Psychometric profiling and impact on politics

Paul-Olivier Dehaye

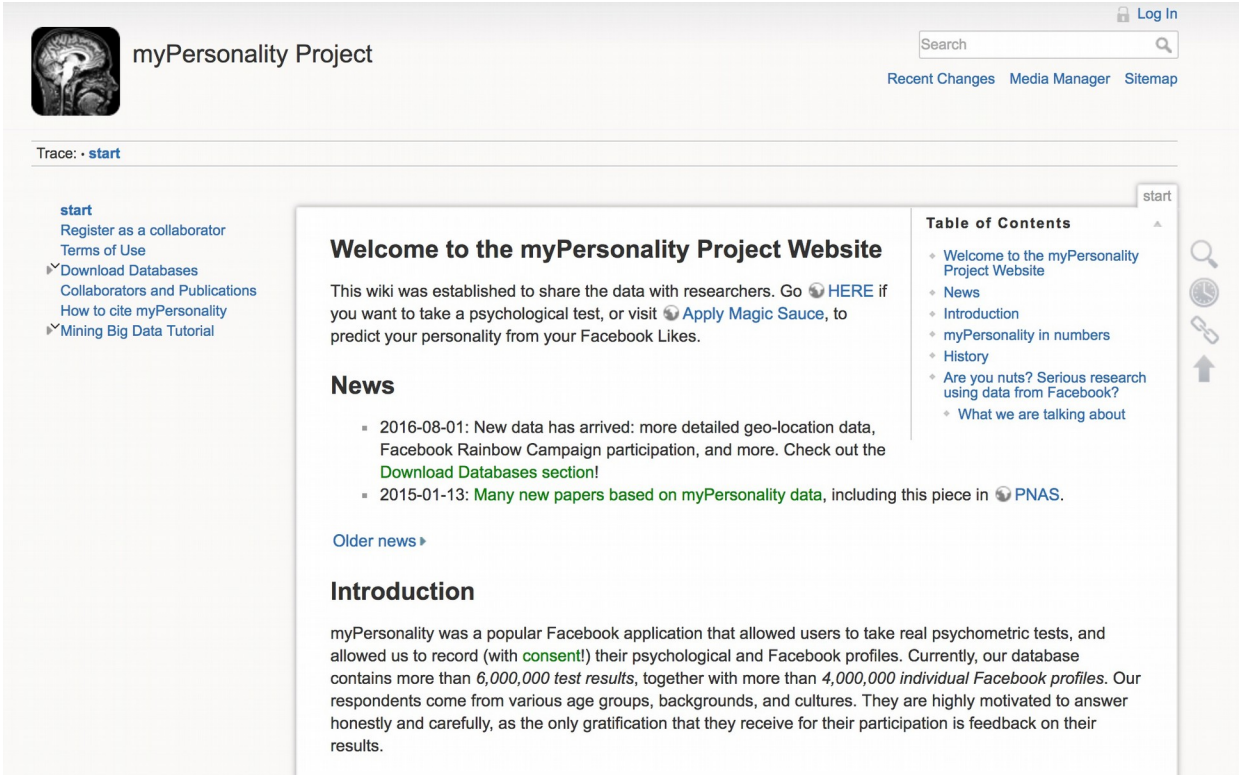
Oslo, April 4th 2017

@podehaye

PersonalData.IO

From “Likes” to psychographics

myPersonality



OCEAN model of personality

Trait	Description
Openness	Curious, original, intellectual, creative, and open to new ideas.
Conscientiousness	Organized, systematic, punctual, achievement oriented, and dependable.
Extraversion	Outgoing, talkative, sociable, and enjoys being in social situations.
Agreeableness	Affable, tolerant, sensitive, trusting, kind, and warm.
Neuroticism	Anxious, irritable, temperamental, and moody.

Kosinski's research

Private traits and attributes are predictable from digital records of human behavior

Michal Kosinski[a,1], David Stillwell[a], and Thore Graepel[b]

[a]Free School Lane, The Psychometrics Centre, University of Cambridge, Cambridge CB2 3RQ United Kingdom; and [b]Microsoft Research, Cambridge CB1 2FB, United Kingdom

Edited by Kenneth Wachter, University of California, Berkeley, CA, and approved February 12, 2013 (received for review October 29, 2012)

We show that easily accessible digital records of behavior, Facebook Likes, can be used to automatically and accurately predict a range

browsing logs (11–15). Similarly, it has been shown that personality can be predicted based on the contents of personal Web sites (16)

Computer-based personality judgments are more accurate than those made by humans

Wu Youyou[a,1,2], Michal Kosinski[b,1], and David Stillwell[a]

[a]Department of Psychology, University of Cambridge, Cambridge CB2 3EB, United Kingdom; and [b]Department of Computer Science, Stanford University, Stanford, CA 94305

Edited by David Funder, University of California, Riverside, CA, and accepted by the Editorial Board December 2, 2014 (received for review September 28, 2014)

Judging others' personalities is an essential skill in successful social living, as personality is a key driver behind people's interactions, behaviors, and emotions. Although accurate personality judgments stem from social-cognitive skills, developments in machine learning show that computer models can also make valid judgments. This study compares the accuracy of human and computer-based personality judgments, using a sample of 86,220 volunteers who completed a 100-item personality questionnaire. We show that (*i*) computer predictions based on a generic digital footprint (Facebook Likes) are more accurate ($r = 0.56$) than those made by the participants' Facebook friends using a personality questionnaire ($r = 0.49$); (*ii*) computer models show higher inter-judge agreement; and (*iii*) computer personality judgments have higher external validity when predicting life outcomes such as substance use, political attitudes, and physical health; for some outcomes, they even outperform the self-rated personality scores. Computers outpacing humans in personality judgment presents significant opportunities and challenges in the areas of psychological assessment, marketing, and privacy.

personality judgment | social media | computational social science | artificial intelligence | big data

psychological traits (11). We used LASSO (Least Absolute Shrinkage and Selection Operator) linear regressions (16) with 10-fold cross-validations, so that judgments for each participant were made using models developed on a different subsample of participants and their Likes. Likes are used by Facebook users to express positive association with online and offline objects, such as products, activities, sports, musicians, books, restaurants, or websites. Given the variety of objects, subjects, brands, and people that can be liked and the number of Facebook users (>1.3 billion), Likes represent one of the most generic kinds of digital footprint. For instance, liking a brand or a product offers a proxy for consumer preferences and purchasing behavior; music-related Likes reveal music taste; and liked websites allow for approximating web browsing behavior. Consequently, Like-based models offer a good proxy of what could be achieved based on a wide range of other digital footprints such as web browsing logs, web search queries, or purchase records (11).

Human personality judgments were obtained from the participants' Facebook friends, who were asked to describe a given participant using a 10-item version of the IPIP personality measure. To compute self-other agreement and external validity, we used a sample of 17,622 participants judged by one friend; to calculate interjudge agreement, we used a sample of 14,410 participants

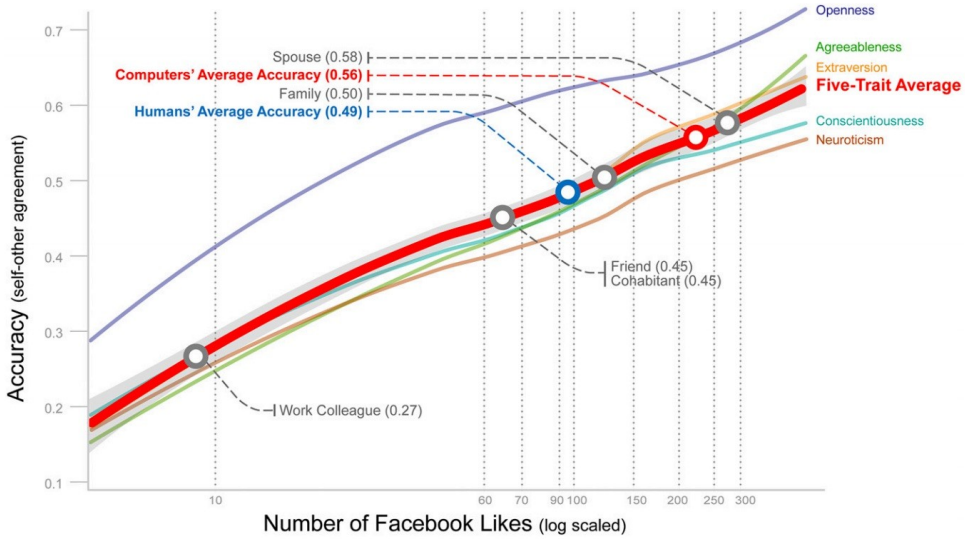
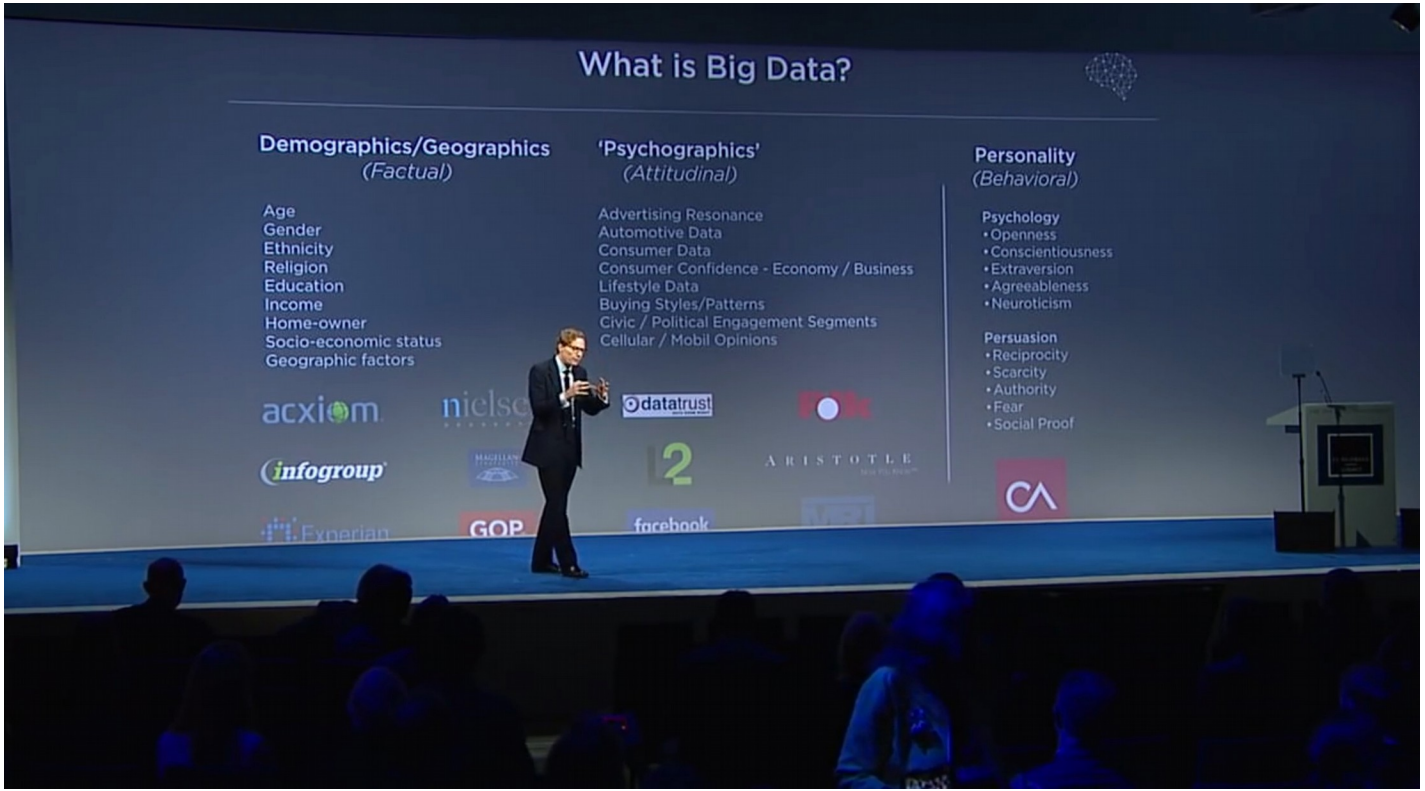


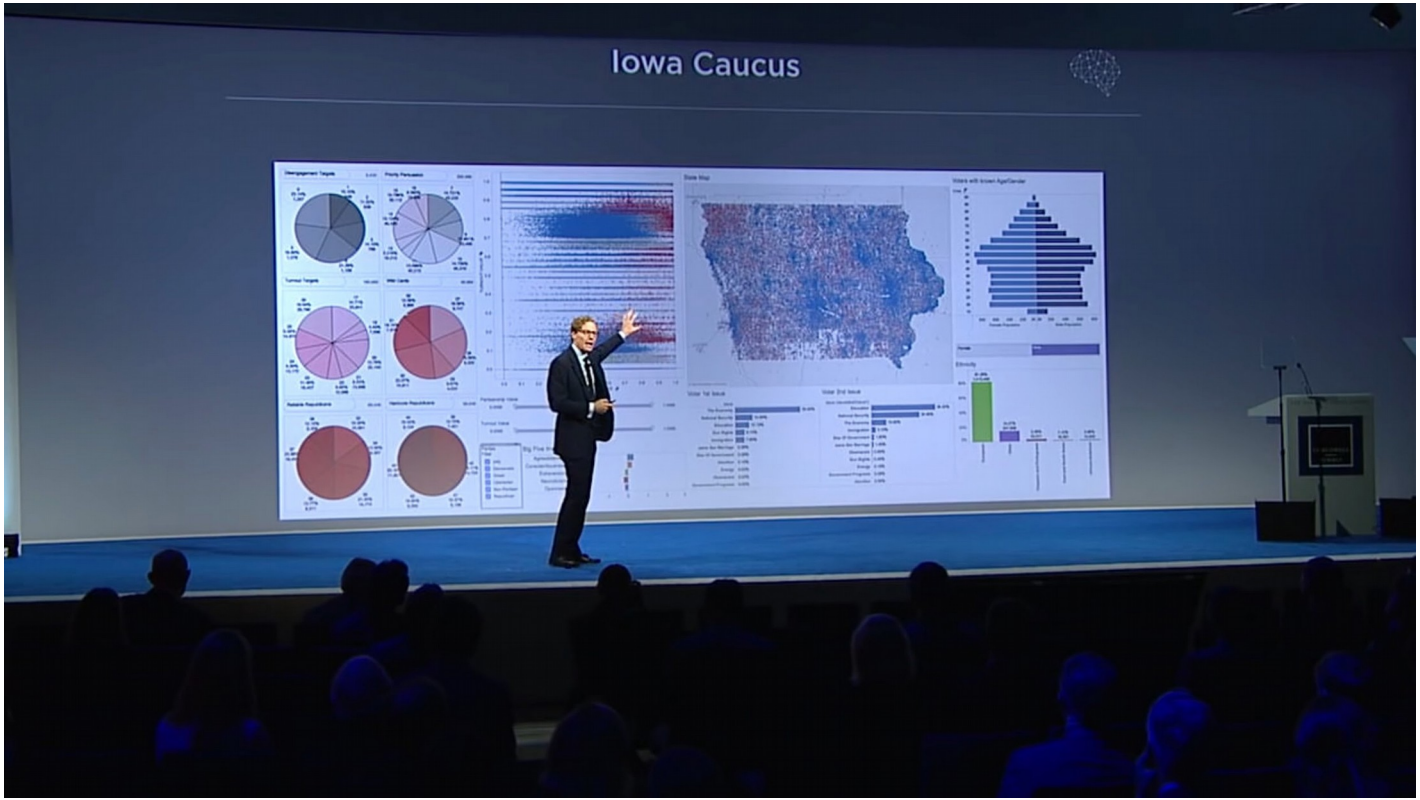
Fig. 2. Computer-based personality judgment accuracy (*y* axis), plotted against the number of Likes available for prediction (*x* axis). The red line represents the average accuracy (correlation) of computers' judgment across the five personality traits. The five-trait average accuracy of human judgments is positioned onto the computer accuracy curve. For example, the accuracy of an average human individual ($r = 0.49$) is matched by that of the computer models based on around 90–100 Likes. The computer accuracy curves are smoothed using a LOWESS approach. The gray ribbon represents the 95% CI. Accuracy was averaged using Fisher's *r*-to-*z* transformation.

Cambridge Analytica

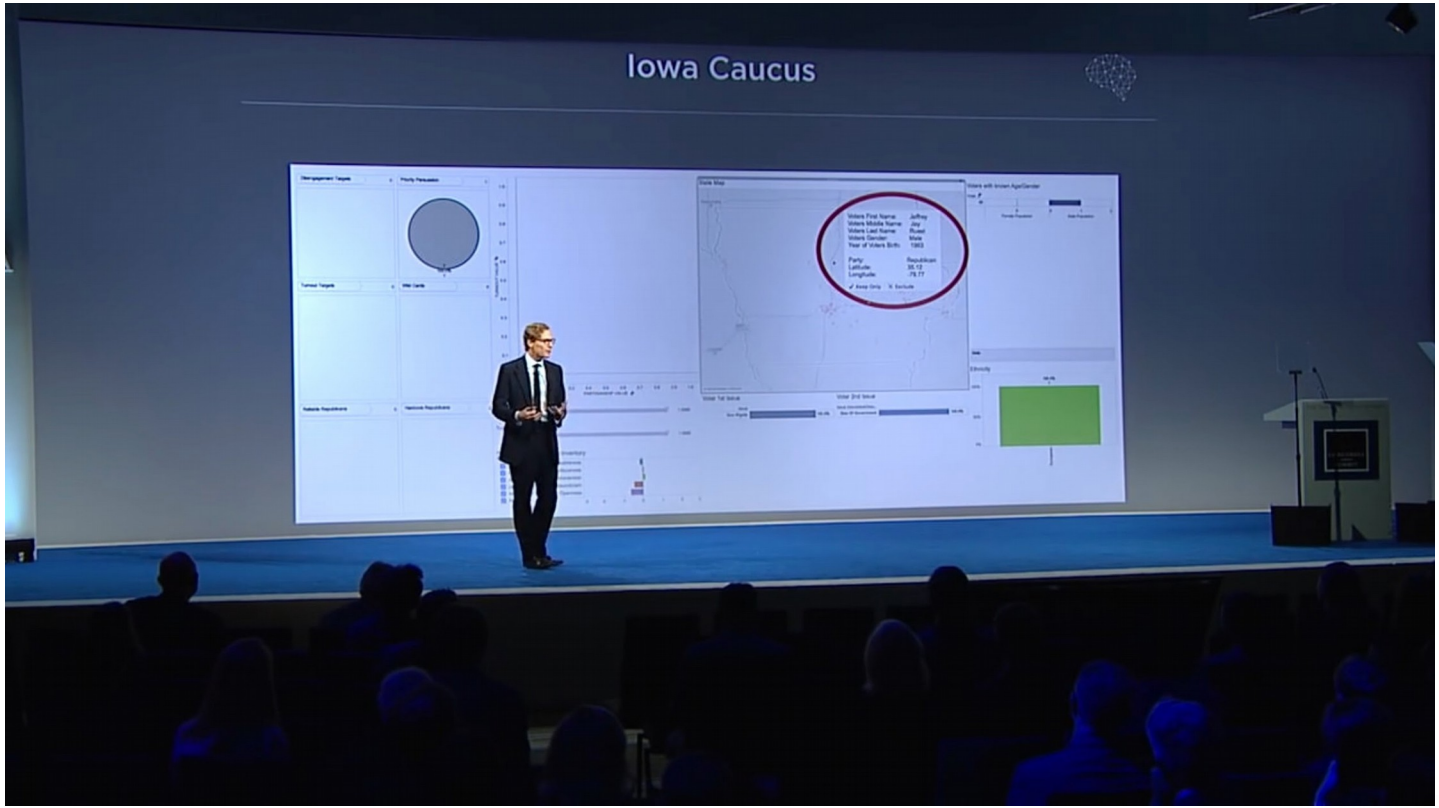
Concordia Summit (Sept 2016)



Concordia Summit (Sept 2016)



Concordia Summit (Sept 2016)



Academic ethics, or lack thereof

UK world sport football opinion culture business lifestyle fashion environment tech travel

home › world › US americas asia australia africa middle east cities development europe

Ted Cruz

Ted Cruz using firm that harvested data on millions of unwitting Facebook users

Exclusive: Documents reveal donor-funded US startup embedded in Republican's campaign paid UK university academics to collect psychological profiles on potential voters

This article is 1 year old

23,367

Harry Davies

@harryfoxdavies

email

Friday 11 December 2015 22.22 GMT

amazonmechanical turk
Artificial Artificial Intelligence

Your Account | HITs | Qualifications

Introduction | **Dashboard** | **Status** | **Account Settings**

Mechanical Turk is a marketplace for work.
We give businesses and developers access to an on-demand, scalable workforce.
Workers select from thousands of tasks and work whenever it's convenient.

303,617 HITs available. View them now.

Make Money
by working on HITs

HITs - *Human Intelligence Tasks* - are individual tasks that you work on. Find HITs now.

As a Mechanical Turk Worker you:

- Can work from home
- Choose your own work hours
- Get paid for doing good work

Find an interesting task → Work → Earn money

Get Results
from Mechanical Turk Workers

Ask workers to complete HITs - *Human Intelligence Tasks* - and get results using Mechanical Turk. Get Started.

As a Mechanical Turk Requester you:

- Have access to a global, on-demand, 24 x 7 workforce
- Get thousands of HITs completed in minutes
- Pay only when you're satisfied with the results

Fund your account → Load your tasks → Get results

Photo: Rainier Ehrhardt/Getty Images

FACEBOOK FAILED TO PROTECT 30 MILLION USERS FROM HAVING THEIR DATA HARVESTED BY TRUMP CAMPAIGN AFFILIATE

Mattathias Schwartz
March 30 2017, 8:01 p.m.

@podehaye

PERSONALDATA.IO

FOIs to Cambridge

Summary of Results

Request partially successful The request has been partially successful (some information was provided, but not all)	1
Request refused The Data Controller refuses to provide the information.	1

4 requests to this public body

FOI request about FOI requests
to Cambridge University (United Kingdom)
Request awaits classification, 3 weeks, 3 days ago

Processing notes for FOI-2016-515
to Cambridge University (United Kingdom)
Request partially successful, 1 month, 1 week ago

Request acting in concert with FOI-2016-515
to Cambridge University (United Kingdom)
Request awaits classification, 1 month, 2 weeks ago

FOI for documents exchanged between Cambridge Psychometrics Centre and SCL/Global Science Research May-June 2014
to Cambridge University (United Kingdom)
Request refused, 2 months, 1 week ago

RSS Feed
Atom Feed

SCL Group

Strategic Communication Laboratories

Cambridge Analytica

Commercial

Elections

Analytics

Digital

Sovereign

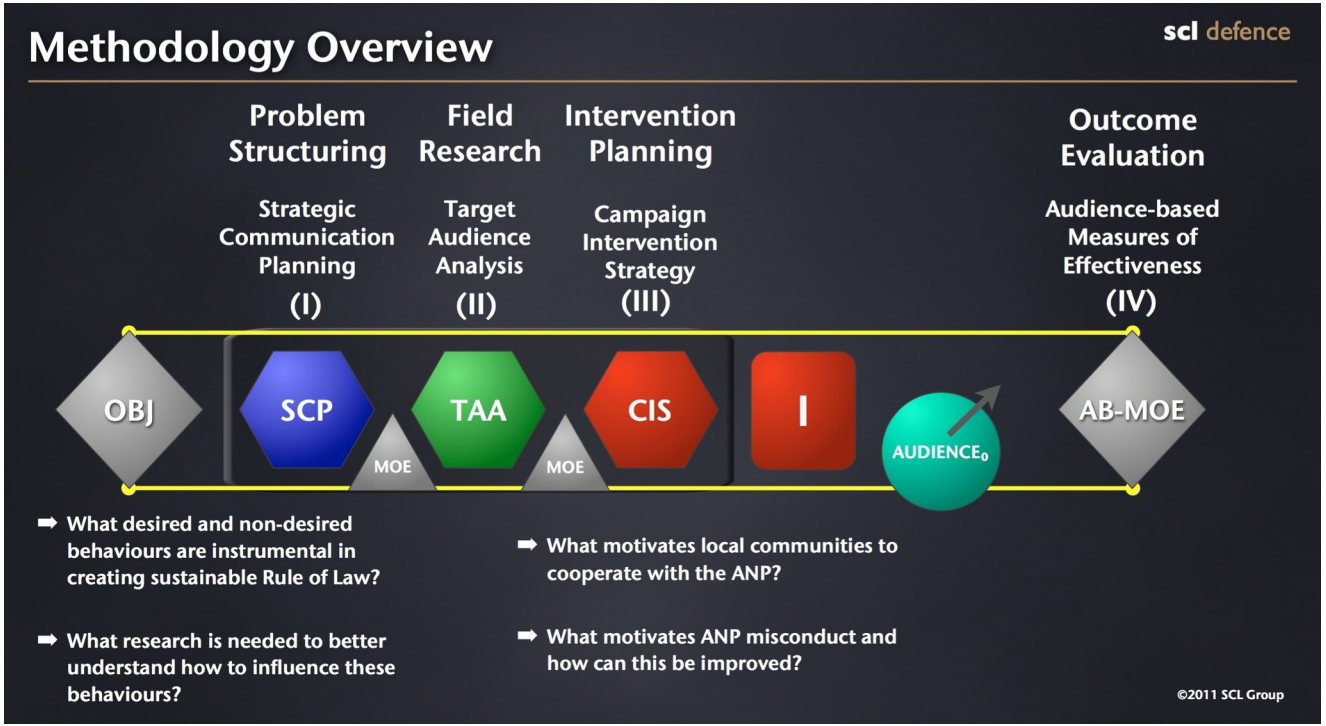
Defence

SCL Group

IOTA Global

BehaviouralDynamics Institute

Methodology

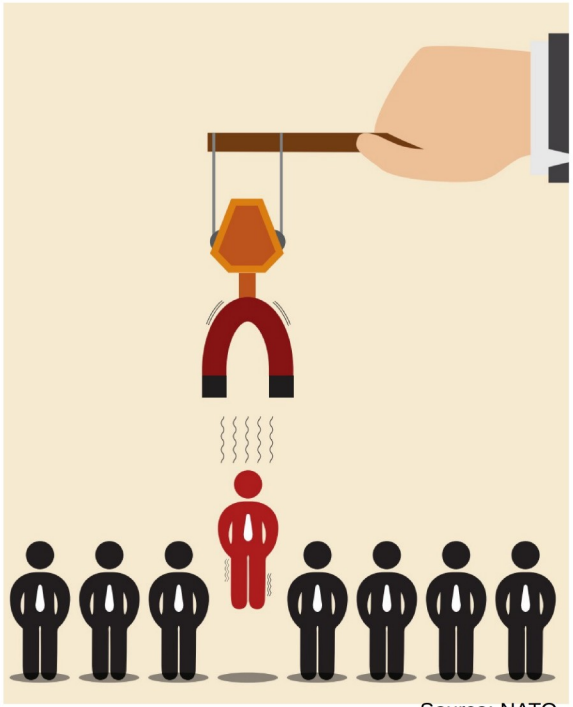


Source: “Policing our Own” report on Afghanistan operations, 2011

Methodology

Source: “Policing our Own” report on Afghanistan operations, 2011

Target Audience Analysis



Source: NATO

Self-identifying, cohesive, social groups w/ shared culture:

- **Ethnic groups**
- **Chinese Netizens (not: Chinese 18-30)**

"Which behaviour change can we expect, which triggers exist?" (polling, field research,...)

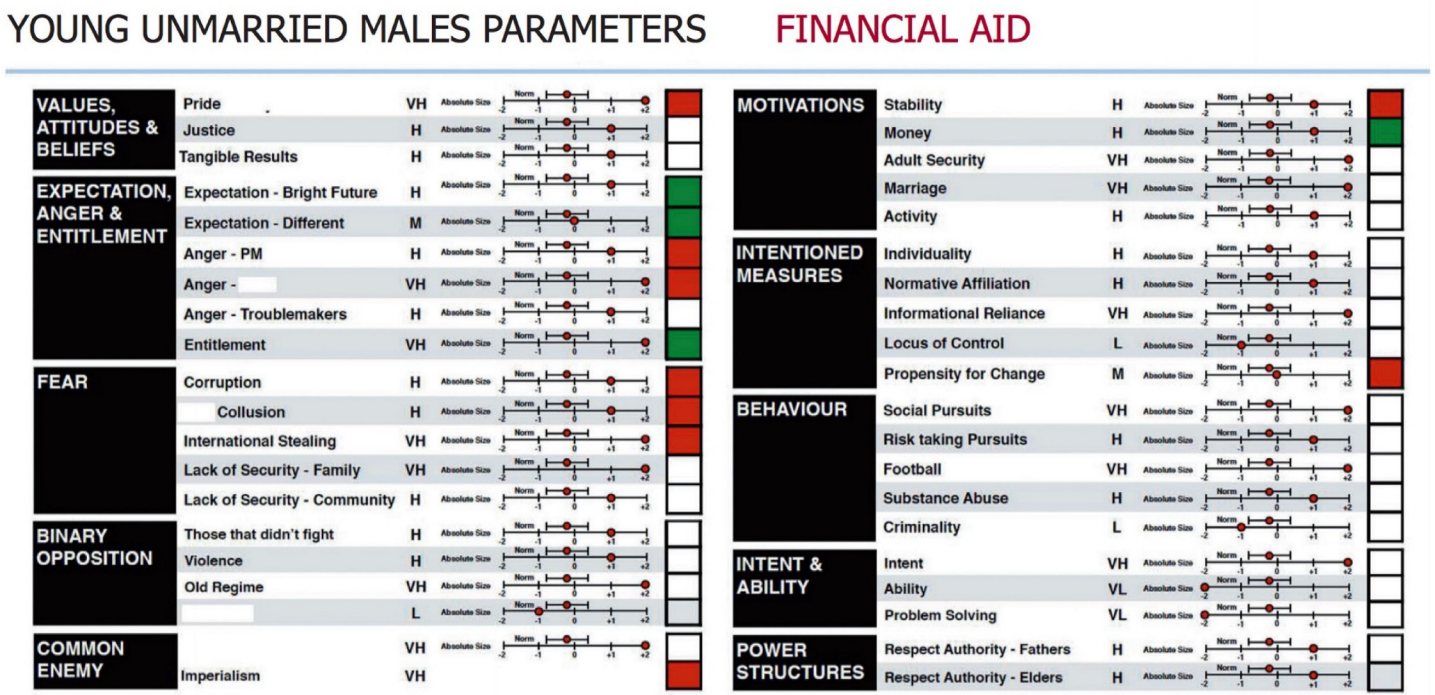
DESCRIPTIVE	PROGNOSTIC	TRANSFORMATIVE
AUDIENCE STATISTICS	INFORMATIONAL	MESSAGE APPEALS
LANGUAGE	PROPENSITY FOR CHANGE	COMMON ENEMIES
LITERACY	EMIC LOGIC	BINARY OPPOSITION
CURRENT BEHAVIOUR	NORMATIVE AFFILIATION	SOURCE CREDIBILITY
SIZE	LOCUS OF CONTROL	REWARD STRUCTURES
LEADERSHIP	MOTIVATIONS	DECISION PATH
FINANCING	POLARISING MOTIVATING PROPENSITY	FILTERS
RELEVANT ISSUES		NOISE
HISTORIC CONTEXT	INSTRUMENTAL	ATTITUDES
CHANNEL CREDIBILITY	INFLUENCEABILITY	INITIATING SETS
GROUP COMPOSITION	BELIEFS	RITUALS
MISSION	INTENT	ABILITY
VALUES	SKILL	EXPECTANCY
GROUP MEMBERSHIP	POWER STRUCTURES	FEARS
CHANNEL EXPOSURE	IDEOLOGY	
NEEDS	FRAGILITY / RESISTENCE	

Source: NATO

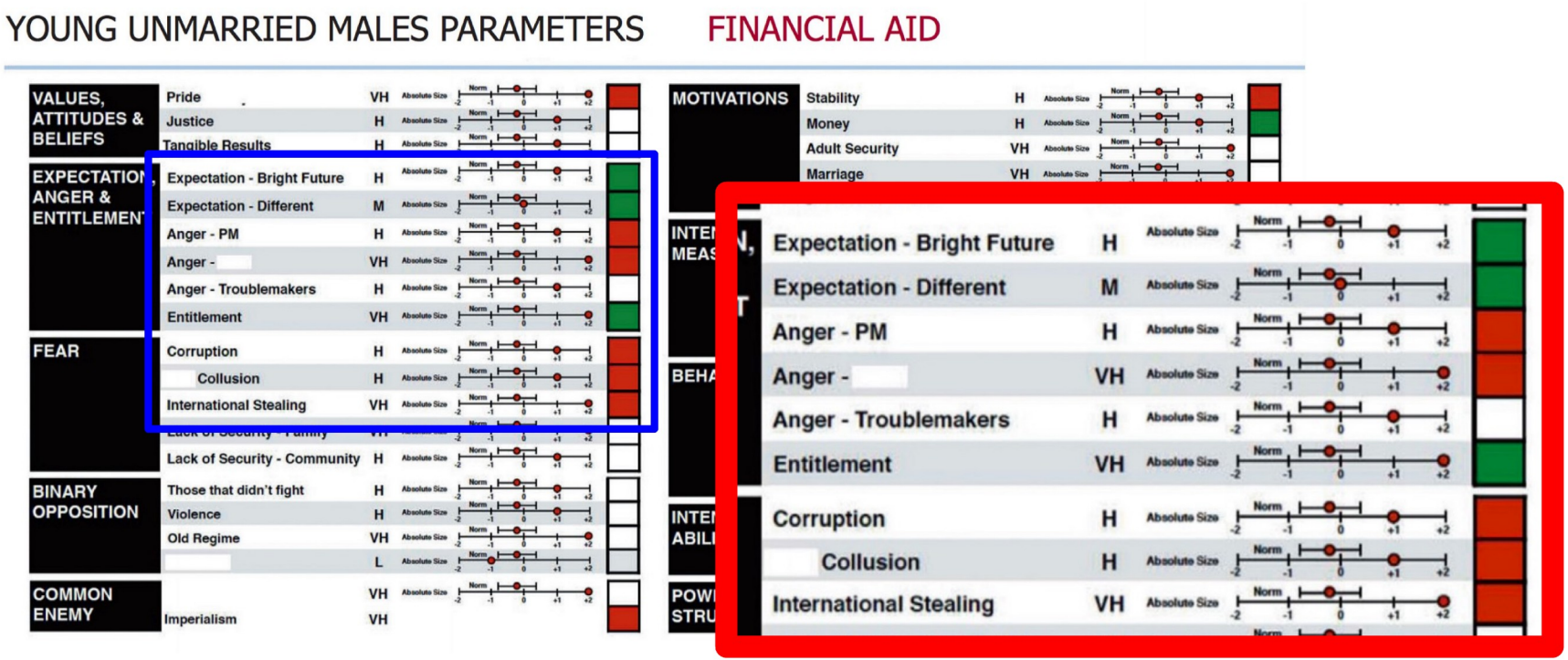
Intervention strategy

- Cash handouts
- Cash-for-gun program
- Mandatory military service
- Training programme
- Event
- “Smart” propaganda

Audience-based measure of effectiveness



Audience-based measure of effectiveness



Audience-based measure of effectiveness

YOUNG UNMARRIED MALES PARAMETERS — FINANCIAL AID

VALUES, ATTITUDES & BELIEFS	Pride	VH
	Justice	H
	Tangible Results	H
EXPECTATION, ANGER & ENTITLEMENT	Expectation - Bright Future	H
	Expectation - Different	M
	Anger - PM	H
	Anger -	VH
	Anger - Troublemakers	H
	Entitlement	VH
FEAR	Corruption	H
	Collusion	H
	International Stealing	VH
	Lack of Security - Family	VH
	Lack of Security - Community	H
BINARY OPPOSITION	Those that didn't fight	H
	Violence	H
	Old Regime	VH
		L
COMMON ENEMY		VH
	Imperialism	VH

MOTIVATIONS	Stability	H
	Money	H
	Adult Security	VH
	Marriage	VH
	Activity	
INTENTIONED MEASURES	Individuality	
	Normative Affiliati	
	Informational Reli	
	Locus of Control	
	Propensity for Cha	
BEHAVIOUR	Social Pursuits	
	Risk taking Pursui	
	Football	
	Substance Abuse	
	Criminality	
INTENT & ABILITY	Intent	
	Ability	
	Problem Solving	
POWER STRUCTURES	Respect Authority -	
	Respect Authority -	

For more (Libya)

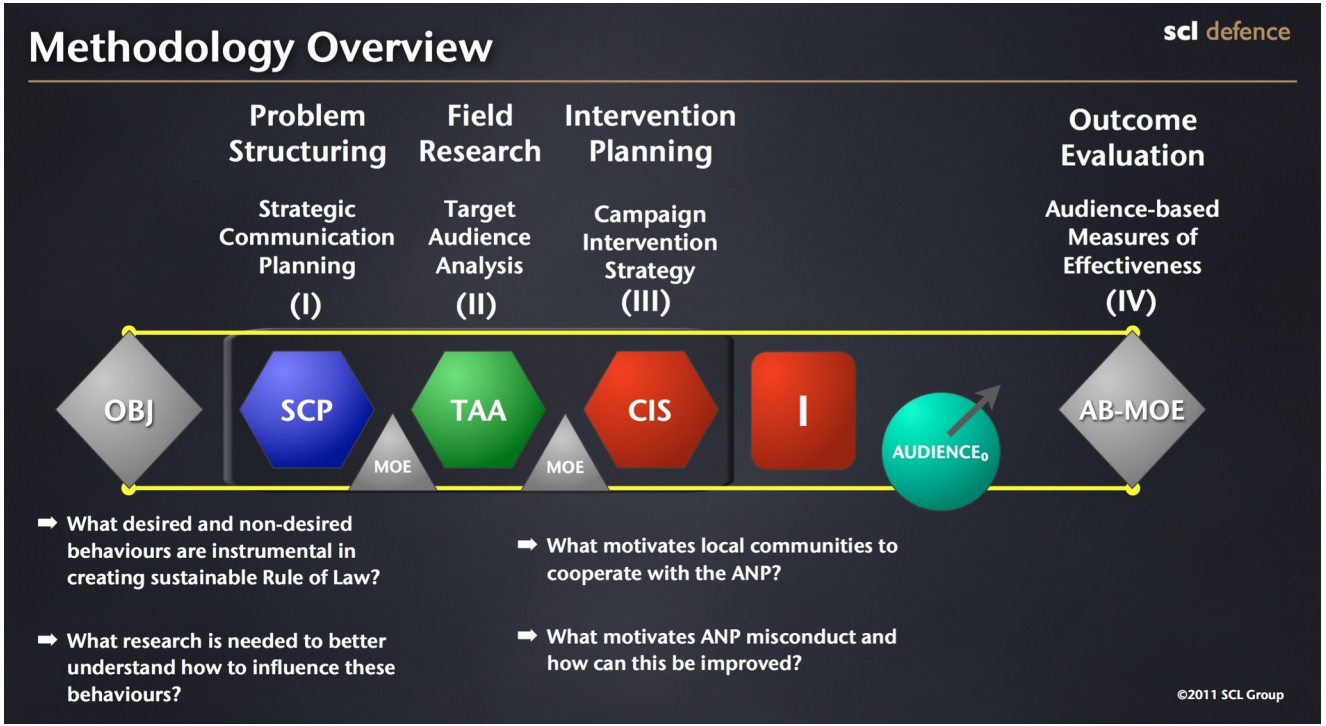
A traffic-light system to “influence” young unmarried males in Libya (source: Nudgestock 2 Festival, at 13:32).

The (dis)information mercenaries now controlling Trump’s databases

Now that Trump, his SuperPACs and even their vendors have got a ton of data on every American, what could they do with that? We look at the PSYOPS dashboards that have been built by the same vendors to manipulate populations in Libya, Afghanistan and countless other countries

http://tinyurl.com/scl-disinformation

Methodology



Source: “Policing our Own” report on Afghanistan operations, 2011

Where Cambridge Analytica fits

Western data turn (TAA self-segmentation)

Western data turn (TAA behaviors)

pollin
g

ML

Registration
Voting history
Turnout probability

Partisanship
Ideology
Issues

Western data turn (TAA triggers)

pollin
g

ML

Openness
Conscientiousness
Extraversion
Agreebleness
Neuroticism (>< Emotional Stability)
Need for Cognition
Need for Affect (?)
Locus of Control (?)
Reciprocity
Scarcity
Authority
Fear
Social proof

Western data turn (TAA triggers)

pollin
g

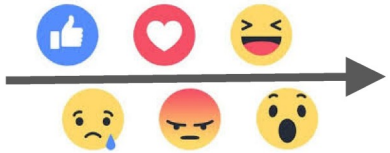
ML

Openness
Conscientiousness
Extraversion
Agreebleness
Neuroticism (>< Emotional Stability)
Need for Cognition
Need for Affect (?)
Locus of Control (?)
Reciprocity
Scarcity
Authority
Fear
Social proof

Western data turn (Interventions)

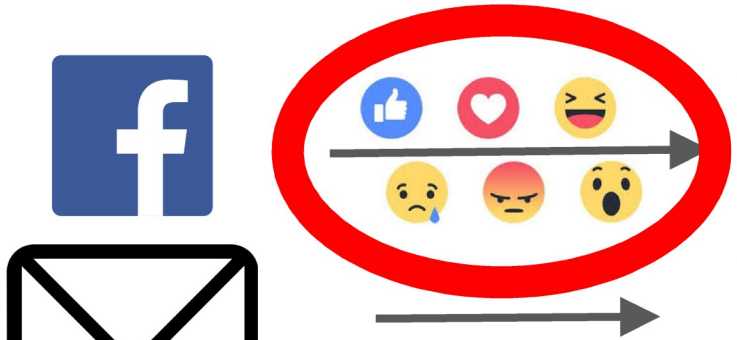
WWW

SMS



Hat ($)
Rally
Retweet
Reshare
NLP Facebook comment
Facebook Reactions
Dark posts

Western data turn (Interventions)



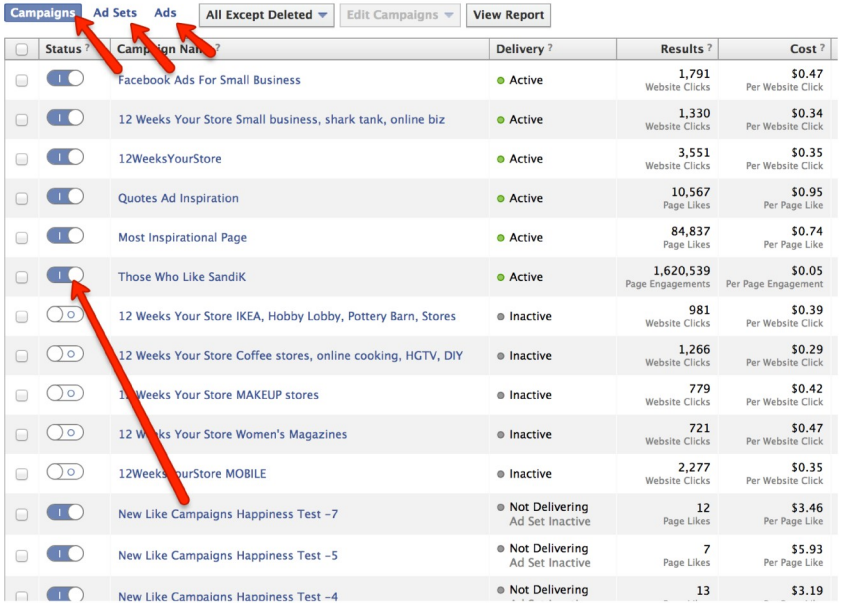
WWW

SMS

Hat ($)
Rally
Retweet
Reshare
NLP Facebook comment
Facebook Reactions
Dark posts

- Listicles
- Clickbait
- Reactions?

Western Data Turn (Interventions)



Trump

175k ad variation peak /day

programmatic access

thin pipeline → high machine learning gain

Plausible deniability

No theory between “interventions” and “Target Audience Analysis”

No need for communication between teams

Assets are Facebook Audiences

Political campaign does not get tarred with profiling

AI-shielding

Evasion of electoral rules

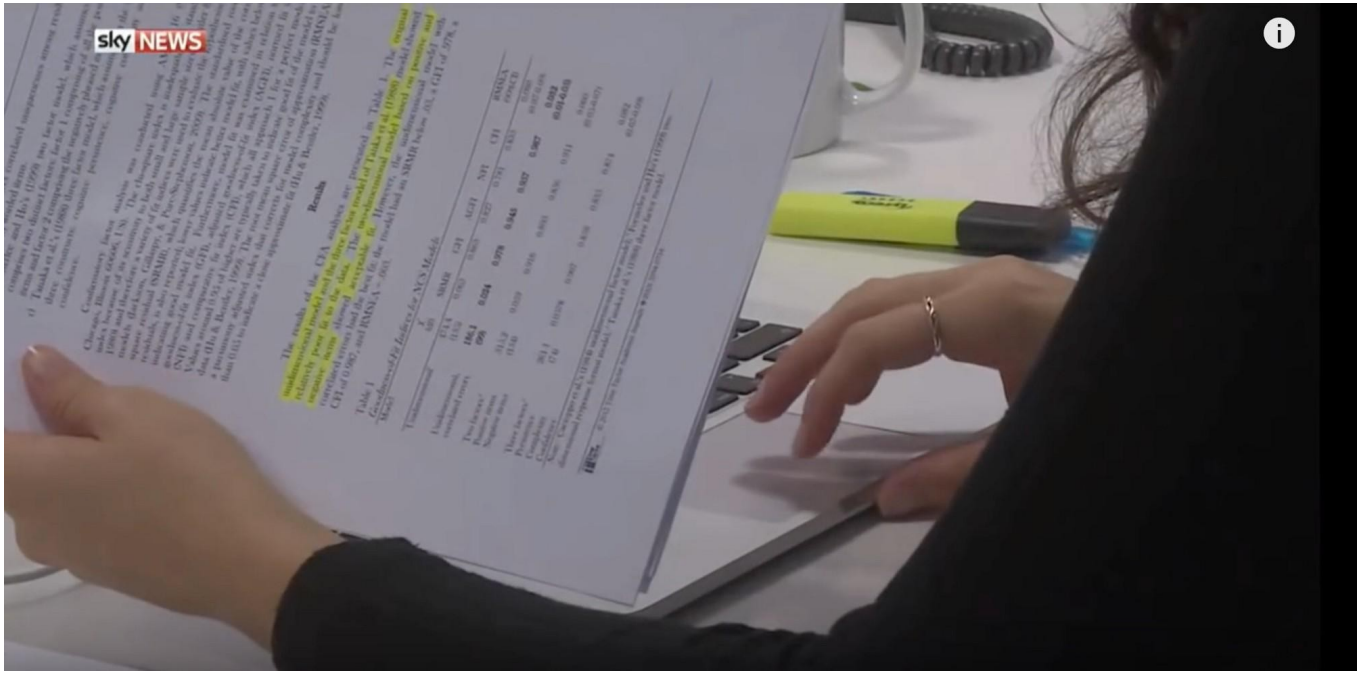
Accelerate self-segmentation with provocative content

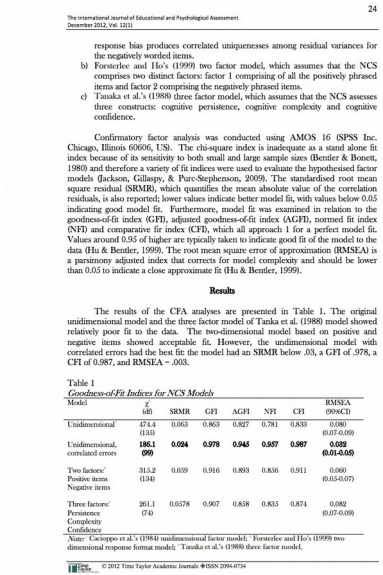
Bloomberg (Oct 2016)

Parscale was building his own list of Trump supporters, beyond the RNC's reach. Cambridge Analytica's statistical models isolated likely supporters whom Parscale bombarded with ads on Facebook, while the campaign bought up e-mail lists from the likes of Gingrich and Tea Party groups to prospect for others. Some of the ads linked

(downplayed later)

Evidence: psychographic targeting





The International Journal of Educational and Psychological Assessment
December 2012, Vol. 12(1)

response bias produces correlated uniquenesses among residual variances for the negatively worded items.

b) Forsterlee and Ho's (1999) two factor model, which assumes that the NCS comprises two distinct factors: factor 1 comprising of all the positively phrased items and factor 2 comprising the negatively phrased items.

c) Tanaka et al.'s (1988) three factor model, which assumes that the NCS assesses three constructs: cognitive persistence, cognitive complexity and cognitive confidence.

Confirmatory factor analysis was conducted using AMOS 16 (SPSS Inc. Chicago, Illinois 60606, US). The chi-square index is inadequate as a stand alone fit index because of its sensitivity to both small and large sample sizes (Bentler & Bonett, 1980) and therefore a variety of fit indices were used to evaluate the hypothesised factor models (Jackson, Gillaspy, & Purc-Stephenson, 2009). The standardised root mean square residual (SRMR), which quantifies the mean absolute value of the correlation residuals, is also reported; lower values indicate better model fit, with values below 0.05 indicating good model fit. Furthermore, model fit was examined in relation to the goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normed fit index (NFI) and comparative fit index (CFI), which all approach 1 for a perfect model fit. Values around 0.95 of higher are typically taken to indicate good fit of the model to the data (Hu & Bentler, 1999). The root mean square error of approximation (RMSEA) is a parsimony adjusted index that corrects for model complexity and should be lower than 0.05 to indicate a close approximate fit (Hu & Bentler, 1999).

Results

The results of the CFA analyses are presented in Table 1. The original unidimensional model and the three factor model of Tanka et al. (1988) model showed relatively poor fit to the data. The two-dimensional model based on positive and negative items showed acceptable fit. However, the undimensional model with correlated errors had the best fit: the model had an SRMR below .03, a GFI of .978, a CFI of 0.987, and RMSEA = .003.

Table 1
Goodness-of-Fit Indices for NCS Models

Model	χ^2 (df)	SRMR	GFI	AGFI	NFI	CFI	RMSEA (90%CI)
Unidimensional	474.4 (135)	0.063	0.863	0.827	0.781	0.833	0.080 (0.07-0.09)
Unidimensional, correlated errors	**186.1 (99)**	**0.024**	**0.978**	**0.945**	**0.957**	**0.987**	**0.032 (0.01-0.05)**
Two factors:[c] Positive items Negative items	315.2 (134)	0.039	0.916	0.893	0.856	0.911	0.060 (0.05-0.07)
Three factors:[c] Persistence Complexity Confidence	261.1 (74)	0.0578	0.907	0.858	0.835	0.874	0.082 (0.07-0.09)

Note: [a]Cacioppo et al.'s (1984) unidimensional factor model; [b]Forsterlee and Ho's (1999) two dimensional response format model; [c]Tanaka et al.'s (1988) three factor model.

© 2012 Time Taylor Academic Journals ISSN 2094-0734

http://tinyurl.com/ca-cognition

"Method Effects and the Need for Cognition Scale"

Evidence: collected data

Cambridge Analytica

23rd March 2017

[redacted]

USA

c. Modelled data

These are data that represent predictions we have made about you as an individual using models that we have developed as part of our general business offering. Our predictions are based on proprietary algorithms and methodologies that leverage the previous 2 categories of data at our disposal.

THE RECIPIENTS OR CLASSES OF RECIPIENTS OF PERSONAL DATA TO WHOM THE DATA WAS OR MAY HAVE BEEN DISCLOSED:

Clients	Service providers
Political campaigns	Digital marketing platforms
Independent expenditure groups	Mail vendors
Non-profit organizations	Call centers
Commercial entities	Research partners
	Affiliated data processors
	Legal counsel

Some names and identifying particulars are not being disclosed to protect the identity of third parties.

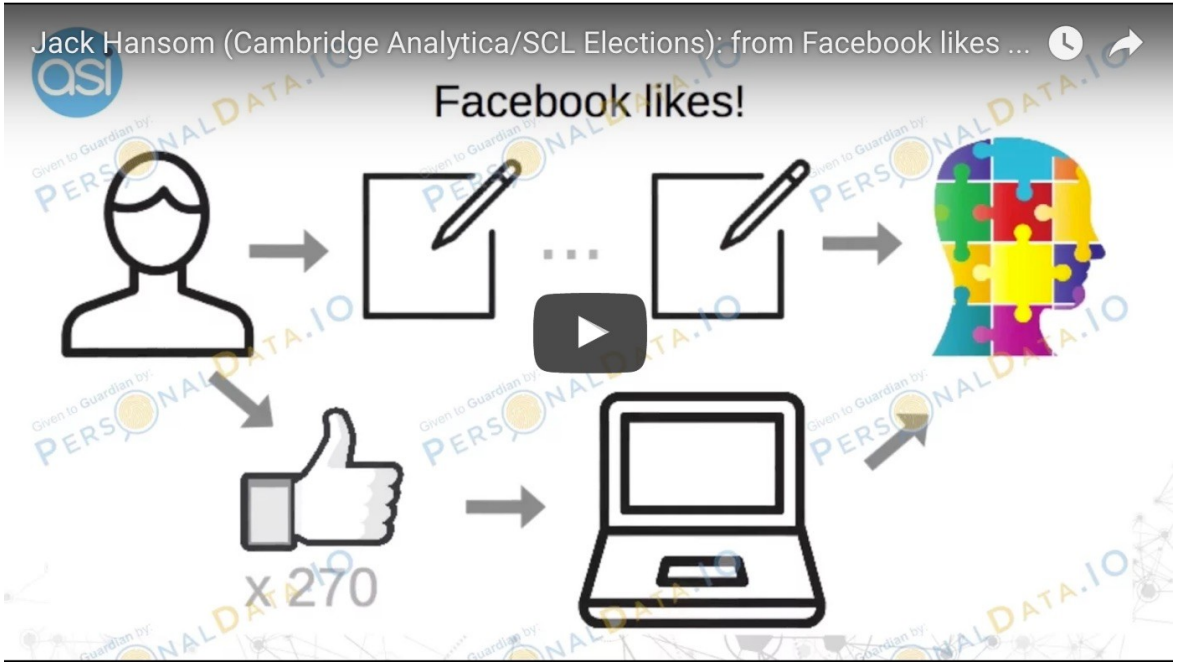
Yours sincerely,

Julian Wheatland, Group COO

For and on behalf of Cambridge Analytica

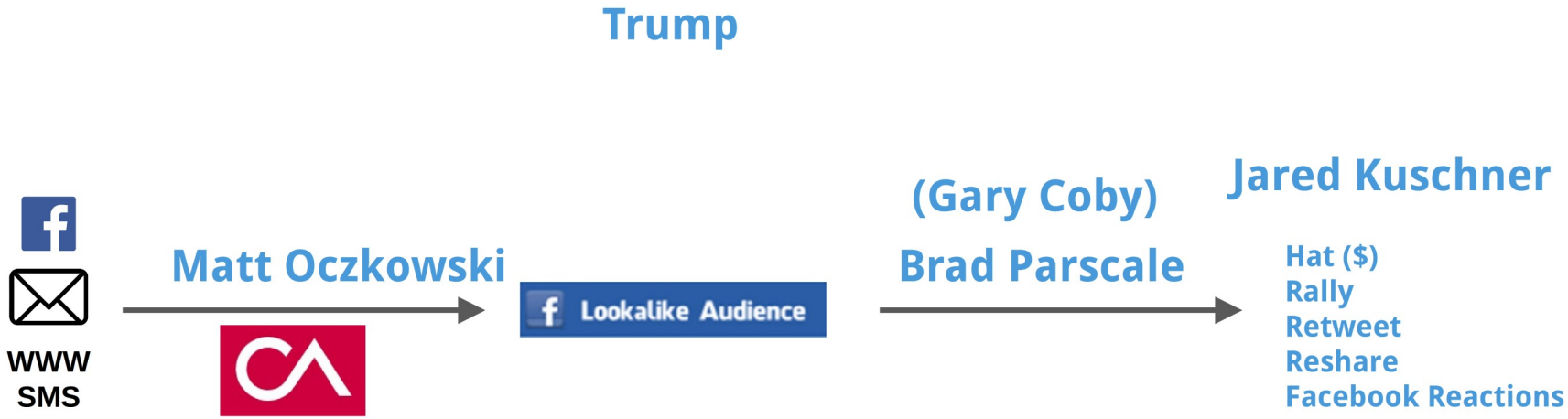
National Debt Importance Rank [1-10]	10
Gun Rights Importance Rank [1-10]	3
Traditional Social and Moral Values Importance Rank [1-10]	9
Environment Importance Rank [1-10]	5
Education Importance Rank [1-10]	4
National Security Importance Rank [1-10]	7
Immigration Importance Rank [1-10]	8
Socially Progressive Civil Rights Importance Rank [1-10]	6
Jobs and Economy Importance Rank [1-10]	1
Healthcare Importance Rank [1-10]	2
Registered Partisanship	Very Unlikely Republican
Unregistered Partisanship	Very Unlikely Republican
2016 General Election Turnout Propensity	Very High

Evidence: use of “Likes”



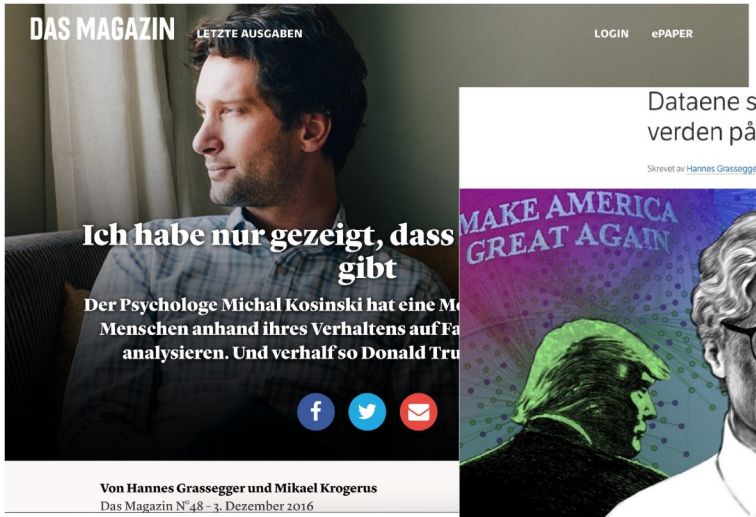
http://tinyurl.com/ca-fb-likes

Data flow in Trump campaign



pyschographics: “Not that much”; “Not that deep, no”

Some impact...



Tages-Anzeiger

nrk beta

VICE

Some impact...

Politics
The Observer

Robert Mercer: the big data billionaire waging war on mainstream media

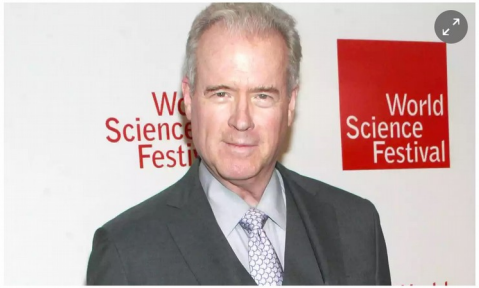
With links to Donald Trump, Steve Bannon and Nigel Farage, the rightwing US computer scientist is at the heart of a multimillion-dollar propaganda network

< 201,247

Carole Cadwalladr

@carolecadwalla

Sunday 26 February 2017 09.00 GMT



Robert Mercer in New York in 2014. Photograph: DDP USA/Rex Shutterstock

Data protection
The Observer

Watchdog to launch inquiry into misuse of data in politics

Investigation follows revelations of digital firm's involvement in Brexit

< 4,816 4,575

Jamie Doward, Carole Cadwalladr and Alice Gibbs

Saturday 4 March 2017 22.29 GMT

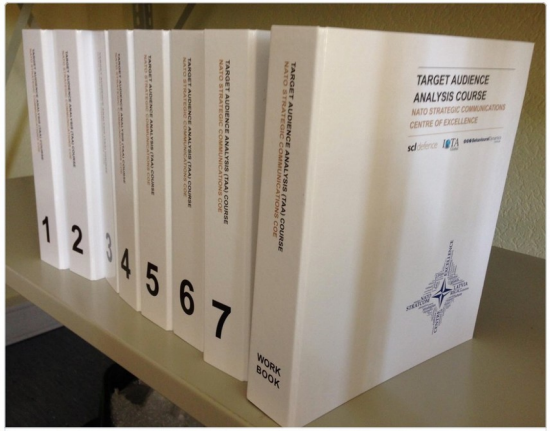
Information supplied by Cambridge Analytica was said to have been vital to the Leave campaign's success in the EU referndum. Photograph: Bloomberg/Bloomberg via Getty Images

theguardian

Information warfare

von Clausewitz

NATO in Latvia



Behavioural Conflict
@BehaviouralC

Follow

8wks; 250hrs instruction; 8 folders; 20 students; 11nations; @CanadaLatvia @STRATCOMCOE @iotaglobalIO TAA course ends

10:19 AM - 17 Jul 2015

5 2

Marit Rye Ramberg
@MaritArmy

Follow

8 weeks in Latvia doing #NATO course in TA Analysis. I'm now a senior trainer in the #BDI methodology.
stratcomcoe.org/lv/NewsandEven …
@iotaglobalIO

RETWEETS
2

11:17 AM - 20 Jul 2015

2

Tweet your reply

Optimism?

Awareness rising

T+marketing Follow

MARKETING TECH FAVORITES FAKE NEWS | HIRE A DIGITAL STORYTELLER

Paul-Olivier Dehaye Follow

Mathematician. Free society by bridging ideas. #bigdata and its #ethics, #AcademicFreedom, citizen...

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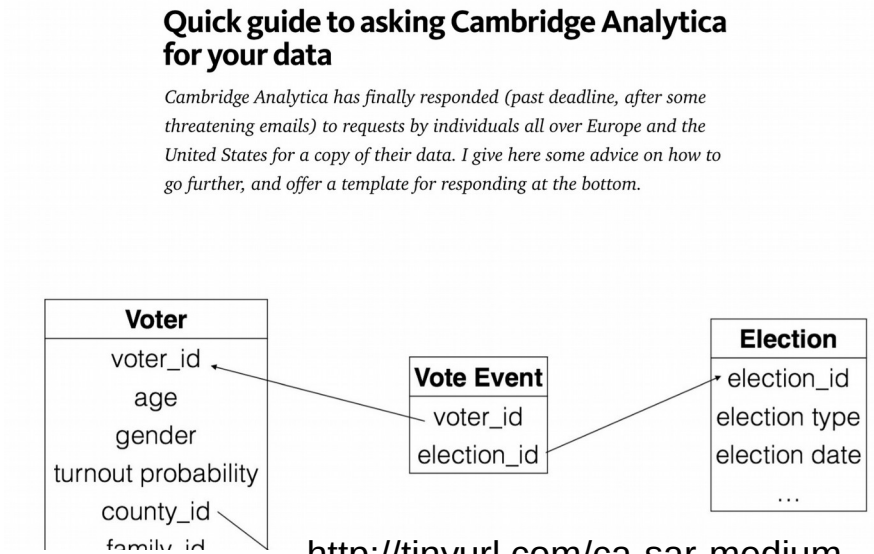
Facebook forced to disclose more information about its ad targeting

Facebook now tells each of its users which advertisers are tracking them individually through so-called Custom Audiences. This change was most likely brought by my legal actions against Facebook, conducted through PersonalData.IO. This change opens up exciting new possibilities for investigative journalism and the #MyData movement, explained below.

Original request

On December 15th 2016, I asked Facebook, through PersonalData.IO, the

http://tinyurl.com/fb-pivot

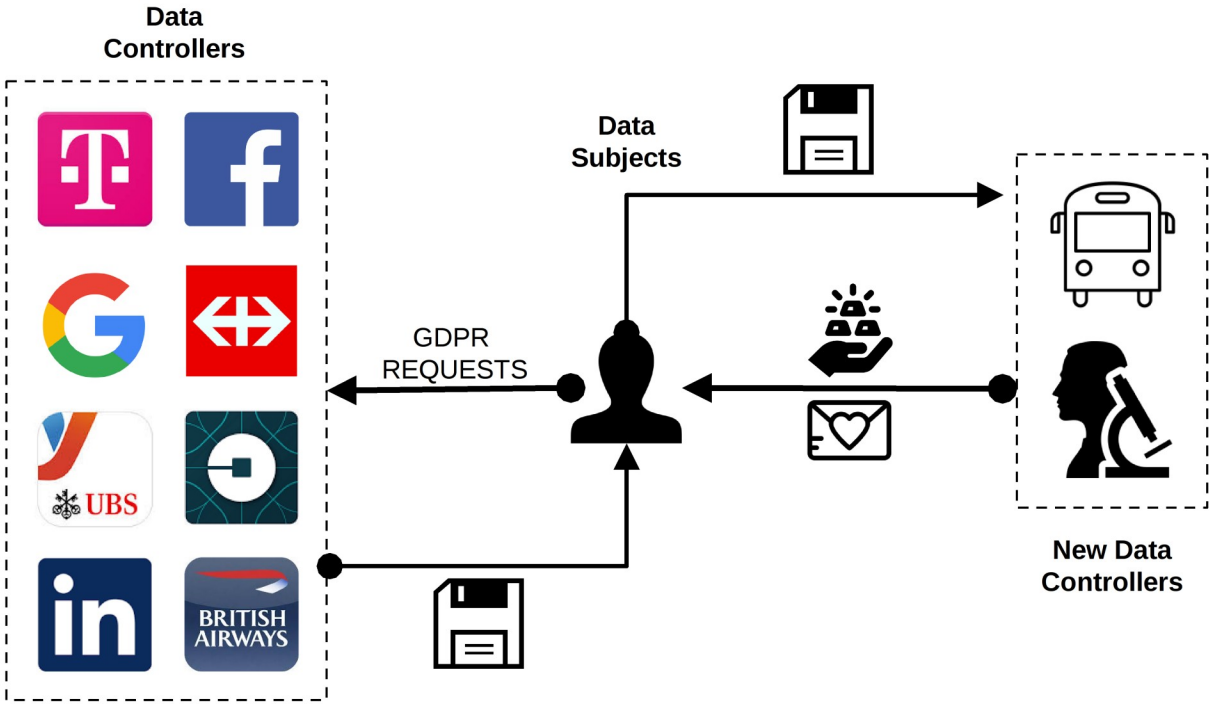


Quick guide to asking Cambridge Analytica for your data

Cambridge Analytica has finally responded (past deadline, after some threatening emails) to requests by individuals all over Europe and the United States for a copy of their data. I give here some advice on how to go further, and offer a template for responding at the bottom.

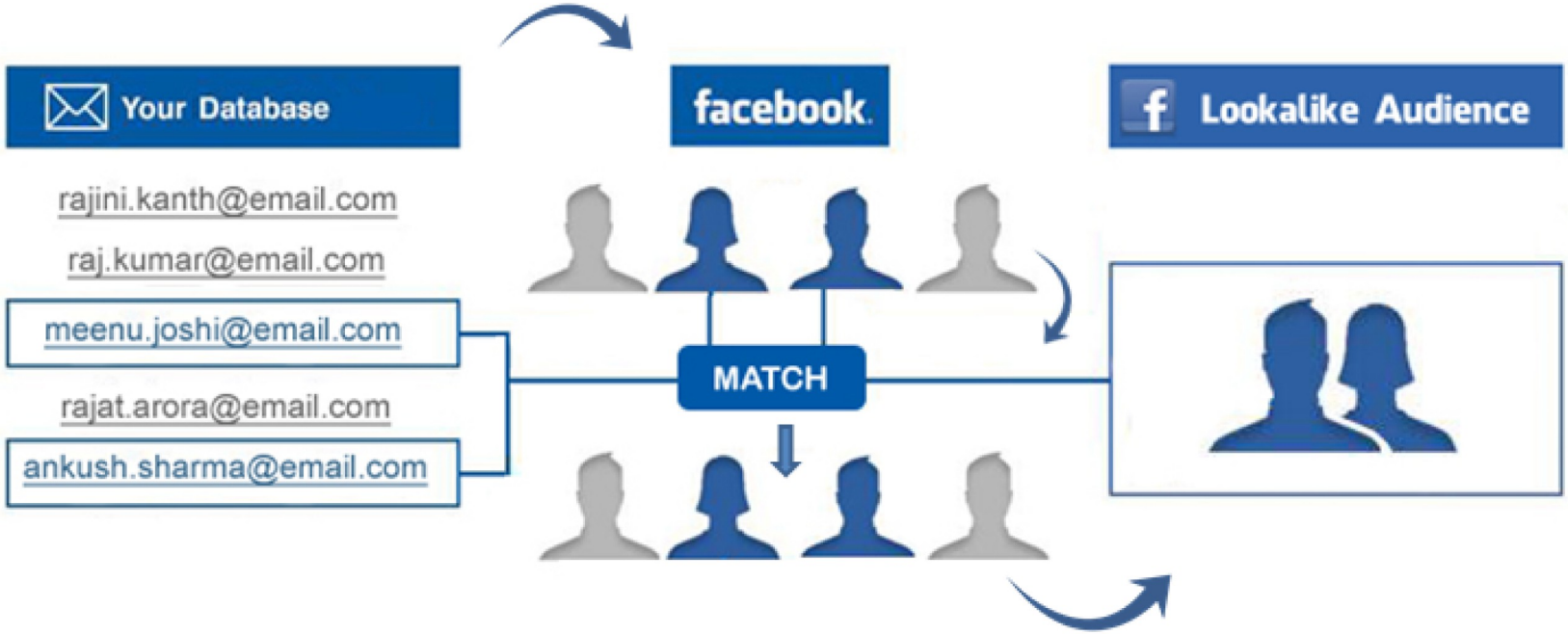
http://tinyurl.com/ca-sar-medium

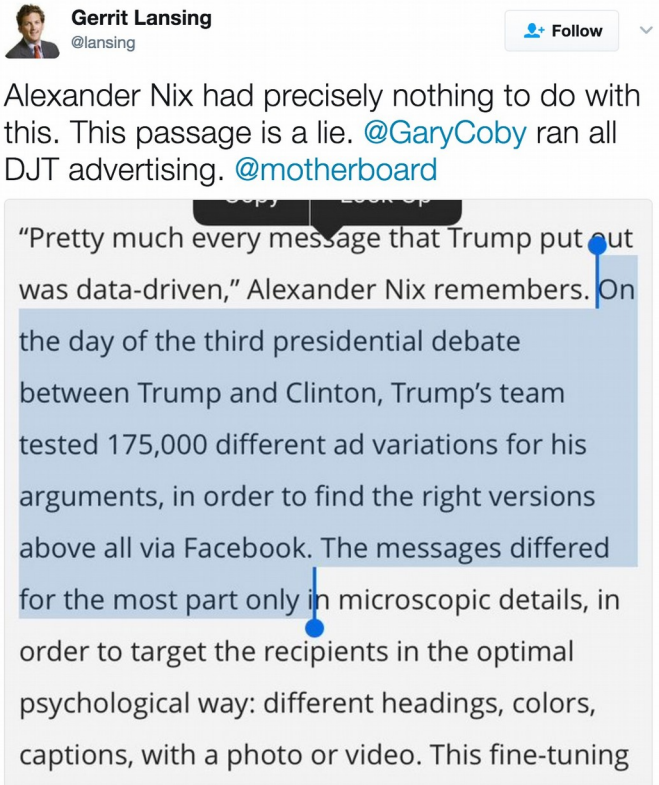
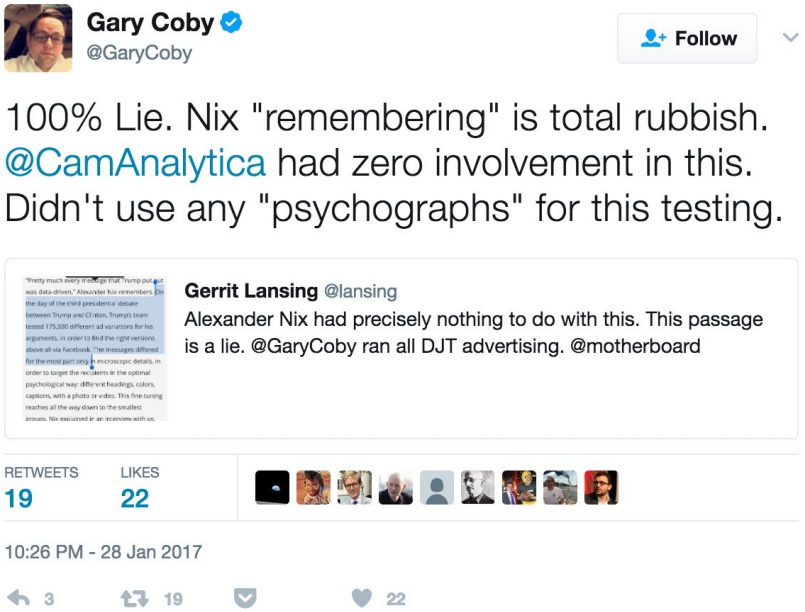
Right to portability (GDPR)



Thank You!

Facebook Lookalike



Effectiveness increases with size; restriction: threshold

Gary Coby comments