THE QUANT CONFERENCE 2019

WORLD'S LARGEST QUANT CONFERENCE OF ITS KIND

NOVEMBER 1 LONDON



Opening Remarks





KEYNOTE: What the past tells us about the future



Stephen Norman

Director, DTSQUARED; Ex-CIO, RBS; Ex-CTO, Merrill Lynch

"I've seen things you wouldn't believe...starships on fire off the shoulder of Orion I watched c-beams glitter in the dark near the Tannhäuser Gate".

What the past tells us about the future

Stephen Norman

Quant Conference London 1 Nov 2019



 $[DT]^2$

"Those who have no history are doomed to repeat it"



The picture's pretty bleak, gentlemen...the world's climate is changing, the mammals are taking over, and we all have a brain the size of a walnut." $[DT]^2$

30 years of the FTSE-100



Source: Yahoo Finance

 $[DT]^2$

 $[DT]^2$

Black Monday: the making of a legend





Adrian Pinkus

Source: Autopilot - Own work, CC BY-SA 3.0



August 1998 - a surprising dinner



Source: Yahoo Finance

 $[DT]^2$



As the ruble collapsed, so did LTCM





	Region	Y2K exceptions	Bad Quality	Rejection Score	
Lux'bg	West	130	10	8%	
Norway	West	50	2	4%	
Belgium	West	30	0.5	2%	
Italy	West	20	0.6	3%	
Greece	East	100	7	7%	
Finland	East	10	0	0%	
Poland	East	15	0.2	1%	
Holland	East	40	3	8%	
Russia	North	150	20	13%	
Belarus	North	40	0.5	1%	
Sweden	North	50	1	2%	
Switzer	North	20	0.4	2%	
• •	North	10	0.7	7%	
Norway	South	90	4	4%	
Germany	South	95	3	3%	
France	South	40	1	3%	
Eire	South	20	0.2	1%	

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Business Partner

 $[DT]^2$



Collapse of the dot coms



Source: Yahoo Finance

 $[DT]^2$



 $[DT]^2$

Collapse of the dot coms on the NASDAQ



Jun-02 Sept-02 Dec-02 Mar-03 Jun-03 Sept-03 Dec-03 Mar-04 Jun-04 Sept-04 Dec-04 Mar-05 Jun-05 Sept-05 Dec-05

 $[\mathbf{DT}]^2$

Since Y2K, there has <u>always been a major US/Euro reg.</u> initiative





 $[DT]^2$



 $[DT]^2$



There will always be crazes.







1979 - 2019: constant migration to the vanilia.



New assets, old facts:



HOW-TO KNOWLEDGE IS FREELY AVAILABLE

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 $[DT]^2$

- COMPUTE POWER IS ON DEMAND & CHEAP
- LOTS OF CODE IS OPEN SOURCE AND FREE

DATA REMAINS EXPENSIVE & VALUAB



Only the first movers make money.



 $[DT]^2$

RIGHT NOW...





 $[DT]^2$

.. feels like a bubble. Two bubb

- 1. Tech IPOs
 - (Uber, WeWork, Pinterest, Lyft...)
- 2. Fintech, Insurtech....





<u>Blockchain is a bust</u>

- Crypto/blockchain is a cute tech ecosystem
- Based on a simple fallacy
- Technically it's nuts but...
- ...the supertechies are hypnotised by its ingenui
- Consultants are bewitched by \$\$\$
- Practitioners are running (away) hard
- And the "business" is afraid to ask

The Emperor has no clothes!

 $[DT]^2$



USD: time for a change?

- The \$-clearing weapon has been over-used
- China and Russia hate it
- It will be slow but eventually...
- ...there will be an alternative.
- PS. It will not be cryto.
- PPS. Bitcoin is here to stay

There will always be surprises Would you want it any other way

 $[DT]^2$

Handover to legends of the industry...



 $[DT]^2$



 $[DT]^2$

🟥 collibra **Business Partner**

 $[DT]^2$

SCOPE OF THIS TALK

A LEDGER

DATE	SUPPLIER	TRAN NO	TYPE	QTY	PRODUCT	DELIVERY STATUS	PAY STATUS
3 Mar 19	Calif Fruit	401943	BUY	8900	Apples	Ordered	LOC
3 Mar 19	Del Monte	401944	BUY	10000	Pineapples	Arrived	Pending
4 Mar 19	Walmart	401945	SELL	500	Pears	Packed	Billed



A PERMISSIONED BLOCKCHAIN LEDGER













(Permissioned) blockchain solutions¹

- IBM blockchain system trade financing has saved 75% time IBM spent on transaction disputes
- Walmart has created a supplier blockchain. You can tell where a mango comes from in 2.4 seconds, and it used to be days...
- Everledger provides a distributed ledger that assures the identity of diamonds, from being mined and cut to being sold and insured that "can reduce blood diamond trade".
- UK Government Chief Scientific Advisor: *capital markets still rely on paper records to* reconcile a trade between counterparties. Blockchain can provide transparency & keep the regulators happy
- Interbank settlement of "stocks and shares." Autonomous Research says blockchain could take 30% out of \$54 billion annual coss of securities processing, saving \$16 billion. By 2021!
- Blockchain may help the nemesis of big IT projects, the national patients' record scheme.
- Chancellor Philip Hammond says blockchain technology may help solve the Irish border question.

¹ In ascending hype order













THESE CLAIMS ARE ALL BOGUS

 $-[DT]^2$

 $[DT]^2$

THESE CLAIMS ARE ALL BOGUS

NOT BECAUSE THEY ARE UNTRUE BUT BECAUSE YOU CAN ACHIEVE THE SAME BUSINESS FUNCTIONALITY QUICKER, CHEAPER AND MORE RELIABLY WITH CONVENTIONAL TECHNOLOGY

 $[DT]^2$

SO WHY USE BLOCKCHAIN ?

1.TRUST

2. IMMUTABILITY

3. NO MIDDLEMEN

4. SMART CONTRACTS

It's 1890 in this idyllic Alpine village

But all is not well...

 $[DT]^2$





 $[DT]^2$
The trust credentials of distributed ledgers rest on a beguiling confusion:

that it is better to have many private versions of the truth than a single public version that everyone can see and dispute

Business Partner

 $[\mathbf{DT}]^2$

SO WHAT JUSTIFIES THE EXPENSE?



3. NO MIDDLEMEN

4. SMART CONTRACTS



 $[DT]^2$



"The picture's pretty bleak, gentlemen. ... The world's climates are changing, the mammals are taking over, and we all have a brain about the size of a walnut."



PANEL: Legends of the industry on its future



Stuart Roden Ex-Chairman of Lansdowne Partners



Ewan Kirk CIO and Founder, *Cantab*

Off the Record Stuart Roden



Matthew Sargaison Co-CEO, Man AHL

Off the Record Matthew Sargaison



Stuart MacDonald

Managing Partner, Bride Valley Partners



KEYNOTE: Talent as an Asset Class: Alpha via Quantitative People-Selection



AIR SUMMIT

TALENT AS AN ASSET CLASS ALPHA VIA QUANTITATIVE PEOPLE-SELECTION

SHAM MUSTAFA | CO-FOUNDER & CO-CEO, CORRELATION ONE

The fundamental law of active management

$R = \sqrt{N} x C$ #Investment Information Information **Opportunities** Coefficient

Ratio

The fundamental law of active management

X



Bets



Skill per Bet

Quant investors exploit the fundamental law



✓ More bets via automation

 \checkmark

A simplistic model of quant investing: The Stock Screen



Once a model is built, increasing its scope of bets is trivial



BY AUTOMATING YOUR FILTERING LOGIC, YOU CAN MASSIVELY INCREASE YOUR TOTAL NUMBER OF BETS

However...

A MODEL, NO MATTER HOW SMART, ONLY HAS "EDGE" IF IT IS AHEAD OF THE CURVE



... until it became a crowded trade in the 1990s and 2000s

There is enormous power in discovering new asset classes



Home > News > Research > How Does Yale Do It? By Being Different

Research March 13, 2019

How Does Yale Do It? By Being Different

Yale's asset allocation bears no resemblance to the average university endowment.

 Over the past 10 years, Yale's \$29.4 billion endowment has earned annual returns of 7.4%, outpacing its benchmark and institutional fund indices, and adding \$6.5 billion in value—roughly the size of the University of Chicago's entire endowment –during that time. And for six of the past 10 years, Yale's 10-year record has ranked first in the Cambridge Associates universe.

How has it managed to achieve this success on a consistent level over the long term? Not by being like everyone else, that's for sure—and definitely not by being passive. A look at the asset allocation of Yale's endowment shows just how vastly different its thinking is from other university endowments.

Yale has more than three times the allocation to venture capital and real estate than the educational institution mean, and more than twice the allocation to leveraged buyouts. At the same time, it has one-sixth the domestic equity allocation, less than half the fixed-income allocation, 50% less than foreign equity, and the amount it holds in cash is nearly

Yale's endowment has outperformed by discovering nontraditional asset classes

There is enormous power in discovering new asset classes

Bitcoin's emergence created a new asset class opportunity for early investors



What is the undiscovered asset class today?



What is the undiscovered asset class today?

People!



Do people qualify as an asset class?

✓ LARGE NUMBER OF INDEPENDENT INSTANCES

HIGH VARIANCE IN PERFORMANCE ACROSS INSTANCES

VARIANCE IN PERFORMANCE OF A SINGLE INSTANCE OVER TIME

SIGNIFICANT BOTTOM-LINE IMPACT GIVEN CORRECT OR INCORRECT INSTANCE SELECTION

If talent is an asset class, how should we conceptualize "**talent alpha**"?

The fundamental law of talent alpha



The fundamental law of talent alpha



PEOPLE BETS



Common practices today



- More bets only through high turnover
- Recruit from a few, highlycompetitive talent pools

- ☆ Imprecise qualitative interviews
- Track-record analysis (luck or skill?)
- X No backtesting of interview process

How it can be done better



Breadth of Funnel x Filter Accuracy = Quality of Hires

How to improve your candidate funnel THOUGHTFULTALENT PROGRAMS BOOST EMPLOYER BRANDS AND ENGAGE CANDIDATES AT SCALE



CODE JAM

Google CodeJam is a global hackathon that attracts 25,000 candidates per year



HACKERCUP

Facebook launched the HackerCup in 2011. The competition series has over 1.1 million likes on Facebook.



THE DATA OPEN

Correlation One and Citadel partner to run The Data Open, a series of live data science competitions for top students.

CASE STUDY #1: CITADEL THE WORLD'S BIGGEST AND MOST PRESTIGIOUS LIVE DATA SCIENCE COMPETITION



Problem

Citadel wanted dramatically expand the breadth of its funnel and win top 1% candidates over leading tech firms like Google and Facebook

Solution

A series of global live data science competitions for students of over 25 top universities around the world

Results

The competitions attracted over 25,000 elite students to Citadel's candidate funnel

CASE STUDY #1: CITADEL THE DATA OPEN EARNED A HARVARD BUSINESS SCHOOL CASE STUDY



"There is a war for talent among hedge funds. Finding great investors has always been a challenge for us in finance. Great investors are like great basketball players. They're hard to come by. They have a gift - the ability to assimilate information, draw conclusions, and act on their beliefs. It's a really unique and hard skill to find."

- Ken Griffin, CEO, Citadel





CASE STUDY #2: XTX MARKETS AN ONLINE FORECASTING COMPETITION FOR TOP QUANTS AROUND THE WORLD

XTX Markets Global Forecasting Competition



Problem

XTX Markets wanted to hire the world's best quants no matter where they lived in the world.

Solution

An online, global forecasting challenge, where contestants developed models to predict financial data

Results

Over 4,000 candidates applied. Top performers included graduates from top schools like Harvard and Stanford, but also outliers from areas like Latvia, Bulgaria, and New Zealand.

How to improve your filter accuracy DECOMPOSE THE IDEAL CANDIDATE PROFILE INTO DISTINCT WORKFLOWS AND SKILLS



Multi-factor talent assessment frameworks for data, engineering, and investment talent. correlation.

one

The frameworks generate candidate data points across multiple, independent factors.

Candidates that pass the automated screen are ultimately sent through for human processing.

CASE STUDY #2: IMC MARKETS AUTOMATED ASSESSMENTS TO EVALUATE QUANT AND TRADING SKILLS IN CANDIDATES

Skill Benchmark Report on Every Candidate

	TIMET	TIME TAKEN 0:59:0		OUESTIONS CORRECT			COHORT PERCENTLE			GLOBAL PERCENTE
JANT TRADER EXAM	0:						88.53%			96.88
PERFORMANCE	ISTRIBUTI	ON					404	LOGHU	1011	
- 200						- 11	THE I	ANDIDATES	SCORE	
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160										
140										
120						1	11			
100										
80							1.			
60										
40										
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0 5 1	0 15 20	25 30	35	40 45	50	55	60 65	5 70	75	Store
PERFORMANCE	Y SKILL CA	TEGORY								
SKRES TESTED								CU	ESTIGNS CO	RRECT
SDAIN TEACEDC	-								1.000	

Problem

IMC Markets wanted to improve the accuracy of its preinterview candidate filter, so hiring managers could prioritize their time on top candidates

Solution

Custom-built data science skills assessments, automated and benchmarked against population-level averages

Results

A new filter that is 5x more predictive of candidate success than other filters (e.g. university grade point average)

Get in touch @ sham@correlation-one.com

KEYNOTE: What you don't know



David Hand

Emeritus Professor of Mathematics and Senior Research Investigator, Imperial College

What you don't know counts

David J. Hand Imperial College, London



Princeton University Press January 2020

Machine learning Big data Data exhaust Open data **Statistics** Analytics Anonymised data Data trail Personal data Pseudonymised data Artificial intelligence Alternative data Confidential data **Observational data** Data science Experimental data Administrative data Survey data 3

Big data M	achine learning						
on the Open	data	Data exhaust					
Statistics		Analytics					
Anonymised data	Data trail	Personal data					
Pseudonymise	icial intolliaonco						
Alternative data	Confidenti	Confidential data					
Observational da	ita	Data science					
Experiment	tal data	Administrativo date					
Survey data		4					

- These all tell you about the data you have
- But they don't tell you about the data you don't have
- They don't tell you about the problems that can arise because you are missing some crucial data
- The data you don't have can be even more important than the data you do have
- The data you don't have or cannot see are dark data
-elephant powder



-elephant powder

-measles eradication





- measles eradication



-elephant powder

- -measles eradication
- -bullet holes in aircraft



- -elephant powder
- measles eradication
- -bullet holes in aircraft
- Hurricane Sandy





https://www.nasa.gov/mission_pages/shuttle/flyout/shuttleachievements.html



Temperature (°F) at launch





Number of O-rings experiencing thermal distress

Temperature (°F) at launch

It took months for the official investigation to conclude

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But Morton Thiokol's stock price crashed 11.86% on the day of the disaster (changes of more than 4% in its price were rare) It took months for the official investigation to conclude

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The stock prices of other companies involved in constructing the shuttle launch vehicle also slumped, but by less

Wasatch Div	ision
Interolfice Mer	no 🗔 🗍
31 July 1985 2070;FY86:07	Constants
TO;	R. K. Imnd Vice President, Engineering
CC:	B. G. Brimion, A. J. McDonald, L. B. Sayer, J. E. Kapp
TROH)	R. N. Boisjoly Applied Hechanics = Reg. 3525
SOB.)RUTE	SRM 6-Ring Brosion/Potential Failure Criticality
Dis letter i Intinuspess of	s written to insure that management is fully guare of the fine current 0-Ring etunion problem in the SRM joints from an Gandpoint.
The mistakenly of failure and lead to a solu This position joint erosion realing.	y accepted position on the joint problem was to fly without fear 1 to run a series of design evaluations which would ultinately reion or at least a significant refection of the erosion problem. Is now frestically changed as a result of the SRM 164 mornis which wroted a macondary Ording with the primary Ording mewar

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It is my honset and very real feer that if we do not take insediate action to dedicate a tess to solve the problem with the field juint having the number one priority, then we stoud in jeopardy of losing a flight along with all the launch pud facilities.

1.05 R. H. Bolsjoly

Concurred by: R. Kapp, MangEr Applied Mechanics

COMPANY PRIVATE

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ache K	

Japan US

Heart disease rate / 100000

Japan US 41 < 87

	Japan		US
Heart disease rate / 100000	41	<	87
% men who smoke	35	>	17

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"Known" to be because of protective effect of diet high in omega-3

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So what would be diagnosed as a "heart attack" in the US is likely to be classified as a "stroke" in Japan

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So what would be diagnosed as a "heart attack" in the US is likely to be classified as a "stroke" in Japan

Stroke rate

33.6 > 23.7

Fifteen types of dark data

Not mutually exclusive: they can occur together

These are Donald Rumsfeld's known unknowns and unknown unknowns

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(1) Pundit's views on share prices when they don't tell you

These are Donald Rumsfeld's known unknowns and unknown unknowns

(1) Pundit's views on share prices when they don't tell you

(2) Crowdsources views on the movements of a particular share price

Type 3: choosing just some cases

A psychic's successful predictions

Type 4: self-selection

The customers who shop at a particular store

Type 5: missing missing variables Who survived the *Titanic* ?

Crew	Third class
	passengers
212/908	151/627

Crew		Third class
		passengers
212/908		151/627
= 23.3 %	<	= 24.1 %

Crew	Third class
	passengers
212/908	151/627
= 23.3 %	< = 24.1 %
Crew	Third class
	passengers
192/885	75/462

Men

Crew		Third class passengers
212/908		151/627
= 23.3 %	<	= 24.1 %

	Crew		Third class
			passengers
Males	192/885		75/462
	= 21.7 %	>	= 16.2 %

Crew		Third class
		passengers
212/908		151/627
= 23.3 %	<	= 24.1 %

	Crew	Third class
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Females	20/23	76/165

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	Crew	Third class
		passengers
Males	192/885	75/462
	= 21.7 %	> = 16.2 %
Females	20/23	76/165
	= 87.0 %	> = 46.1 %
Sometimes data are dark by design

UK Equality Act (and other similar elsewhere): People must not be treated differently on the basis of their group membership rather than on the basis of their own merits (for certain "protected characteristics": sex, religion, etc)

Sometimes data are dark by design

UK Equality Act (and other similar elsewhere): People must not be treated differently on the basis of their group membership rather than on the basis of their own merits (for certain "protected characteristics": sex, religion, etc)

→ must not include these characteristics in any decision-making process

But the EU Gender Directive (2004/113/EC) included a clause saying:

"proportionate differences in individuals' [insurance] premiums and benefits ...[are allowed]

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[when there are] relevant and accurate actuarial and statistical data."

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where the use of sex is a determining factor in the assessment of risk ...

[when there are] relevant and accurate actuarial and statistical data."

That meant different driving insurance premiums for males and females were allowed provided there was data showing the risks differed But in 2011, the European Court of Justice decided this was incompatible with the principle of equal treatment for men and women

From 2012, it was illegal to have differential insurance premiums based on gender

But in 2011, the European Court of Justice decided this was incompatible with the principle of equal treatment for men and women

From 2012, it was illegal to have differential insurance premiums based on gender

Females previously had lower motor insurance premiums, but these differences would no longer be allowed, *even though the data showed females to be safer drivers*

Change in size of premiums



Overall average premiums

£	Before	After
Men	658	619
Women	488	529

50

- more young men can now afford insurance

- more young men can now afford insurance
- so more young men on the road

- more young men can now afford insurance
- so more young men on the road

→ more of the riskier drivers on the road

- more young men can now afford insurance
- so more young men on the road

→ more of the riskier drivers on the road

- fewer young women can now afford insurance

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 - UK: men cause 95% of "deaths by dangerous driving"

 - UK: men commit 82% of speeding offences

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- fewer young women can now afford insurance
- so fewer young women on the road
 → fewer of the safer drivers on the road

→ more accidents and higher premiums for everyone

The consequences can be surprising

The consequences can be surprising

From *The Times*, 31 July 2018:

Man changes his gender to get cheaper car insurance

"Legally I'm a woman," the man from Alberta told the Canadian Broadcasting Corporation, after successfully obtaining a new birth certificate that declared him female. "I did it for cheaper car insurance." The consequences can be surprising

From *The Times*, 31 July 2018:

Man changes his gender to get cheaper car insurance

"Legally I'm a woman," the man from Alberta told the Canadian Broadcasting Corporation, after successfully obtaining a new birth certificate that declared him female. "I did it for cheaper car insurance."

Reducing his insurance bill by £649 per year

The law might require data to be concealed in ways which are not conducive to effective statistical modelling:

GDPR

So what do we do about dark data?

Use what you do know about what you don't know

Use what you do know about what you don't know

- Not Data Dependent (NDD)

Use what you do know about what you don't know

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It's missing for reasons unrelated to the data

Use what you do know about what you don't know

- Not Data Dependent (NDD)

It's missing for reasons unrelated to the data

- Seen Data Dependent (SDD)

Use what you do know about what you don't know

- Not Data Dependent (NDD)

It's missing for reasons unrelated to the data

- Seen Data Dependent (SDD) It's missing for reasons related to data you have got

Use what you do know about what you don't know

- Not Data Dependent (NDD)

It's missing for reasons unrelated to the data

- Seen Data Dependent (SDD) It's missing for reasons related to data you have got
- Unseen Data Dependent (UDD)

Use what you do know about what you don't know

- Not Data Dependent (NDD) It's missing for reasons unrelated to the data
- Seen Data Dependent (SDD) It's missing for reasons related to data you have got
- Unseen Data Dependent (UDD) It's missing because of the values you would have obtained

Modelling *how* you don't know what you don't know

Modelling *how* you don't know what you don't know *NDD*: equivalent to a smaller sample

Modelling *how* you don't know what you don't know

NDD: equivalent to a smaller sample

SDD: predict what you don't know from what you do

Modelling *how* you don't know what you don't know

NDD: equivalent to a smaller sample

SDD: predict what you don't know from what you do

UDD: need to make extra assumptions
















The power of dark data

Deliberately darkening data

Algorithmic performance is evaluated by seeing how they do on data they *have not yet seen*

Surveys collect data on a sample of cases, treating the others as *dark*

In clinical trials treatments are randomised and researchers are blinded, so the treatment received is *dark*

And the number of deaths in Amsterdam attributed to syphilis increased dramatically

And the number of deaths in Amsterdam attributed to syphilis increased dramatically

Previously invisible data is made *visible* by making other data *invisible*

And the number of deaths in Amsterdam attributed to syphilis increased dramatically

Previously invisible data is made *visible* by making other data *invisible*

Strategic application of ignorance

Simulation Smoothing Bootstrap Boosting

can all be viewed as generating previously unseen, dark, data

...

Your medical records Your financial records

Passwords keep data dark

Allowing you to selectively reveal data

Opt in and opt out?



In conclusion

Sophisticated strategic use of dark data can be a very powerful tool

But dark data has serious risks

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But dark data has serious risks

The drunk looking for wallet beneath a lamppost

In conclusion

Sophisticated strategic use of dark data can be a very powerful tool

But dark data has serious risks

The drunk looking for wallet beneath a lamppost

If you ignore dark data, you are behaving like that drunk



Princeton University Press January 2020



PANEL: What allocators are looking for in the digital age?



James Price

Senior Investment Consultant, *Willis Towers Watson*



Kishen Ganatra

Director of Business Development, QMA



Matthew Roberts Partner, Fulcrum Asset Management



Stuart MacDonald

Managing Partner, Bride Valley Partners



KEYNOTE: AI-Based Macro Investment Strategy, human-machine collaboration and the problem of causality



Sebastien Guglieta

Co-Head of AI Strategies Group, Brevan Howard

AI-Based Macro Strategy

human-machine collaboration and the problem of causality



S.GUGLIETTA - BREVAN HOWARD

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identifying, predicting and trading causality

2. Causality as a Deep Object

few stylized theoretical facts

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4. Building an AI-Based Macro-Investment Strategy

how to make AI work in real life

5. Understand the Why(s)

meta-learning and inferring causal structures

Disclaimer

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Why Use Al

identifying, predicting and trading causality

Macro Financial Markets as a Large Network

• Think about an asset *A* as being a 'node' immersed in a very large web of relationships where the other nodes are essentially hundreds of macro variables describing the state of the economy and few other assets.





Understanding, Predicting and Trading Causality

• Identify causality is key in order to make profitable predictions



5

Causalities as Algorithmic Subtleties

- Identifying causalities?
 - Initial selection of macro driving factors
 - Stability
 - Interaction between factors
 - Cycles, boom-burst phenomenon and reflexivity
- Market is a *deep object* with *deep algorithmic subtleties* that are hardly captured by invoking multi-linear models.



Causality as a Deep Object

few stylized theoretical facts

Learning Algorithmic Complexities

• Machine Learning: efficient solution to learn algorithmic subtleties of a system $\mathcal{M}: X \to Y$ that transforms a 'thing' X into another 'thing' Y



Building a machine learning model? Remember a profound thought from R.
Solomonoff (A Formal Theory of Inductive Inference, 1964):

Proposition

Learning is compressing complexity by accepting a given amount of uncertainty.

Fighting Uncertainty

- $_{\odot}\,$ Building a model of such a system ${\cal M}$ is about reducing its apparent complexity and fighting against its inherent uncertainty.
- The task should be easier if the amount of remaining disorder which is not captured by the model is relatively small: a model always fights against the system's entropy (*).

Proposition

Complexity is not disorder. A model is searching for order.

A macro-investment model is trading order. It does not trade noise.

^(*) Shannon entropy measures the remaining microscopic uncertainty despite a good macroscopic description.



• In algorithmic and information theories it all begins with data.

• What can we say about a string S containing 1 billion of 0? A short efficient narrative - an algorithm, much shorter than S itself - is:

'1 billion of O'

• But, what can we say about a random string *S* that contains 1 billion of 0 and 1?



 Nothing. Impossible to find out an efficient macroscopic description of such a string so that the remaining microscopic uncertainty is small:

'random series of 1 billion of 0 and 1'



Narrative Against Entropy

 Model = 'random series of 1 billion of 0 and 1'? Its Shannon's entropy is very high because the exact knowledge of S values stemming from this description is very small.

• Crucial implication for macro-investment model:

Proposition

If a model fails to capture enough algorithmic subtleties then it will suffer from high entropy.



• A string of 0 and a random string are both intuitively trivial. They are not interesting in terms of organized complexity.

 However, many natural structures (biotope) and many social systems (financial markets, economies) are clearly not trivial: they contain a nontrivial history.

Proposition

Complexity arises from complex historical processes

Bennett's Logical Depth

- C.H. Bennett (*Logical Depth and Physical Complexity*, IBM Research, Yorktown Heights, 1988).
- Notion of organized complexity which is central for systems with a subtle causal history.

Definition

The Bennett's logical depth of a system is the time required by a short algorithm (in the sense of a standard universal Turing machine) to generate it. It measures the time needed by a minimal program to compute a certain string.

• This crucial inclusion of computing time means that a high - or deep - value in logical depth shows that a system has a rich causal history.



Implication for AI-Based Macro Strategies

• Deep systems cannot be produced from shallow machines. A shallow model trying to simulate a system with a deep causal structure can't work.

 A macro systematic strategy – with deep algorithmic subtleties – based on structural VAR or multi-linear models – with shallow algorithmic subtleties - is doomed to fail.

• Bennett's logical depth: algorithmic formalization of historical processes. It measures the computational content $\mathcal{L}(S)$ of a system S that differs from the Kolmogorov complexity $\mathcal{K}(S)$ which measures its information content.



Making Predictions Needs Slow Growth Law

- Shallow or deep evolutionary systems cannot generate very sudden innovative computational structures.
- Bennett's slow growth law states.

Proposition

When such a system S_t evolves, $\mathcal{L}(S_t)$ cannot grow suddenly. Making predictions about a system requires that this system must satisfy a slow growth law.



Why AI Works AI-based macro strategy works in theory

The Problem of Learning is Mainly One of Programming

 The difficulty of making predictions about a system depends on its computational and informational content. Learning a system requires to model its algorithmic subtleties.

- Two main approaches to create AI:
 - Ontology Teaching: large formalized knowledge base for supporting reasoning in a variety of domains. Machines do what we tell them to do explicitly.
 - Machine Learning: algorithmic structures trained with data so that they learn by their own. Machines eventually evolve.

 Writing an explicit ontology with many billion incompressible lines of code would take a very long time. It is impossible and quoting Turing *"some more expeditious methods seems desirable"*.
Turing's Legacy

• A.W. Turing in *Computing Machinery and Intelligence* (Mind, New Series, Vol. 59, No. 236, Oct. 1950) about the simulation of the intelligence of an adult mind I(a).

MIND

A QUARTERLY REVIEW

OF

PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. The Imitation Game.

I PROPOSE to consider the question, 'Can machines think?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

Why AI Works – Revisiting the Turing's Proof

• Historical process that brought I(a) to the state it is in.

We distinguish:

- the initial state of the child mind I_0 (i.e. algorithmic structure)
- the education and other experience L to which I_0 has been subjected (i.e. supervised and unsupervised learning)
- Instead of writing a very complex program simulating I(a) it is easier to produce one simulating I_0 which is less complex and compressible.

• The problem has **been divided into two parts**:

The child program I_0 and the learning process L so that:

$$\boldsymbol{I}(\boldsymbol{a}) = \mathsf{L}[\boldsymbol{I}_0]$$

AI? Deep Learning + Reinforcement Learning

The revolution introduced by Turing is the possibility to create this:
*learning machine I*₀
which is able to evolve, adapt and grow in complexity helped with the right:
learning program L[.]

• This approach works because a proof of concept exists: the human mind.



Machine Learning Enables Artificial Intelligence

• *S* is a deep object with a large informational and computational complexity.

I(S) is an incompressible AI that simulates exactly S.

- A very long program is required to build I(S). But it is technically impossible to write a code with such a deep algorithmic complexity.
- Therefore, any other method which is able to produce a program generating I(S) will be unsurpassable.
- A learning machine decomposing I(S) into a [child program] that slowly becomes more complex with the right [education program] is a solution as it is shown by the human mind as a proof of concept.



- So what? **AI works in theory**.
- In practice, if machine learning is powerful to explore the frontiers of a systematic reasoning it struggles to form logical bifurcations. The learning process needs to consume a large amount of data (in order to grasp the algorithmic subtleties of the studied system).
- Following G. Kasparov: the solution is to build a 'centaur' with is a collaboration between human expertise and machine learning.



Building an Al-Base Macro Strategy

how to make AI work in real life

Inspiring Theoretical Building Blocks

• Solomonoff 's Theory of Inductive Inference, mathematically formalized combination of:



Ockham's razor or simplicity principle

Models should not multiplied beyond necessity



Principle of Multiple Explanations

If more than one model is consistent with observations, keep all the models

'Centaur' learning workflow inspired by Bayes' Probability Theory



Posterior (Hypothesis|Data) \approx Likelihood (Data|Hypothesis) \times Prior (Data)

• Data-driven 'reasoning on steroids' inspired by Turing's theory of computation



Turing's universal machine

Everything computable by a human using fixed rules can also be computed faster and better by a Turing's machine. Explore the frontiers of reasoning with data.

Macro Driving Factors – Human Expertise

 Ever growing set of economic and financial data in order to describe the macro factors interdependencies (100 macro features for each economy, some can depend on hidden co-founders)



Select and Compress Macro Information



Algorithmic Workflow | Machine Learning I_0

 Unsupervised machine learning techniques build various macro-indicators reflecting different aspects of an economy



• Machine learning techniques are used to model how this *abstraction of the economy* impacts asset prices by invoking a deep learning architecture



 Fight against the lack of stability and time variability: cross-validation and ensembling techniques are used to ensure the stability of the models and extensive grid-searches are used to tune the hyper-parameters.



Algorithmic Workflow | Machine Learning $I(a) = L[I_0]$

• Reinforcement learning techniques are used to exploit these predictions.



Network Topology | Combining Two Architectures



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AI-Based Model in Motion



Al-Based Macro Strategy, human-machine collaboration and the problem of causality |

Understand the Why(s)

meta-learning and inferring causal structures

Going Beyond Pattern Recognition

- Betting on stability: classical machine learning techniques assume that the trained solution will be applied on the same kind of data as the training data.
- Instability curse: in real life, stability (e.g. distributional properties) is at best local. Generalization is always a difficult problem.
- For now, efficient machine learning solutions have to be highly specific (e.g. one specific model for one specific asset, practical centaur approach).

- Usually, these deep learning systems remain blind to cause and effect.
- In order to achieve a super-human performance (systematically being better than an expert), they need to learn more about causes and effects, to reason about causal relationships. This is a much harder problem.

Reasoning with Logical Graphs

 Deep learning systems usually focus on correlation without causation. They are often left at a loss when they are tested on 'real life' conditions that are dissimilar to the ones they were trained on.



• Causal model from a Bayesian perspective:

$$P_{F \to A}(F, A) = P_{F \to A}(A|F) \cdot P_{F \to A}(F)$$



Ground Truth Mechanisms

- Following Y. Bengio, there is a need to go beyond transfer learning and it requires causal learning and causal reasoning.
- The aim is to build framework 'where one learns from a set of distributions arising from not necessarily known interventions, not simply to capture a joint distribution but to discover the underlying causal structure'.
- Naive example: F = raining causes $A = open \, umbrella$, and not vice-versa.
- Changing the marginal probability of *raining* (because the weather changed) does not change the mechanism that relates F and A (captured by P(A|F), but will have an impact on the marginal probability P(A).
- Conversely, an agent's intervention on $A = open \, umbrella$ will have no effect on the marginal distribution of F = raining. That asymmetry is generally not visible from the (F, A) training pairs alone, until a change of distribution occurs.

Logical Representations Through a Deep Learning Lens

- A possible solution should combine deep learning and formal reasoning with logical representations (remember the CYC ontology, which is aimed to reproduce human competence in common-sense reasoning).
- But how? Very recently Y. Bengio et al. have proposed the beginning of a promising solution in A Meta-Transfer Objective for Learning to Disentangle Causal Mechanisms. The main idea is to build a meta-learner:
 - '[They] propose to meta-learn causal structures based on how fast a learner adapts to new distributions arising from sparse distributional changes (e.g. due to interventions, actions of agents and other sources of nonstationarities).'
- '[They] show that under this assumption, the correct causal structural choices lead to faster adaptation to modified distributions because the changes are concentrated in one or just a few mechanisms when the learned knowledge is modularized appropriately'



Thank You

Questions ...

Al-Based Macro Strategy, human-machine collaboration and the problem of causality |





- -





Sandrine Ungari

Head of Cross-Asset Quantitative research, Société Générale

1 NOVEMBER 2019

SHORT-TERM TREND FOLLOWING

How to monetise intraday trading patterns



Sandrine Ungari Gilles Drigout Phone: +44 20 7762 5214 Phone: +33 1 42 13 74 50 sandrine.ungari@sgcib.com _gilles.drigout@sgcib.com

Please see important disclaimer and disclosures at the end of the document.

IMPORTANT DISCLOSURES



THE SHORT VOLATILITY CONUNDRUM

- Same trade: selling 1-month straddles on the S&P, held until expiry
- But different hedging policies: no hedging (insurer point of view), hedging at the close (market maker point of view)



Source: SG Cross Asset Research/Cross Asset Quant



MONETIZING BEHAVIOURAL PATTERN

- When negative news appears outside trading hours, markets drop sharply at the open.
- The downtrend tends to persist until the close of the session.
- During the next session, prices tend to revert, with the formation again of a new trend during the day.



Intraday price dynamic in the stock market

Source: SG Cross Asset Research/Cross Asset Quant



THE INTRADAY TREND FOLLOWING STRATEGY IN PRACTICE

The intraday trend following strategy over one day (S&P on 17 December 2018)³ 2640 Q. 2.1% down 2600 2560 2520 16:00 08:30 12:00 4:00 14:30 16:00 00:00 00:30 11:00 11:30 12:30 13:00 13:30 15:00 15:30 4% notional) 3% 2% % 1% change 0% -1% Pos -2% -3% 16:00 08:30 00:00 0:30 11:00 11:30 2:00 12:30 3:00 3:30 4:00 4:30 15:00 5:30 16:00 0% position (% notional) -1% -2% .3% Net 4% 6:00 0:00 0:30 11:00 11:30 12:00 2:30 13:00 3.30 4:00 4:30 5:00 5:30 6:00 08:30 5.0 (dq) 4.0 E 3.0 e 2.0 113 1.0 cum 0.0 6 -1.0 Strat -2.0 16:00 06:30 10:00 10:30 12:00 12:30 13:00 13:30 14:00 14:30 15:00 15:30 16:00 11:00 11:30 Source: SQ Cross Asset Research/Cross Asset Quant



FOCUSING ON THE SHORT TERM

- Following the commoditization of low frequency systematic strategies, intraday strategies are now becoming more accessible to investors.
- We introduce a simple trading rule. It aims at capturing intraday trends.
- When applying this signal to S&P 500 Mini Futures over a period of 15 + years. The strategy delivers an overall good risk / return profile, with a shape of 0.78 on the period.



The intraday-trend strategy on the S&P, an attractive return profile

Source: SG Cross Asset Research/Cross Asset Quant, SG Trading, Bloomberg



A DEFENSIVE PROFILE

- The strategy is long daily variance and short intraday variance
- It exhibits a defensive profile
- Performance is proportional to overall volatility levels.



The higher the uncertainty, the better the expected return of the intraday trend strategy

Source: SG Cross Asset Research/Cross Asset Quant, SG Trading, Bloomberg



THE INTRADAY TRAVELER

- When prices are trending, realised volatility tends to increase with time.
- When prices revert to the mean, realised volatility decreases as the time span on which returns are measured decreases
- Prices are trend following intra-day and mean reverting extra-day



Source: SG Cross Asset Research/Cross Asset Quant, SG Trading, Bloomberg



THE KEY DRIVERS OF PERFORMANCE

- We developed an analytical framework for understanding the performance drivers of the strategy
- The performance is driven by three factors.
- The first and the second factors benefit from the daily trend and the trend's uncertainty, respectively. They both have a positive impact on the strategy's performance.
- The third factor captures the reversion to the mean of intraday prices. It has a negative impact on the performance.



Source: SG Cross Asset Research/Cross Asset Quant



THE PRACTICAL DAY TRADER

- We have applied this same signal to 30+ liquid futures.
- Before taking into account transaction costs, most of them exhibit a strong intraday trend pattern. The most profitable ones remain US equities, VIX and some FX pairs.







BEWARE OF TRADING COSTS

- Trading costs are different across assets
- They also change during the trading day. It is generally more expensive to trade the open and the close.



Beware the costs on less liquid markets

Source: SG Cross Asset Research/Cross Asset Quant



THE DEVIL IS IN THE EXECUTION

- Intraday strategies have a high turnover. They are particularly sensitive to transaction costs.
- After taking into account for transaction costs, only US and European equities remain sufficiently profitable.



Day trading across assets - fine-tuning the signal

Source: SG Cross Asset Research/Cross Asset Quant, SG Trading, Bloomberg



A DETOUR IN THE WORLD OF LEVERAGED ETFS

- Our assumption is that end of day flow activity has a great impact on intraday trend patterns.
- Passive mutual funds, ETF managers and option hedgers are all forced into trading at the end of the day. They create volatility and trends around the close.
- We study the case of leveraged ETFs using out ETFs team's database.



The incredible success story of ETFs

Source: SG Cross Asset Research/ETF

ASSESSING THE IMPACT OF 'NON DELTA-ONE' ETFS

We introduce the leveraged ETF impact indicator as the ratio between:

- The sum of the "signed" AUM of ETFs related to this future multiplied by the absolute value of the ETF daily return
- And the end-of-day dollar volume of each futures market.
- We also introduce the leveraged ETF crowdedness indicator





CAN ETF REBALANCING EXPLAIN THE INTRADAY TRADING PATTERN?



The impact of ETF flows on intraday trend followers





SG RESEARCH ON SYSTEMATIC STRATEGIES



In preparation :

- Value investing in Fixed Income
- Tail risk hedging


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SG LEADER IN CROSS ASSET RESEARCH



SG LEADER IN GLOBAL CROSS ASSET RESEARCH



EX

2018



Equity

#7 Equity Sector Research9 Sector Research Teams in the Top 517 Sector Research Teams in the Top 10



PANEL: Cutting edge research



Andrea Nardon Partner, Portfolio Manager, Sarasin & Partners



Antoine Jacquier

Researcher, Alan Turing Institute



Declan Sheehy VP of EMEA Asset Owners, Backstop Solutions



Greg Winterton

Managing Director, AlphaWeek



PRESENTATION: Autonomous data testing and signal discovery



PRESENTATION: Your Turnkey Asset Management Solution



Juan Colon Co-Founder and CEO, *Darwinex*





SOUTH WINNER AWARD 2017 Best Fintech & Most Scalable start-up



Darwinex Private LABEL

Turnkey Asset Management

The Quant Conference, November 1st, 2019

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Why we're all here 😊

The (long & winding) road from asset manager rags to riches



You want to grow MONEY. But you can't grow MINE 😣



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How we solve the problem

We fast track independent managers, on merit



From strategy to revenue, in WEEKS



darwinex.com



How it works





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That's all you FOCUS on. 24/7.365/365



Investors buy your DARWIN

The DARWIN wraps your strategy so you collect asset management revenues



DARWIN = Turnkey Asset Management



We make it ALL happen

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7

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1 Eco-system, 2 venues

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- What investors pay
- Who raises AuM?
- What's your cost?

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> Management + Success Fee YOU SET

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Competitive Brokerage (you & investors) Limited Up-front (single Thousands) Variable Platform fee: Cap intro fee: YOU set capacity & fees



Meet our Darwin EXchange

"Everyone's alpha for 20% of Everyone's Profit" Exchange





10

Introducing the Darwinex Private Label service

Your Private Label is your turnkey asset management franchise.





Meet AccurateQuant

Chicho is a Spanish regulated asset manager





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Movement Feedback

This is what fellow aspiring & emerging managers have said over the years



darwinex.com

"I really like the Darwinex concept and the way you guys run it!

But I have a concern that it may be sold in the future, to someone who tries to change it..."

Emerging Manager, via Intercom



"First I would like to congratulate you and your team on an amazing website and service. Darwinex is Head and Shoulders above competitors"

Investor, to Customer Service



"... the ingenuity of matching emerging managers with capital online, and landing investors with real funds,... it's just clever and a self-sustaining loop kind of thing" Andrei, via Quora



"... Darwinex looks like a grown-up social trading platform, with good safeguards for investors and an attractive package for ambitious discretionary and algo traders"

Prospective user, via Quora



User A: *"I don't listen to economic "press" it's all designed to draw suckers in"*

User B: *"Agree – the only piece I listen to is Darwinex's Trader Movement Podcast"*

Spontaneous Exchange on Twitter



"Probably the best broker around and Darwinex is setting a new standard for the competition"

Anchorpoint, via MyFXBook



What we bring to YOUR table

1. 100% FOCUS

- We preserve your bandwidth
- You tackle the genius bit



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- Trade with a competitive bróker, on your platform of choice
- 0 up-front expense. 0 fix overhead

6. By managers, for YOU

- We ARE in the same shoes as you
- It's as much about the vision, as it is about the money



3. 0 operational risk

- All costs variable
- Leverage infrastructure proven on thousands of managers and trillions of volume

5. Aligned model

- We NEED you to succeed long term
- We're not here to bill legal fees, charge cap intro retainers, etc.

4. Shortest path to revenues

- From strategy to wrapper in days (managed account) / weeks (wrappers)
- EUR 60 MM AuM (seed + 3rd party AuM)





Interested? Visit our BOOTH!





PANEL: Current trends in alt data





Daniel Mitchell Co-Founder and CEO, *Hivemind*

Yuan Liu

Justin Zhen Co-Founder, *Thinknum*

Senior Researcher, Aspect Capital

PRESENTATION: Unlocking alternative data





Saeed Amen Founder, Cuemacro



PRESENTATION: Alternative data trends in institutional investment



Jose Terriquez Analyst, *Neudata*



Neudata Alternative data trends in

institutional investment

Jose Terriquez, Analyst

What is alternative data?

Alternative (adj.) al·ter·na·tive | \ ol-'tər-nə-tiv

- different from the usual or conventional



What is alternative data? Dataset types













Coordinates are mapped to POI

SDK installed in a mobile app

SDK captures app users location





Alt approach to traditional data









Corporate earnings statement

NLP – parse for terminology

Compare QOQ terminology

Maximise alpha (avg. 22% per year)

[Source: Cohen et al, 2019]





What is alternative data? Is this really a new phenomenon?

CURRENT IMPLEMENTATION OF ALTERNATIVE DATA



Yes

No, but plan to incorporate in the next 12 months

No

[Note: Based on 30 respondents. Source: Greenwich Associates 2018 Future of Investment Research Study]

[Source:Greenwich Associates, Q3 2018]



What is alternative data? Is this really a new phenomenon?

% Growth - data generated globally (Sep 19)





[Source: Data Driven Investor, September 2019]



How do funds typically source this data?

Hypothesis to dataset

Dataset to hypothesis





Neudata What do we do?





Neudata Our universe



500 asset managers



625+ data providers



880+ datasets





Data trends





Excludes all other regions & datasets defined by Neudata as global



350

Public equity applicability

N. American dominance

Daily frequencies





Pricing trends






Supply side trends







Supply side trends

- Regulation (Google)
- Legislation (web scraping, open banking)
- "Where one door closes, another one opens"





Trend Recap

O Datasets that apply to North American public equities are the most popular.

102 Lower price datasets are more common than you may think (and we expect this to remain the case).

As the market for data grows, there will be more legislation that will affect the supply of data.





Thank you

For further enquiries please contact jose@neudata.co







DEBATE: Systematic vs Discretionary



Francesco Filia CEO and CIO, Fasanara Capital



Steve Mobbs

Previously Co-Founder and currently Consultant Founder Member, Oxford Asset Management



Chris Jones

Capital

Chief Executive, Graham

PANEL: Front office of the future. How does technology transform the way AMs and Banks work?



Matthew Hampson

Deputy Chief Digital Officer, Nomura Wholesale Division

Ashley Lester Global Head of Multi-Asset Research, *Schroders*



Rob Boardman CEO, Virtu Execution Services

Brice Rosenzweig Global Head of Data & Innovation Group, Bank of America Merrill Lynch

Off the Record Brice Rosenzweig



Closing Remarks



THANK YOU FOR COMING

THE QUANT CONFERENCE

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