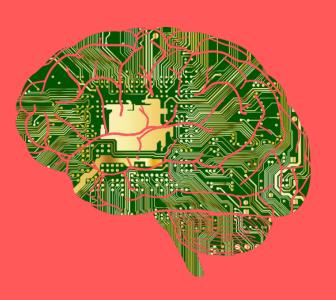


Data Science vs Engineering



Piero Cornice SIGNAL



MY BACKGROUND

Software Engineering, University of Bologna

> Delay-Tolerant Networks

...moved to video streaming

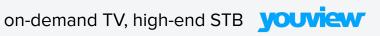
middleware for PS3, FireTV stick



Started working on **embedded software**...



on-board information for Trenitalia



...shifted to backend development...



HD video coding/streaming over WiFi



worked on the current sat-nav UI

...prototyped a **recommender system** using **NLP**...

...ended up doing working at $SIGN\Delta L$

OUTLINE

- 1. WHAT WE DO
- 2. DATA SCIENTISTS and ENGINEERS

 (vs → √)
- 3. WHAT WE DON'T DO
 (TO DO WHAT WE DO)
- 4. EPILOGUE

SIGNAL AI

WHAT WE DO



WHAT WE DO

Empower decision making through media monitoring

Enable PR & Comms to answer strategic questions

SIGNAL

WHAT WE DO





David Benigson (CEO)
Miguel Martinez (Chief Data Scientist)

2013

Started life with three people in a garage



2020

150+ employees, three offices (London, NYC, HK) 20 engineers, 9 data science researcher (+ visiting researchers)



WHAT WE DO

We ingest 4+ million articles / day

> currently 76+ billion articles indexed, 24+ TB of data

Real-time* NLP to extract information

- > entities
- > topics
- > saliency
- > quotations
- > sentiment
- > ...

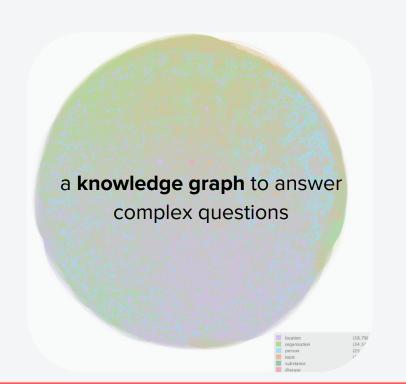
Customers can search for articles in a web application and receive relevant real-time alerts.

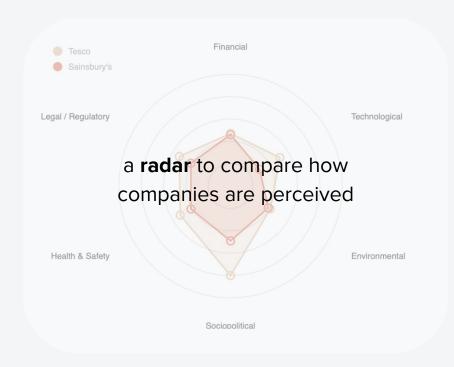
* Real time = on average, pipeline lag is < 1 minute 97% of the time.



WHAT WE DO

Other things we're working on...





A selection of our 500+ world class clients.

Financial Services







Accounting







Legal







Agency















Energy







Not for Profit







Investment Houses







Tech











WHAT WE DO

BRITAIN'S FASTEST-GROWING PRIVATE TECHNOLOGY Year Headquarters 2020 2019 Company Activity end location Dec 19 Digital banking services provider Fast London Revolut Dec 19 Football trading platform Central London Football Index Mar 20 Fmail security provider Central London Tessian Dec 19 Central London Experience marketplace Pollen Dec 19 Oxfordshire Retail communication provider VoCoVo 5 Dec 19 Central London Professional services marketplace Bark.com 6 Central London Dec 19 Female health technology developer Elvie Central London Dec 19 Marketing technology Whalar Mar 20 Central London Elderly care platform Elder Dec 19 9 Central London Consumer lending platform Lendable 10 Dec 19 Reading Consumer insight platform Qmee 11 Central London Dec 19 E-commerce software developer Paddle Central London Dec 1 12 Mobile healthcare app **Babylon Health** Mar 2 13 Central London Data analytics provider Dec Quantexa West London 14 Solar technology developer Dec 15 Bboxx Central London Business finance provider OakNorth Bank Dec South London 16 Meal kit delivery services Ma Mindful Chef Central London 17 Anti-money laundering software Ap ComplyAdvantage 16 Oxford Biotechnology De Oxgene Oxford 19 nalysis technology Oxford Nanopore Technologies D Altrincham 20 5 ransformation software Central London 36 Matillion 21 latform Central London Moteefe 22 form Telford Signal Al 23 chnology North London Rebound Returns 24 10 West London TelcoSwitch ne menswear supplier Central London Spoke ct hotel booking platform 12 26 Central London Personalised stationery retailer Triptease Central London Treasury management platform Papier Central London Canttrin

The Sunday Times Sage Tech Track 100

UK companies with the fastest-growing sales over their latest three years

September 2020

https://www.fasttrack.co.uk/league-tables/tech-track-100/



WHAT WE DO

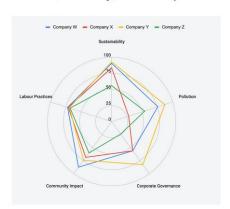
Introduction | Research | Talent | **Industry** | Politics | Predictions

#stateofai

NLP is used to automate quantification of a company's Environmental, Social and Governance (ESG) perception using the world's news

- NLP can derive ESG perception scores by assessing the relationships and sentiments of products and companies with respect to client-specific ESG reputation pillars (e.g., environment, diversity, and more).
- Investors are increasingly demanding evidence of ESG performance.
- This approach uses NLP to tag millions of news articles daily to identify and understand relevant coverage using entity linking, saliency and topic classification.

	Company W	Company X	Company Y	Company Z
Sustainability	91	84	93	56
Pollution	76	28	87	54
Corporate Governance	56	56	83	24
Community Impact	88	69	74	60
Labour Practices	72	71	69	68



State of AI Report 2020

October 2020

https://www.stateof.ai/

(slide 119)

stateof.ai 2020



SIGNAL AI

DATA SCIENTISTS

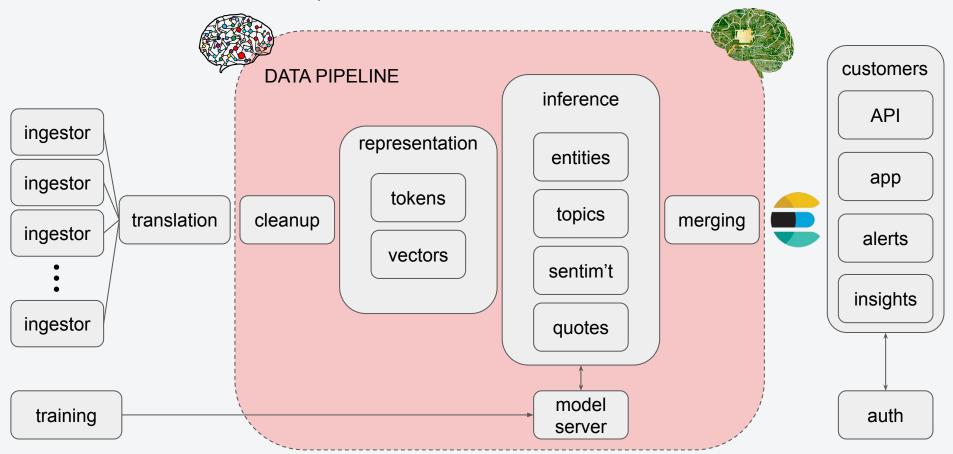
and

ENGINEERS

(vs → ✓)

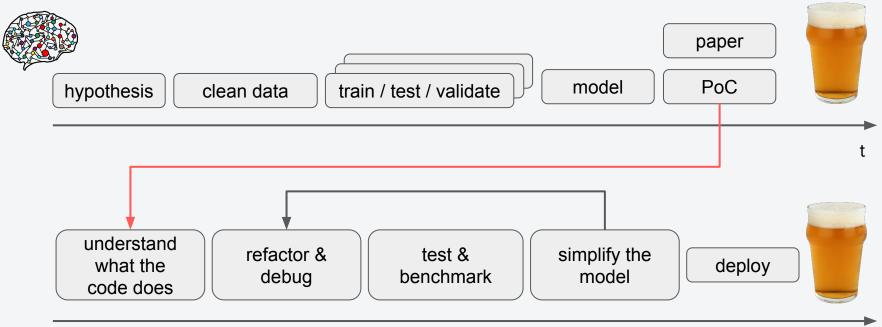
SIGNAL

THE REAL-TIME PIPELINE, AS SEEN FROM SPACE



SIGNAL

THE WATER BEER-FALL MODEL







RESEARCH vs ENGINEERING

Research work entails uncertainty and long times

- > High cost if a line of research is not successful
- > Data Scientists drink their beers while Engineers work
 - > Engineers are not happy

Engineers inherit code that...

- > has to be understood, optimised and tested
- > once deployed, may give different results than what Data Scientists achieved
 - > Data Scientists are not happy

Long time to market

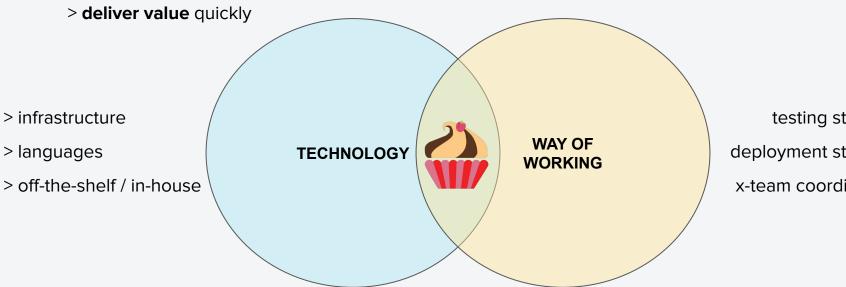
the **company** and its **customers** are not happy



CHASING THE SWEET SPOT

In order to stay competitive, at Signal we found a combination between technological choices and our way of working.

> resolve the tension between Data Science and Engineering



testing strategy <

deployment strategy <

x-team coordination <



DATA SCIENTISTS vs ENGINEERS

Research implies uncertainty and long times

Engineers **inherit** code not ready for production



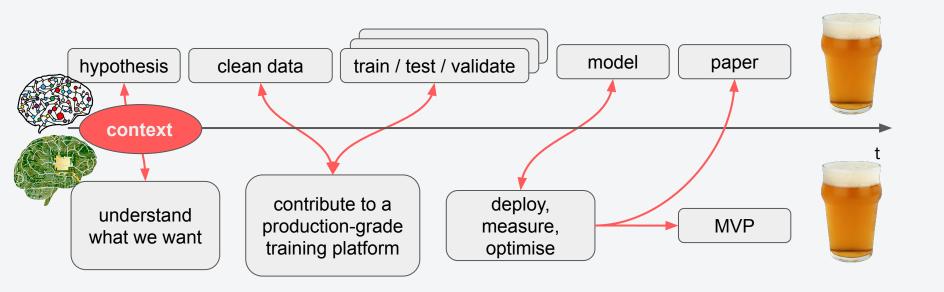
What if **Data Scientists** and **Engineers** could **pair from Day One**?







DATA SCIENTISTS **W** ENGINEERS (A TALE OF TWO BEERS)



POC → MVP (value)

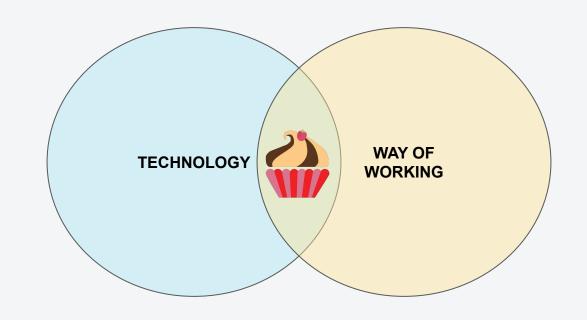


WE MADE A MVP. NOW WHAT?

How to **evolve** a MVP

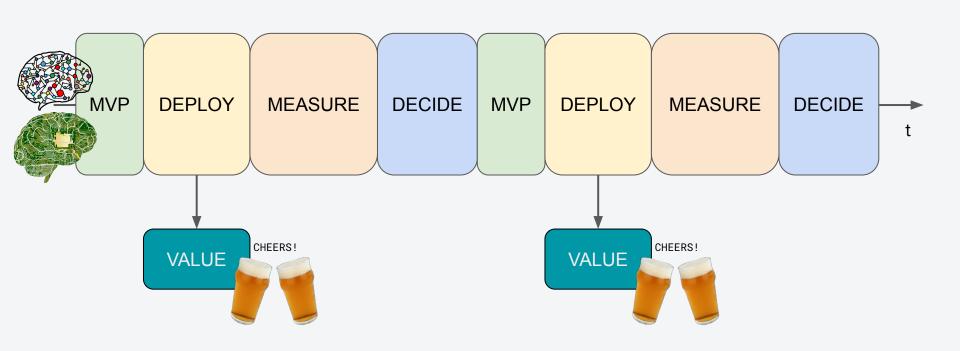
into a fully-fledged product?







XP MODE = ON (BRING THE BEERS!)





LESSONS LEARNED

Engineers have to accept failure

Data Scientists have to accept that quality without performance is a no-go

Shared understanding:

- > Engineers know what Data Scientists want to achieve, and how
- > Data Scientist know what the NFRs Engineers care about, and adjust accordingly

ML code is tested for quality and performance as it's being developed

Teamwork! Sense of **ownership**, pride, and satisfaction

CHEERS!



Engineers and Data Scientists can have beers together!



BEFORE WE MOVE ON...



SIGNAL AI

WHAT WE DON'T DO (TO DO WHAT WE DO)



WHAT WE DON'T DO (TO DO WHAT WE DO)

Some common practices in the industry:

> Kubernetes
> Kafka
> Imperative languages

> Automated tests
> Scrum
> Code reviews

We don't do

ANY

of those



WHAT'S GOING ON???



BUT KUBERNETES IS AWESOME!

Introduces complexity

Docker

I. Turner-Trauring, "Let's use Kubernetes!" Now you have 8 problems" (2020) https://pythonspeed.com/articles/dont-need-kubernetes/



BUT KAFKA IS AWESOME!

Introduces complexity

We sometimes need **persistence**

> Being already locked-in to AWS, we use **Kinesis**.



FUNCTIONAL PROGRAMMING

Loved by **Engineers**



G. Kim, "Love Letter To Clojure (Part 1)" (2019) https://itrevolution.com/love-letter-to-clojure-part-1/



WHAT ABOUT PYTHON?

Loved by **Data Scientists**

GOOD: many libraries for Machine Learning

BAD: some libraries have side effects

UGLY: supports functional, yet it's imperative



LEAN PRINCIPLES

"Be lean, my friend"

SCRUM: maximize the **team**'s ability to adapt

- > roles (scrum master, ...)
- > tools (backlog)
- > rituals (sprints, scrum of scrums, ...)

LEAN: maximise the **flow** that generates value

- > Eliminate waste
- > Amplify learning
- > **Decide** as late as possible
- > **Deliver** as fast as possible
- > **Empower** the team
- > Build **integrity** in
- > Optimize the **whole**





CAN YOU REVIEW MY CODE, PLEASE?

Code reviews are expensive.

- > Do the reviewers have **enough context**?
- > What if they **disagree** with the design?

Our recipe: Pair, pair, pair

- > **Share context** and **agree** on design from the beginning.
- > Learn from each other.

The code is reviewed as it is being written



TESTING IN PRODUCTION

The **real world** can only be found in **production**.

Our recipe: Frequent, incremental deployments

- > Easy to **monitor**
- > Easy to **rollback**
- > Easy to recover

Strategic questions:

- > What's the worst thing that can happen?
- > Is it that bad?
- > What can we do to mitigate it?

C. Sridharan, "Testing in Production: the hard parts" (2019) https://medium.com/@copyconstruct/testing-in-production-the-hard-parts-3f06cefaf592





IT'S ALL DOWN!!

Disasters: they happen

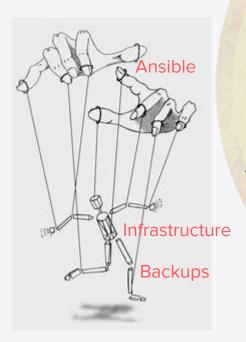
If it hurts, do it more!

DISASTER RECOVERY GAME DAY

simulate that all the production environment is compromised



DISASTER RECOVERY GAME DAY



Full restoration of **primary** product functionality (with content)

> within 3 hours

Other less-critical components

> within 7.5 hours

Automation avoids wasting time on mechanical actions

> we use **Ansible** to control **Terraform** for infrastructure deployment



SUCCESS STORY: SENTIMENT DETECTION

Problems

- > Complex model (attention mechanism + Bayesian layer)
- > Python's multiprocessing not efficient enough

Solution: Ray* + improvements to the ML model

Result: Computation time and costs went down → we could release the product



- * Ray is a Python framework for building and running distributed applications
 - > efficient use of CPU cores
 - > fine-grained tuning of resources (took some time to get right)





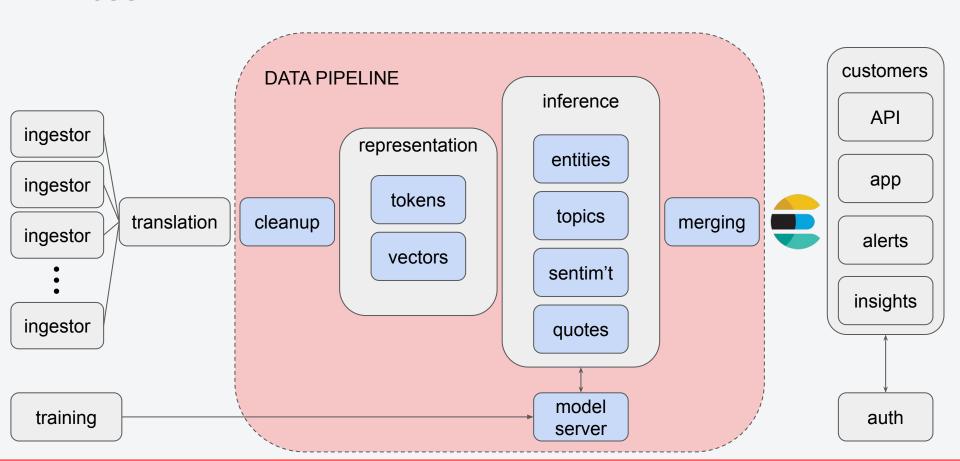
SUCCESS STORY: SENTIMENT DETECTION

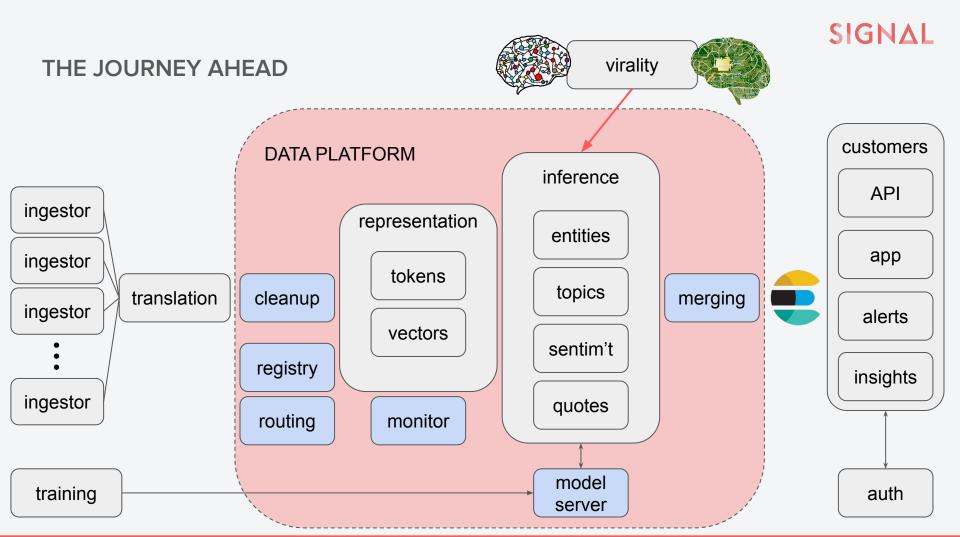


	Accuracy	
SIGNAL	65.45%	
G	53.77%	
Azure	49.44%	

SIGNAL

THE JOURNEY AHEAD







LESSONS LEARNED

Iterate fast by reducing waste

- > adopt simple technologies when possible
- > write code **together**, rather than asynchronous reviews
- > no barriers to **continuous deployment**



LESSONS LEARNED

Robustness emerges from embracing uncertainty

- > reduce surprises with **functional programming**
- > rely on **real-time metrics** and alerts
- > learn from failure

SIGNAL AI

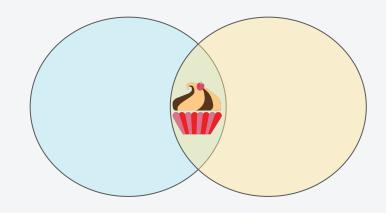
EPILOGUE



EPILOGUE

In order to stay competitive, at Signal we found a combination between **technological choices** and our **way of working**.

- > Pairing between Data Scientists and Engineers
- > Challenge common practices
- > Lean principles all the way down
- > Embrace uncertainty and failure to be robust



PS: The **recruitment process** is extremely important

- > Don't focus on technologies, algorithms, data structures
- > Focus on solving business problems and hands-on pairing



SOME BOOKS THAT INSPIRED ME

> Optimising the flow

G. Kim, K. Behr, G. Spafford, "The Phoenix Project", IT Revolution Press (2013)

> Integrating data science

G. Kim, "The Unicorn Project", IT Revolution Press (2019)

> Empowering teams

D. Marquet, "Turn the Ship Around!", Portfolio (2013)

> Designing for change

N. Ford, R. Parsons, P. Kua, "Building Evolutionary Architectures", O'Reilly (2017)

THANK YOU!







www.linkedin.com/in/pierocornice