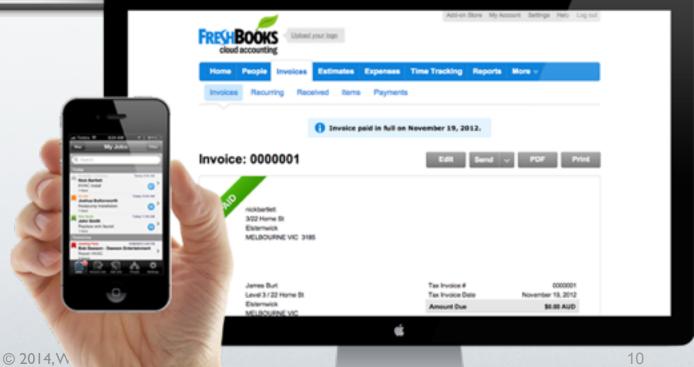
5:22 PM

iPod 😴









Requirements

Traditional payments do not work for bottoms-up economy

Long application form + day/weeks to approve + approval difficult for individuals

600 Parmar Onin Application Type New Logal Name Change Logal Name Change Logal Name Change Ch					
	Fiduciary Change				_
Merchant Application	Additional location		Asserbéten.	Chain.	7
Husine as Information Black and is SBA Name; Merchant's Legal Name;					
				⊐	
Physical Street Address (se PO 814)		Legal Address:			П.
City, State, Zip:		City, State, Zip.			┑
DBA Phone:	Fac	Corp Phone:		Fac	1
Contact Name (erea assur)	Email (required to intensel)	Contact Name	Continuations)	Embli (represents interes)	П
Marchaels Curbons Service Phonal Copyried	to reg	mortivities (5	spired Homel No	PAPEC	┨.
Merchant Profile Number (Of locations:	Wisa/Master C	Master Cardi Discover Information #Type: clear wyono Law Pull-puritions		
Sale Proprietor Plantnership Taxe Eventy (50 nC) ULC Taxe Eventy (50 nC) ULC Type of goods or Service solid Years in business under current Federal Tax (10# Do you currently accept Visa/MC Does the Merchant accept trans	Ownership: O'Discover: O Yes O No actions before the ouston	ner receives pro	Soper Warker Ledging Indian India Reside A self-branke Other OUCT OF SERVI	Next (leftepint) MO/TO (Manual Manual Magnet (O)	s s s
How long does customer wait be Does the Merchant offer warrantes if Yes for how long in weeks Is the Merchant Seasonal? O Yes Annual Wis atMasterCardDis or	O No. Pyes when is Merch	berships or other hant Closed 7			
Annual VisaMasterCardDiscover Sales 5 Average Ticket 5 Member Rank (Acquire) Information For Debt Sponsorthip					
	Phone #: 760-340-1145	Carrolton Bar 1740 E. Jopp Batimore, MC	ik: Pi a Rd, Suite 2		

Poor conversion rate for micro-businesses and fundraisers

Payments requirements for bottoms-up economy

- Easy and fast merchant onboarding
- Underwrite individuals or micro-businesses with little or no traditional business history
- Prevent collusion and takeover fraud

QCon New York, 2014 © 2014, WePay Inc. 13

Fraud threats are everywhere

Information Week

Target Confirms Hackers Stole 40 Million Credit Cards

The New York Times
Neiman Marcus Data Breach Worse Than First Said

The New York Times

Michaels Stores' Breach Involved 3 Million

The Register

Krebs: Lexis-Nexis, D&B and Kroll hacked

CyberSource Online Fraud Report

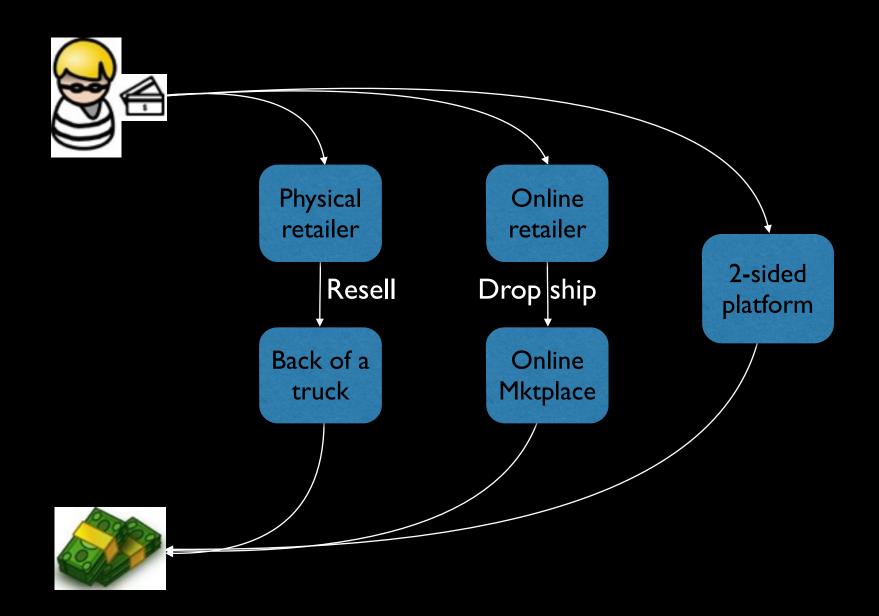
Estimated \$3.5 Billion Lost to Online Fraud

Entrepreneur,

April 18 2014

Online Debit, Credit Fraud Will Soon Get Much Worse. Here's Why.

Fraudsters want to monetize their stolen cards



Solution outline

1. Lots of risk data from many sources

- a) What data
- b) How to collect
- c) What infrastructure

2. Multi-level risk decisioning

- a) Machine learning
- b) Rules
- c) Manual

3. Metrics & feedback

Data

Data approach



Predictive of loss / fraud

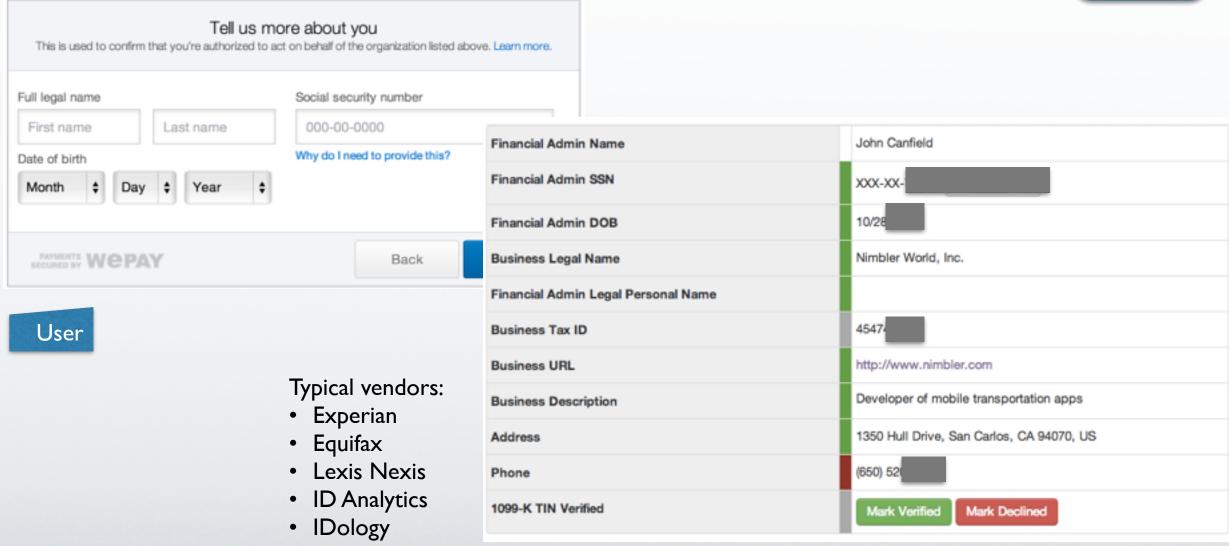
Compliance

More data is better if you have scalable data arch and decisioning

No silver bullet, so move towards big data

Know-Your-Customer (KYC) checks







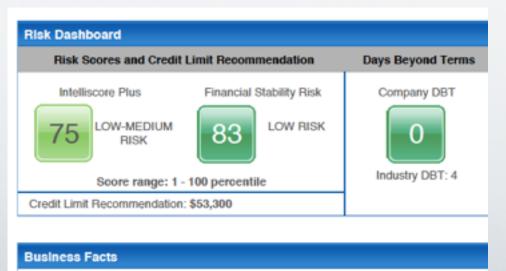
Traditional business credit reports





Business Facts

5 (FILE ESTABLISHED 09/2008) SIC Code: Years on File: State of Incorporation: CA Date of Incorporation: 08/14/2008 SUBDI



y Risk Company DBT not DBT financial Unavailable
9

Business Facts Years on File: 2 (FILE ESTABLISHED 04/2012) State of Incorporation: DE Date of Incorporation: 03/12/2012 Business Type: Institutions - Profit

Typical vendors:

- D&B
- Experian
- Equifax



Years on File:

State of Incorporation:

Business Incorporation Docs

data

IRS DEPARTMENT OF THE TREASURY
INTERNAL REVENUE SERVICE
CINCINNATI OH 45999-0023

Date

Emplo 46-09

Form:

Numbe

IT ONLINE TRAINING LLC

1621 CENTRAL AVE CHEYENNE, WY 82001 For a 1-800

IF YO

WE ASSIGNED YOU AN EMPLOYER IDENTIFICATION NU

Thank you for applying for an Employer Tdentification M

Corp No. 583210 GOVERNMENT OF THE VIRGIN ISLANDS OF THE UNITED STATES -- 0 ---**CHARLOTTE AMALIE, ST. THOMAS, VI 00802** CERTIFICATE OF EXISTENCE To All To Whom These Presents Shall Come: I, GREGORY R. FRANCIS, Lieutenant Governor of the Virgin Islands do hereby certify that I am, by virtue of the laws of the Virgin Islands, the custodian of the corporate records and the proper officer to execute this certificate. I further certify that the records of this office disclose that



Business social media



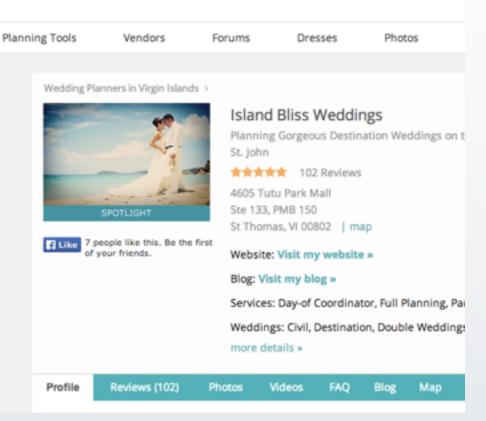




Editorial Reviews and Ratings







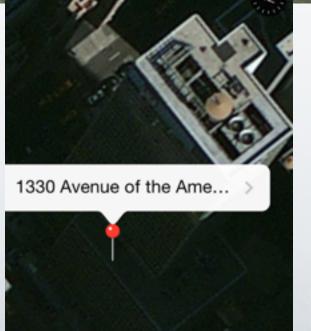


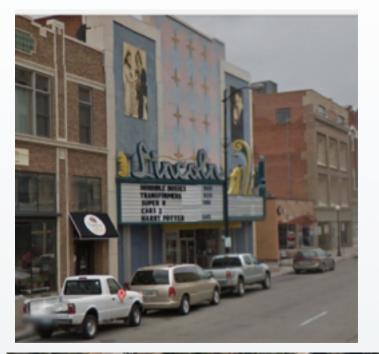


manual spider

Maps / Street View











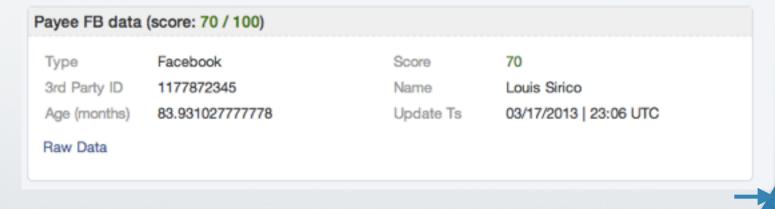


QCon New York, 20

Facebook profile







API

manual

Google



Google	jo

john canfield wepay

Web News Videos Shopping Images More ▼ Search tools

About 28,600 results (0.47 seconds)

John Canfield | LinkedIn

www.linkedin.com/in/johncanfieldbayarea
San Francisco Bay Area - VP, Risk Management at WePay
View John Canfield's professional profile on LinkedIn. LinkedIn is the ... VP, Risk
Management at WePay ... Join LinkedIn and access John Canfield's full profile.

WePay Hires eBay Veteran as Vice President of Risk ...

www.marketwired.com/.../wepay-hires-ebay-veteran-as-vice-... ▼ Marketwire ▼ May 30, 2013 - PALO ALTO, CA--(Marketwired - May 30, 2013) - WePay, the ... John Canfield Joins WePay on the Heels of Social Risk Engine Introduction.

WePay Hires eBay Veteran as Vice President of Risk ...

online.wsj.com/.../PR-CO-20130530-907631.htm... ▼ The Wall Street Journal ▼ May 30, 2013 - **John Canfield** Joins **WePay** on the Heels of Social Risk Engine ... Canfield's appointment is critical to the future growth and success of **WePay**, ...

About - WePay

https://www.wepay.com/about * WePay * John Canfield, VP of Risk. John leads all of our risk strategy, processes and tactics at WePay. Prior to WePay, John founded his own start-up - Nimbler - a ...



Device ID



Device	
Exact ID	a2d51953ab82465187038dd13 a6a012e
Exact ID Match Result	success
Smart ID	6e638addb0c94bd78f342ab45 531e350
Smart ID Confidence	100
Local Time Offset	0
Local Time Offset Range	0
Offset Measure Time	
OS	Windows NT
OS Anomaly	

Typical vendors:

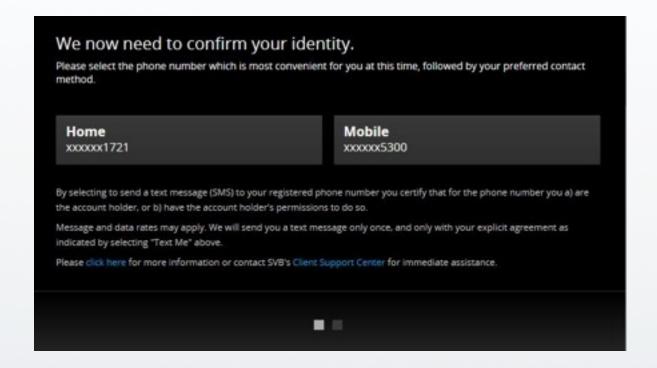
- ThreatMetrix
- iovation
- Experian / 41st Parameter

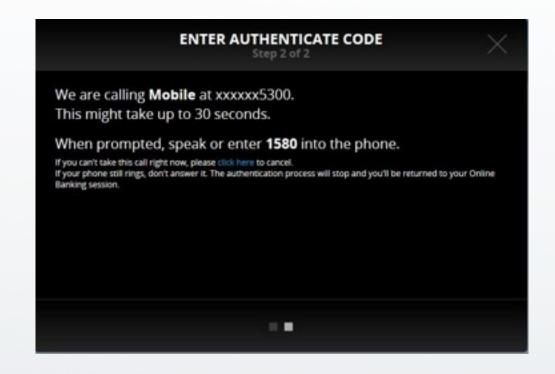
	For Group Admin	Total Users	Blacklisted Users	Blacklisted Groups
By IP:	26	10	7	10
By True IP:	23	8	5	6
By Device ID:	2	4	3	3
By Fuzzy Device ID:	2	4	3	3



Control Verification







Typical vendors:

- Authentify
- Telesign
- Twilio



Transaction History



State Count Count % TPV TPV % Captured 53 100% 89559.73 100% Chargebacks 0 0% 0% Refunds 1 1.89% 215.68 0.24% Unauthorized 0 0% 0%	Payment Stats To Account (60 da	ays)			
Chargebacks 0 0% 0% Refunds 1 1.89% 215.68 0.24% Unauthorized 0 0% 0%	State	Count	Count %	TPV	TPV %
Refunds 1 1.89% 215.68 0.24% Unauthorized 0 0% 0%	Captured	53	100%	89559.73	100%
Unauthorized 0 0% 0%	Chargebacks	0	0%		0%
	Refunds	1	1.89%	215.68	0.24%
	Unauthorized	0	0%		0%
Total: 53 89559.73	Total:	53		89559.73	

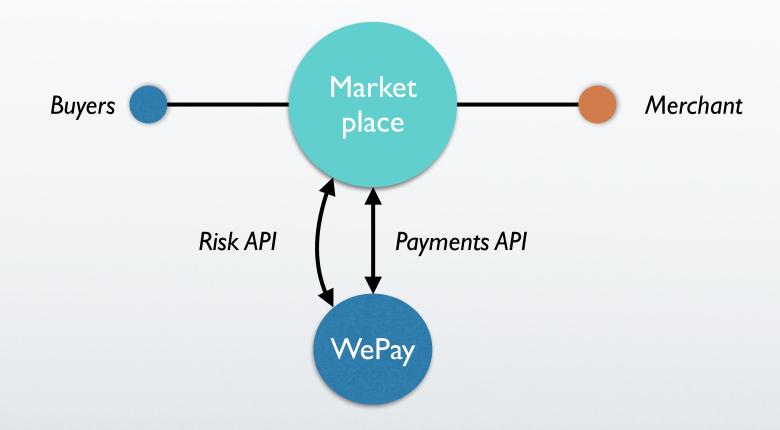
Unauthorized Payment Stats To Account (60 days)						
State	Count	Count %	TPV	TPV %		
Total:	0		0			

Payment Stats To Account (60 day	s)			
State	Count	Count %	TPV	TPV %
Captured	220	97.78%	499089.87	99.06%
Failed	4	1.78%	2029.10	0.4%
InReview	1	0.44%	2697.00	0.54%
Chargebacks	0	0%		0%
Refunds	2	0.89%	1368.83	0.27%
Unauthorized	10	4.44%	35984.00	7.14%
Total:	225		503815.97	

State	Count	Count %	TPV	TPV %
User_CID	2	6.06%	9116.00	7.67%
Decline_InsufficientFunds	7	21.21%	27526.40	23.16%
Decline_General	20	60.61%	73656.40	61.97%
ExcessiveAuthorizations	1	3.03%	2448.00	2.06%
UndefinedResponseCode	3	9.09%	6106.00	5.14%
Total:	33		118852.8	

Data from Partners





Risk API Account Information



		Ch	Src.
Personal			
Address:	380 Portage Ave, Palo Alto, CA 94306	4	10
EIN:	20-4449703	0	*
Office Phone:	(855) 469-3729	4	*
Mobile Phone:	(650) 800-3303	Rick	API
Personal Email:	april@yahoo.com	4	1
Work Email:	april@armarketing.com	4	1 ⊗
Years in Business:	3		0.
Revenue (USD):	\$40,000	4	8
Revenue Fraction:	partial	4 Diel	ADI
Invoice ASAP	1.2 years	4 KISK	API
account age:			

Example Risk API data types

- person
- email
- business name
- address
- phone
- tax id
- website_uri
- employment
- industry_code
- risk_score
- comment
- project
- fundraising_event
- fundraising_team
- acquisition channel

- partner service
- member_to_member_message
- external account
- editorial review
- other_web_content
- revenue
- conversation
- business legal
- business_report
- business description other document
 - device info
 - control verification
 - risk review
 - risk review steps
 - transaction details

Risk API Transaction Information

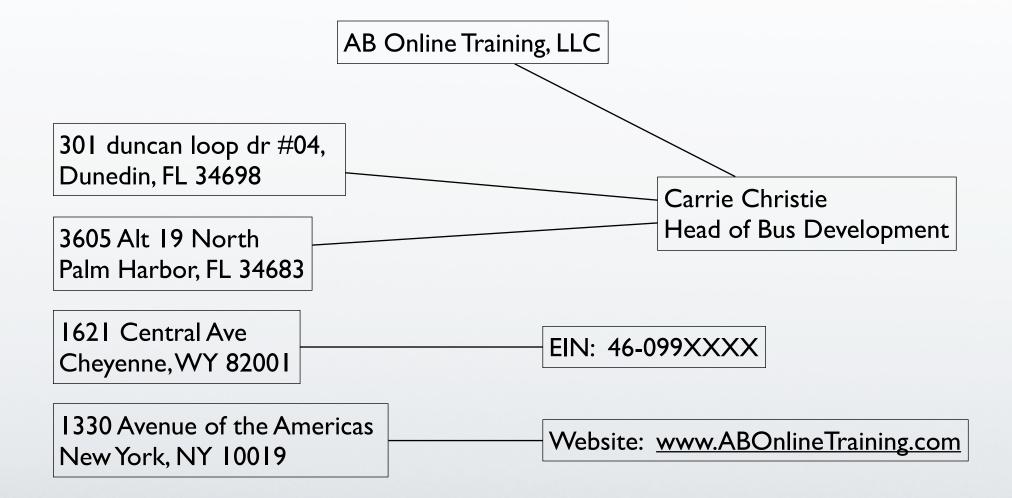
data

		Ch	Src.
Transaction Type:	Services	8	
Delivery Type:	Fully Delivered	4	8
Amount:	\$5000	8	8
Receipt URL:	https://view.invoiceasap.com/view.php?invoi [show full]	4	8
Terms URL:	https://view.invoiceasap.com/view.php?invoi [show full]	4	8
Shipping Addr:			
Shipping Info:		Lin	e Itam

, –			
		Ch	Src.
Line Item 1			
Description:	Search Engine Optimization - hourly	4	1
	Search Engine Optimization - home page and product page		
Qty:	20.00	4	*
Price:	\$100	4	1
Total:	\$2,000	4	*
Line Item 2			
Description:	Social media marketing - February	4	1
	Twitter, Facebook, Google+ social marketing of Nimbler app		
Qty:	1	4	2
Price:	\$3,000	4	*
Total:	\$3,000	4	2

How to effectively organize this data?





Data storage systems



SQL databases:

- MySQL
- Oracle
- . . .

No-SQL databases:

- Document (MongoDB...)
- Key-value (Redis...)
- Graph (Neo4J...)
- Column (Cassandra...)

Other:

- Hadoop
- . . .

Decisioning

What is Machine Learning?

decisioning

2) Surpelicuitied leaening

			BL accts	BL accts		IP to
	01	01			T	
	BL accts	BL accts	by Device	by fuzzy	Txn	Address
Txn #	by IP	by True IP	ID	Device ID	Amount	miles
10000001	0	0	0	0	20.00	22
100000002	8	5	3	3	499.00	15
100000003	0	0	0	0	35.00	539
100000004	0	0	0	0	85.00	0
100000005	0	0	0	0	90.23	2
			BL accts	BL accts		IP to
	BL accts	BL accts	by Device	by fuzzy	Txn	Address
Txn #	BL accts by IP	BL accts by True IP	by Device ID	by fuzzy Device ID	Txn Amount	Address miles
Txn #			-			
	by IP	by True IP	ID	Device ID	Amount	miles
100000016	by IP 0	by True IP 0	ID 0	Device ID 0	Amount 400.00	miles 13
100000016 100000010	<i>by IP</i> 0	by True IP 0 0	1D 0	Device ID 0	Amount 400.00 20.00	miles 13
100000016 100000010 100000011	<i>by IP</i> 0 0	by True IP 0 0 0	1D 0 0 0	Device ID 0 0	Amount 400.00 20.00 75.00	miles 13 1 5
100000016 100000010 100000011 100000012	by IP 0 0 0 0 0	by True IP 0 0 0	0 0 0	Device ID 0 0 0 0	Amount 400.00 20.00 75.00 80.00	miles 13 1 5 8

Label:		
is Fraud?		
0)	
1		
0)	
0)	
0)	
0)	
0)	
0)	
0)	
0)	
0)	
0)	
0)	
0)	
0)	

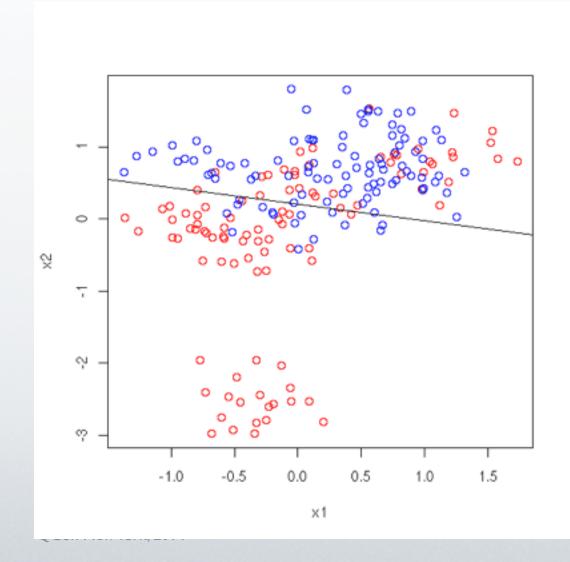
Training

Machine Learning Model

How does machine learning work?



Linear regression classifier

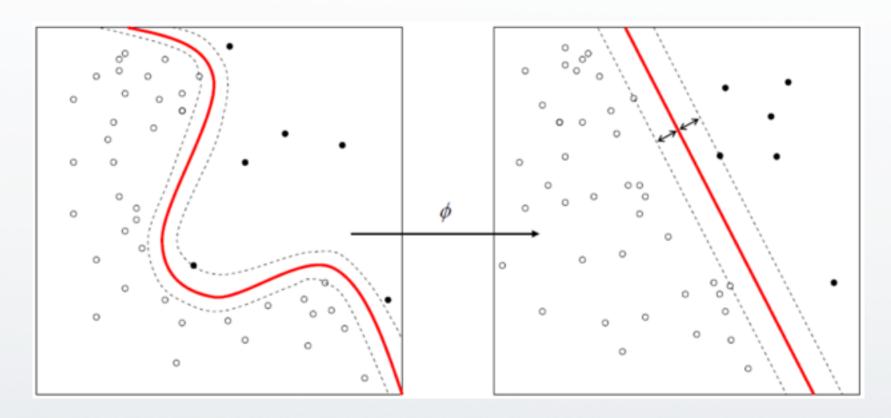


$$y = f(\vec{w} \cdot \vec{x}) = f\left(\sum_{j} w_{j} x_{j}\right)$$

© 2014, WePay Inc. 37

Support Vector Machine



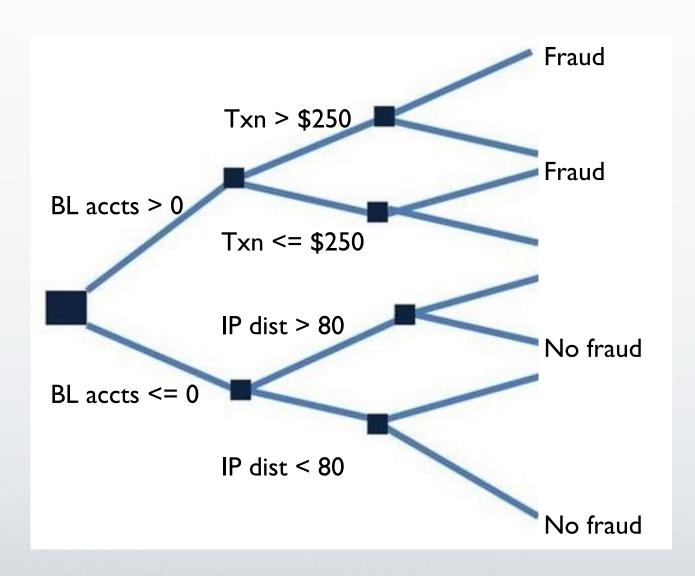


- Polynomial (homogeneous): $k(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i} \cdot \mathbf{x_j})^d$
- Polynomial (inhomogeneous): $k(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i} \cdot \mathbf{x_j} + 1)^d$
- Gaussian radial basis function: $k(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma \|\mathbf{x_i} \mathbf{x_j}\|^2)$, for $\gamma > 0$. Sometimes parametrized using $\gamma = 1/2\sigma^2$
- Hyperbolic tangent: $k(\mathbf{x_i},\mathbf{x_j}) = anh(\kappa\mathbf{x_i}\cdot\mathbf{x_j}+c)$, for some (not every) $\kappa>0$ and c<0

38

Decision Trees





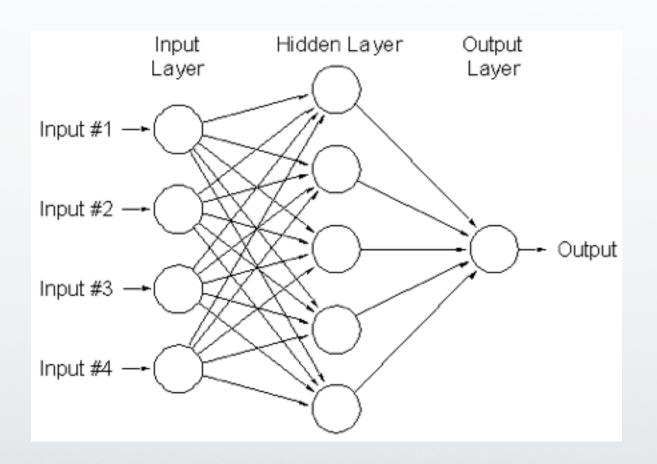
ID3 Training algorithm

Recurse and choose attribute that minimizes entropy:

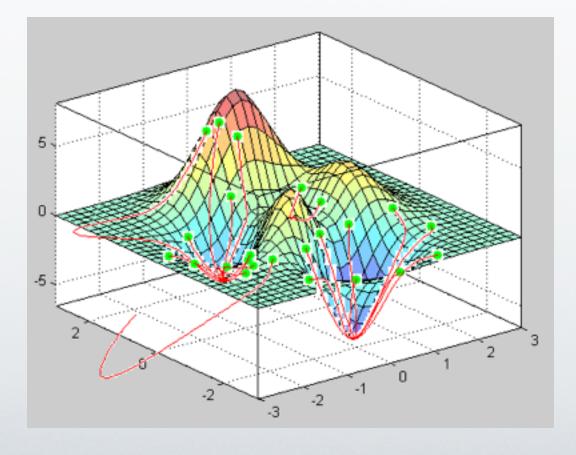
$$H(S) = -\sum_{x \in X} p(x) \log_2 p(x)$$

Neural Network models





Gradient descent training



Meta-algorithms: grid search, bagging, etc

decisioning

You can do:

Or you can do:

Decision Tree Decision Tree I Decision Tree 2

Decision Tree 3

Decision Tree 4

Decision Tree 5

SVMI

SVM 2

SVM 3

SVM 4

SVM 5

Neural Network I Neural Network 2 Neural Network 3 Neural Network 4 Neural Network 5

Logistic Regression I Logistic Regression 2

Logistic Regression 3 Logistic Regression 4

Logistic Regression 5

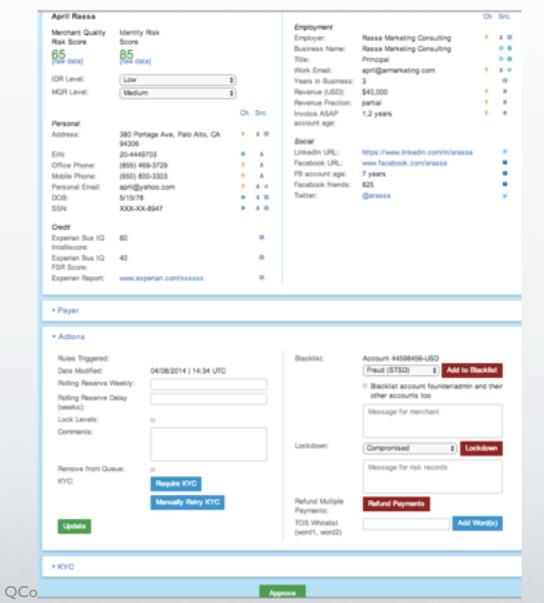
OCon New York, 2014

Rules Engine



```
Rule I (Transaction threshold):
 If (signal.Group 30Day_txn_volume > account.tpv_review_threshold_t30d and
   fact.tpv review threshold t30d > 0)
 then Refer for Review
Rule 2 (Model Score):
 If (model.fraud score > 0.85)
 then Refer for Review
Rule 3 (Re-require KYC):
 If (signal.IDR <= 0) and (signal.MQR <= 0) and (signal.Group 30Day txn volume > 1000.00) and
   (signal.name address match = false)
 then Request Address Remedy
```

Manual Review

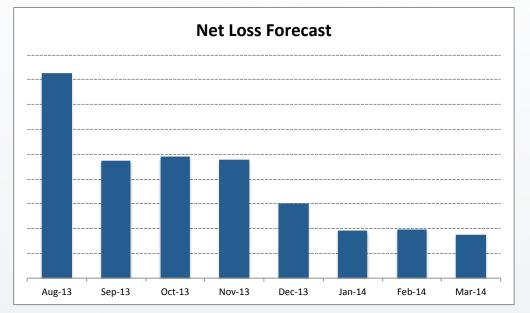


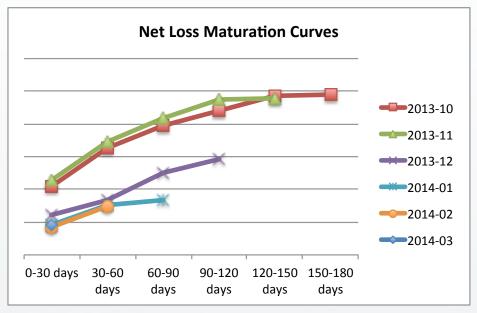
decisioning

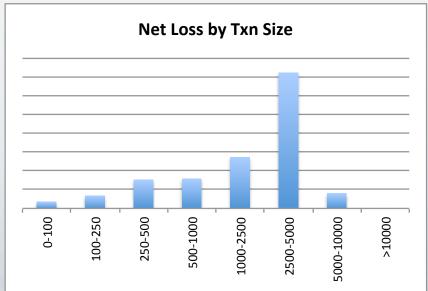
© 2014, WePay Inc. 43

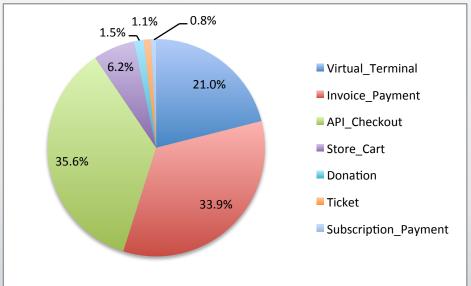
Metrics & Feedback

Metrics & Feedback









metrics

Top Net Loss Accounts					
Loss Week	2014-17				
Orig Month	(AII)				
Net Loss					
Row Labels	Total				
▼ Store_Cart	\$187				
988052845	\$115				
78252	\$72				
▼ Invoice_Payment	\$1,820				
1426156	\$1,166				
1953717721	\$505				
1373219397	\$134				
190996	\$15				
▼ API_Checkout	\$10,156				
846171008	\$1,698				
1692429545	\$1,208				
1570348118	\$674				
858508144	\$663				
	45				

Summary

- 1. Bottoms-up economy is growing and is the high-growth frontier for electronic payments
- 2. Big data needs to be pieced together bit by bit using flexible infrastructure
- 3. Machine learning, rules, and manual review when combined properly gives enables correct decisions on big data

QCon New York, 2014 © 2014, WePay Inc. 46