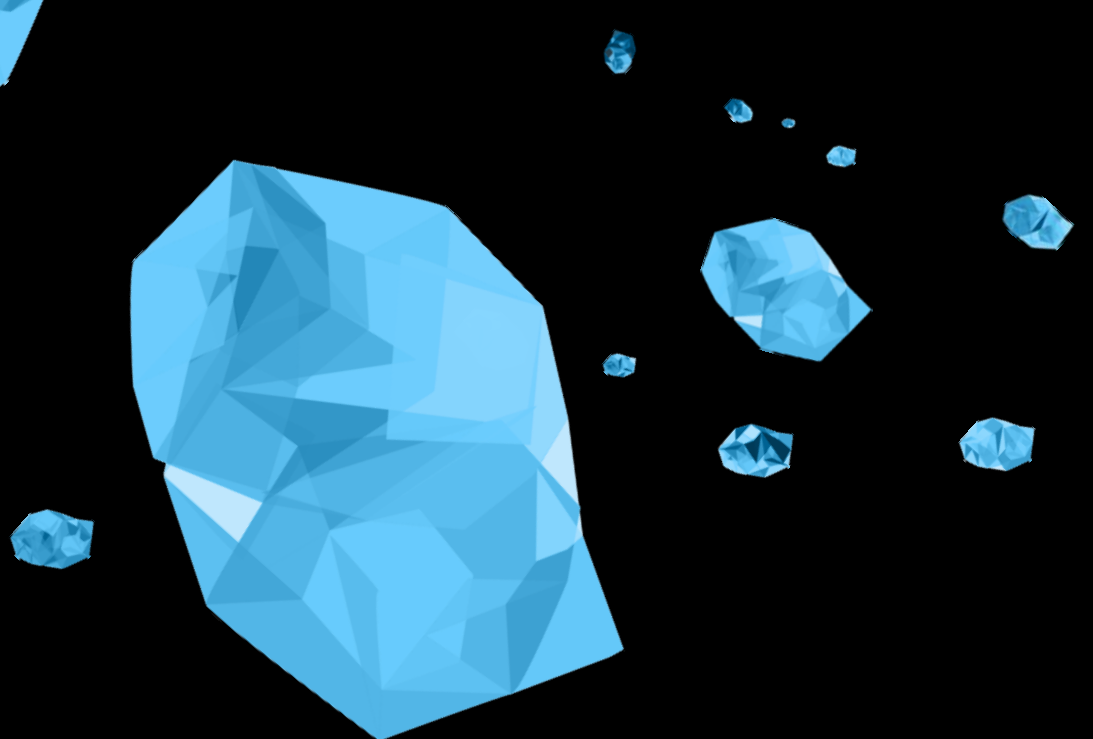
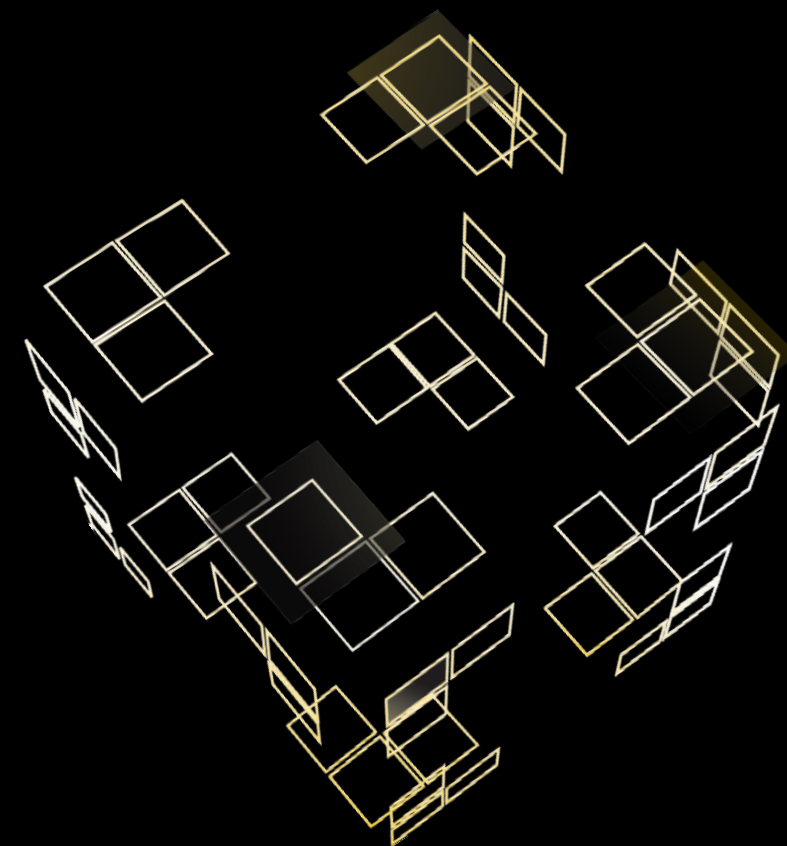


UNIVERSITY OF TWENTE.



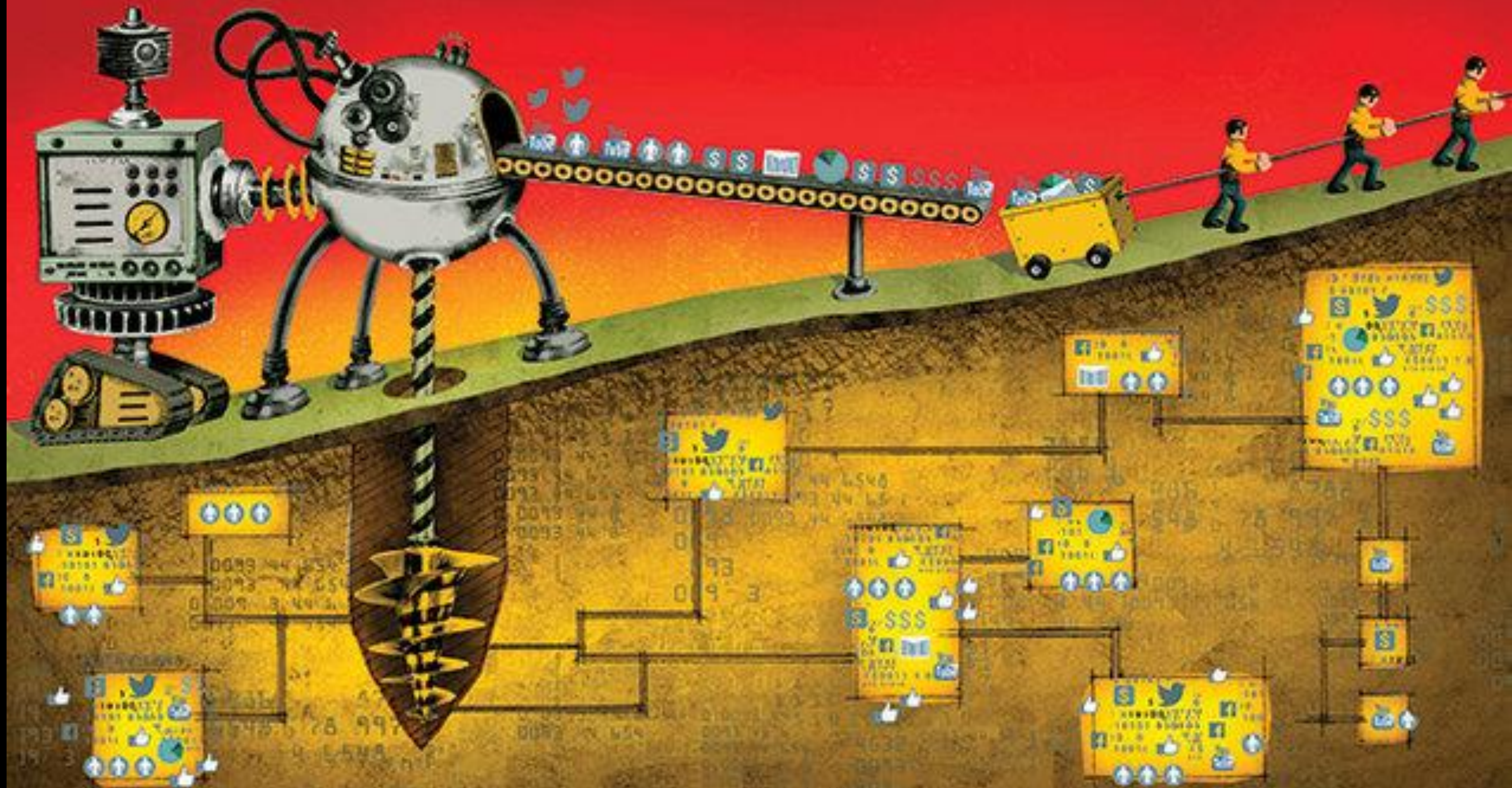
Data analytics Trends, Methods and Tools

PROF.DR. JOS VAN HILLEGERSBERG



INDUSTRIAL ENGINEERING AND
BUSINESS INFORMATION SYSTEMS





Source: www.billboard.com

Why?

<u>Top objective of Big Data and AI investments</u>	<u>#1 Goal</u>	<u>Started</u>	<u>Success</u>	<u>Rate</u>
Advanced analytics/better decisions	36.2%	84.1%	58.0%	69.0%
Improve customer service	23.2%	65.2%	34.8%	53.4%
Decrease expenses	13.0%	66.7%	40.6%	60.9%
Innovation/disruption	11.6%	46.4%	20.3%	43.8%
Speed to market	8.8%	53.6%	29.0%	54.1%
Monetization	7.2%	31.9%	8.7%	27.3%

NVP
NewVantage Partners

Big Data Executive Survey 2018
Executive Summary of Findings



Challenges?

Business adoption of data initiatives remain a challenge

-

Yes

64.7%

No

35.3%

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Big Data Executive Survey 2018
Executive Summary of Findings



Challenges?

Biggest challenge to successful business adoption

Cultural resistance to change	32.5%
Understanding of data as an asset	30.0%
Insufficient organizational alignment & business agility	25.0%
Lack of business direction and executive leadership	7.5%
Lack of technology leadership and solutions	5.0%

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Big Data Executive Survey 2018
Executive Summary of Findings



Challenge?

Biggest challenge to becoming data-driven

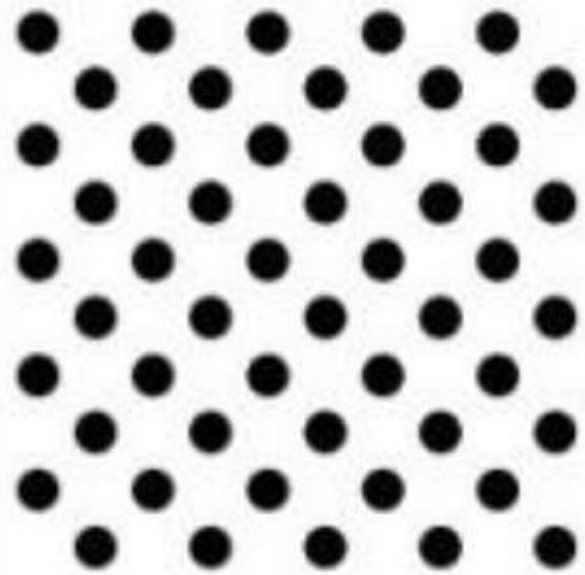
People	48.5%
Process	32.4%
Technology	19.1%

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Big Data Executive Survey 2018
Executive Summary of Findings



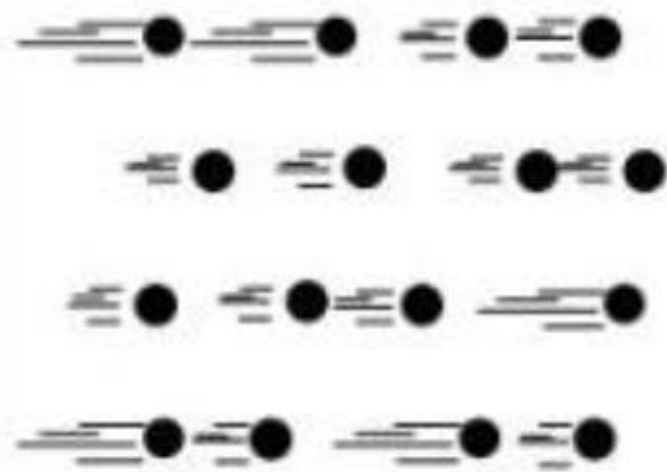
Volume



Data at Rest

Terabytes to exabytes of existing data to process

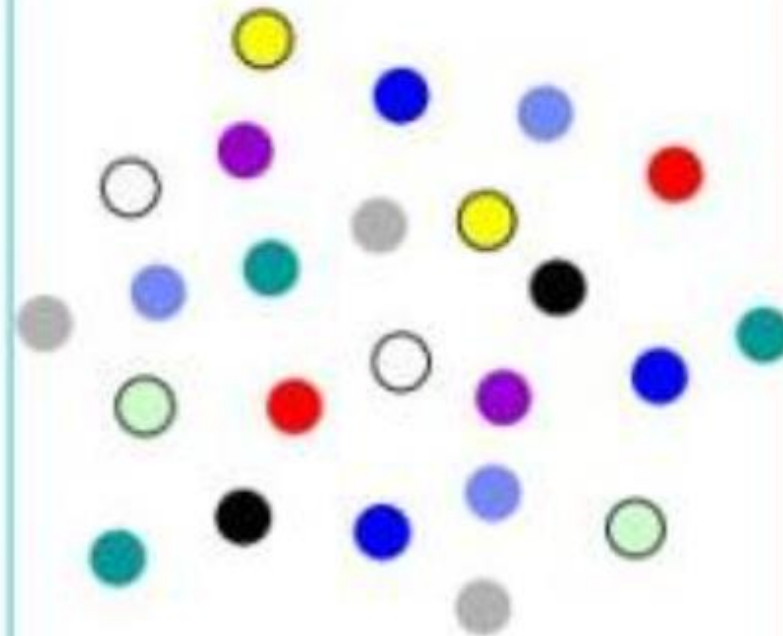
Velocity



Data in Motion

Streaming data, milliseconds to seconds to respond

Variety



Data in Many Forms

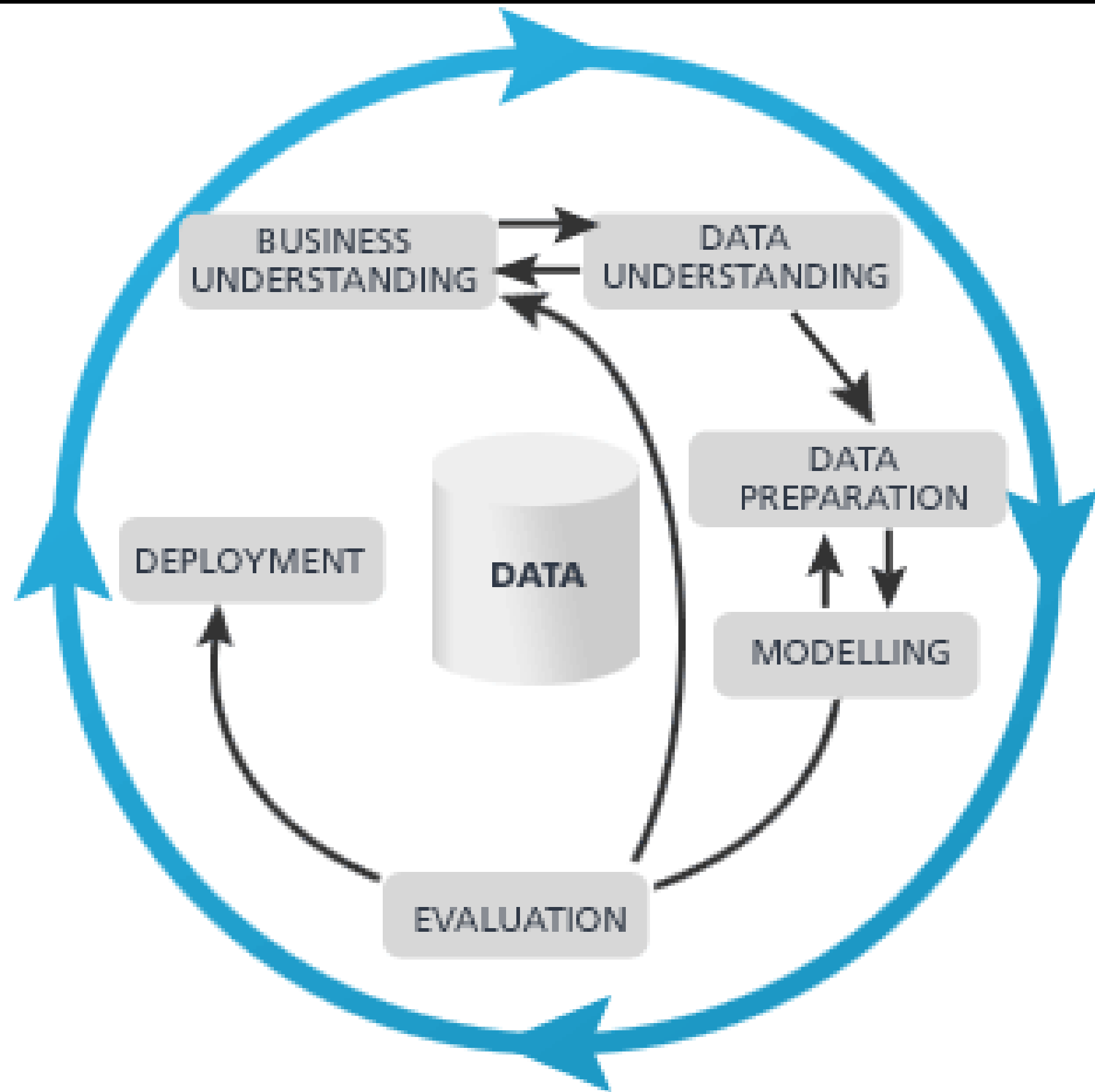
Structured, unstructured, text, multimedia

Veracity*



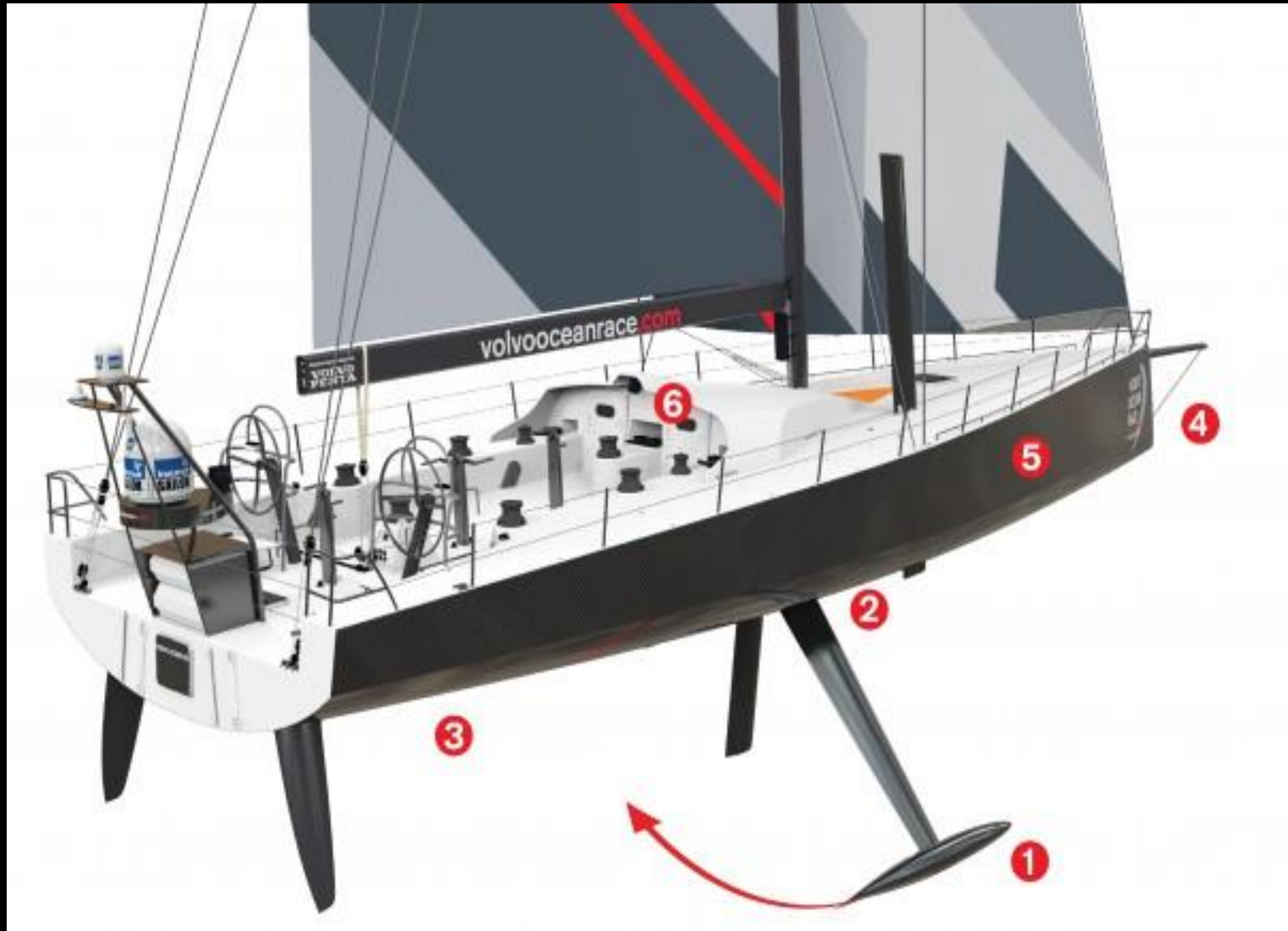
Data in Doubt

Uncertainty due to data inconsistency & incompleteness, ambiguities, latency, deception, model approximations

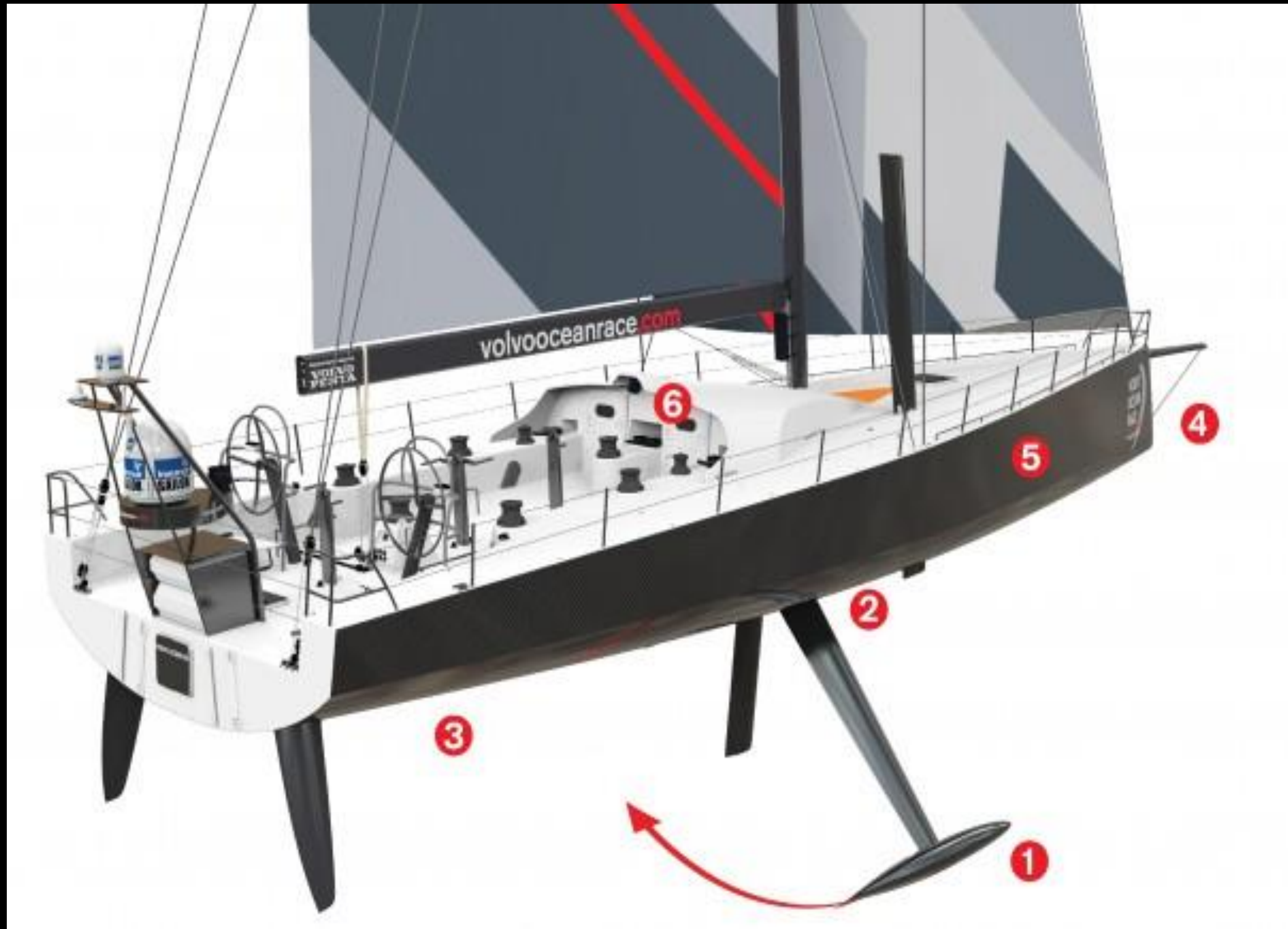


An example – “Help us to Sail Faster using Sensor Data” 12th Volvo Ocean Race



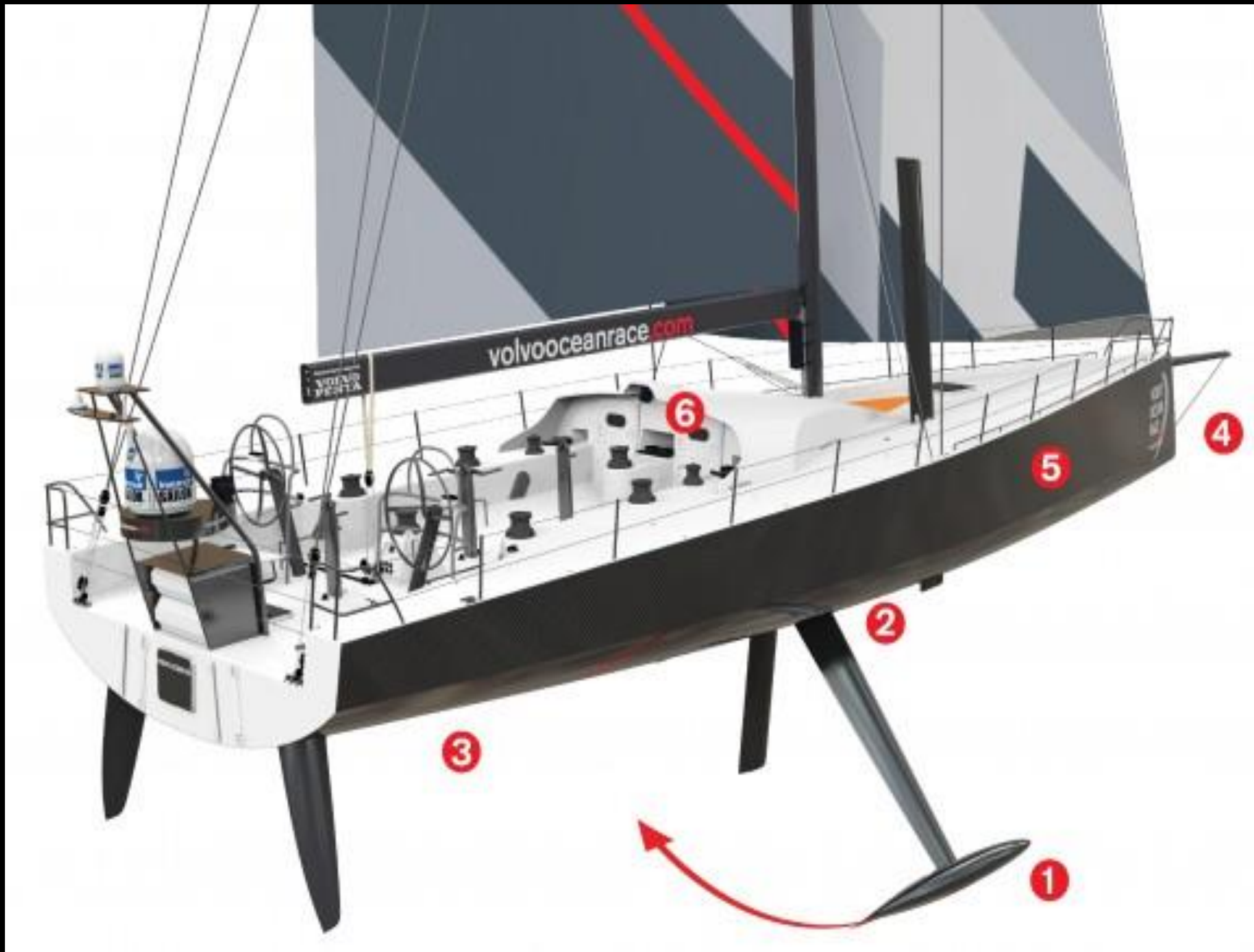


Wind Sensor Data	
True wind speed	Speed of the wind, without the motion of the boat.
True wind direction	Direction of the wind.
True wind angle	Direction of the wind relative to the ship.
Apparent wind speed	Speed of the wind as experienced on the moving boat.
Apparent wind angle	Angle of the wind as experienced on the moving boat



Navigation Sensor Data

Boat speed	Speed of the boat including currents.
Compass heading	Course indicated by the compass.
Speed over ground	Speed of the boat excluding current.
Course over ground	Course relative to the land.
Position GPS	Coordinates of the boat's position.



Boat Sensor Data	
Heel	The angle that the boat heels to one side.
Trim	The angle that the boat heels forward/backward.
Rudder	The angle of the rudder.
Keel	The angle of the adjustable keel.



Data analytics support of Navigator Andrew Cape and UT

Mark Vroling, Floris Smit
David Lamers (BIT), Tim Paauw (TBK/BIT),
Madelon Voets (Euros),
Peter Paul van der Wurff (BIT),
Monique van Leeuwen (BIT)





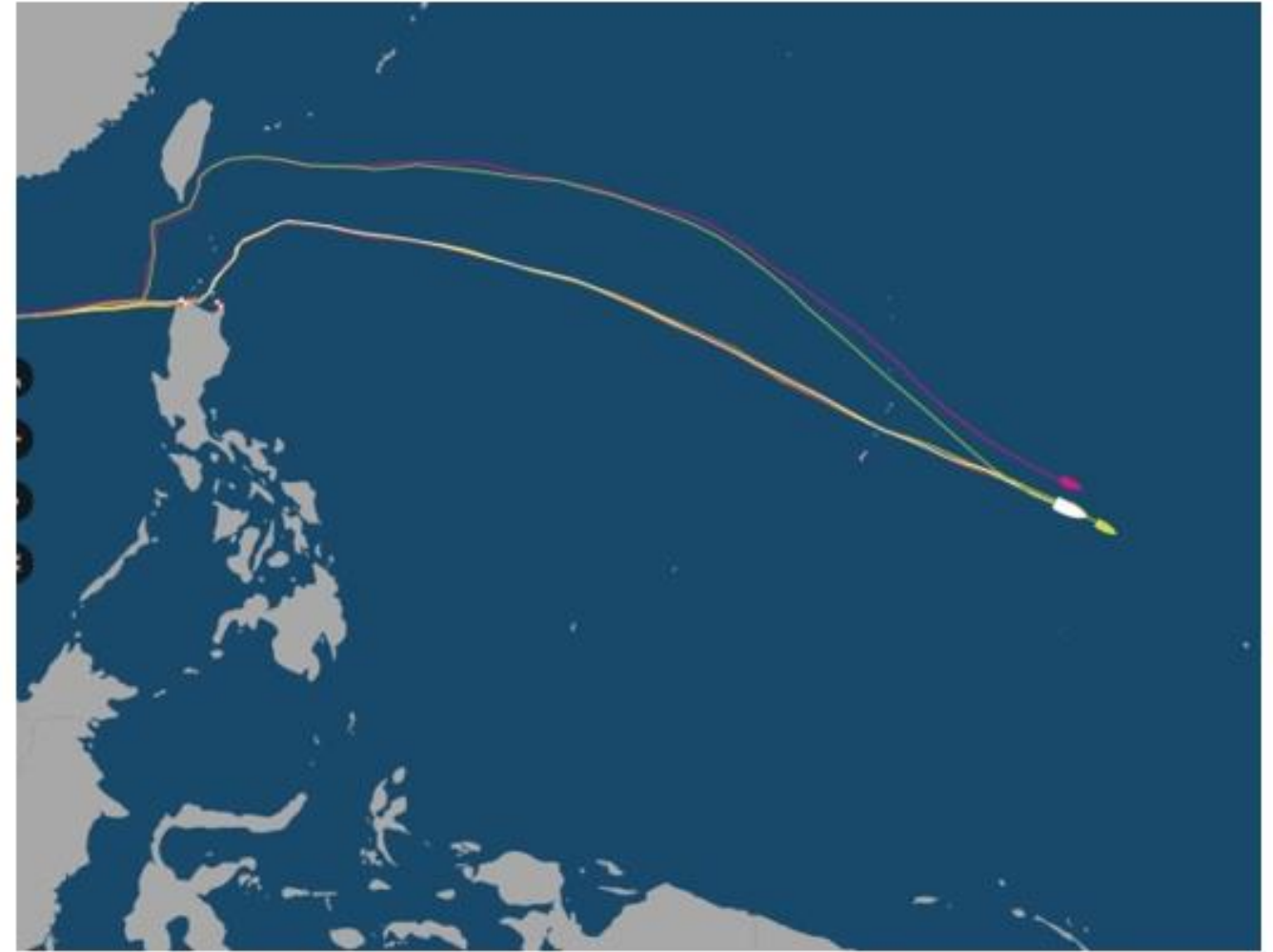


Figure 2: Example of a big decision by two teams to take the northern route that would later give a small but non-decisive advantage in the leg from Sanya to Auckland

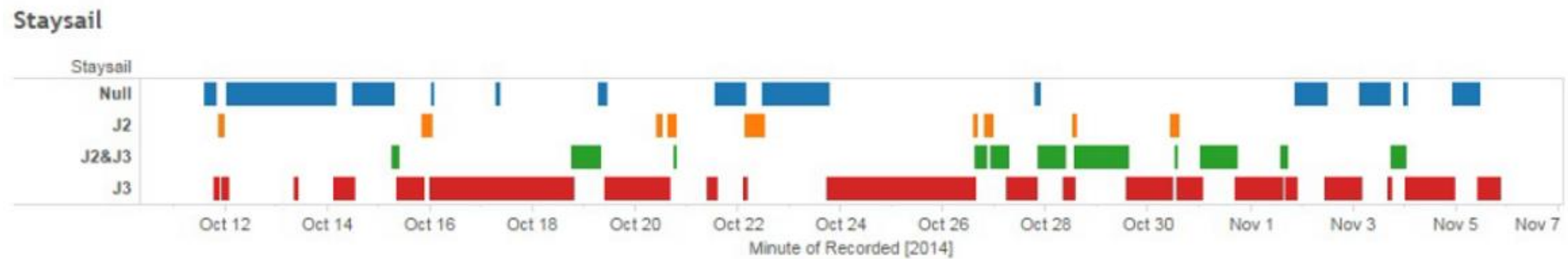
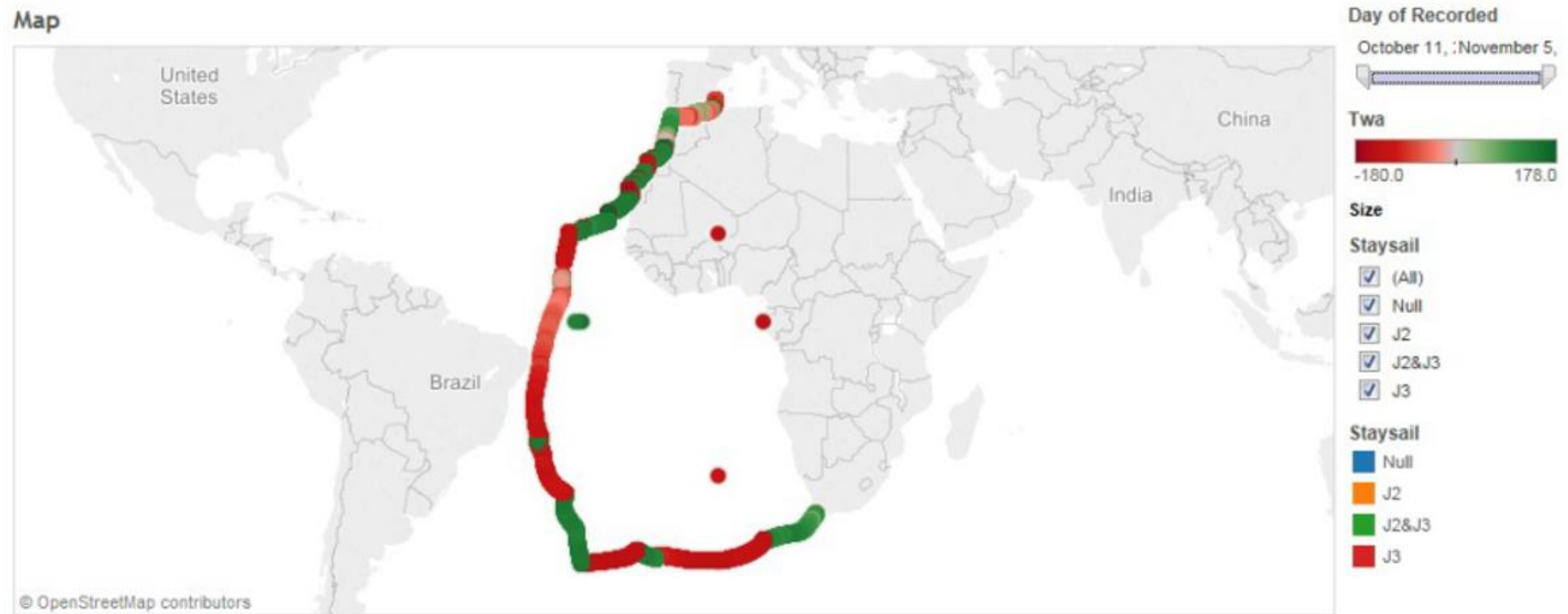


Figure 6: Map Speed Dashboard

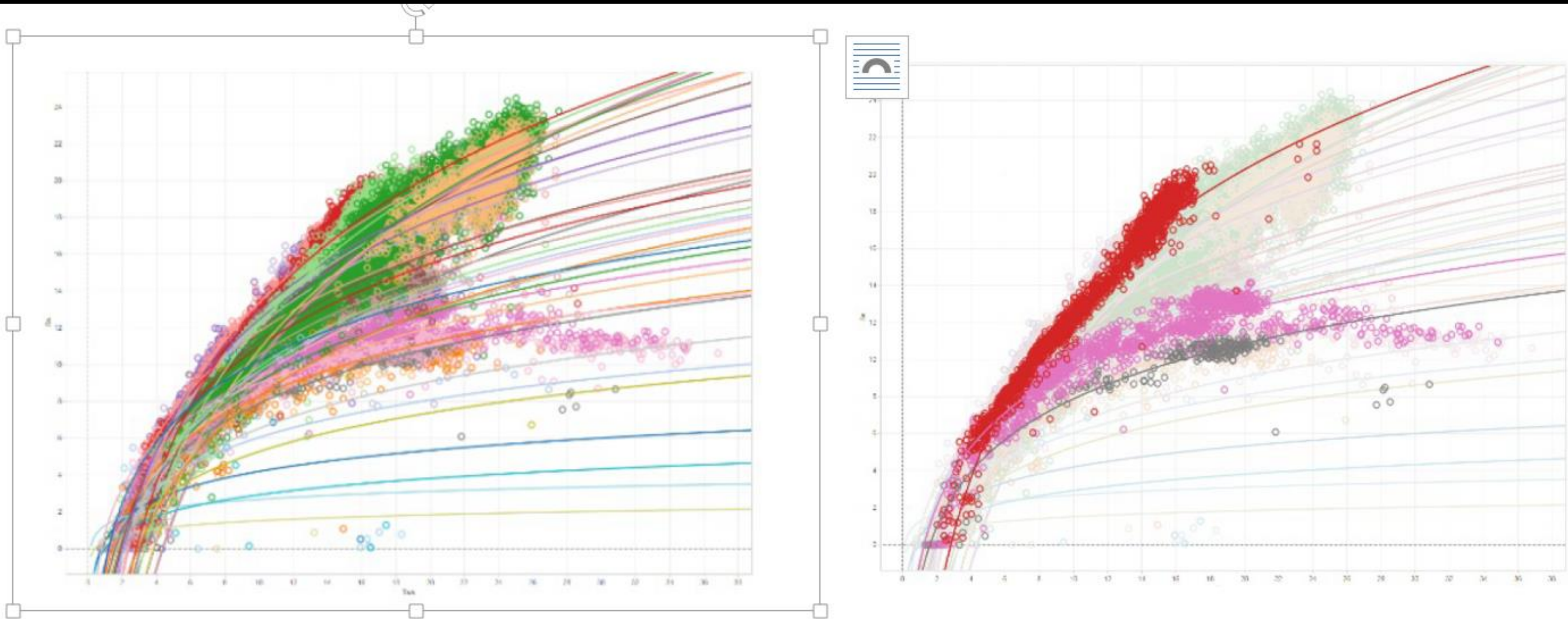
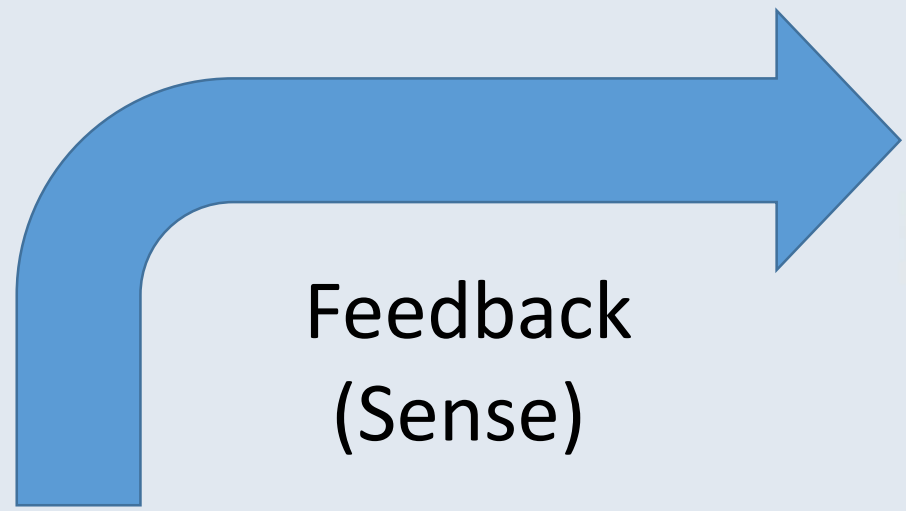


Figure 7: Wind Graphs

True Wind Angle (2 degrees)	True Wind Angle (2 degrees)																												
	40	42	44	46	48	50	52	54	56	58	60	62	64	66	68	70	72	74	76	78	80	82	84	86	88	90	92	94	96
36				J2	J1		J2											J1					J1		J1	J1		J1	J1
34		J1	J1	J1	J1	J2	J2	J2															J1	J1					J1
32		J2	J1	J1	J2	J2	J2	J2	J2	J1	J1		J2						J1	J1			J1		J1		J1		
30			J2	J1	J2	J2	J2	J2		J1	J2	J2	J2	J2	J2	J2	J2	J2	J2				J2	J1			J1		
28	J1	J2	J2	J2	J2	J2	J2	J2	J1	J2	J2	J2	J2	J2	J2	J2	J2	J2	J2	J2	J2	J1	J1	J1	J1		J1		J1
26	J1	J2	J2	J2	J2	J1	J2	J2	J1	J1	J2	J2	J2	J2	J2	J2	J2	J2	J2	J2	J2	J1	J2	J1	J1	J1	J1	J1	J1
24	J1	J1	J1	J1	J1	J1	J1	J1	J2	J1	J2	J2	J1	J2	J2	J2	J1	J2	J2	J2	J2	J2	J2	J1	J1	J1	J1	J1	J1
22	J1	J1	J1	J1	J1	J1	J1	J2	J1	J2	J1	J1	J1	J1	J2	J1	J2	J2	J1	J1	J2	J1	J1	J1	J1	J1	J1	J1	J1
20	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1
18	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1
16	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1
14	J1	FR	J1	J1	J1	J1	J1	J1	MH	MH	J1	J1		J1	J1	FR	FR	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	J1	
12	MH	J1	MH	FR	J1	J1	MH	J1	J1	FR	FR	FR	FR	FR	FR	FR	FR	FR	FR	FR	J1	MH	MH	FR	MH	MH	FR	J1	J1
10	J1	J1	J2	J1	FR	FR	FR	FR	FR	FR	J1	FR	J1	J1	J1	FR	FR	FR	FR	FR	FR	FR	FR	FR	MH	FR	FR	FR	FR
8	MH	MH	MH	A3	FR	J1	MH	J1	MH	J1	J1	FR	FR	J1	FR	FR	MH	FR	FR	MH	FR	FR	FR	FR	MH	MH	MH	MH	FR
6	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	FR	MH	MH	MH	MH	MH	MH	MH	MH
4	MH		MH	MH	MH	MH	MH	MH	MH	MH	FR	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	MH	A3	MH	MH	MH	MH	MH	MH

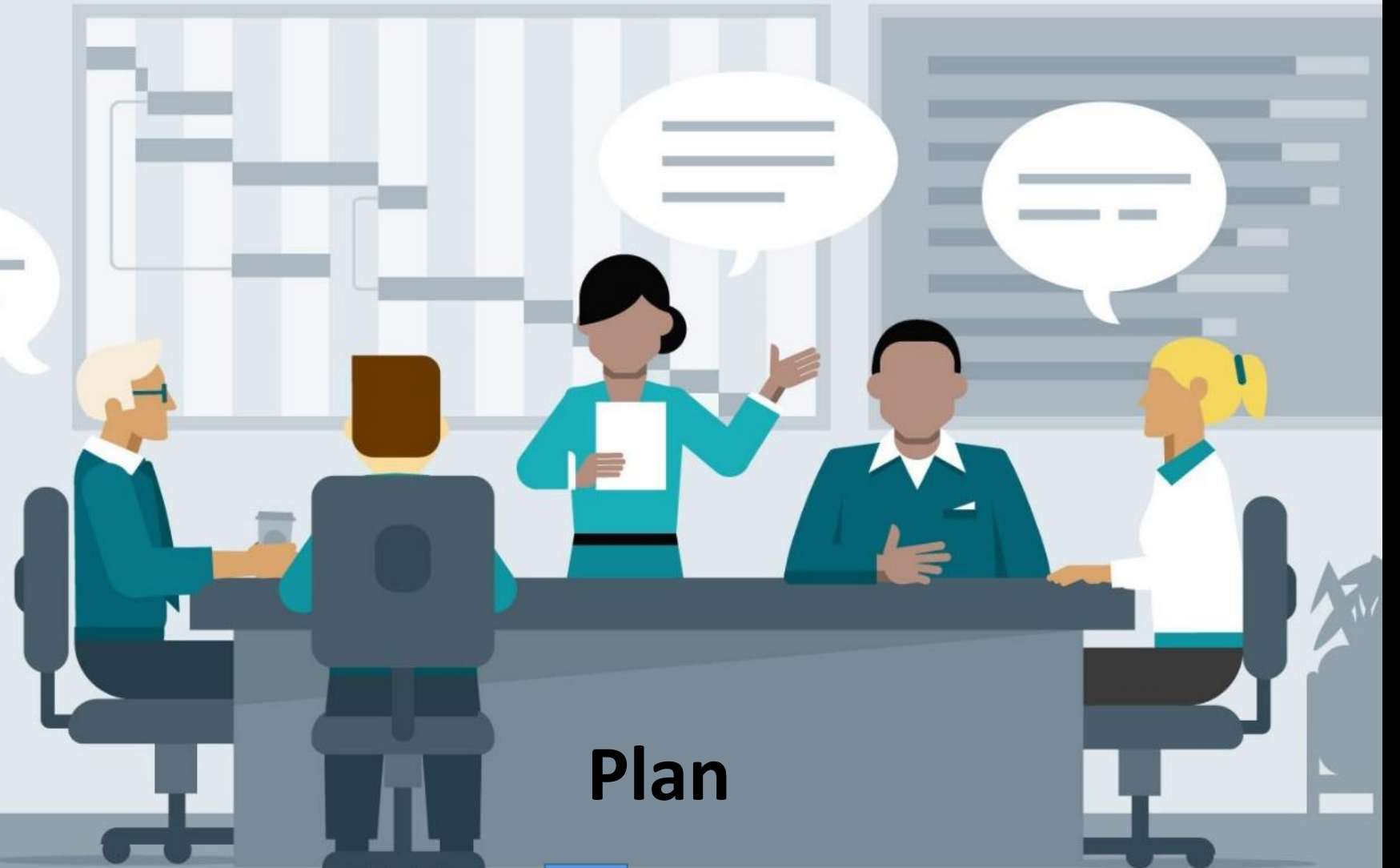


Feedback
(Sense)

Real World



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Plan



Implement
(Execute)

Data mining as solution to detect fraud



Following the money using medical claim reimbursements

- Who are the gate keepers?
- Go for prevention or detection?
- How to deal with a complex changing nature of health care domain?
- How to deal with continuously changing type of fraud?
- What to do with multiple domains in health care?
- How to determine if identified fraud is really fraud?

van Capelleveen, G., Poel, M., Mueller, R. M., Thornton, D., & van Hillegersberg, J. (2016). Outlier detection in healthcare fraud: A case study in the Medicaid dental domain. *International journal of accounting information systems*, 21, 18-31.

- **Fraud:** Purposely billing for services that were never furnished and or supplies not provided, medically unnecessary services and altering claims to receive higher reimbursement than the service produced.
- **Abuse:** The billings of practices that, either directly or indirectly, are not consistent with the goals of providing patients with services that are medically necessary, meet professionally recognized standards, and are fairly priced.

Grey area

Data mining fraud: a multi-disciplinary problem



Who is doing what?

- **Medical subject matter expertise**
- **Fraud expertise**
- **Data science expertise**

Fraud approaches in healthcare

Who commits fraud?

- Providers, a group of providers, patients, insurance provider, combinations?

Different systems, different fraud!

- Pay and chase or a gate keeper?
- Fixed fee, variable costs, diagnosis related
- Negotiated procurement
- Explanation of benefits?

How to fraud?

- Hit and run
- Steal a little all the time



Fraud Schemes in healthcare



- **Billing for services not rendered** (identity theft & phantom billing)
- **Up-coding of services and items**
- **Duplicate billing**
- **Un-bundling of claims** (or creative billing)
- **Medically unnecessary services** (bill padding)
- **Excessive services** (bill padding)
- **Kickbacks**

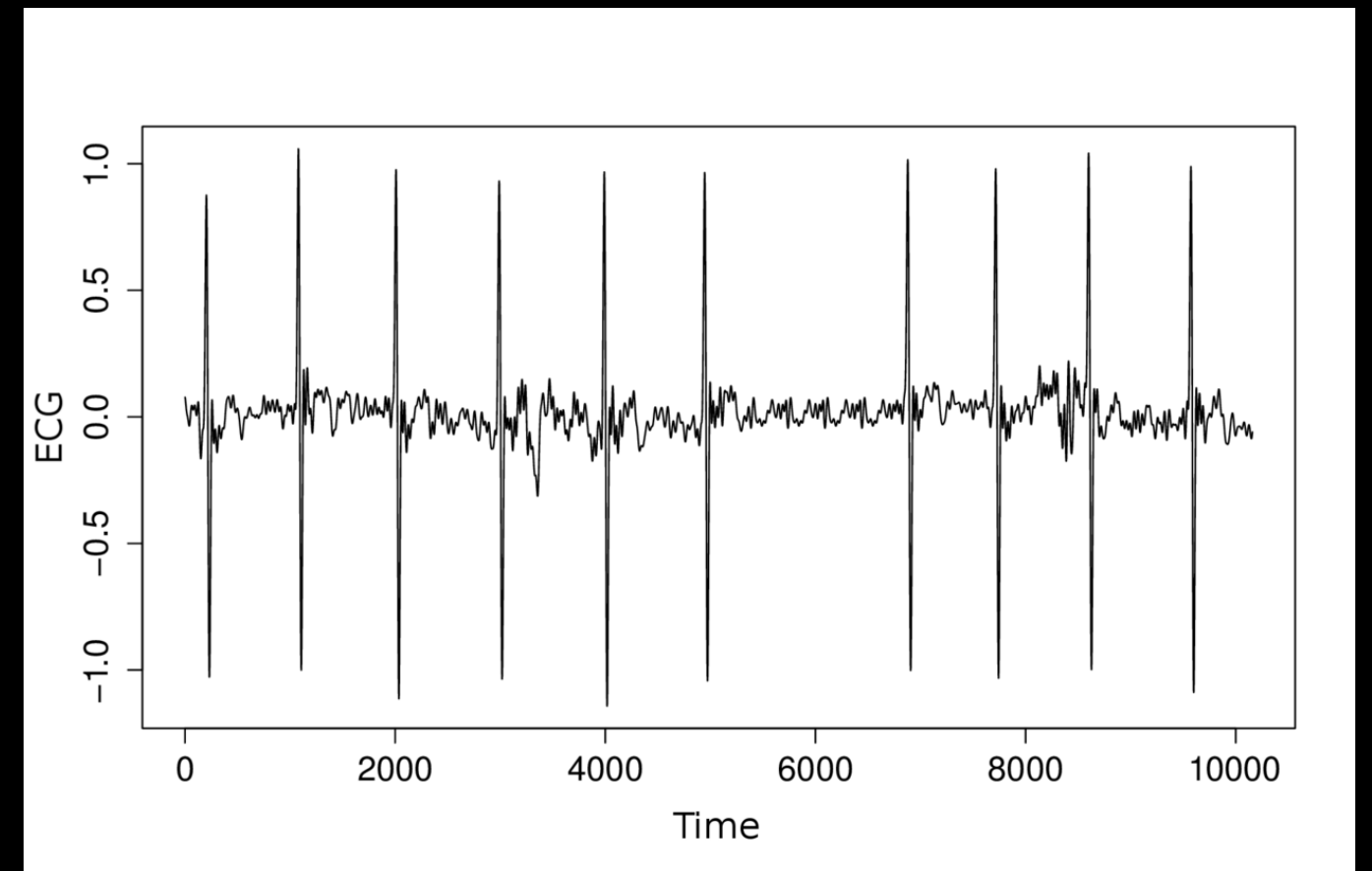
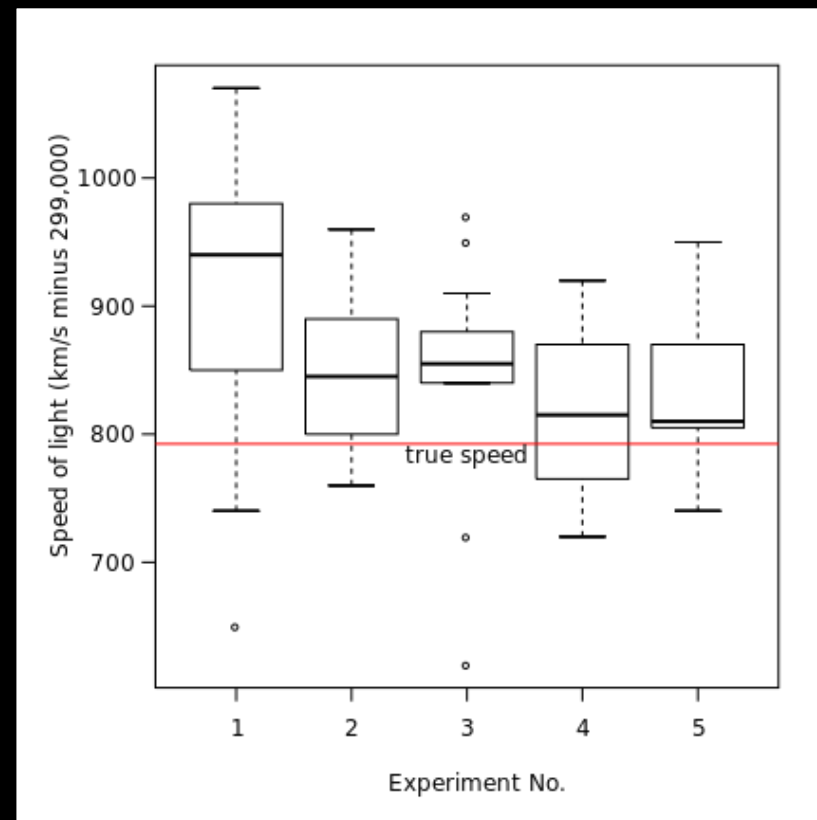
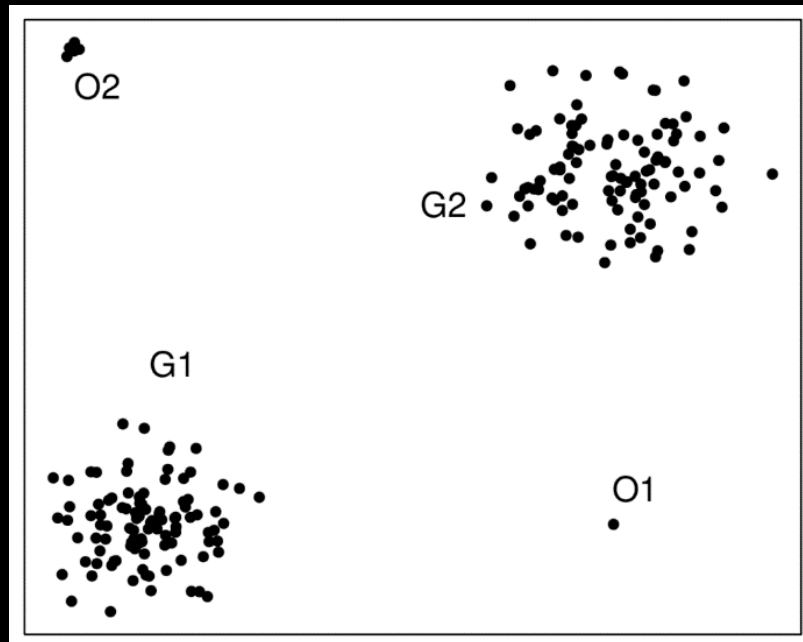
The healthcare data set



- Health insurance claim line dental data
- 30 providers from California (Medicaid insurance)
- Only data from 2016
- Cleaned (no null values, no messy data lines, values and reference are correct)
- Denormalized (no need for the reference tables)
- Adjusted (claim history already processed into the claim no., need to bind claims)
- Thus, minimal data wrangling

Outlier detection

- What is an outlier?
 - An outlier is an observation point that is distant from most of the other observations that group together or follow a pattern or distribution.



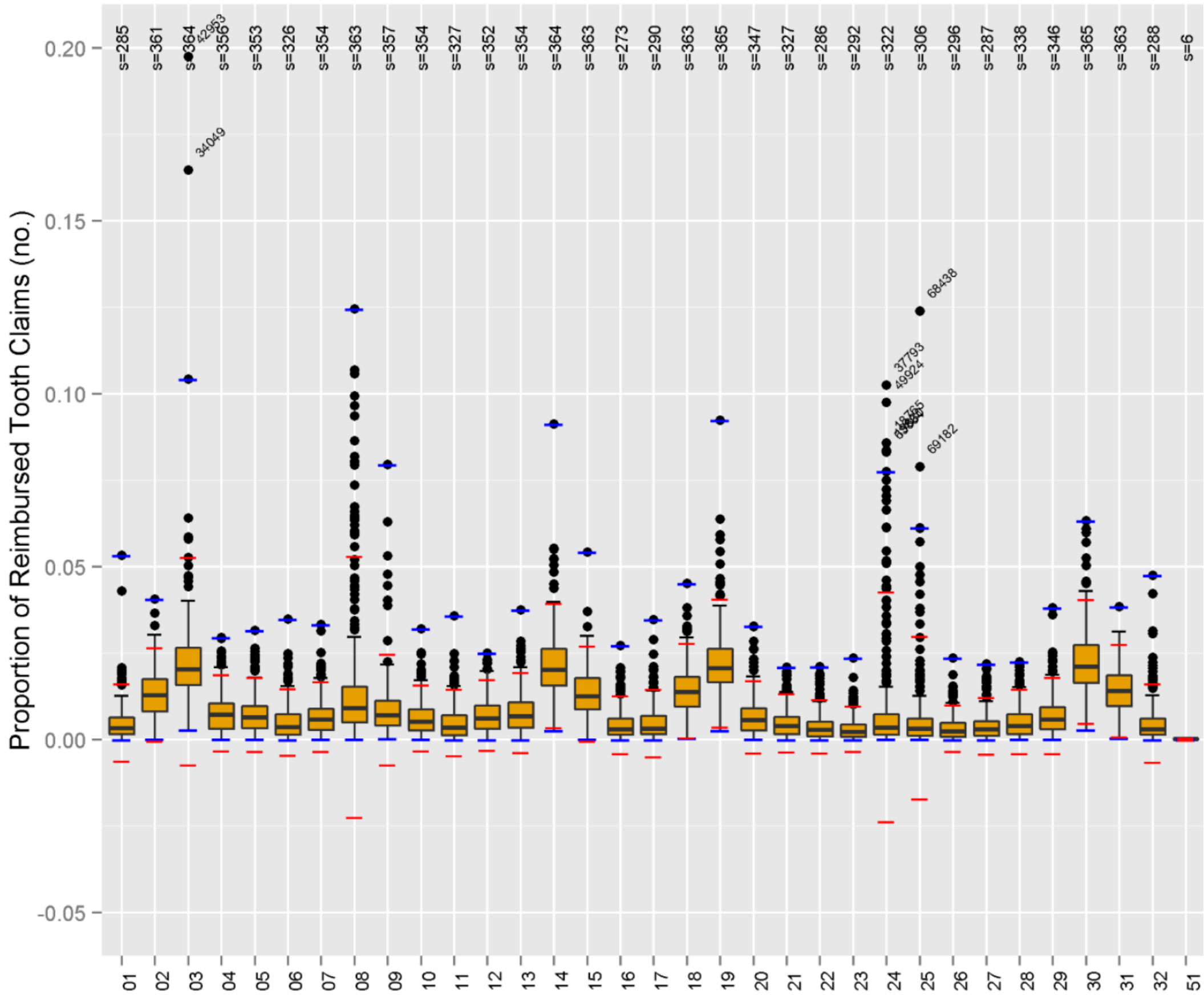
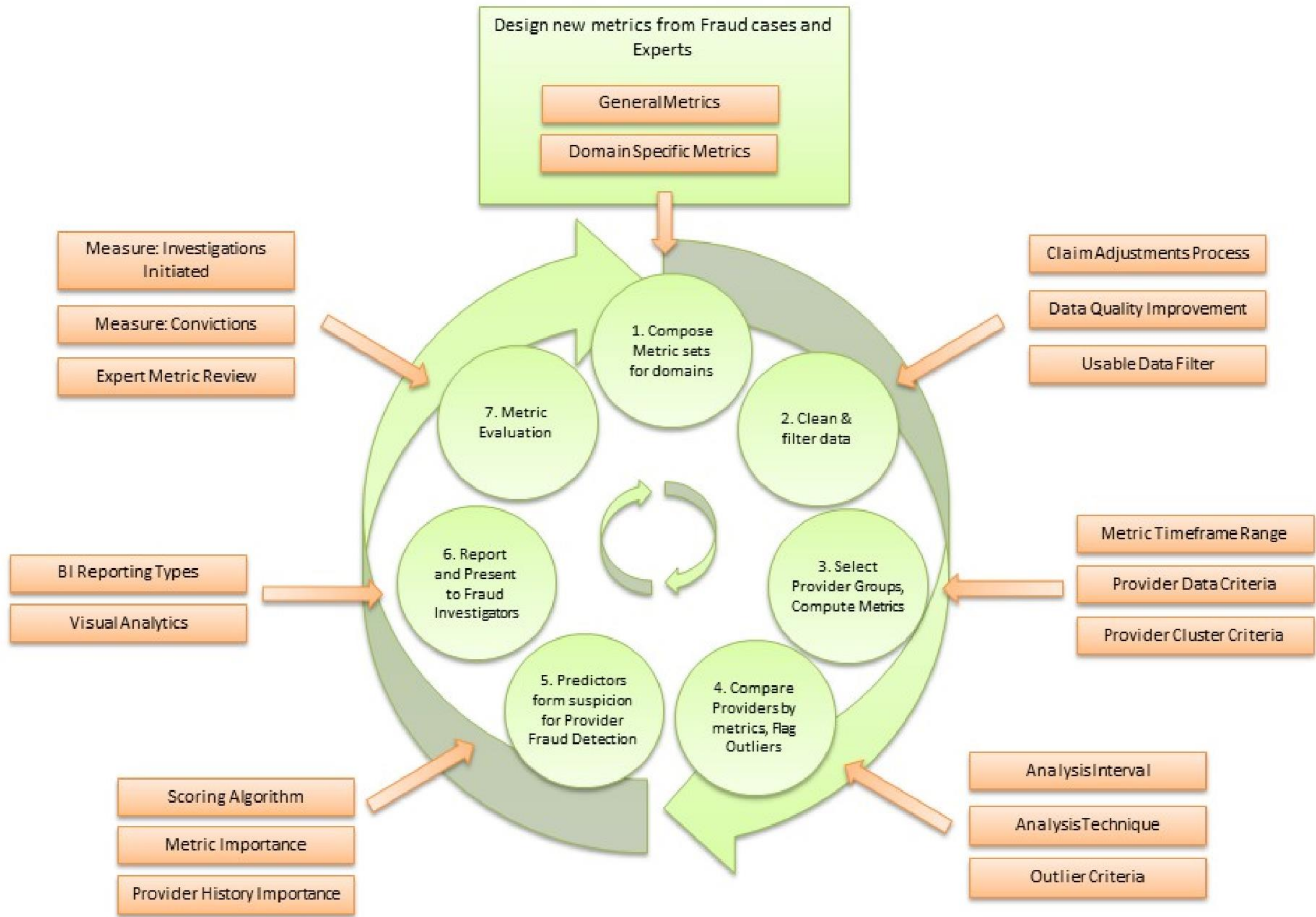
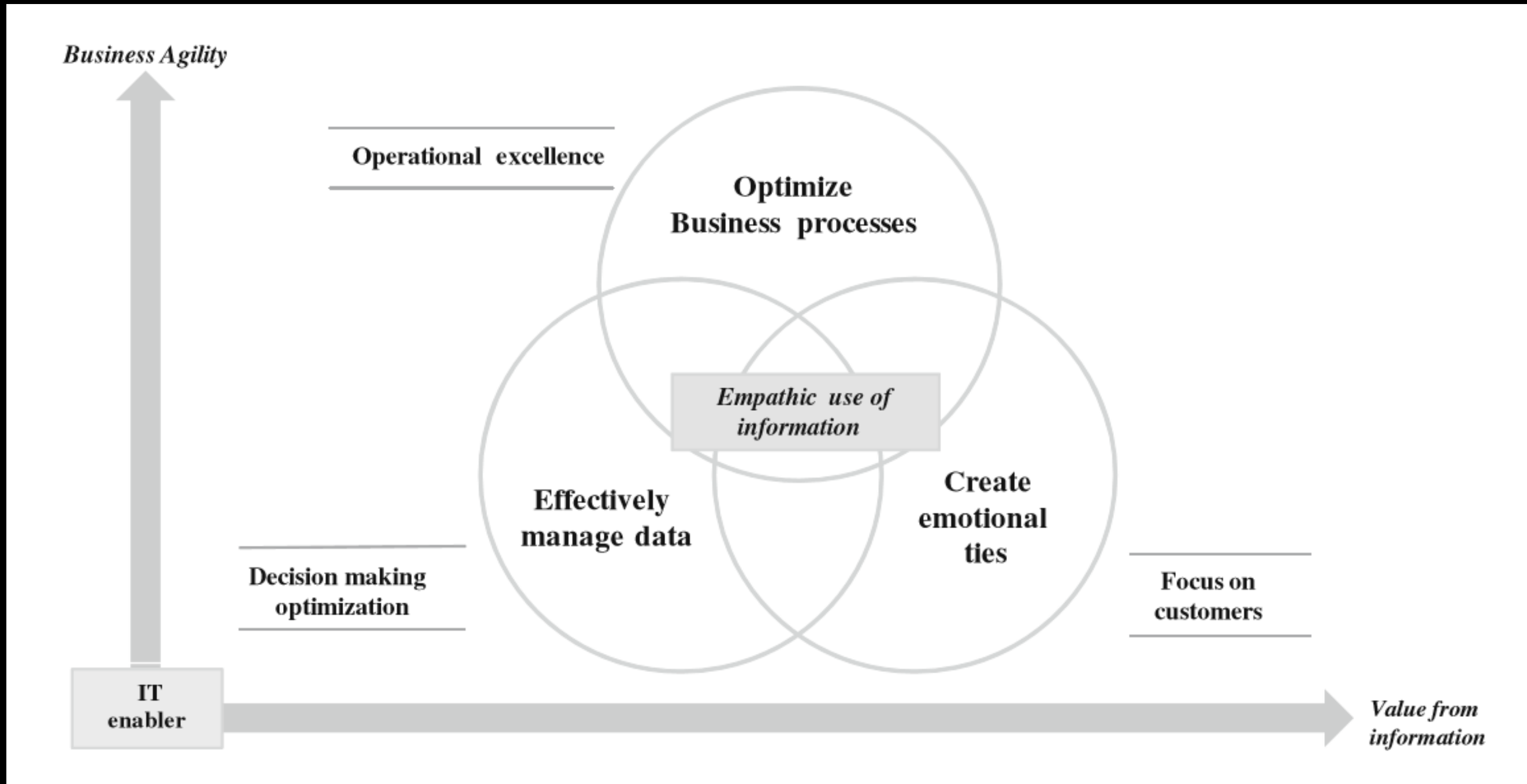


Fig. 3. Tooth Code Analysis



How to use big data?



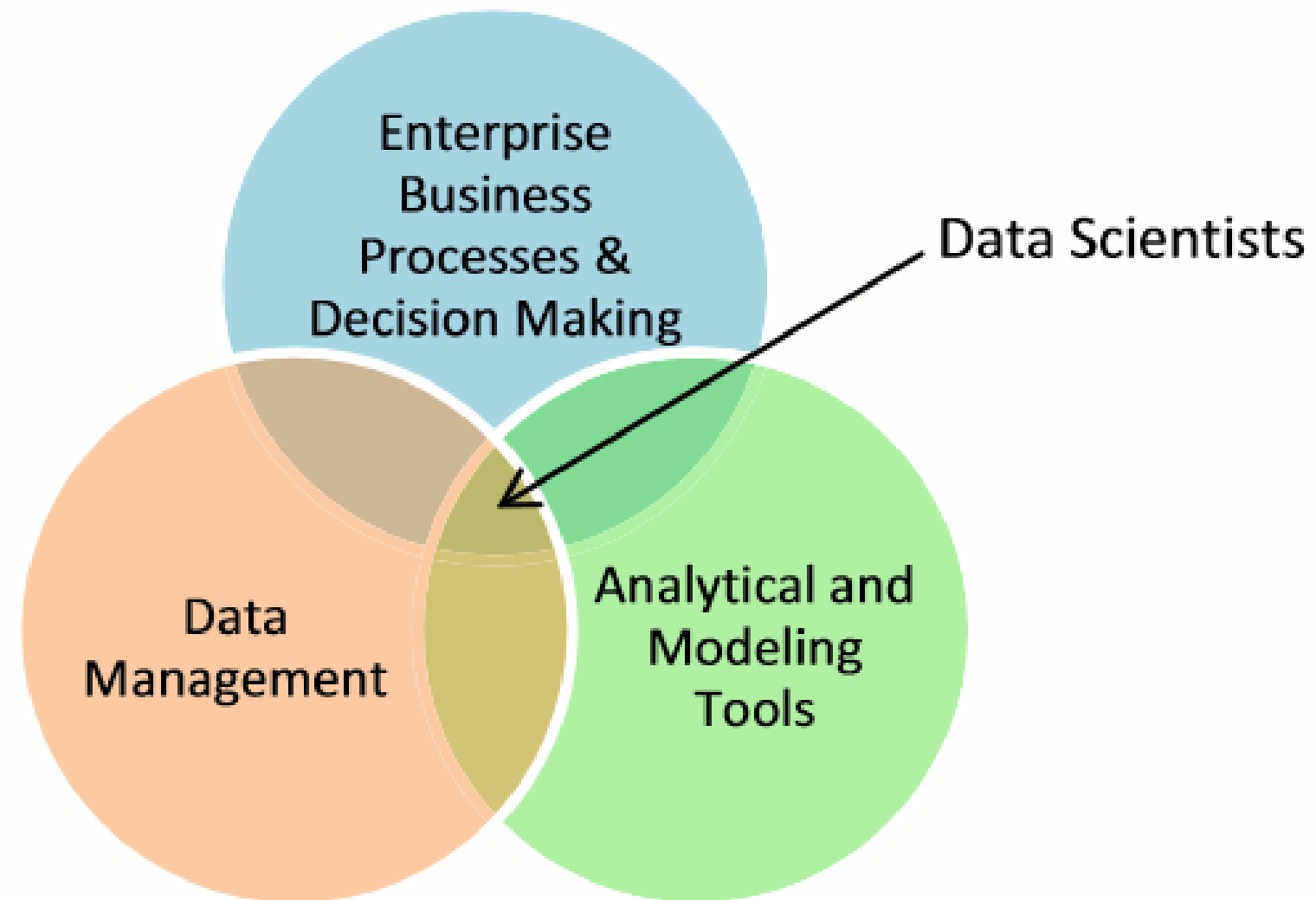
Source. Morabito, V. (2014). *Trends and challenges in digital business innovation*. New York: Springer International Publishing.

Tools for big data analytics just examples by no means a ranking!

- Preparation, Cleaning, Transforming, Wrangling
 - Alteryx, Trifacta, Paxata,...
 - Openrefine.org (open source)
- Analytics, Inference, Mining, Visualization
 - R, SAS, SPSS, Tableau, Qlick, PowerBI, Statistica, Knowledge Studio, Google FusionTables,..
 - knime.org (open source)
- Mining, AI
 - IBM Watson analytics, Wolfram Alpha
 - Rapidminer.com, Weka (open source)
 -

THE WAY FORWARD: SKILLS

Figure 2: Skill sets for data scientists.



Source: Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics*, 36(1), 120-132.

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[Learn more](#)



3. Analytics Techniques
(Explore, Explain, Predict)
..
..
..
..
..
..
..
..

1. Questions
(no overview, no insight, no foresight)
..

2. Owner
(Who wants to know?)
..
..
..
..
..
..

4. Data Sources
(internal, external, open)
..
..
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..
..
..
..

5. Changes needed
(people, process, organization)
..
..
..
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..

6. Challenges
(data availability and quality, skills, risks, regulation,,...)
..
..
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..

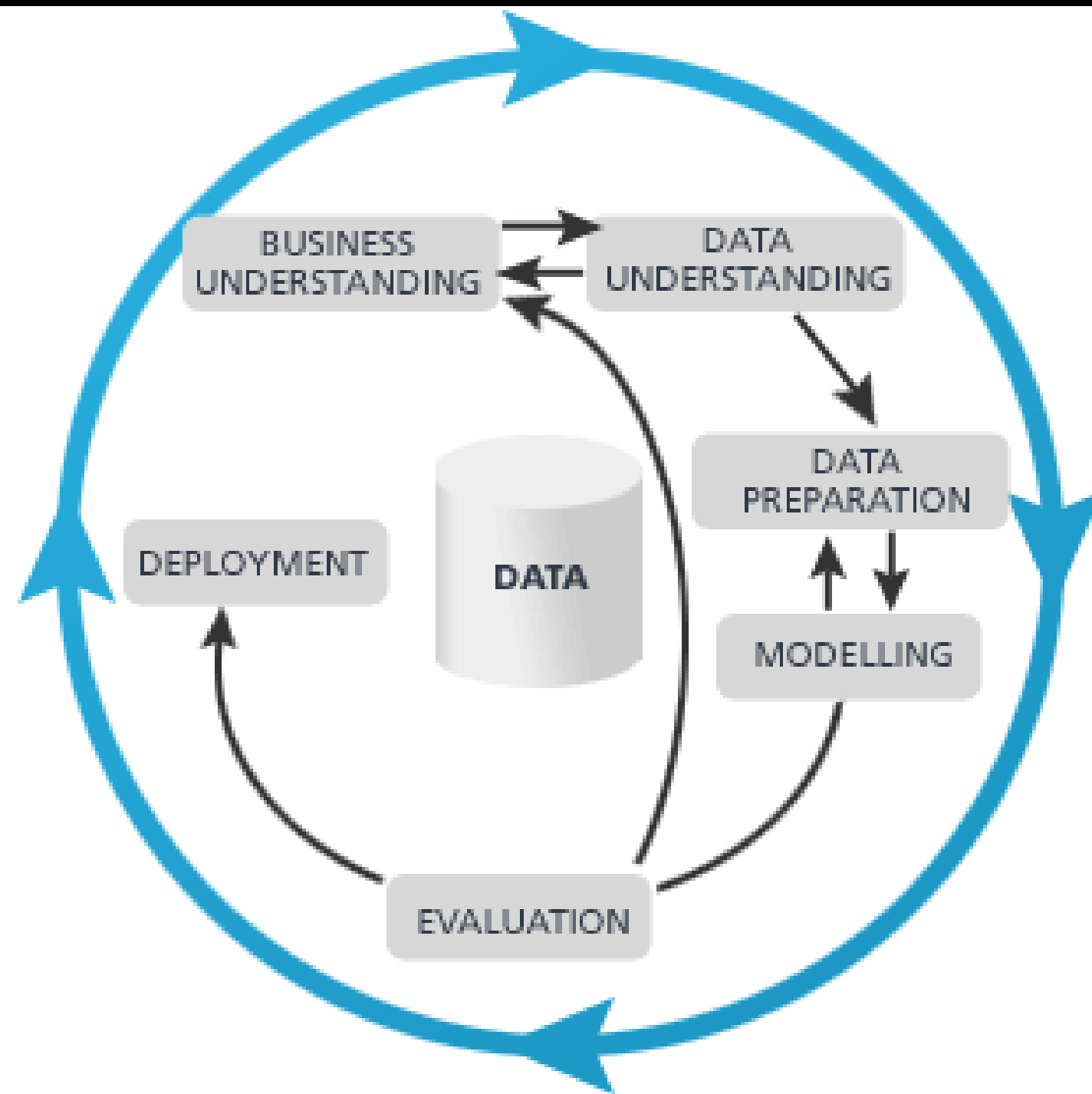
Version:

Organization:

Name:

Source: (Big data canvas J van Hillegersberg ©)

Summary and Questions



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