Visualization is Not Enough

Jeffrey Heer @jeffrey_heer
U. Washington / Trifacta

“We really are in another golden age of visualization.”

- Leland Wilkinson, *May 2019*

Where do the **driving ideas**
of our field come from?

2 MARKET SEE 1

2A PRODUCE !

2A1 ORANGES

2A2 APPLES

2A3 BANANAS

2A4 CARROTS

2A5 LETTUCE

2A6 BEANS

2B CANS

2B1 APPLE SAUCE

2B2 BEAN SOUP

2B3 TOMATO SOUP

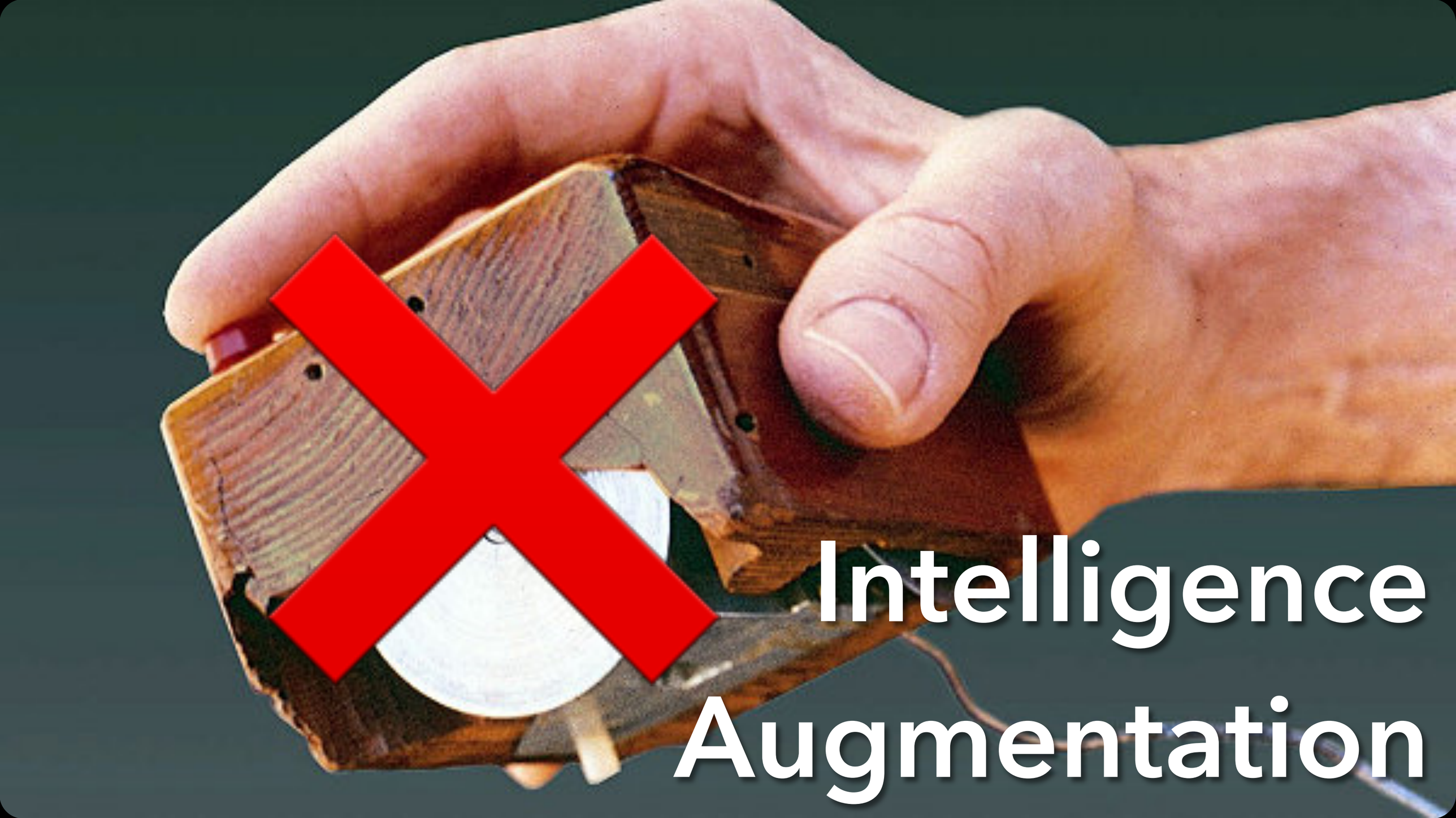
2C CEREALS

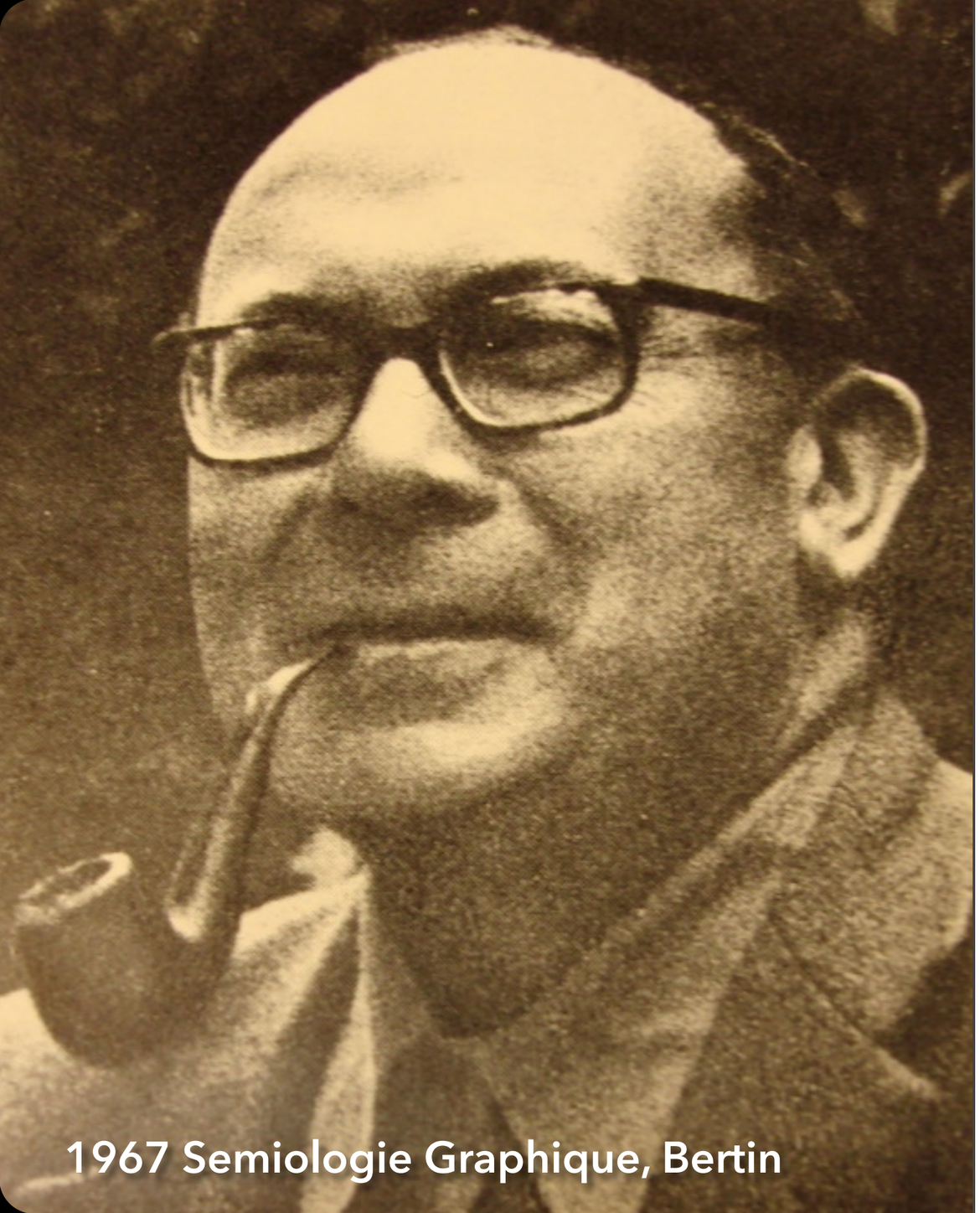
2C1 BREAD

2C2 NOODLES (ELBOW MI

2C3 FRENCH BREAD

1968 Engelbart, Intelligence Augmentation


Intelligence
Augmentation



1967 Semiologie Graphique, Bertin

LES VARIABLES DE L'IMAGE

POINTS LIGNES ZONES

XY
2 DIMENSIONS
DU PLAN

Z

TAILLE

VALEUR

LES VARIABLES DE SÉPARATION DES IMAGES

GRAIN

COULEUR

ORIENTATION

FORME


1966 Tukey & Wilk, Data Analysis & Statistics

Four major influences act on data analysis today:

1. The formal theories of statistics.
2. Accelerating developments in computers and display devices.
3. The challenge, in many fields, of more and larger bodies of data.
4. The emphasis on quantification in a wider variety of disciplines.

1966 Tukey & Wilk, Data Analysis & Statistics

While some of the influences of statistical theory on data analysis have been helpful, others have not.

1966 Tukey & Wilk, Data Analysis & Statistics

Exposure, the effective laying open of the data to **display the unanticipated**, is to us a major portion of data analysis…

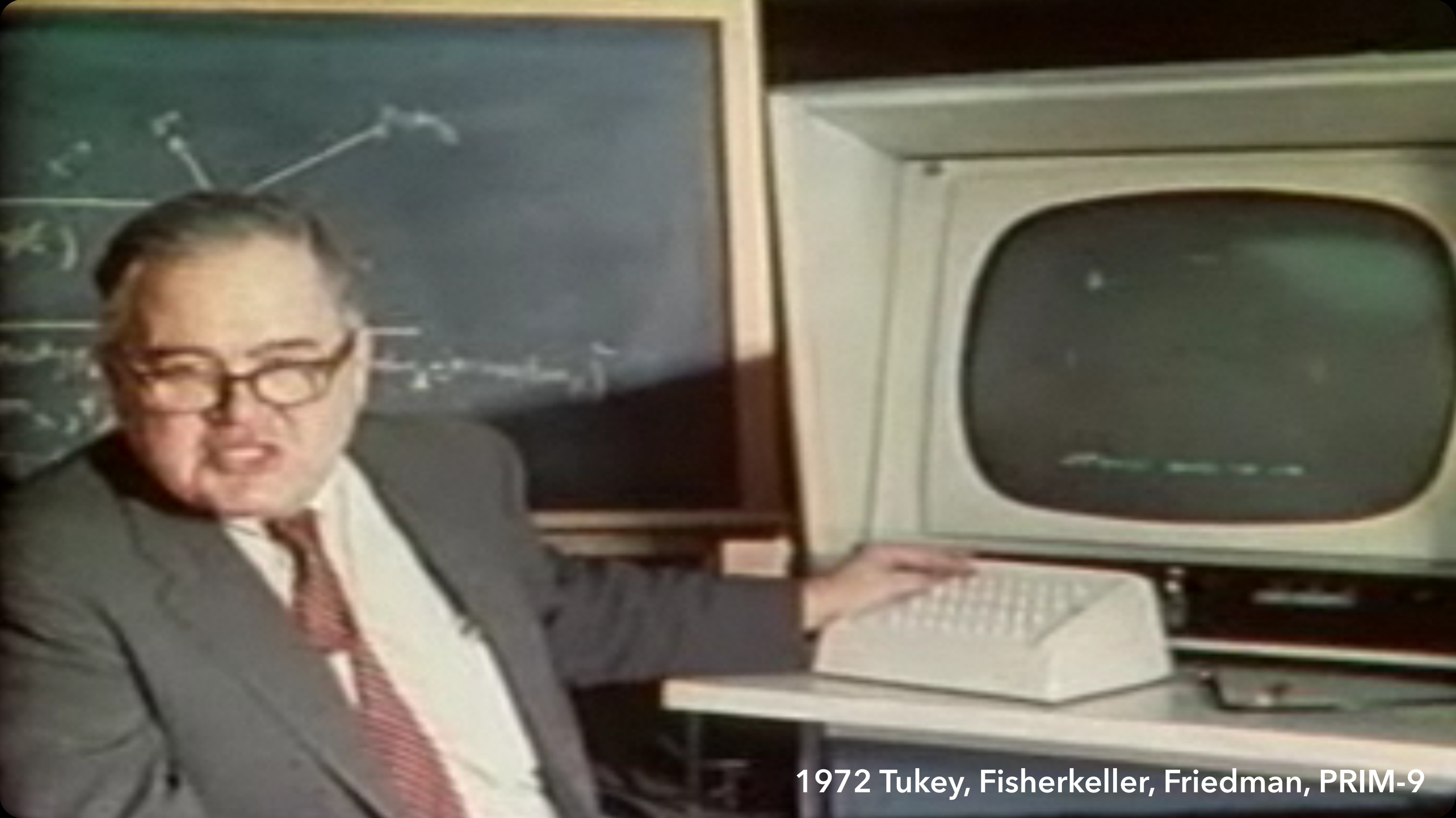
It is not clear how the **informality** and **flexibility** appropriate to the **exploratory character** of exposure can be fitted into any of the structures of formal statistics so far proposed.

1966 Tukey & Wilk, Data Analysis & Statistics

Accordingly, both approaches and techniques need to be structured so as to **facilitate human involvement and intervention**.

Some implications for effective analysis are: (1) it is essential to have convenience of **interaction of people and intermediate results** and (2) at all stages of data analysis, the outputs need to be **matched to the capabilities of the people who use it and want it.**

1966 Tukey & Wilk, Data Analysis & Statistics



1972 Tukey, Fisherkeller, Friedman, PRIM-9

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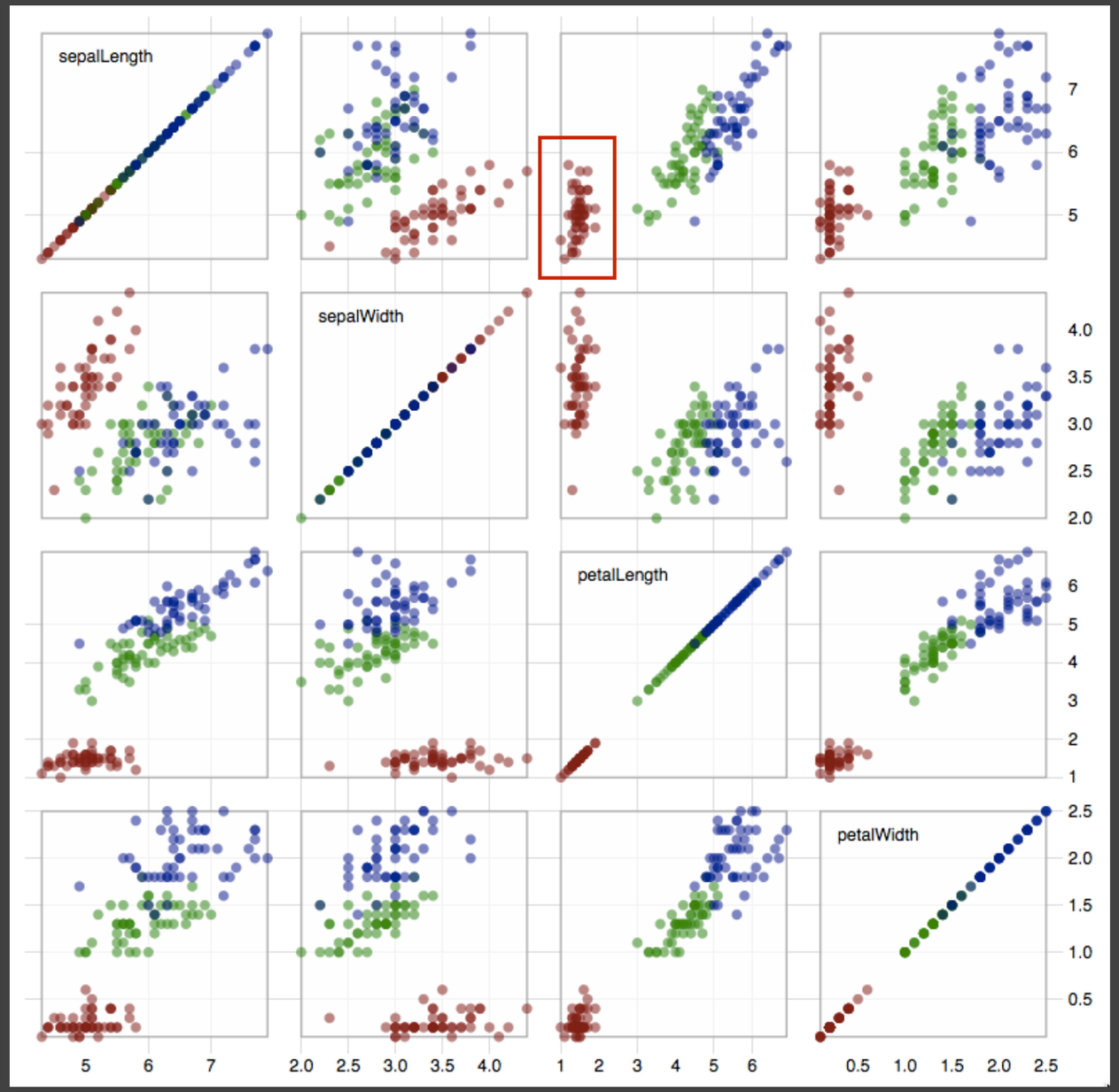
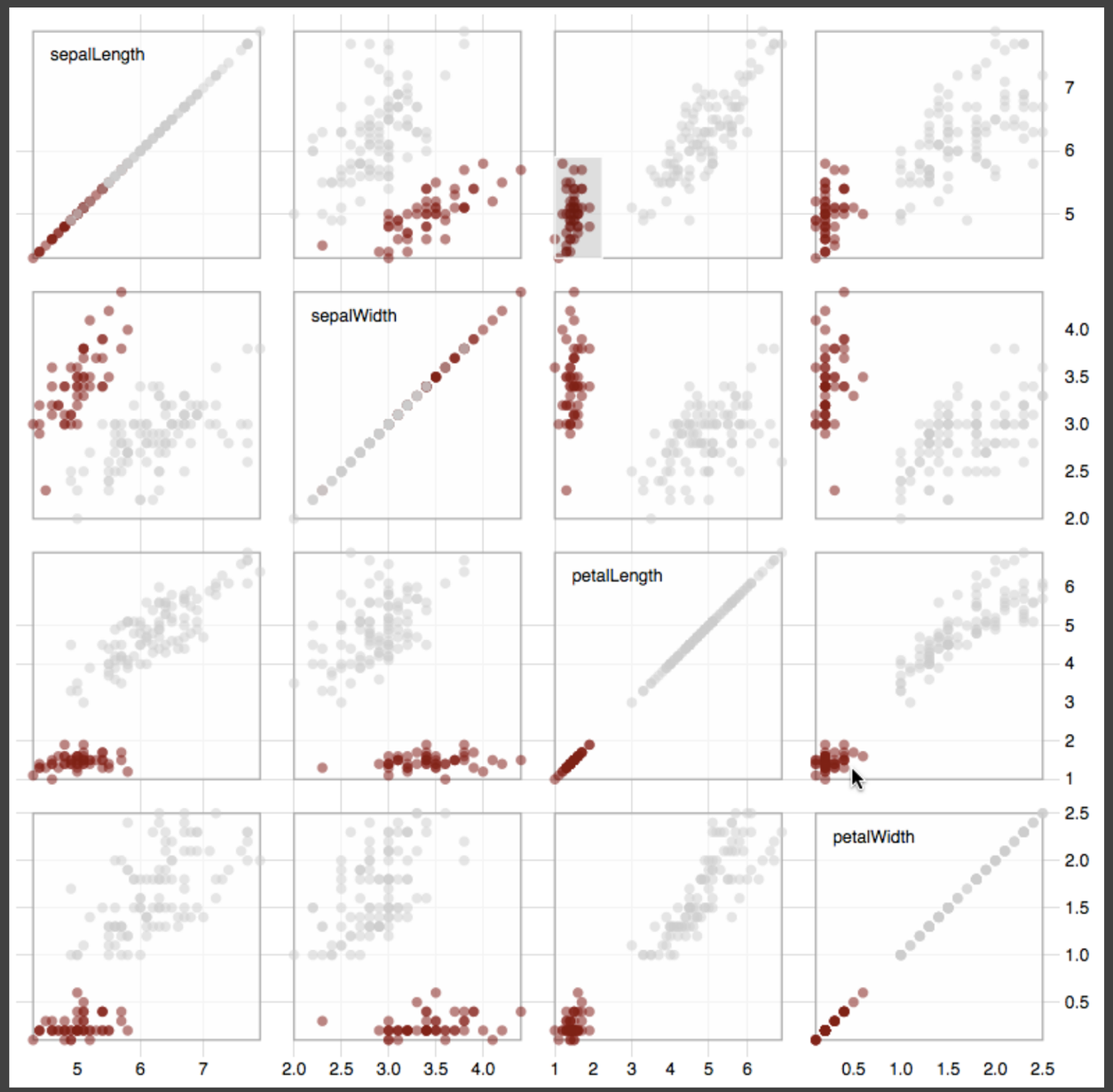




1987 Becker & Cleveland, Brushing Scatterplots

Cartography →

Graphic Design →

Statistics →

Psychology →

Comp Sci →

Vis

CONJECTURE: The most important contributions of our field arise from **interdisciplinary synthesis**.

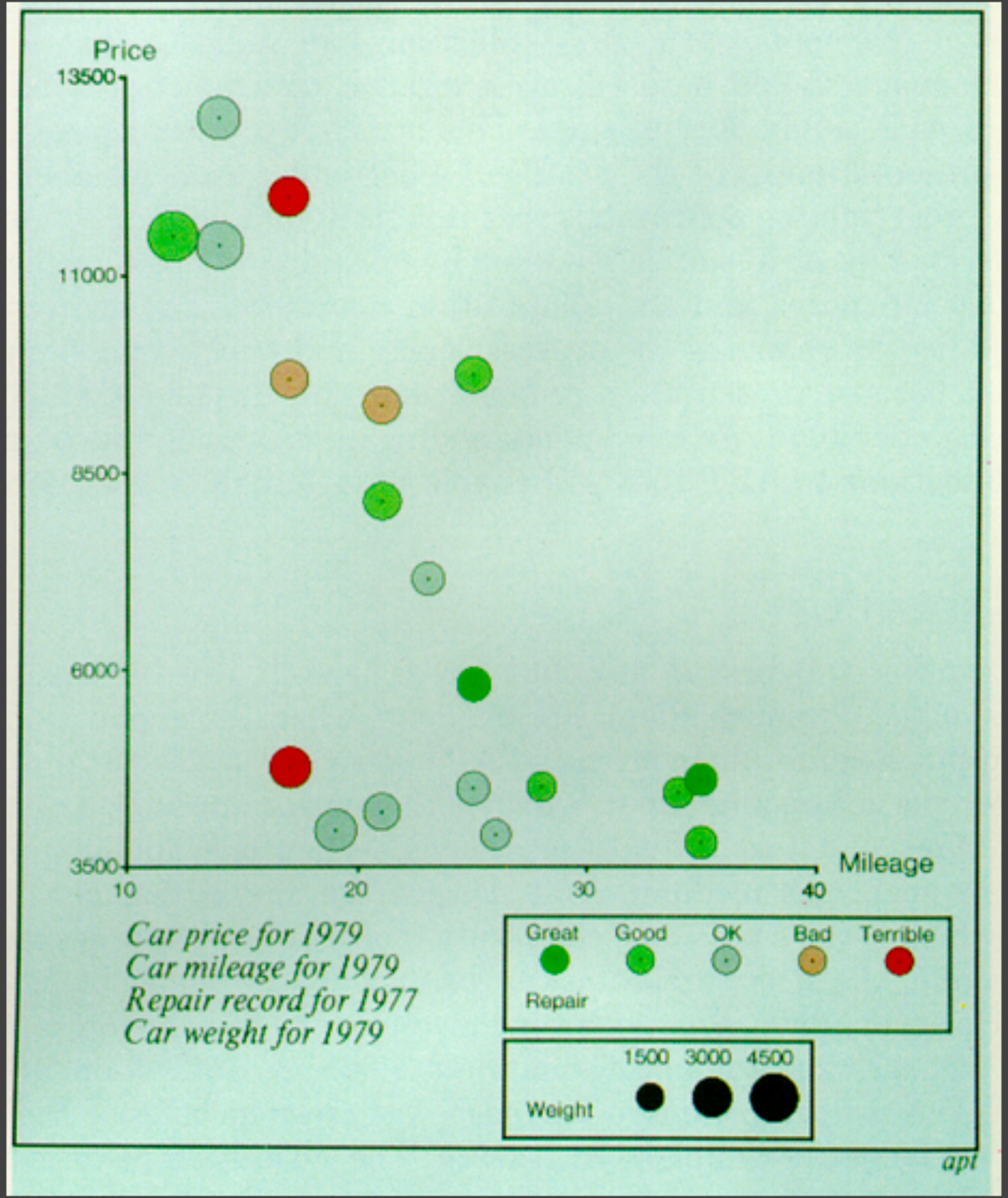
EXAMPLE:
Visualization Systems

APT: A Presentation Tool

Mackinlay's 1986 PhD Thesis on **automatic chart design**.

Input Data:
Cars dataset

Priority-Ordered Input Variables:
1. Price
2. Mileage
3. Repair
4. Weight

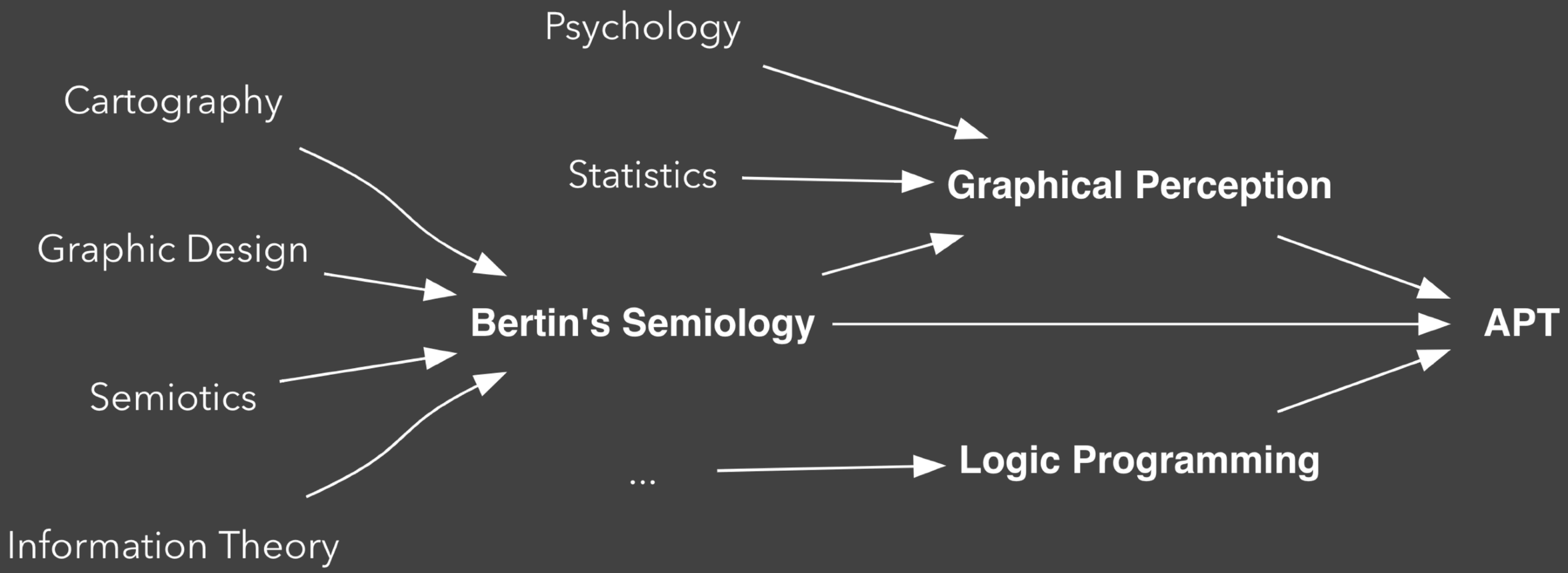


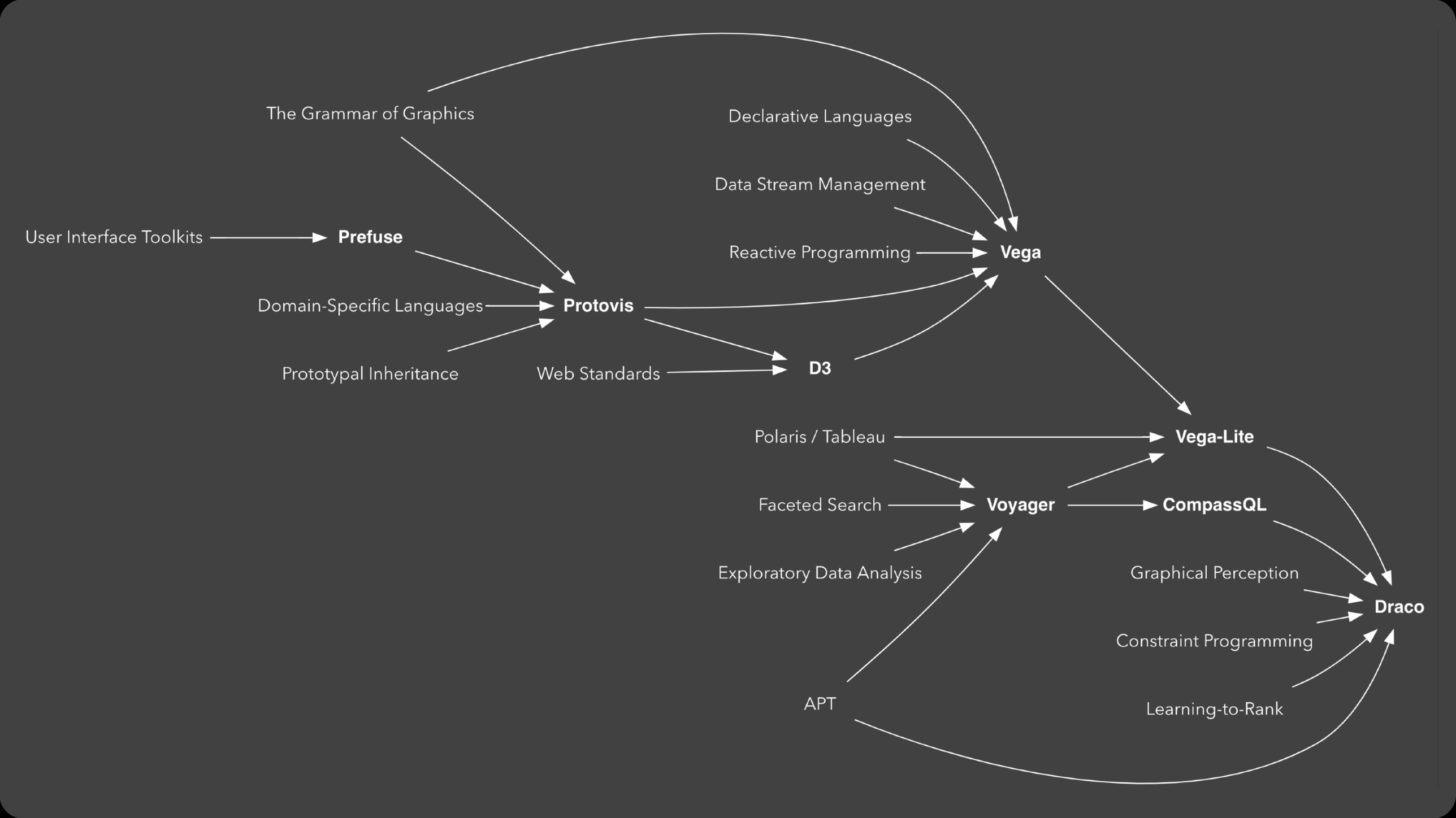
Bertin's Semiology →

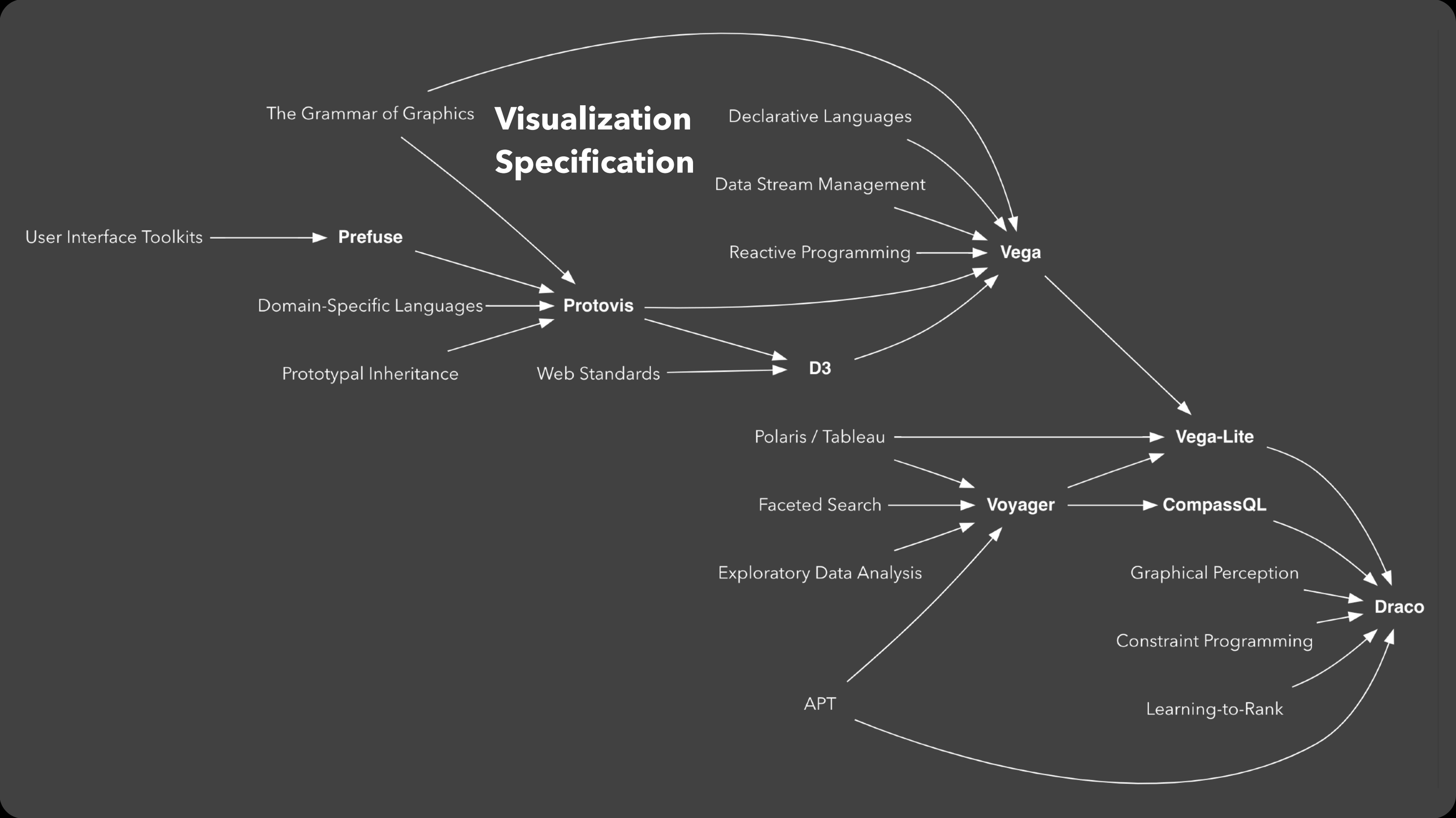
Graphical Perception →

Logic Programming →

APT


Psychology
Cartography
Statistics
Graphical Perception
Graphic Design
Bertin's Semiology
APT
Semiotics
...
Logic Programming
Information Theory


The Grammar of Graphics
Declarative Languages
Data Stream Management
User Interface Toolkits
Prefuse
Reactive Programming
Vega
Domain-Specific Languages
Protovis
Prototypal Inheritance
Web Standards
D3
Polaris / Tableau
Vega-Lite
Faceted Search
Voyager
CompassQL
Exploratory Data Analysis
Graphical Perception
Draco
Constraint Programming
APT
Learning-to-Rank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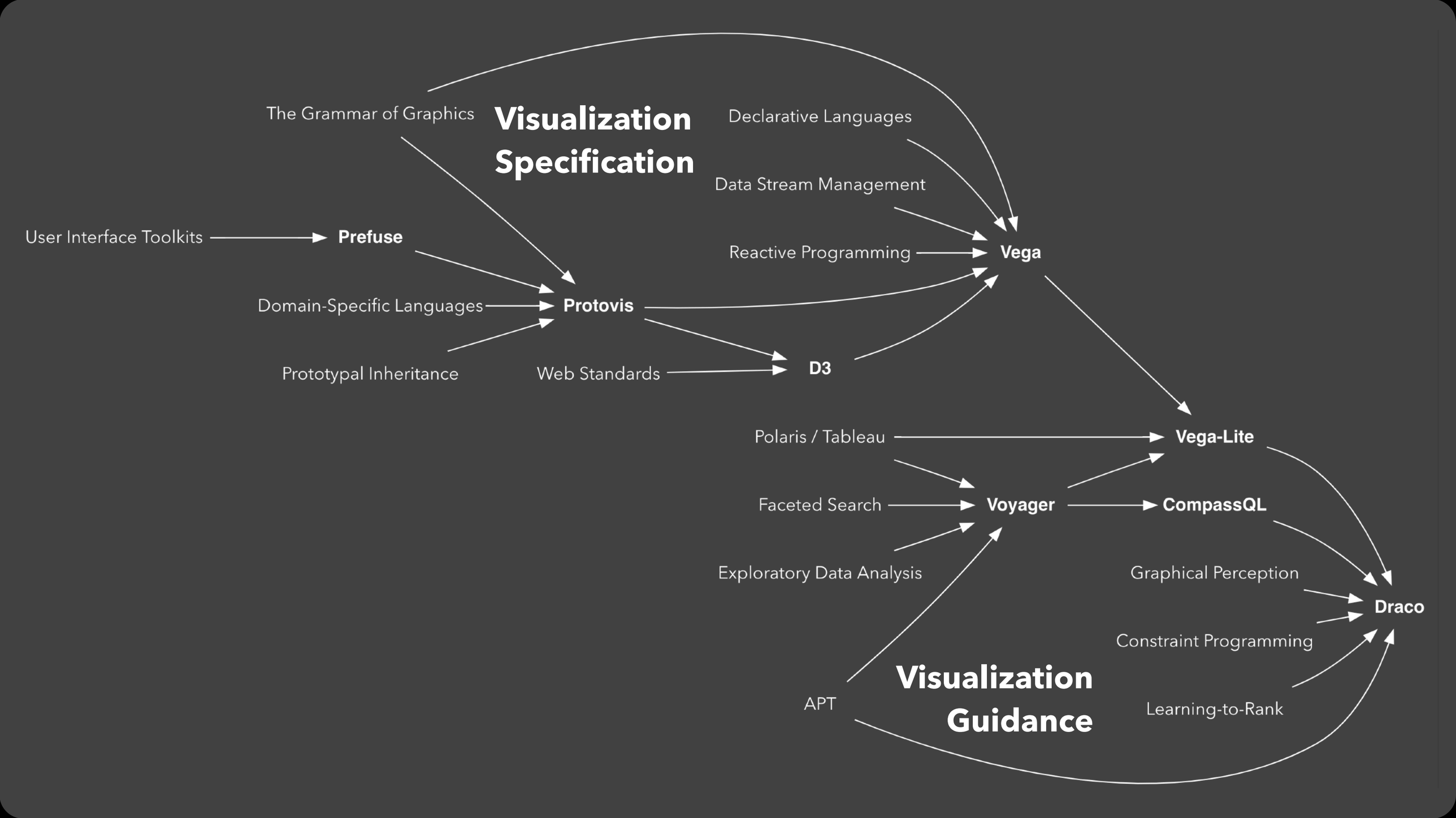
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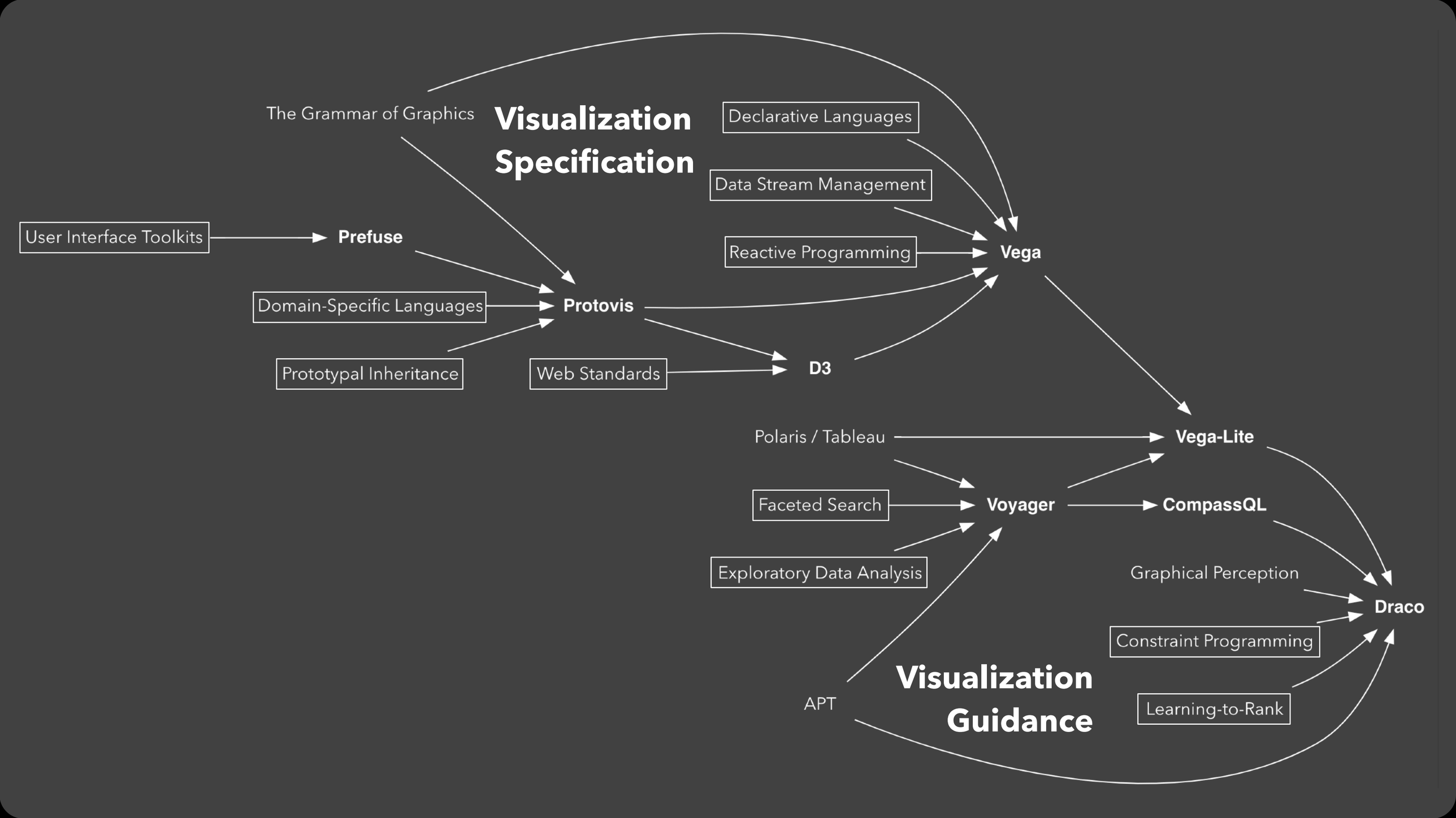
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CONJECTURE: The most important contributions of our field arise from **interdisciplinary synthesis**.

COROLLARY: The practice of **principled interdisciplinary thinking** is our greatest asset.

Cartography →

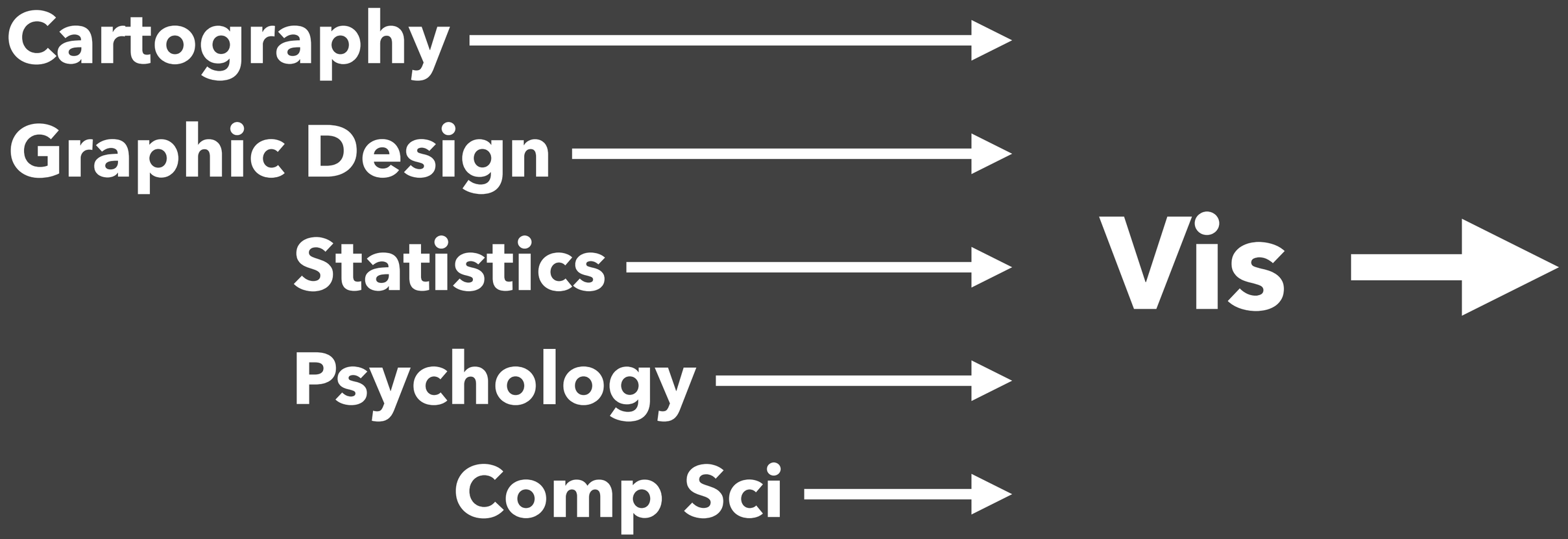
Graphic Design →

Statistics →

Psychology →

Comp Sci →

Vis


Cartography
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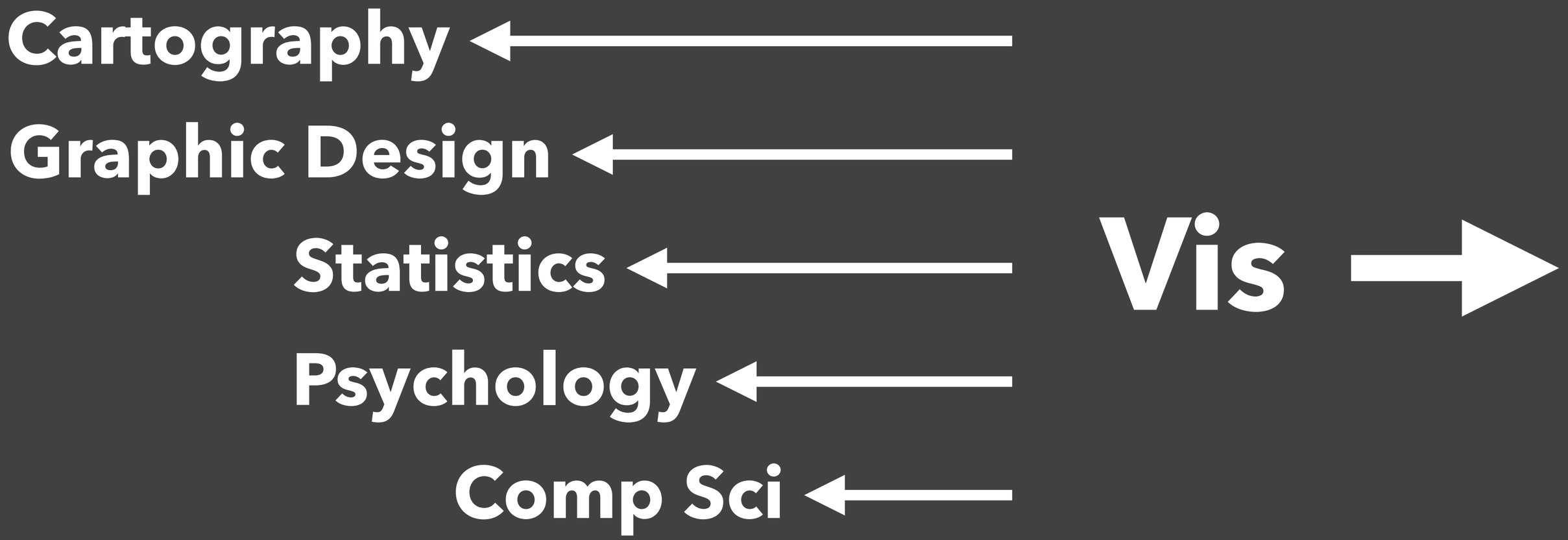
Psychology
Comp Sci
Vis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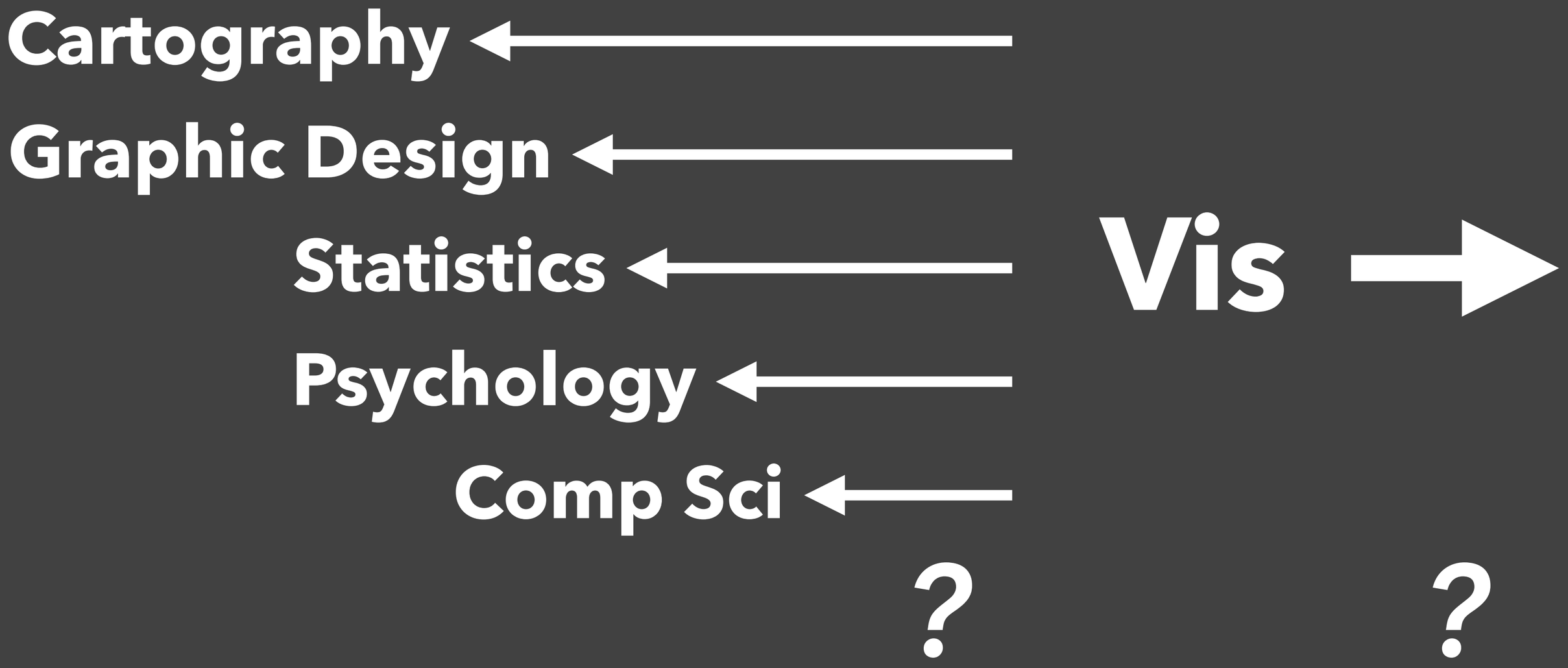
Cartography
Graphic Design
Statistics
Psychology
Comp Sci
Vis
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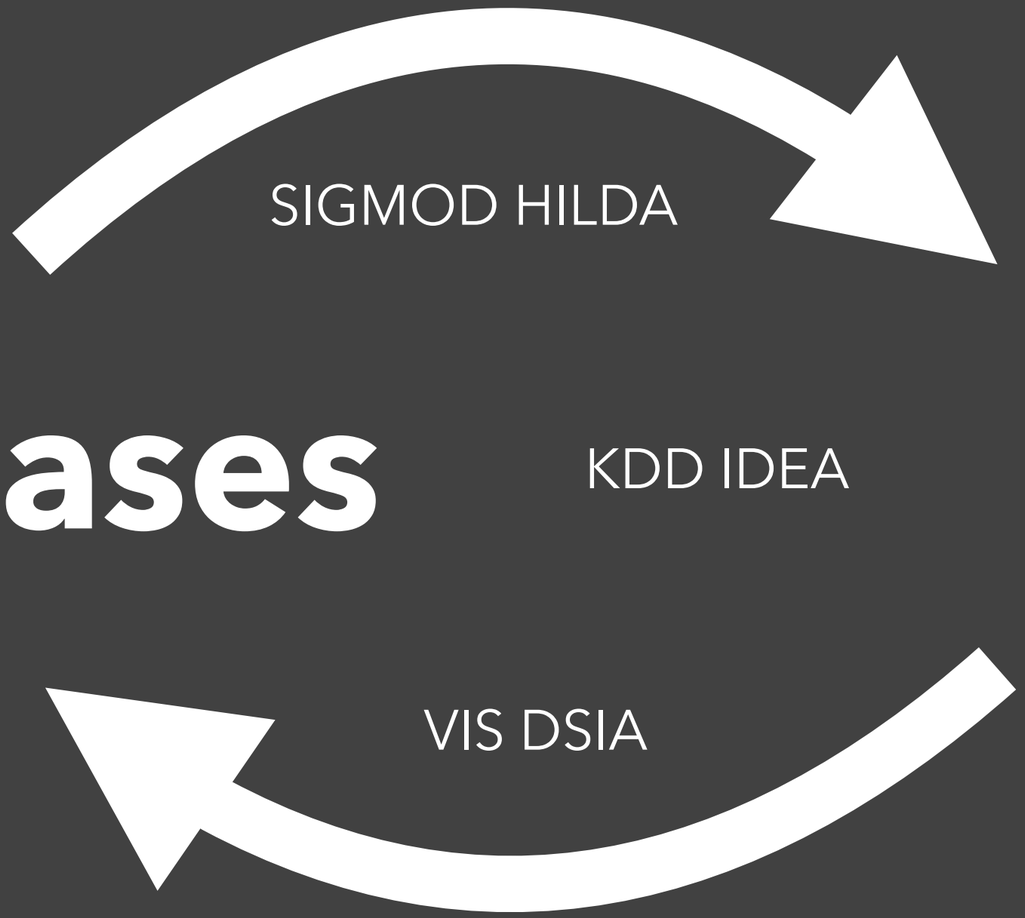
Indexing, Data Cubes, Query Optimization

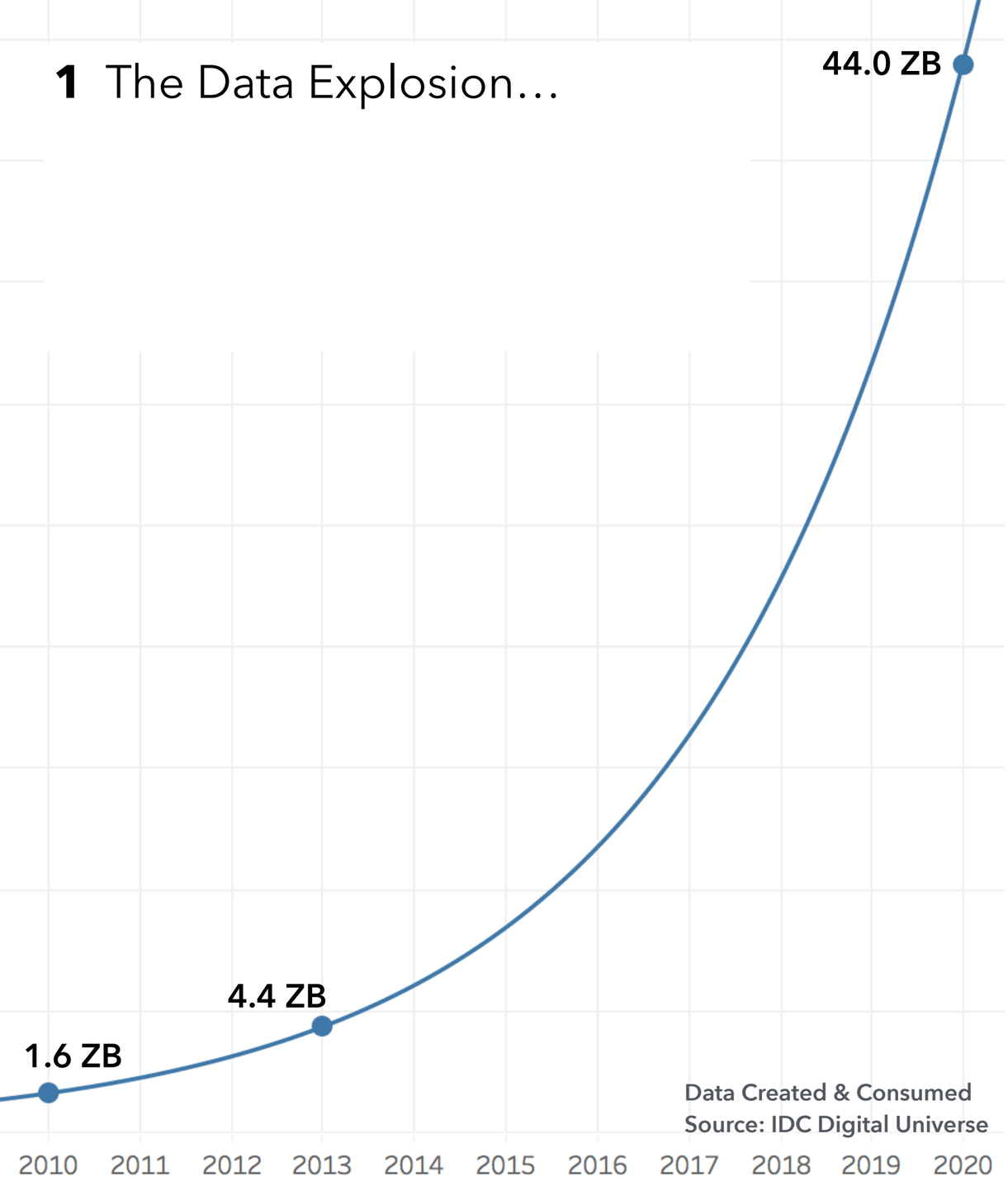
New Requirements, Interaction Models, Prefetching Approaches

Indexing, Data Cubes, Query Optimization



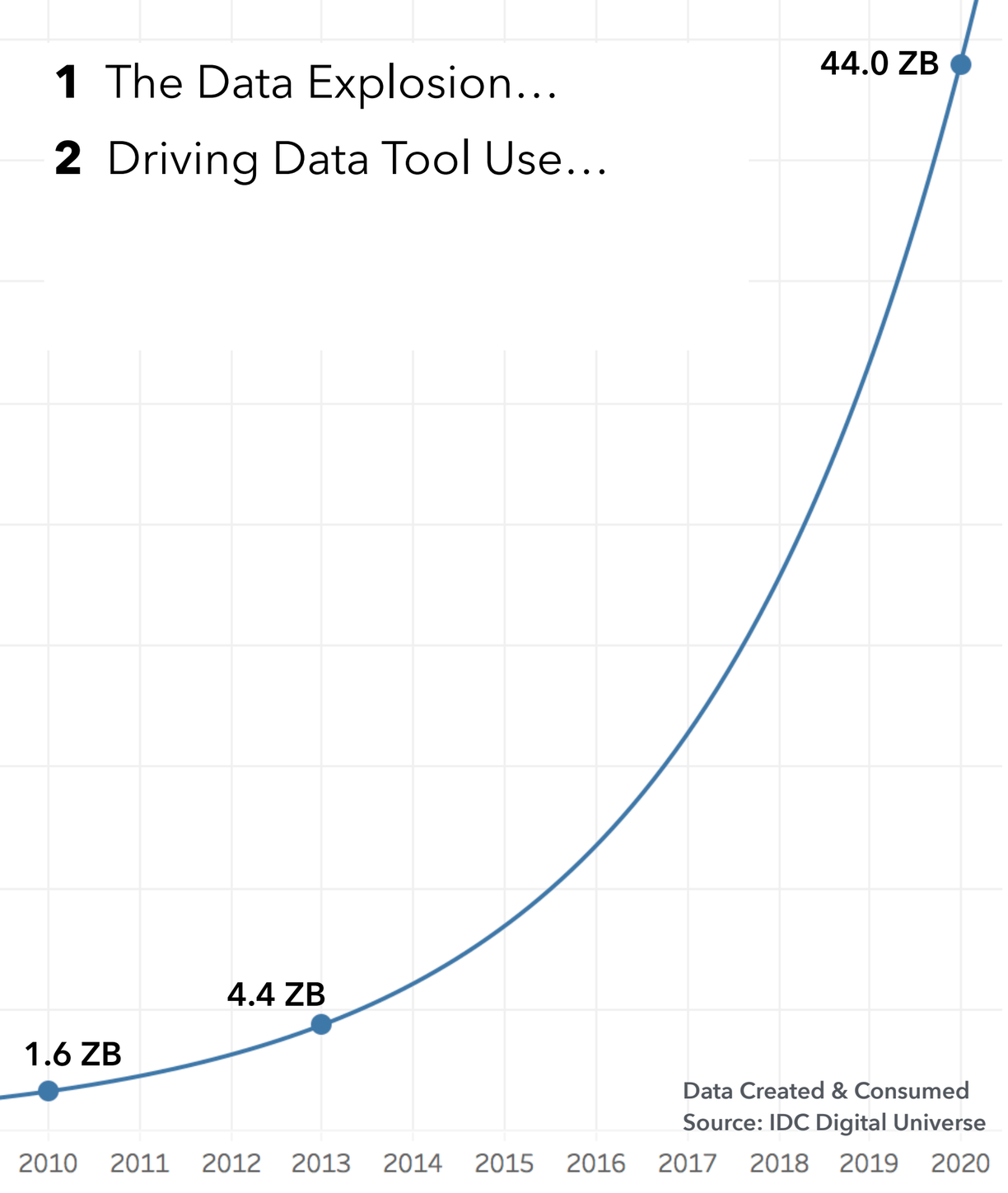
New Requirements, Interaction Models, Prefetching Approaches

1 The Data Explosion…

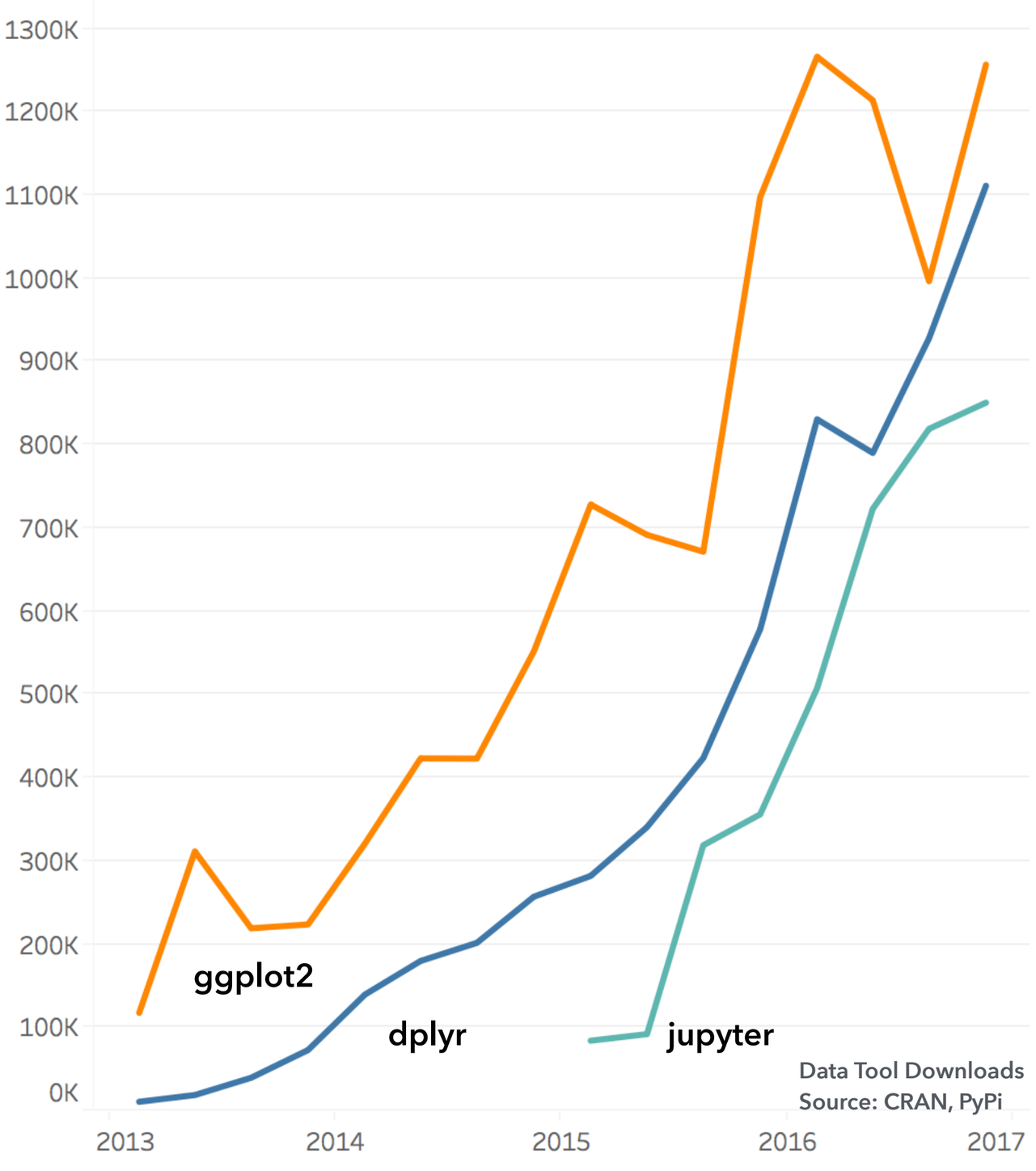


1 The Data Explosion…

2 Driving Data Tool Use…



Data Created & Consumed
Source: IDC Digital Universe



Data Tool Downloads
Source: CRAN, PyPi

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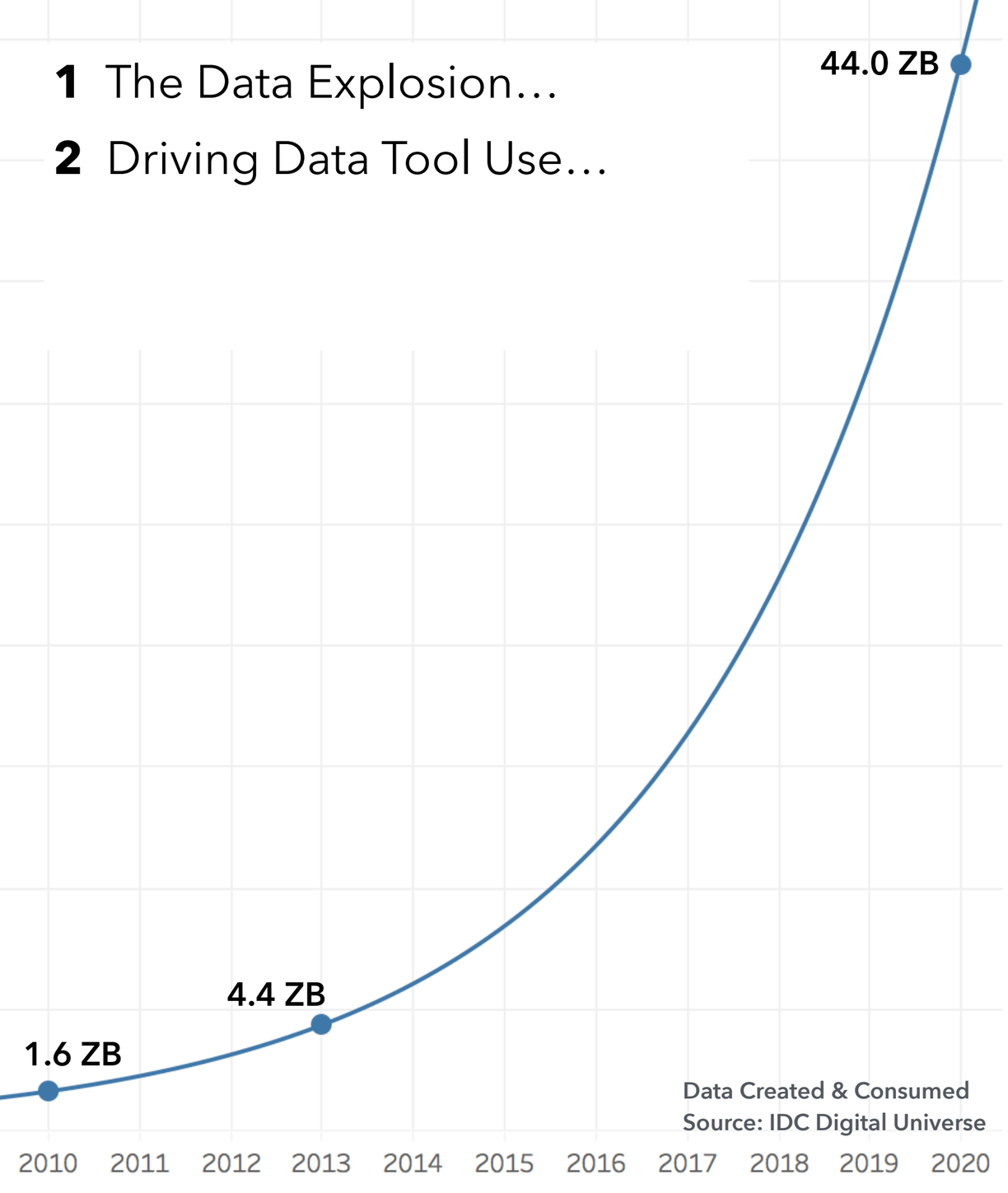
2 Driving Data Tool Use…



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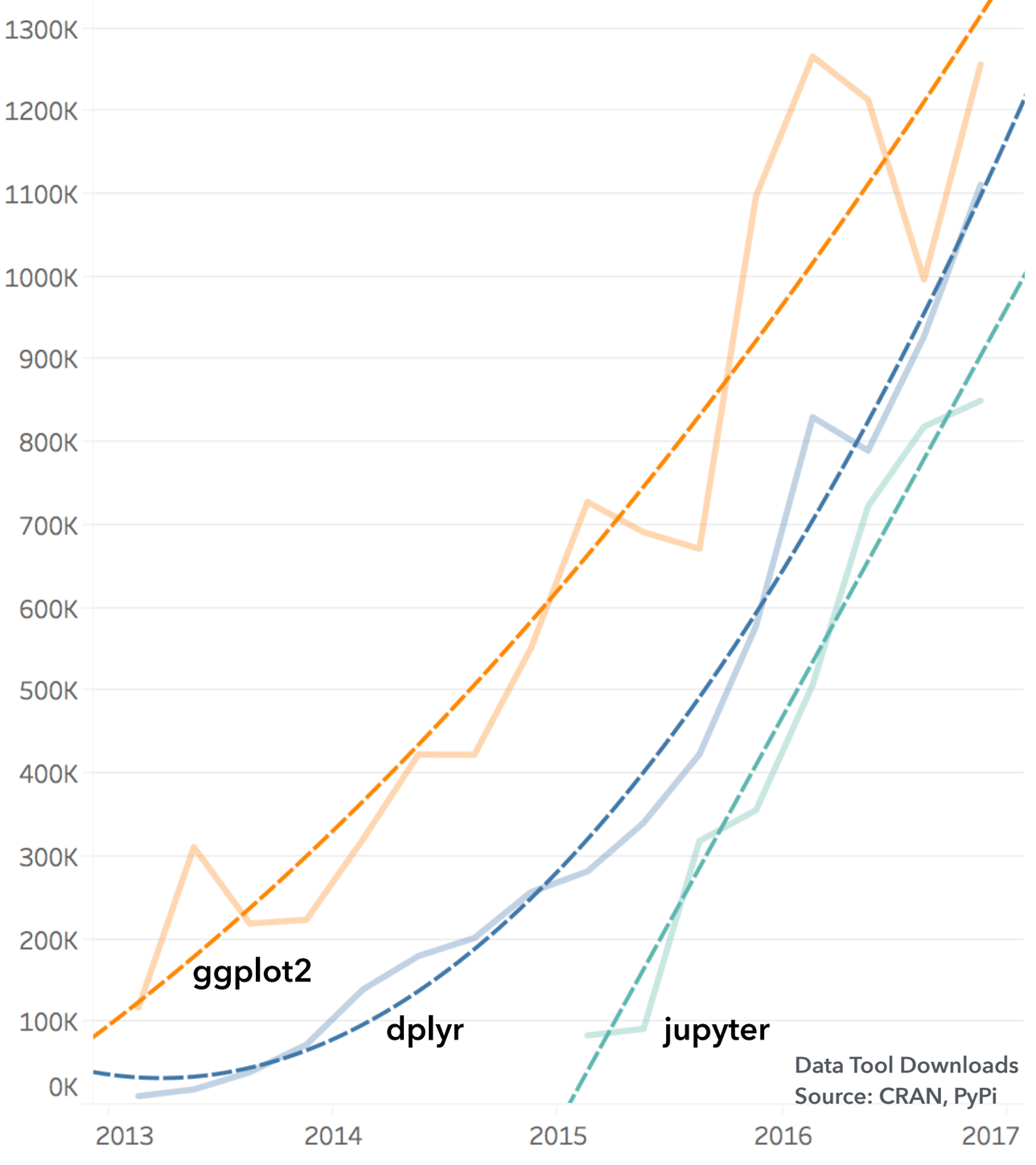

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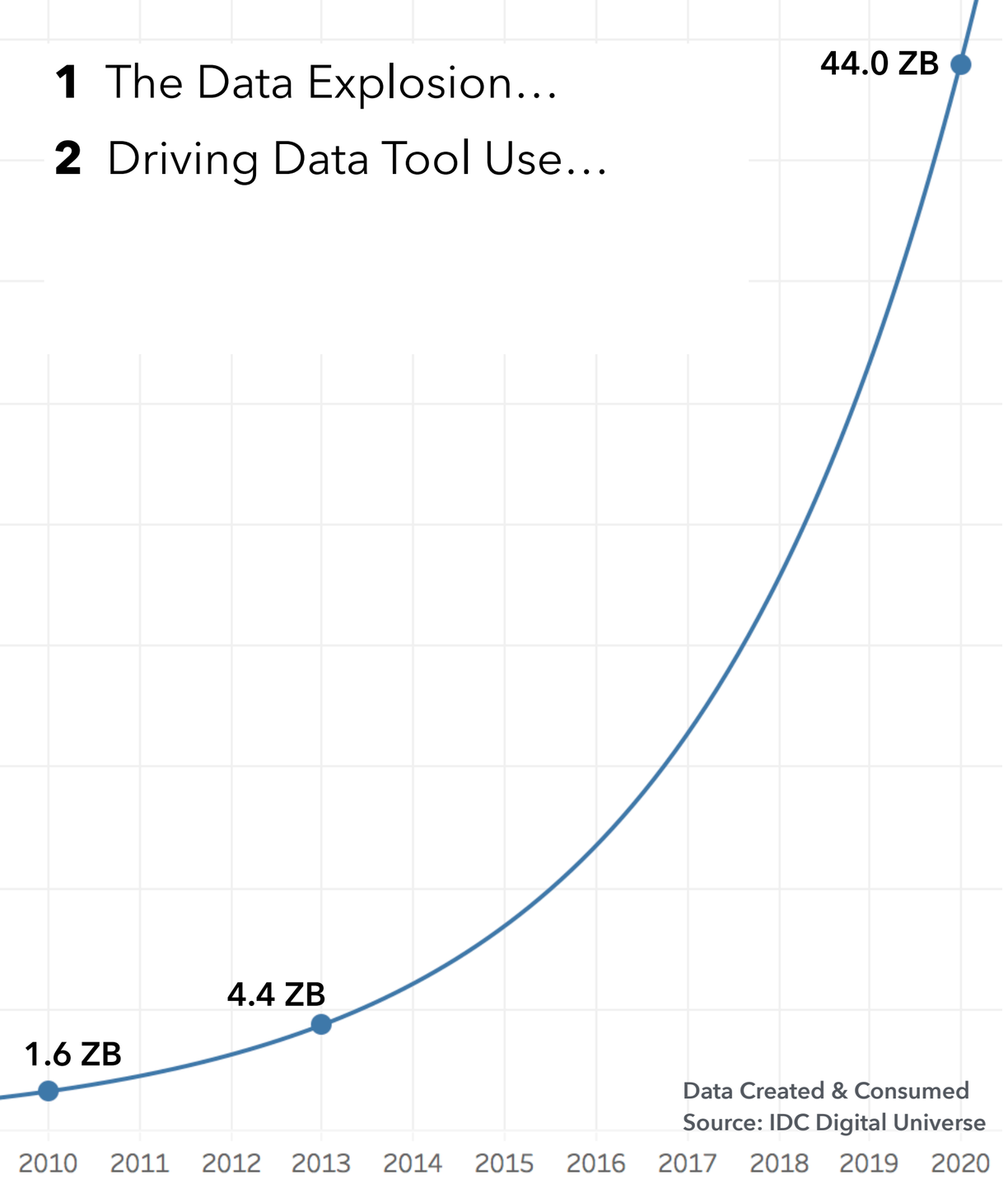

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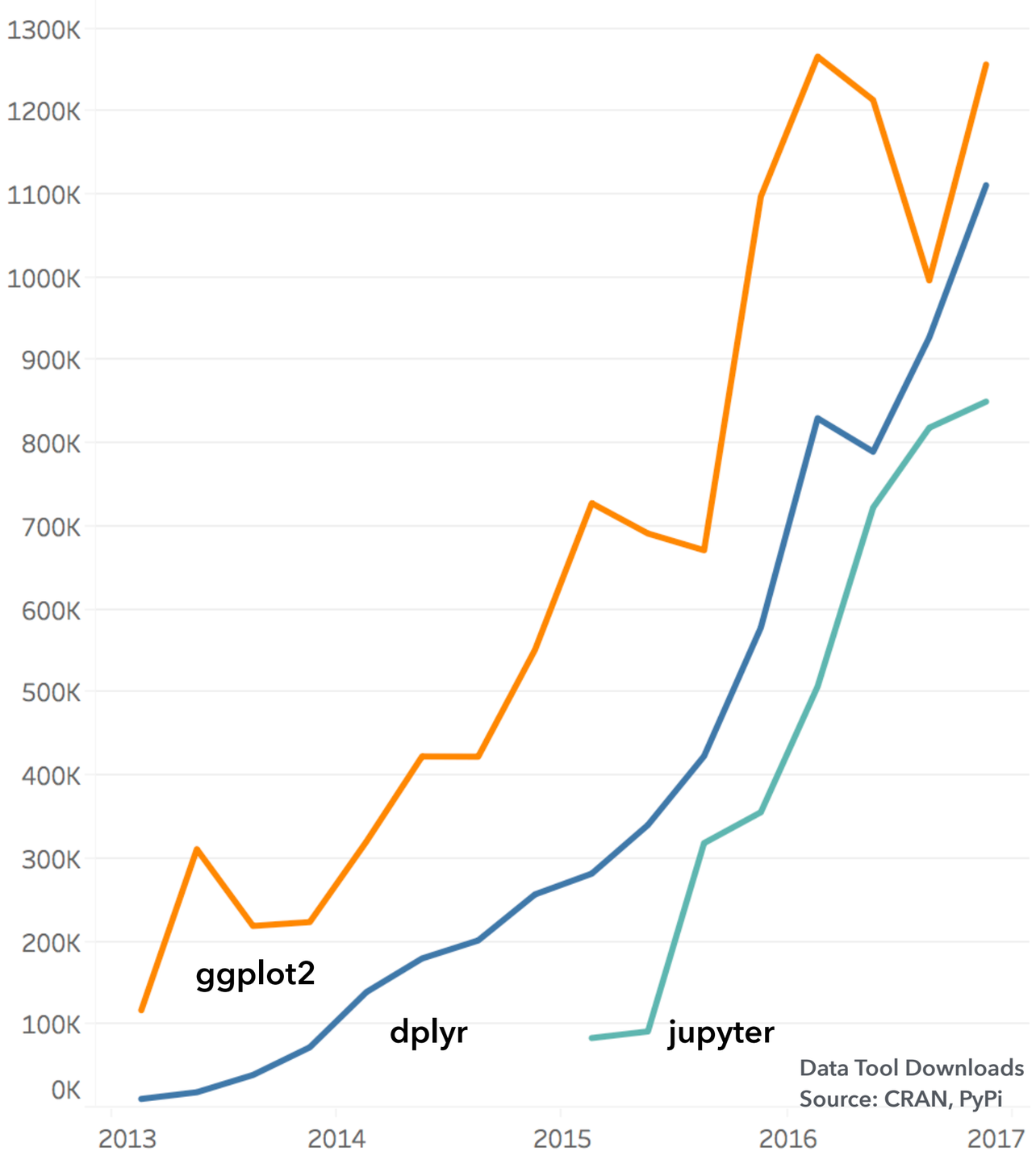
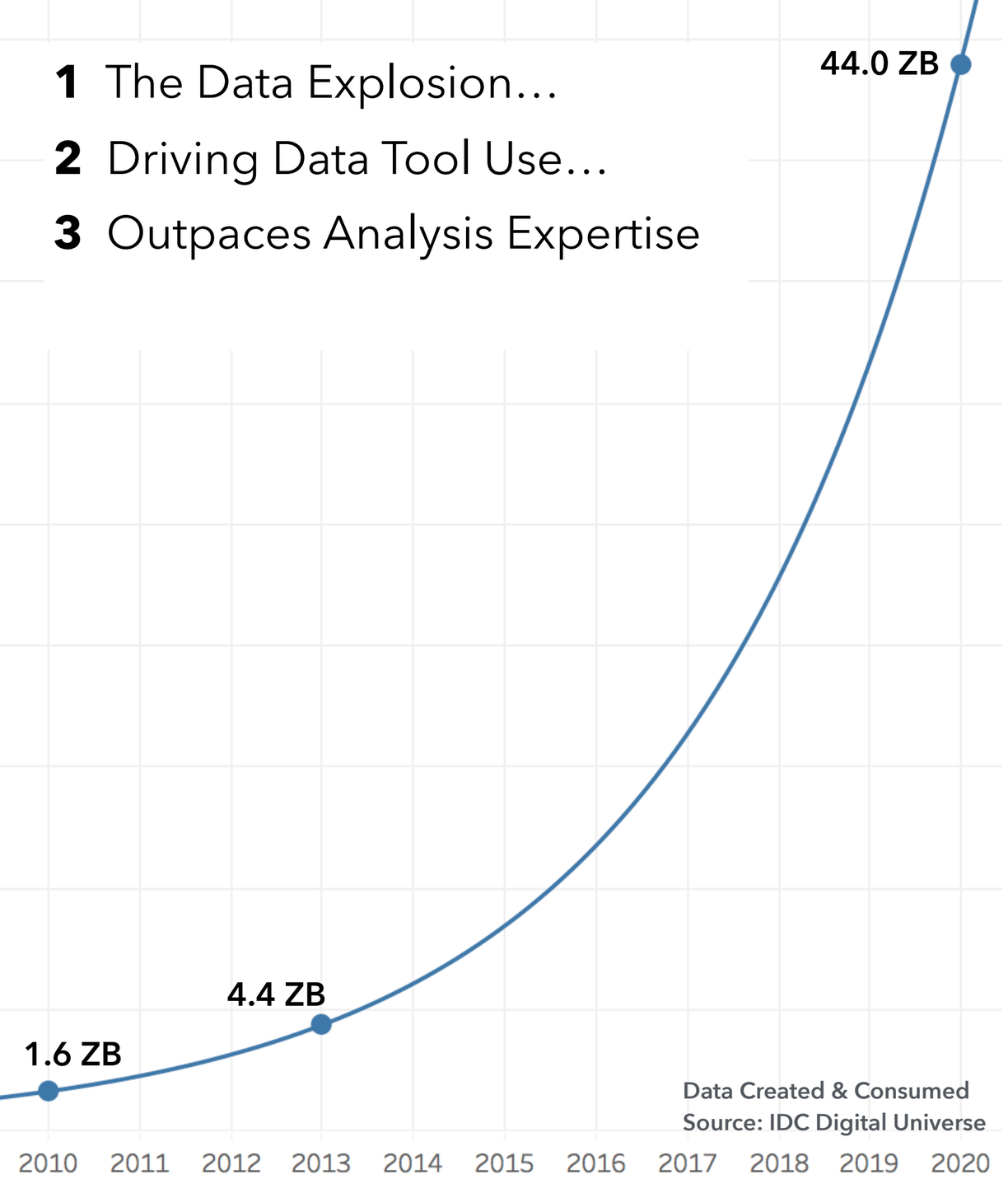


Data Tool Downloads
Source: CRAN, PyPi

1 The Data Explosion…

2 Driving Data Tool Use…

3 Outpaces Analysis Expertise



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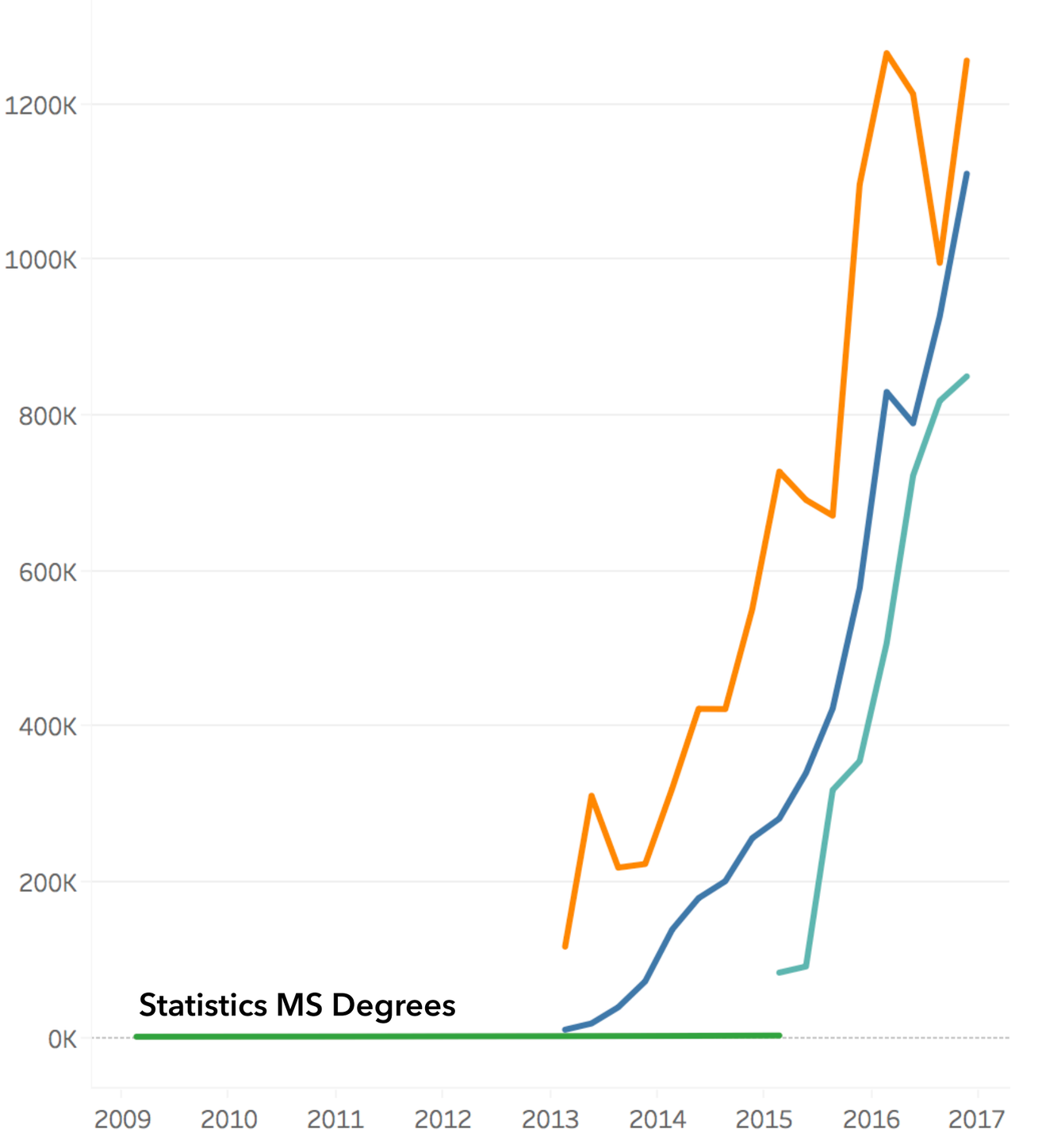
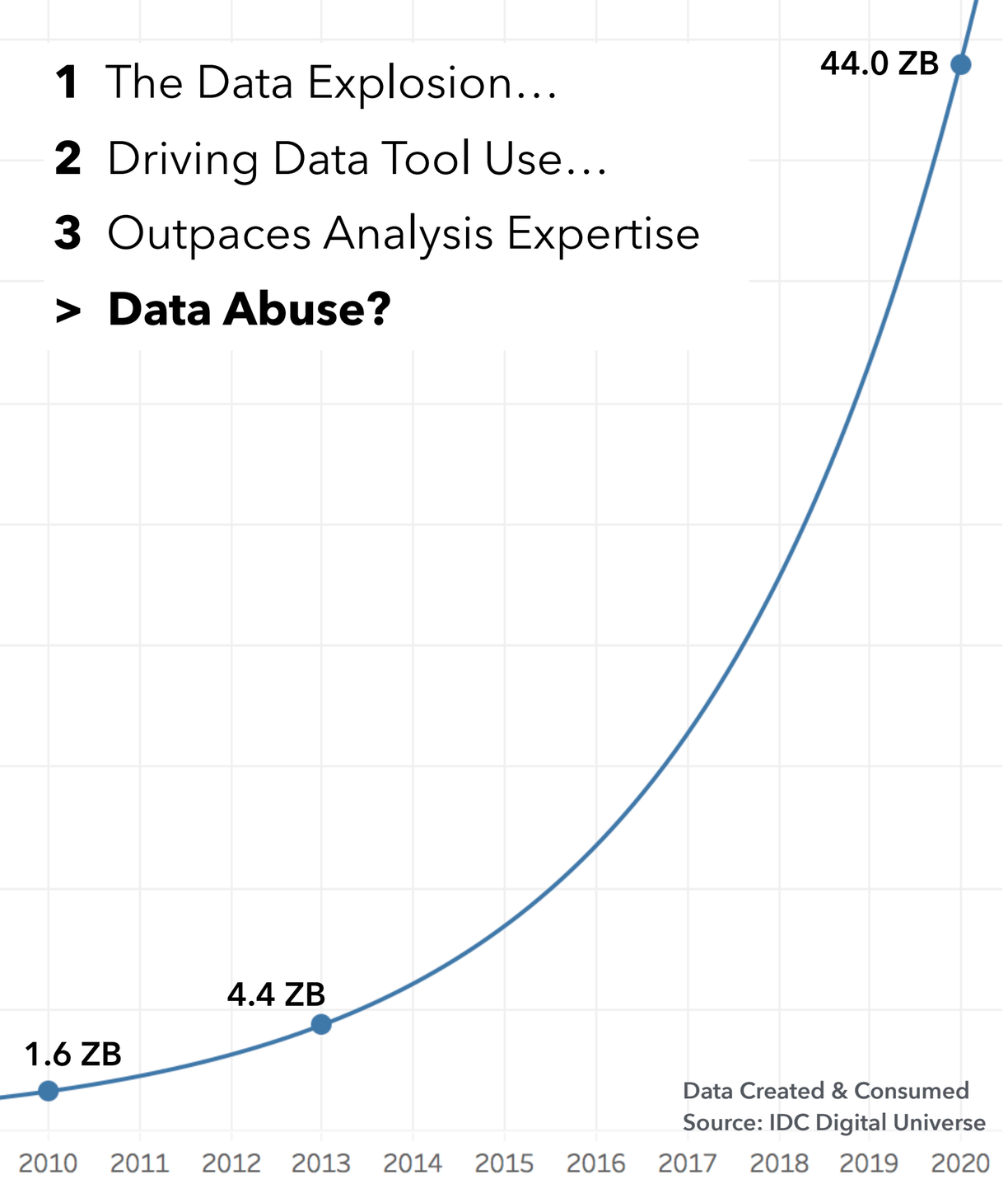


1 The Data Explosion…

2 Driving Data Tool Use…

3 Outpaces Analysis Expertise

> Data Abuse?



Data Created & Consumed
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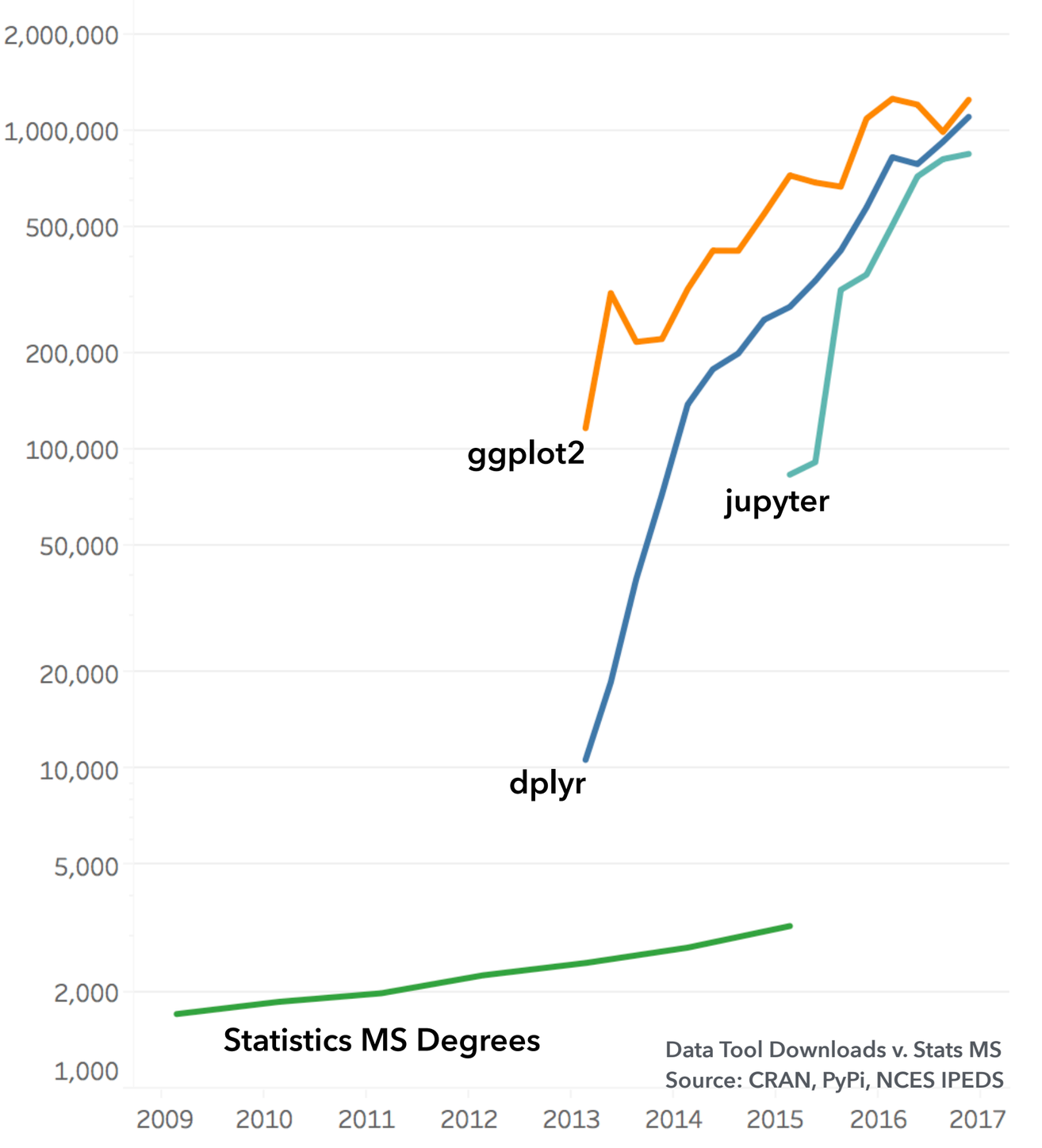


Data Tool Downloads v. Stats MS
Source: CRAN, PyPi, NCES IPEDS

Life-size cutouts of Facebook CEO Mark Zuckerberg are displayed by a progressive advocacy group on the lawn of the U.S. Capitol on Tuesday.

Carolyn Kaster / Reuters

My Facebook Was Breached by Cambridge Analytica. Was Yours?

How to find out if you are one of the 87 million victims

ROBINSON MEYER | APR 10, 2018 | TECHNOLOGY

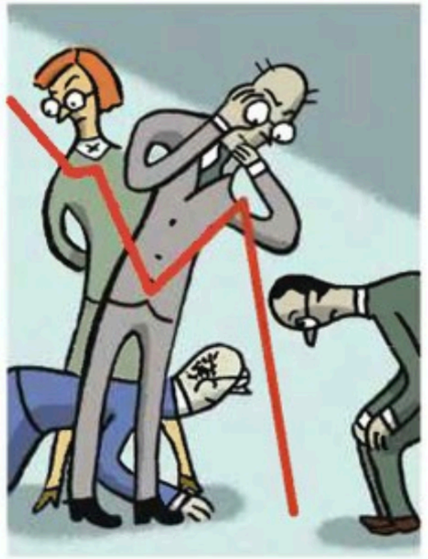
Psychology's Replication Crisis Can't Be Wished Away

It has a real and heartbreaking cost.

ED YONG | MAR 4, 2016 | SCIENCE

THE REINHART AND ROGOFF CONTROVERSY: A *SUMMING UP*

By John Cassidy April 26, 2013

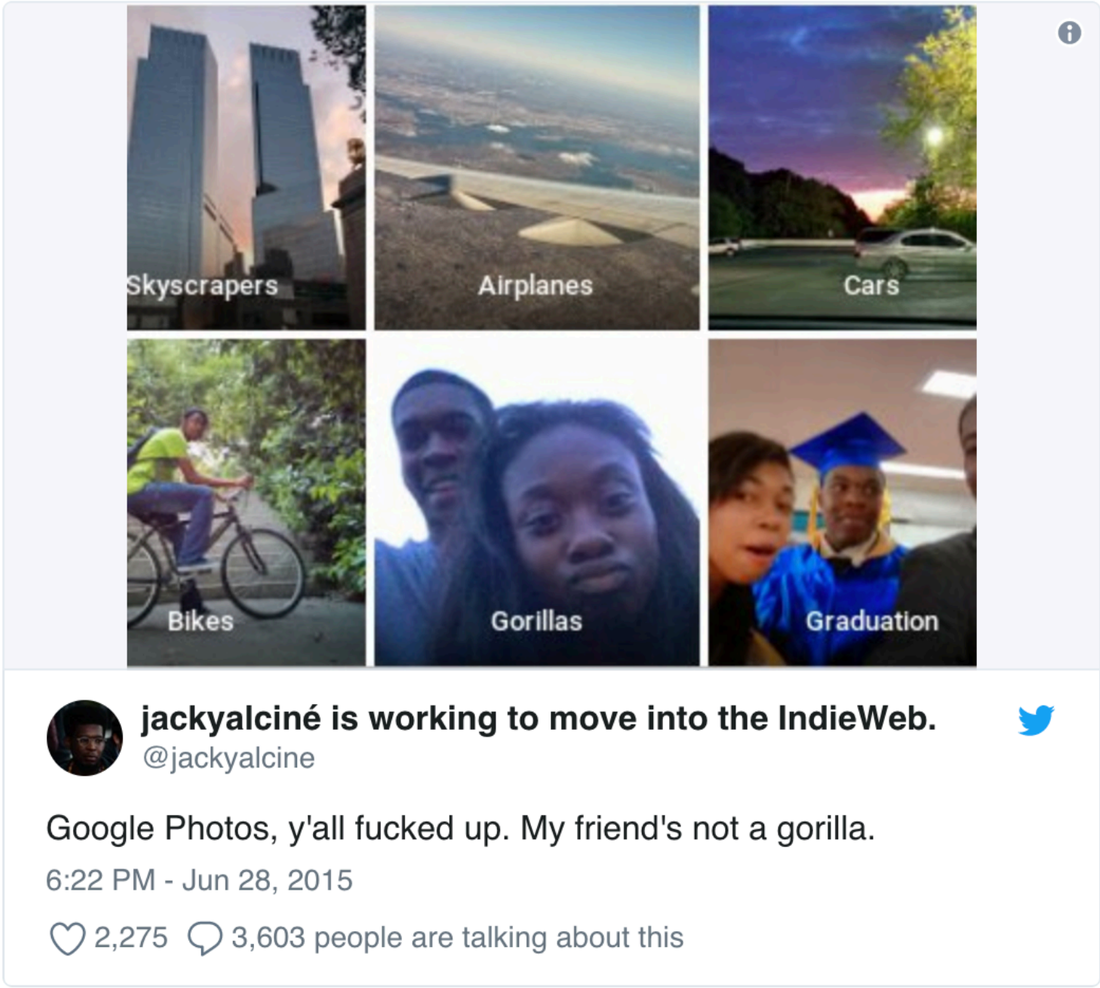


In one of life's little ironies, last Friday's disappointing G.D.P. figures, which reflected a sharp fall in government spending, appeared on the same day that the economists Carmen Reinhart and Kenneth Rogoff published an Op-Ed in the *Times* defending their famous (now infamous) research that conservative politicians around the world had seized upon to justify penny-pinching policies. Addressing a new paper by three lesser lights of their profession from the University of Massachusetts, Amherst, which uncovered data omissions, questionable methods of weighting, and elementary coding errors in Reinhart and Rogoff's original work, and which went around the world like a viral video, the

Inequality

Rise of the racist robots – how AI is learning all our worst impulses

There is a saying in computer science: garbage in, garbage out. When we feed machines data that reflects our prejudices, they mimic them – from antisemitic chatbots to racially biased software. Does a horrifying future await people forced to live at the mercy of algorithms?



Facebook Overestimated Key Video Metric for Two Years

Social network miscalculated the average time users spent watching videos on its platform

“The nature, scale, depth and consequences of the data, technical and ethical breaches understood to have occurred thus far … are unlikely to be confined to a single company, technology or industry.”

US ACM Letter to Senate Commerce & Judiciary Committee

People's **interaction with data** is subject to **misuse** and **abuse**.

Examples of Data Analysis Gone Awry

Poor decisions or operations due to faulty inference.

Inaccurate models due to biased or inaccurate data.

Insufficient accountability and review of analysis procedures.

Lack of monitoring and enforcement of data usage patterns.

Examples of Data Analysis Gone Awry

Poor decisions or operations due to faulty inference.

Inaccurate models due to biased or inaccurate data.

Insufficient accountability and review of analysis procedures.

Lack of monitoring and enforcement of data usage patterns.

Problems arise throughout end-to-end analysis workflows!

A LARGER FRAME:

Interactive Data Analysis

UW Interactive Data Lab

University of Washington

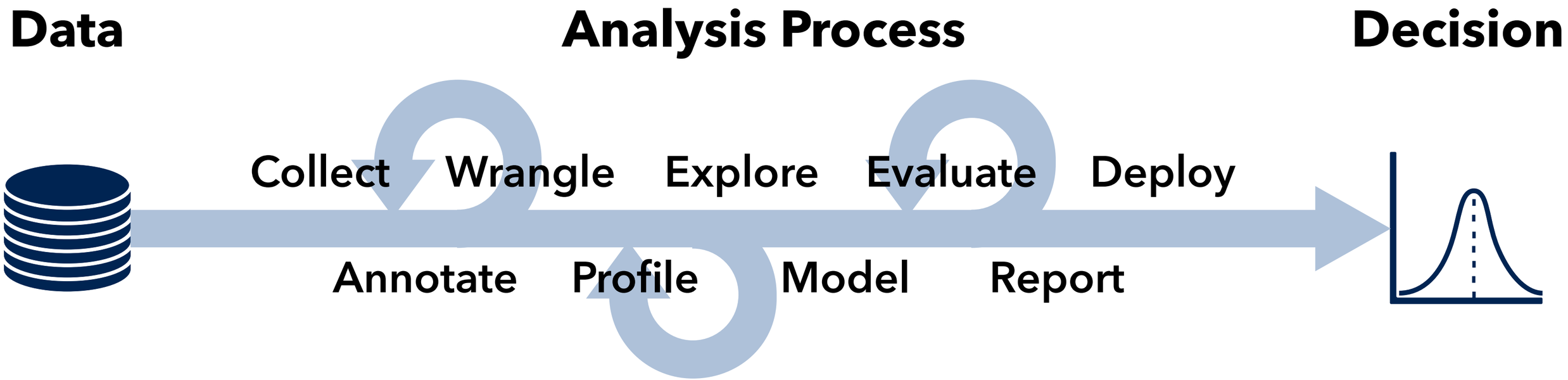
Stanford Vis Group

Stanford University

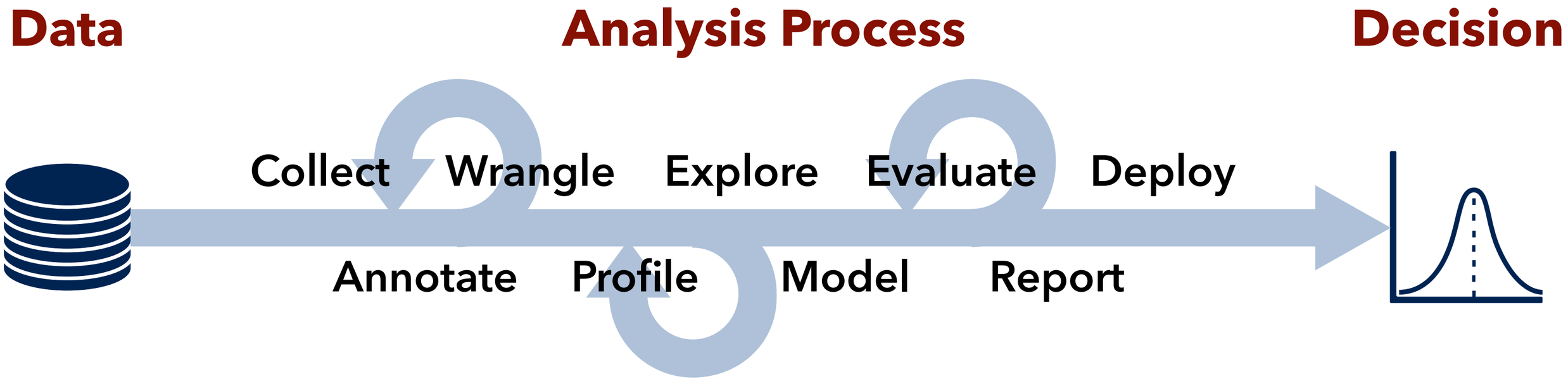
294 h
890 miles

Victoria
Everett
Tacoma
Olympia
Spokane
COLVILLE RESERVATION
FLATHEAD RESERVATION
Flathead National Forest
Great Falls
MONTANA
Missoula
Helena
Yakima
YAKAMA INDIAN RESERVATION
Kennewick
Nez Perce – Clearwater National Forests
Butte
Billings
Bozeman
CROW RESERVATION
Portland
Salem
Payette National Forest
Beaverhead-Deerlodge National Forest
Yellowstone National Park
Salmon - Challis National Forest
Eugene
Bend
OREGON
Boise
Nampa
IDAHO
Idaho Falls
Jackson
Pocatello
Twin Falls
Ogden
Salt Lake City
Sandy
Provo
UINTAH AND OURAY RESERVATION
Redding
NEVADA
Reno
UTAH
Humboldt-Toiyabe National Forest
Sacramento
San Francisco
St. George
Fresno
Death Valley
Las Vegas
NAVAJO

End-to-End Data Analysis Lifecycle



Points of Potential Failure



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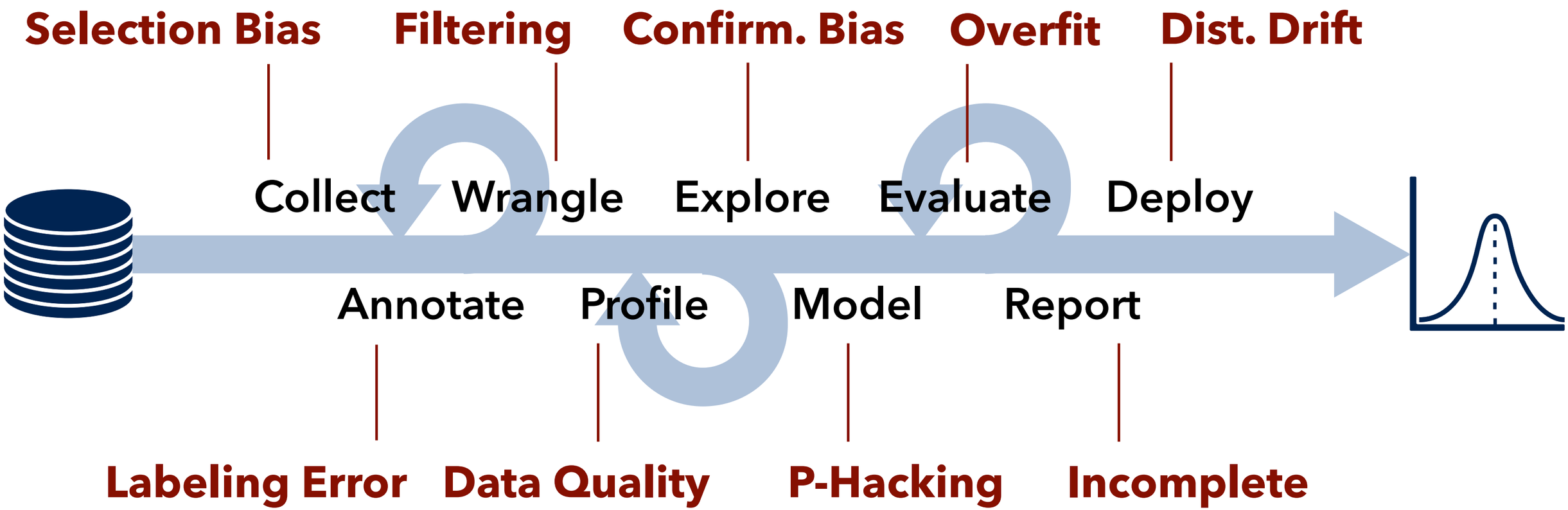
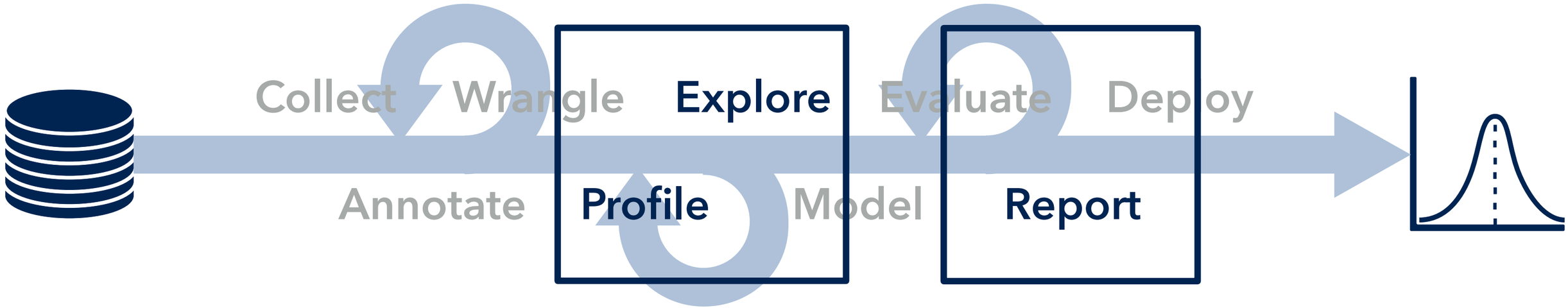


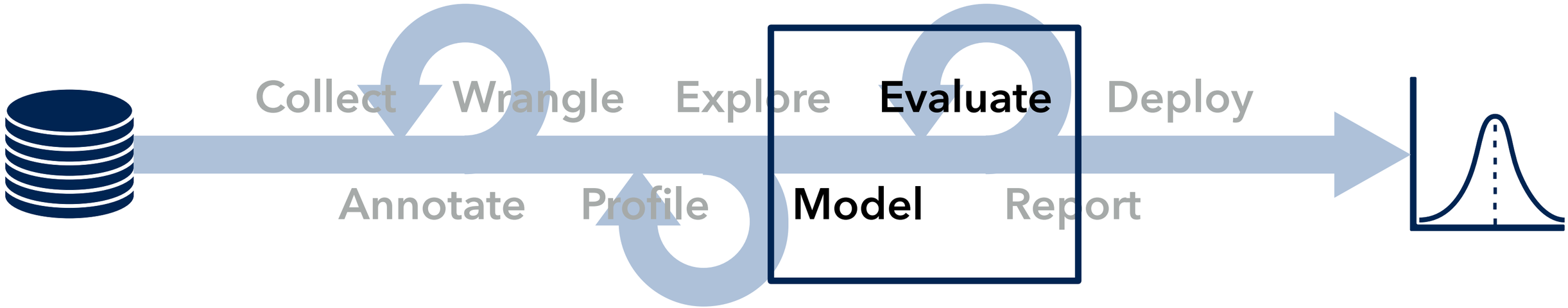
Typical Visualization Concerns



Exploratory Analysis
Data Quality Assessment

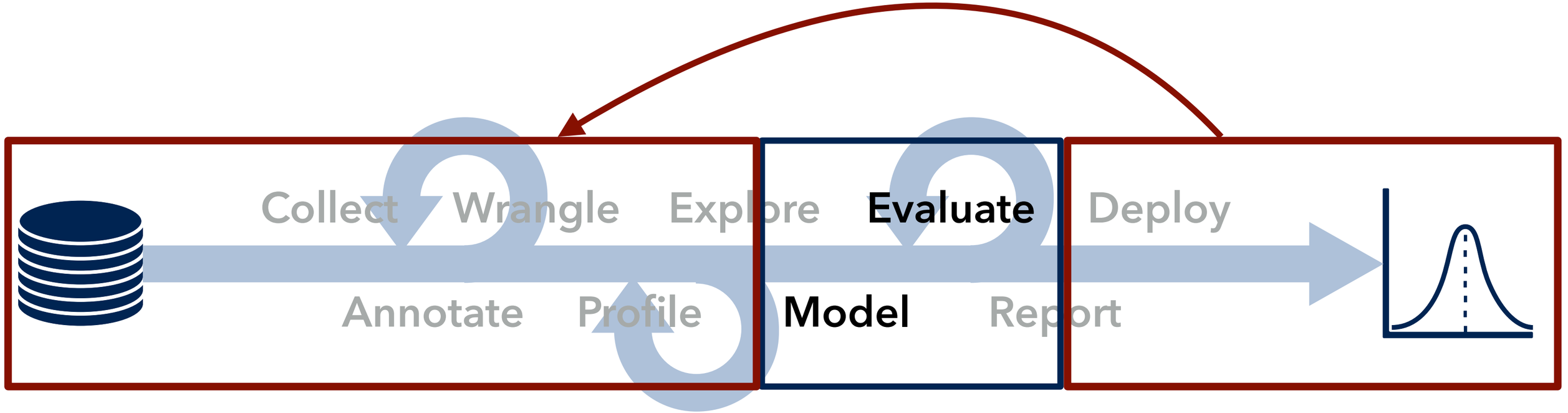
Communication
Narrative Visualization

Typical Statistical Concerns



Appropriate statistical tests and corrections.
Adjust for confounding variables.
Avoid under/over-fitting.

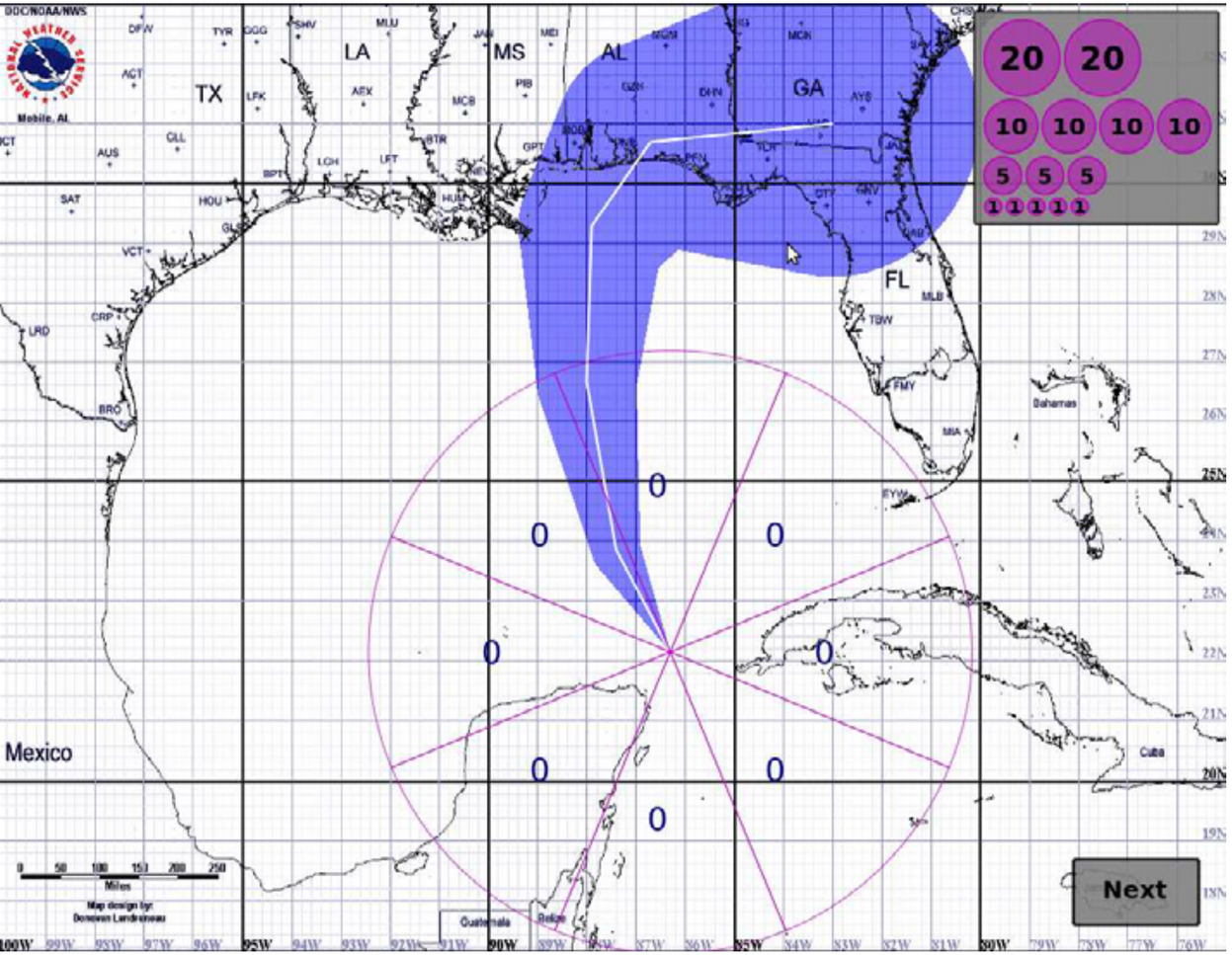
Analysis Lifecycle Concerns



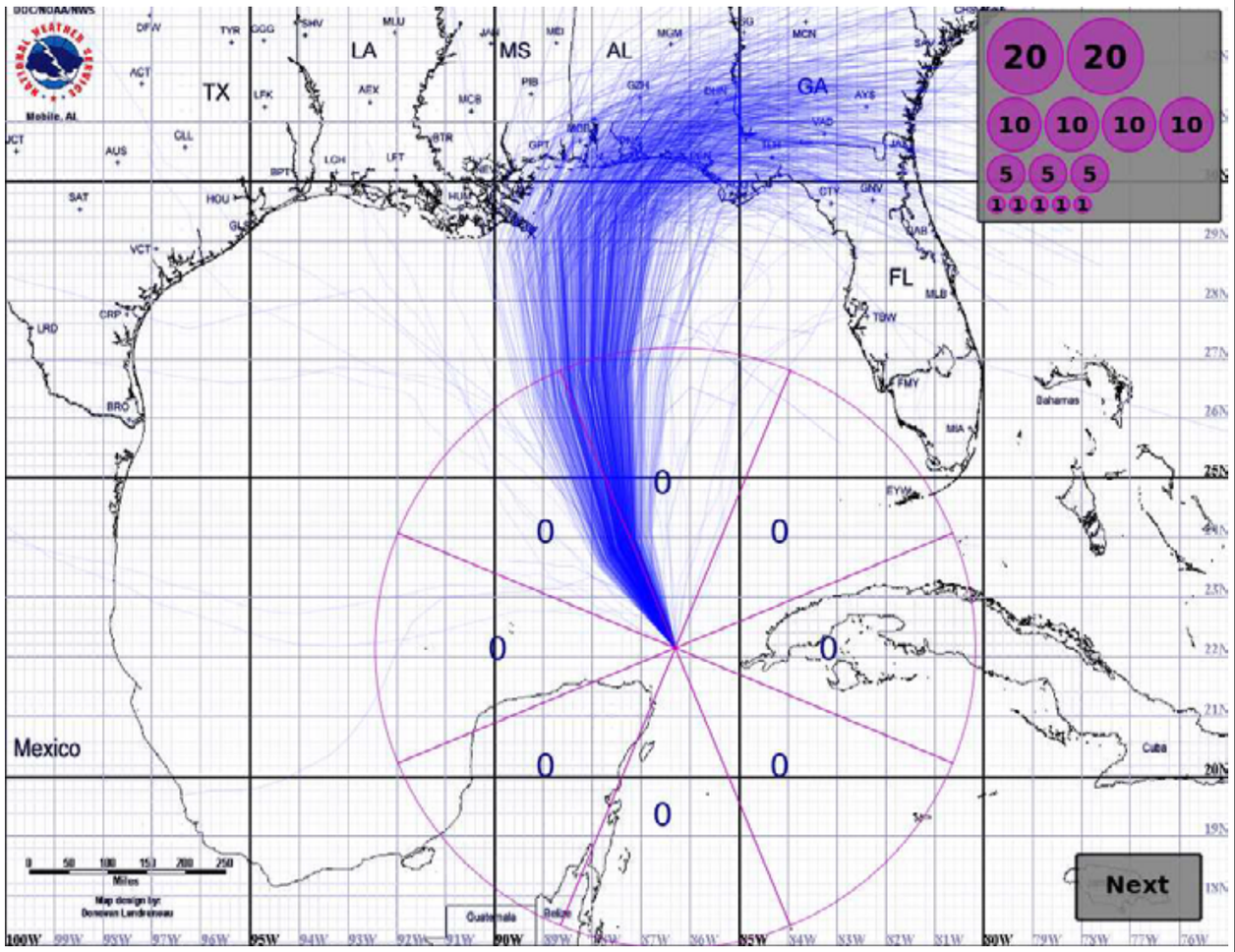
Unaccounted effect of various collection and preparation decisions. What if other decisions were made?

Interpretation & review of results. Application within decision-making context.

EXAMPLE:
Uncertainty Visualization



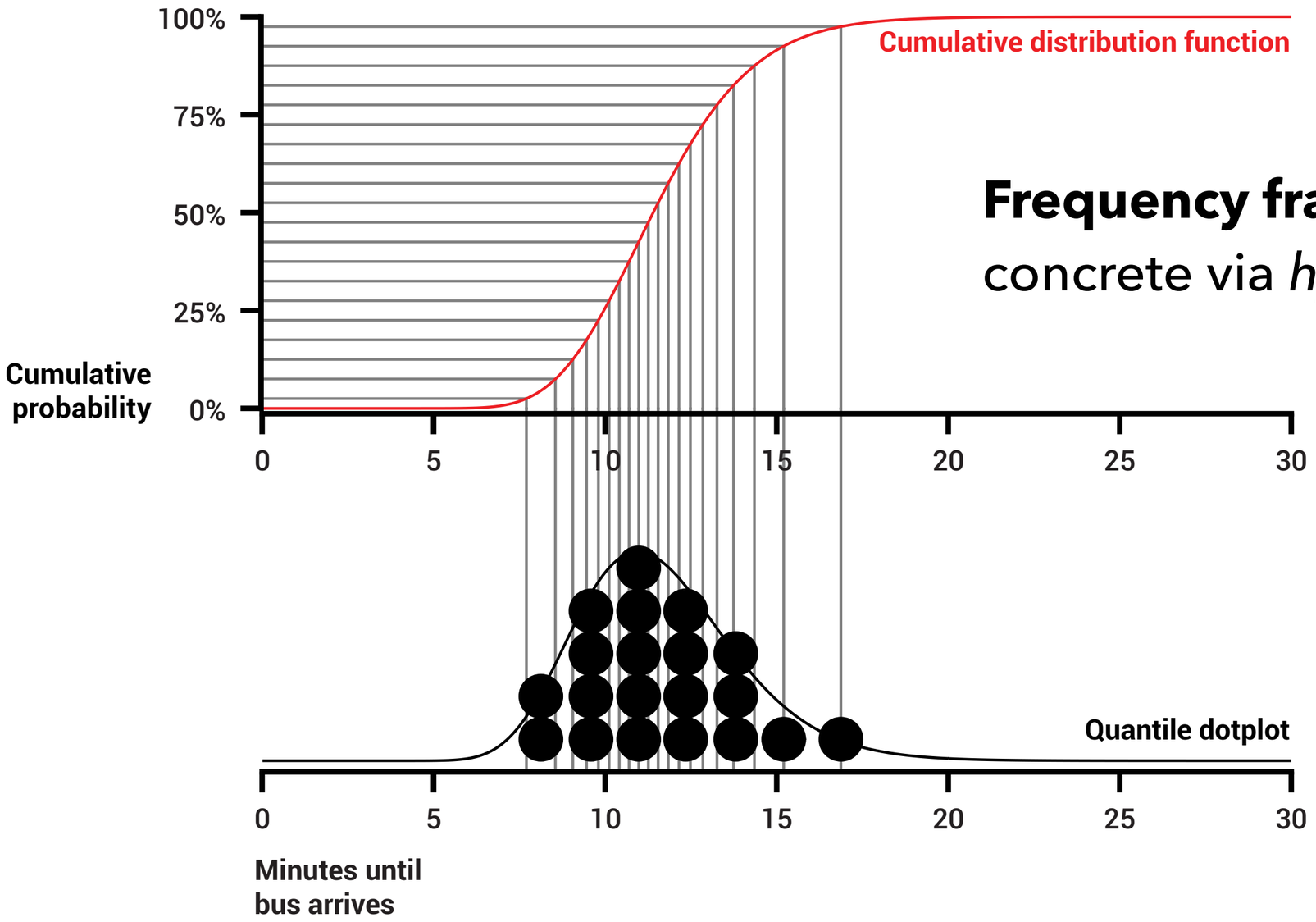
Size or likelihood of hurricane?
Is New Orleans safe?



Frequency framing: Make uncertainty concrete via *hypothetical outcomes*.

[Cox et al. 2013, Padilla et al. 2017]

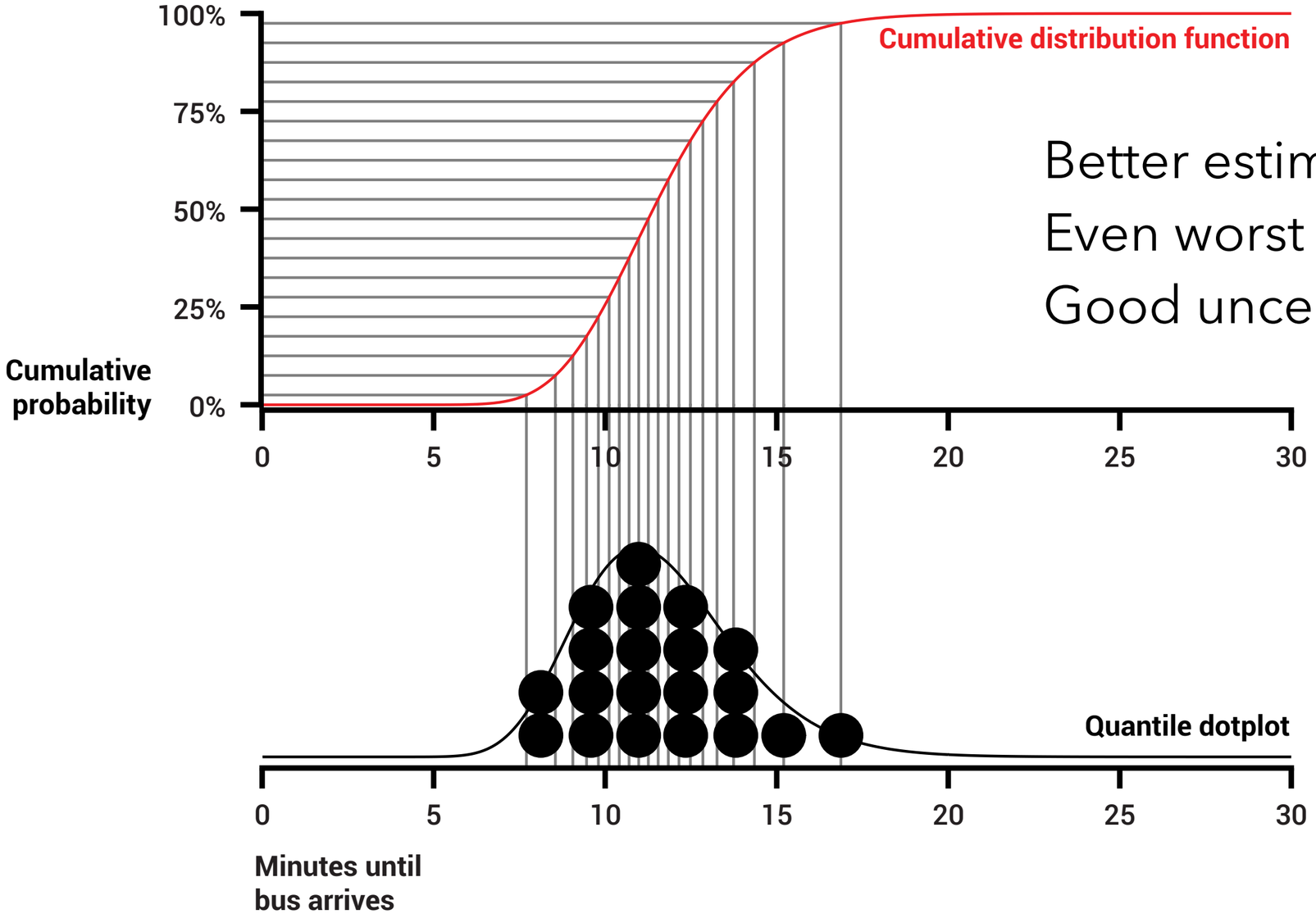
Predicted Bus Arrival: Quantile Dotplot



Frequency framing: Make uncertainty concrete via *hypothetical outcomes*.

[Kay et al. 2016]

Predicted Bus Arrival: Quantile Dotplot



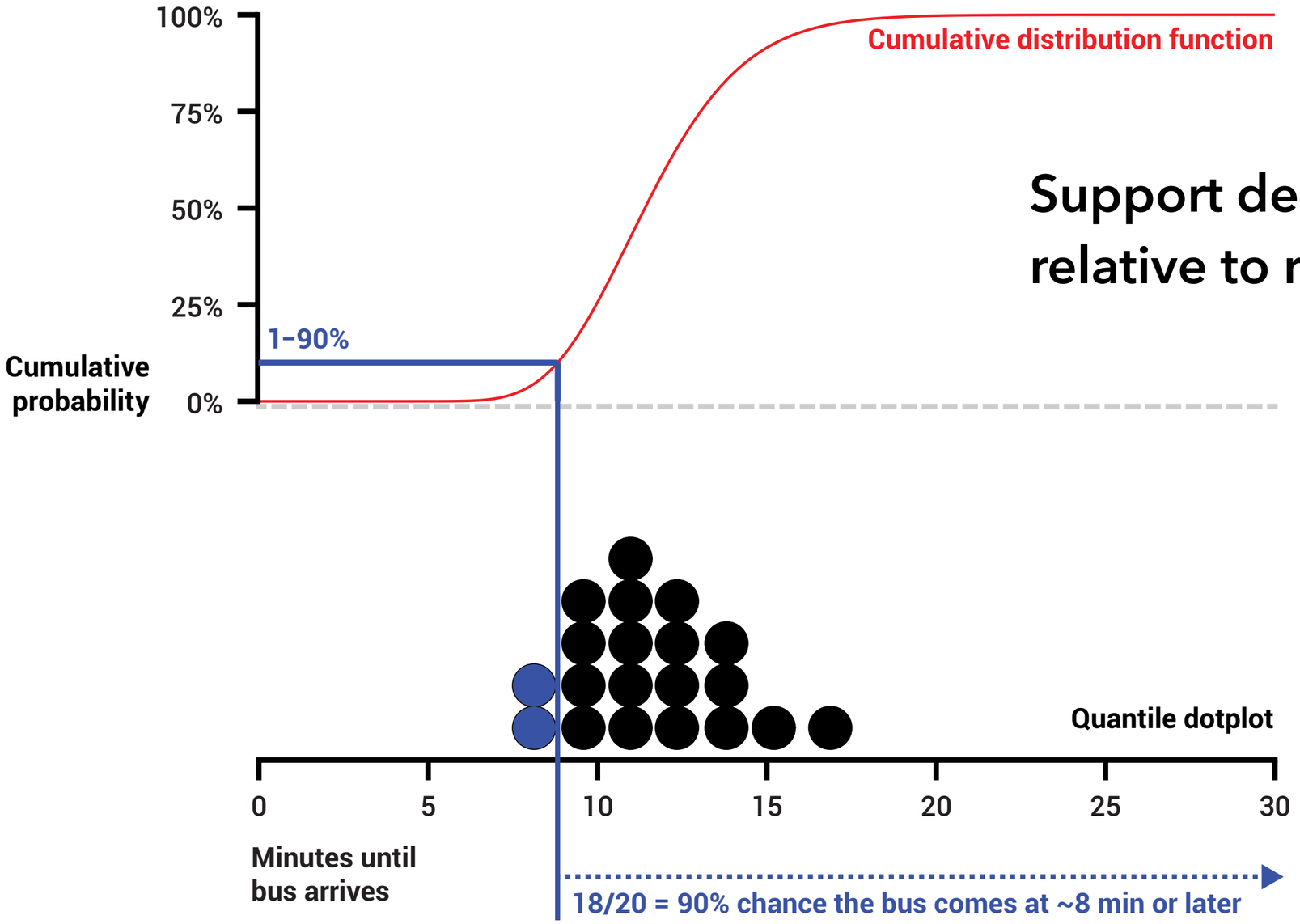
Better estimates, decisions with time.

Even worst performers improve.

Good uncertainty displays possible!

[Kay et al. 2016]

Predicted Bus Arrival: Quantile Dotplot



Support decision making relative to risk tolerance.

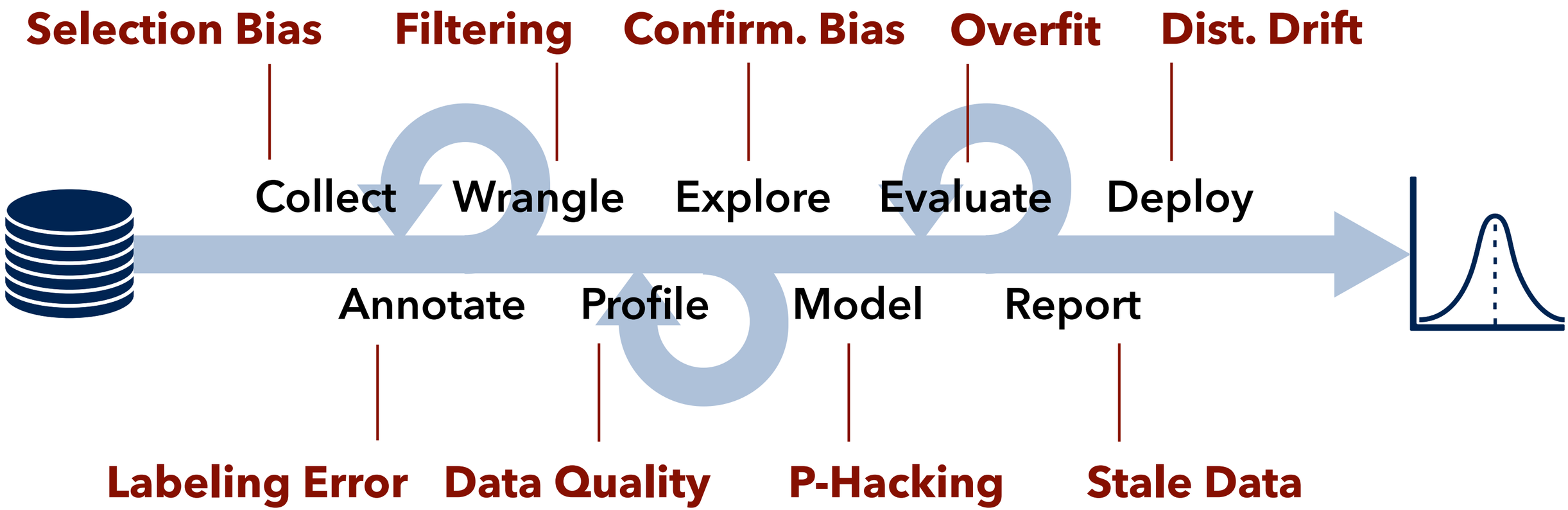
[Kay et al. 2016]

Uncertainty Visualization

Uncertainty Visualization

…is not enough!

Much Remains to Do…



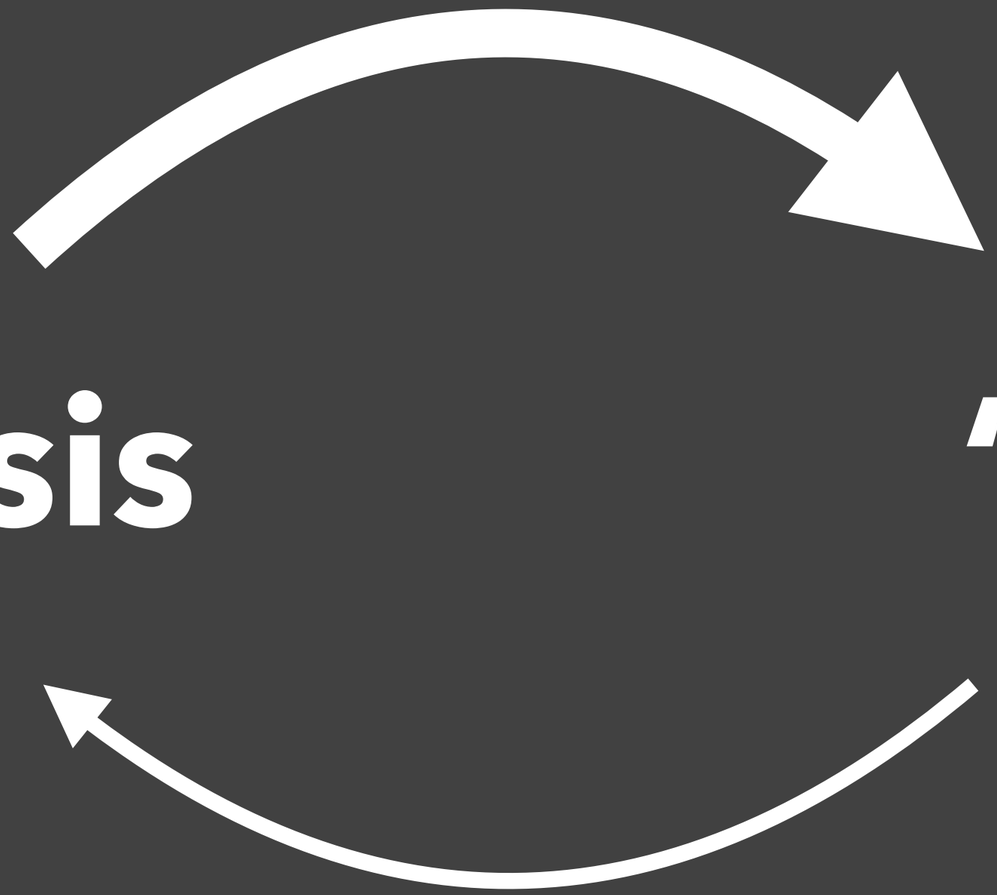
We need **analysis support** tools & methodologies for **end-to-end analysis**, not siloed “statistics” or “visualization” tools.

😀 Reusable components / techniques.

😄 Extensions to analysis environments.

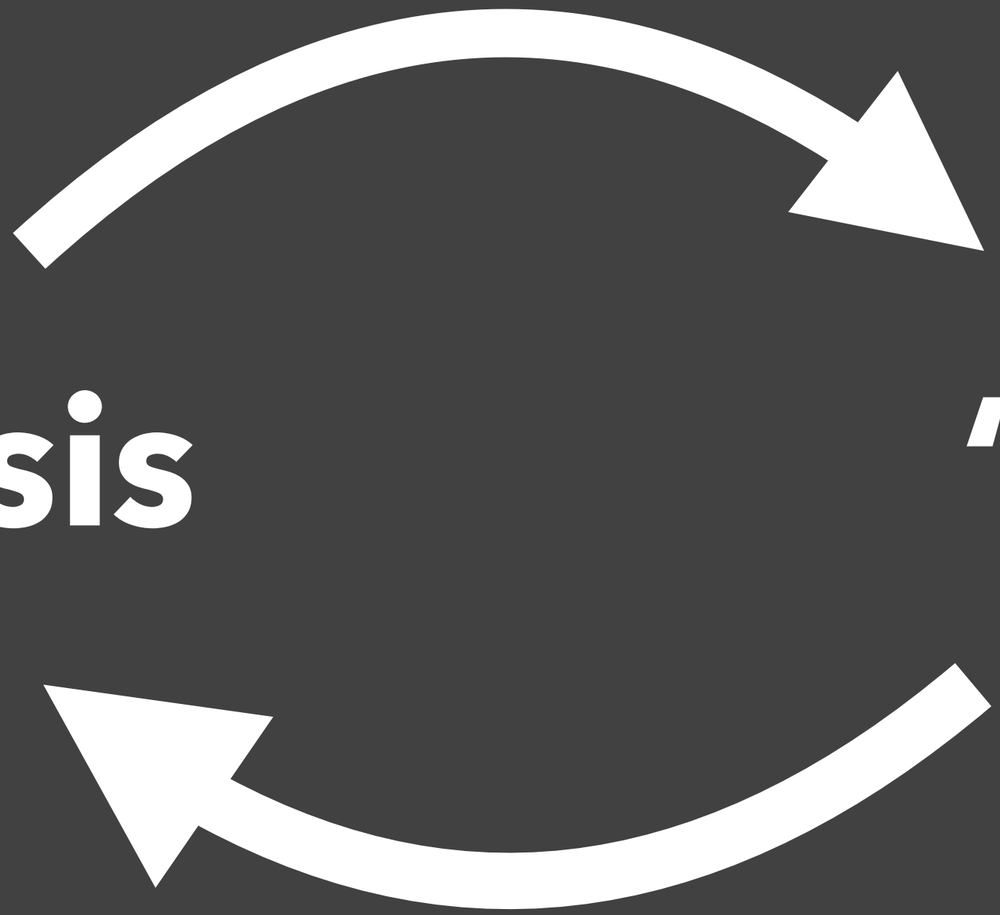
🤔 A bunch of one-off applications.

Concepts, Theory, Techniques, Methodology



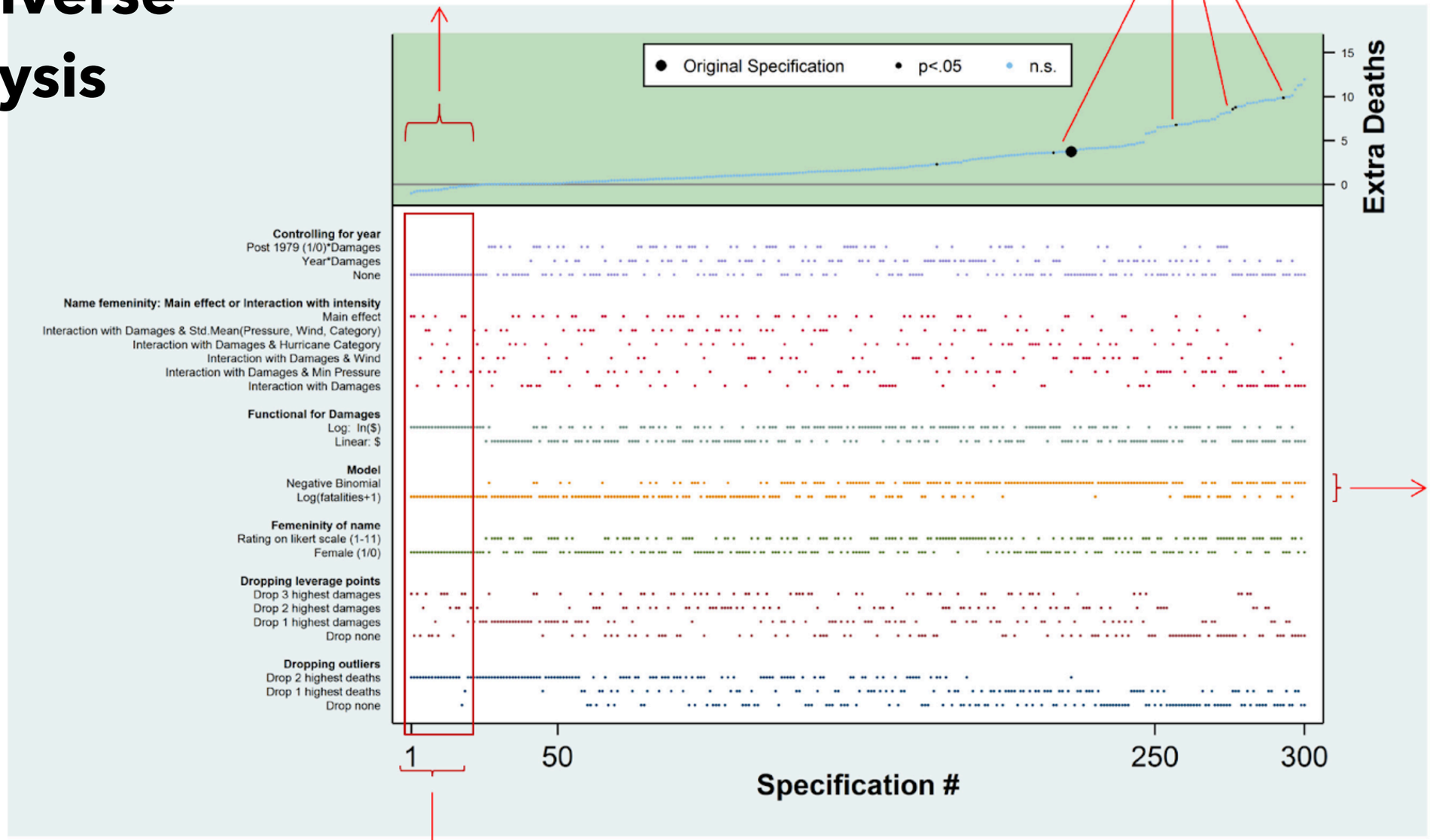
Techniques

Concepts, Theory, Techniques, Methodology



Human-Centered & End-to-End Methodologies, Use Cases, Techniques

Multiverse Analysis



Specification Curve for "Female Hurricanes Are Deadlier Than Male Hurricanes", Jung et al 2014.

[Simonsohn et al. 2015]

Research Opportunities

Capture & Represent Analyst Activity

Concretize EDA results. Guard against false discovery.

Bayesian approaches to knowledge modeling.

“We need a science of elicitation.” - *Jessica Hullman*

Analysis Review & Safeguarding

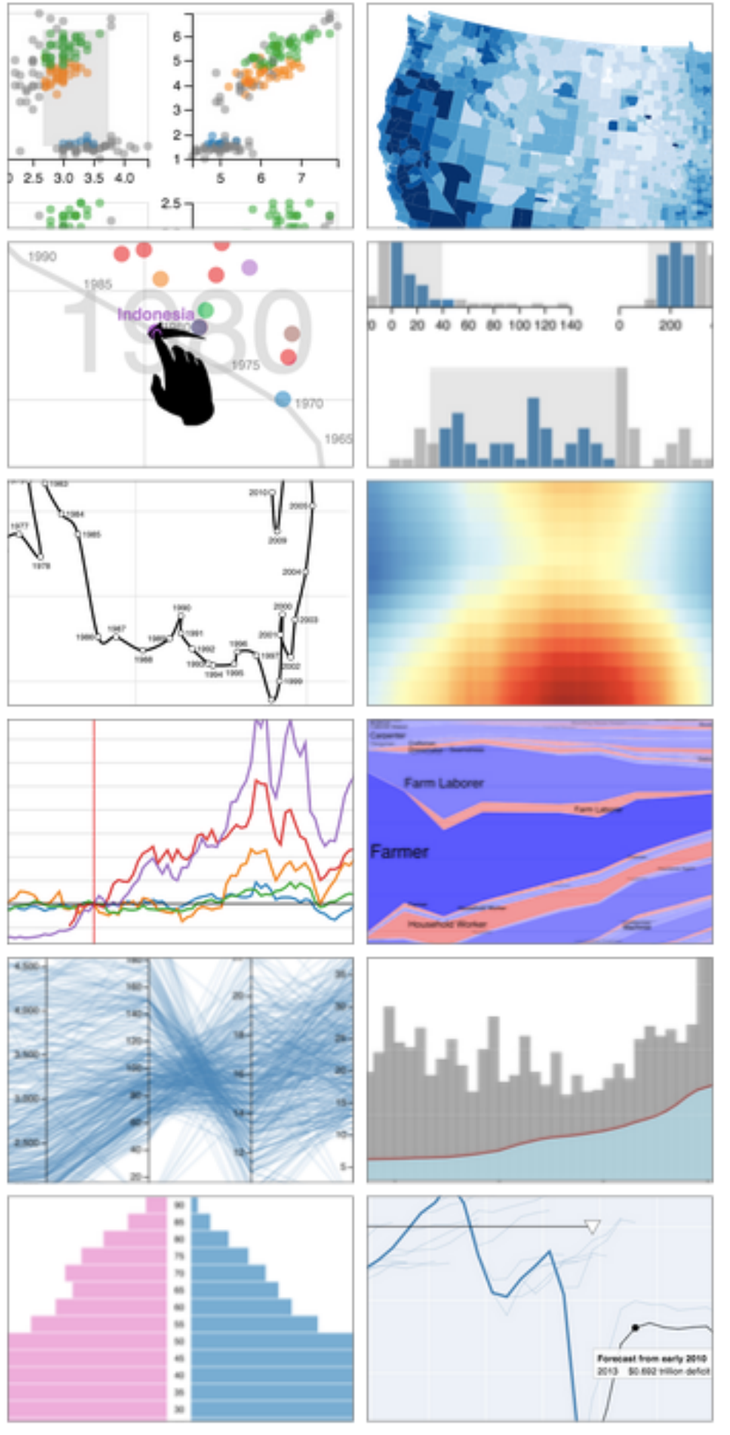
Enable review & auditing of end-to-end analyses.

Monitoring & error analysis for models & data.

Specify, Optimize & Present Multiverse Analyses

Capture alternative decisions, increase analysis robustness, move beyond dichotomous thinking.

Integrate/Extend Shared Analysis Environments

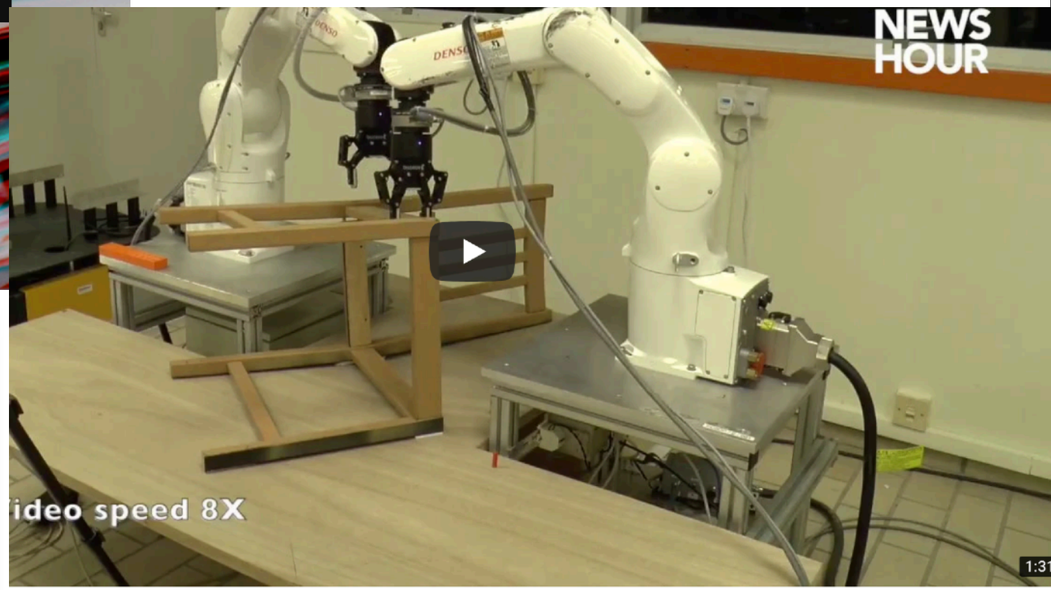


EXAMPLE:

Interactive Machine Learning

Elon Musk's nightmarish warning: AI could become 'an immortal dictator from which we would never escape'

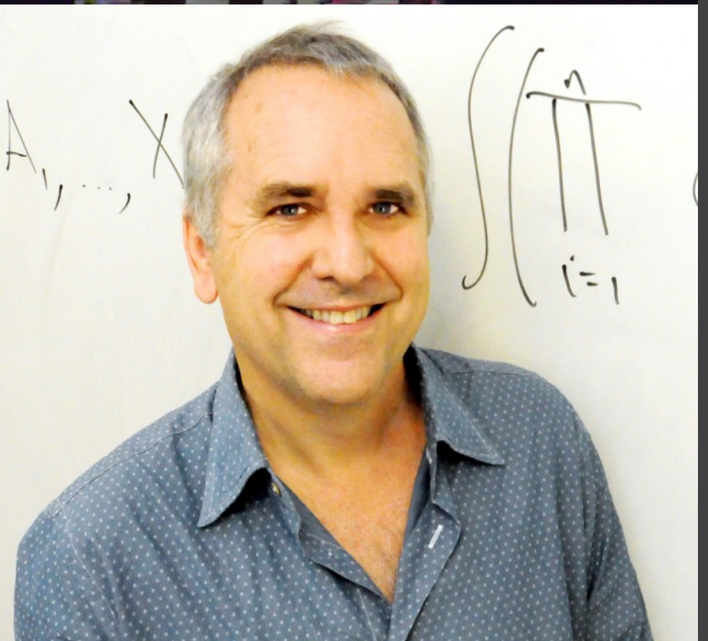
The Verdict Is In: AI Outperforms Human Lawyers in Reviewing Legal Documents



Analysis: Robots have achieved what humans never will – assembling an IKEA chair in less than 21 minutes

"I worry … that enthusiasm for A.I. is preventing us from reckoning with its looming effects on society… if we want it to play a positive role in tomorrow's world, it must be guided by human concerns… *enhancing us, not replacing us*."

Fei-Fei Li, Stanford & Google *[NY Times 2018]*

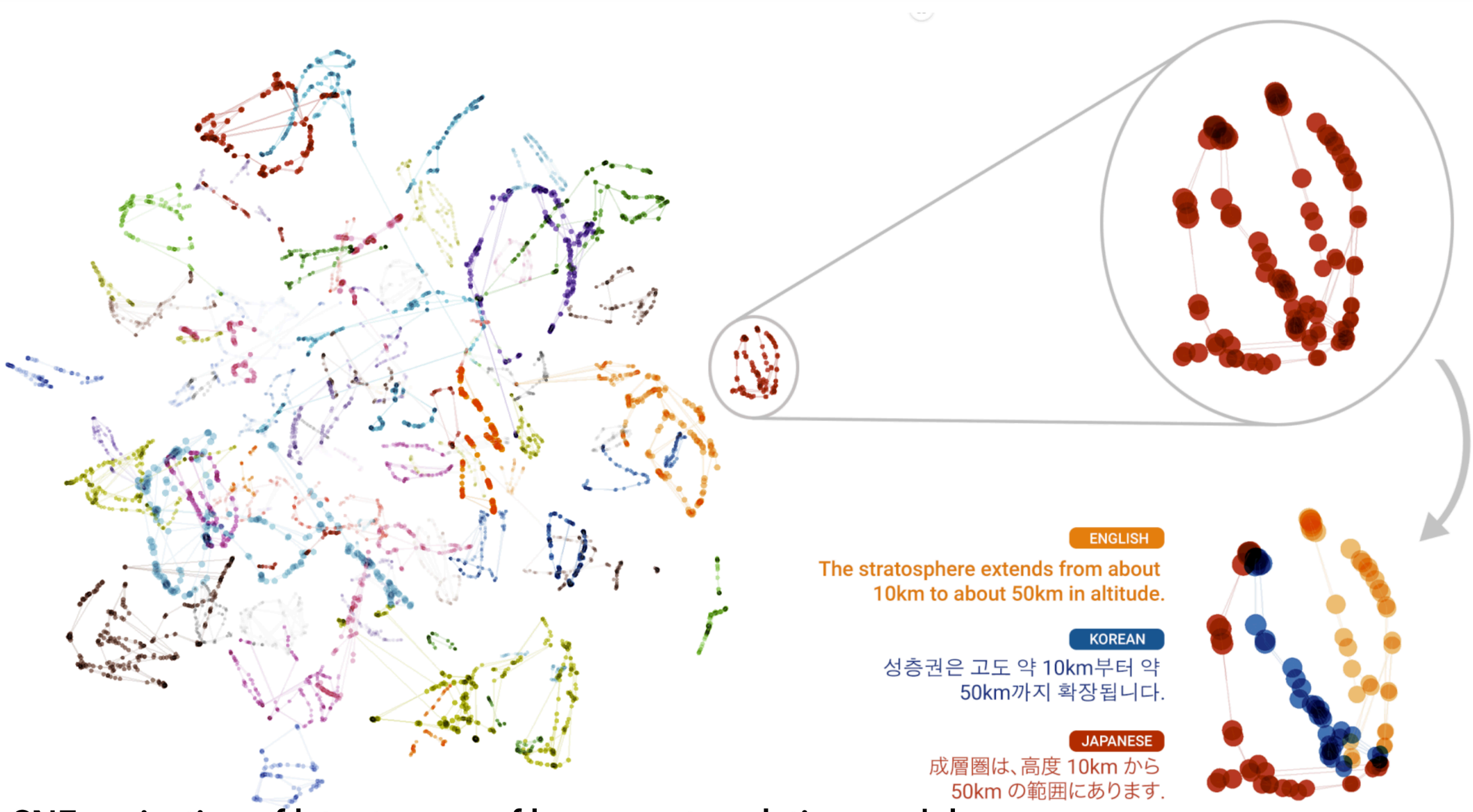


"[We] need well-thought-out interactions of humans and computers to solve our most pressing problems"

Michael Jordan, UC Berkeley *[Medium 2018]*

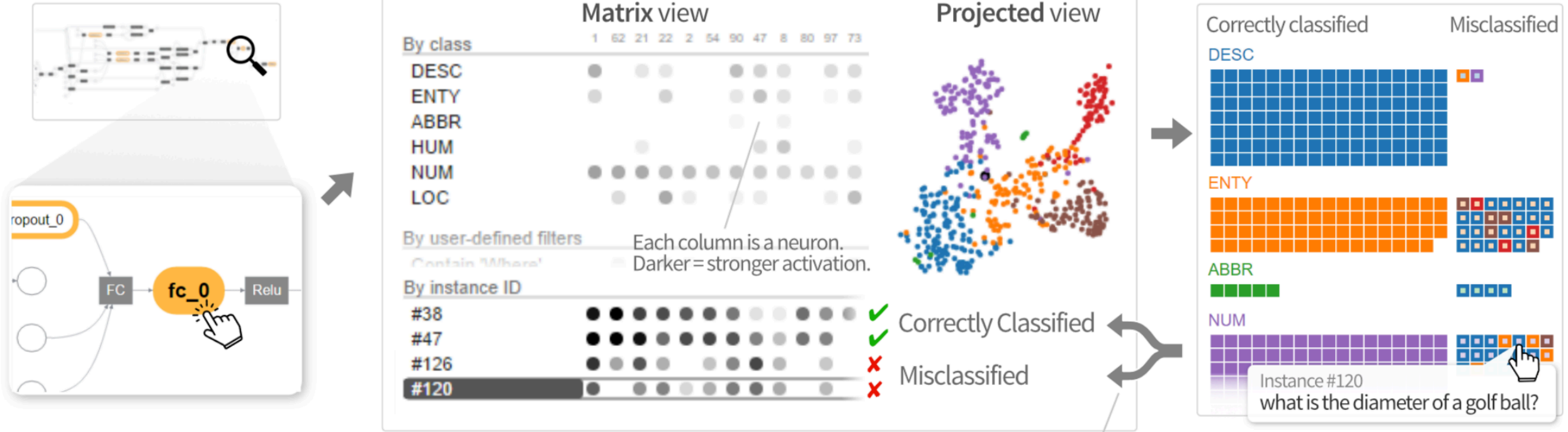
Model Visualization

Machine Translation Embedding [Johnson et al. 2018]

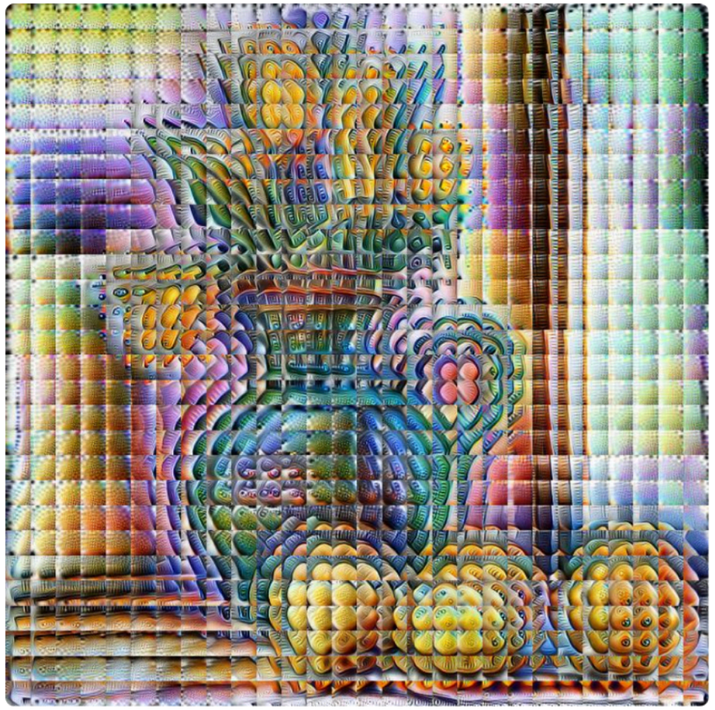


t-SNE projection of latent space of language translation model.

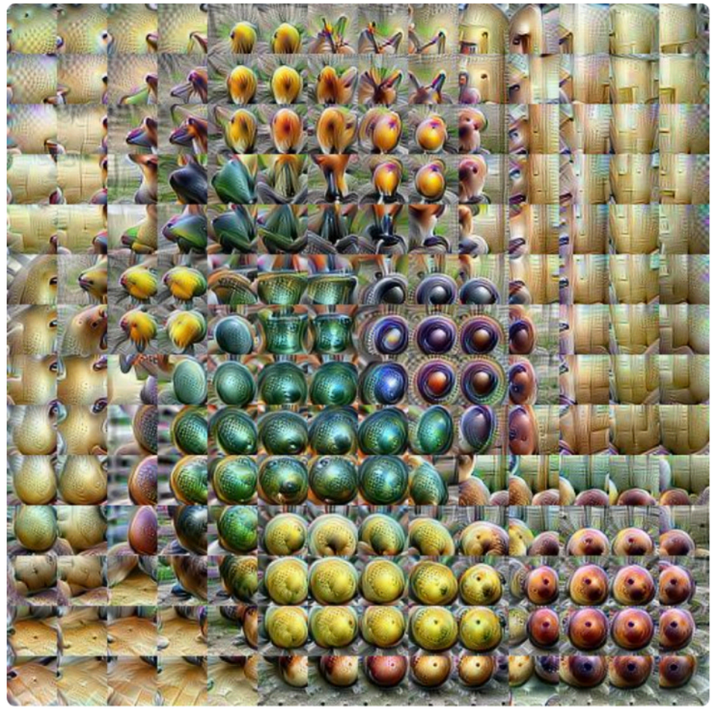
ActiVis [Kahng et al. 2017]



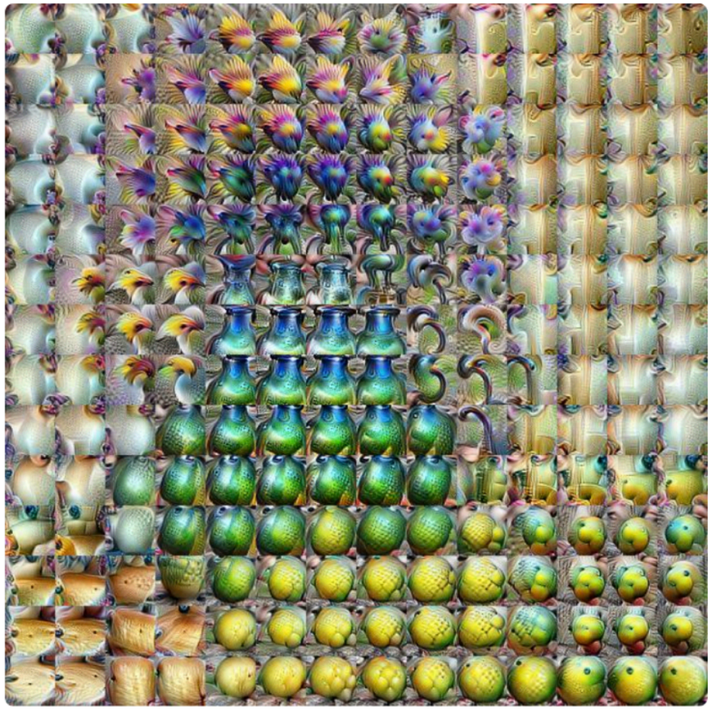
Feature Visualization & Attribution [Olah et al. 2018]



MIXED3A



MIXED4A



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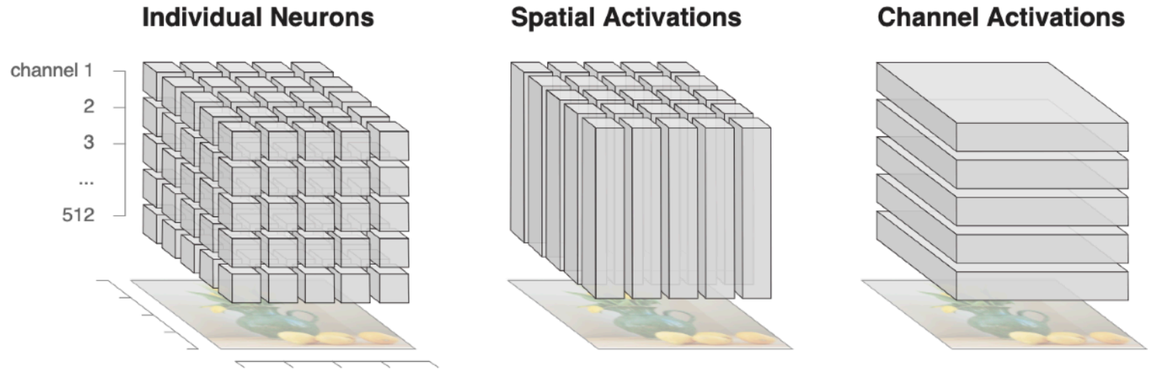
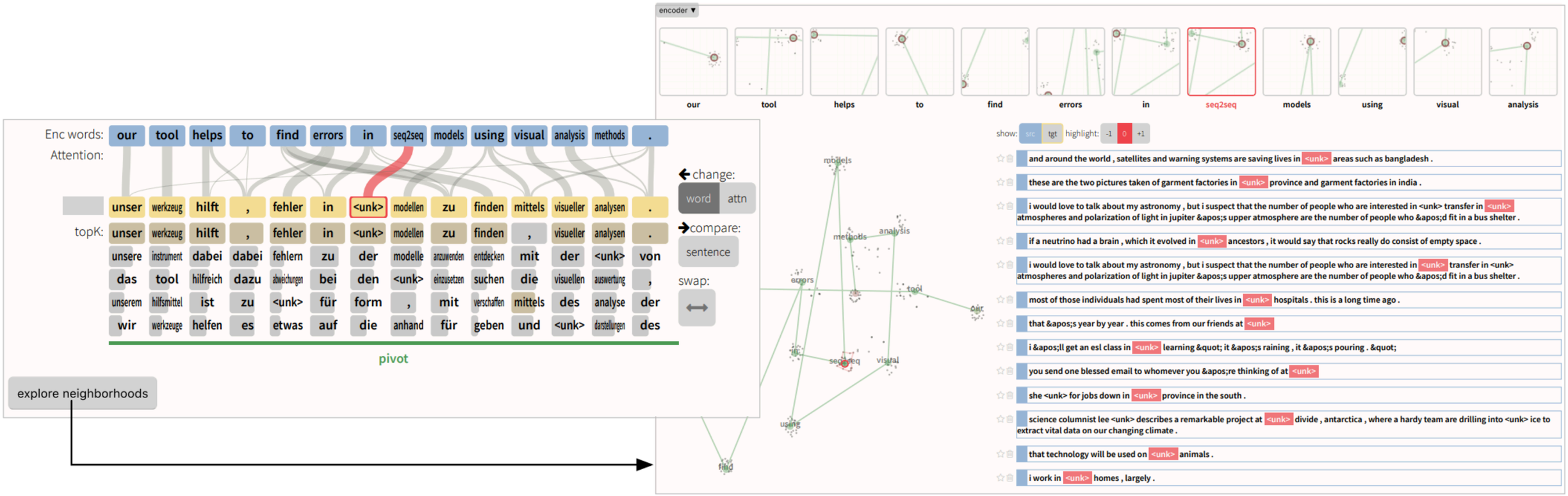
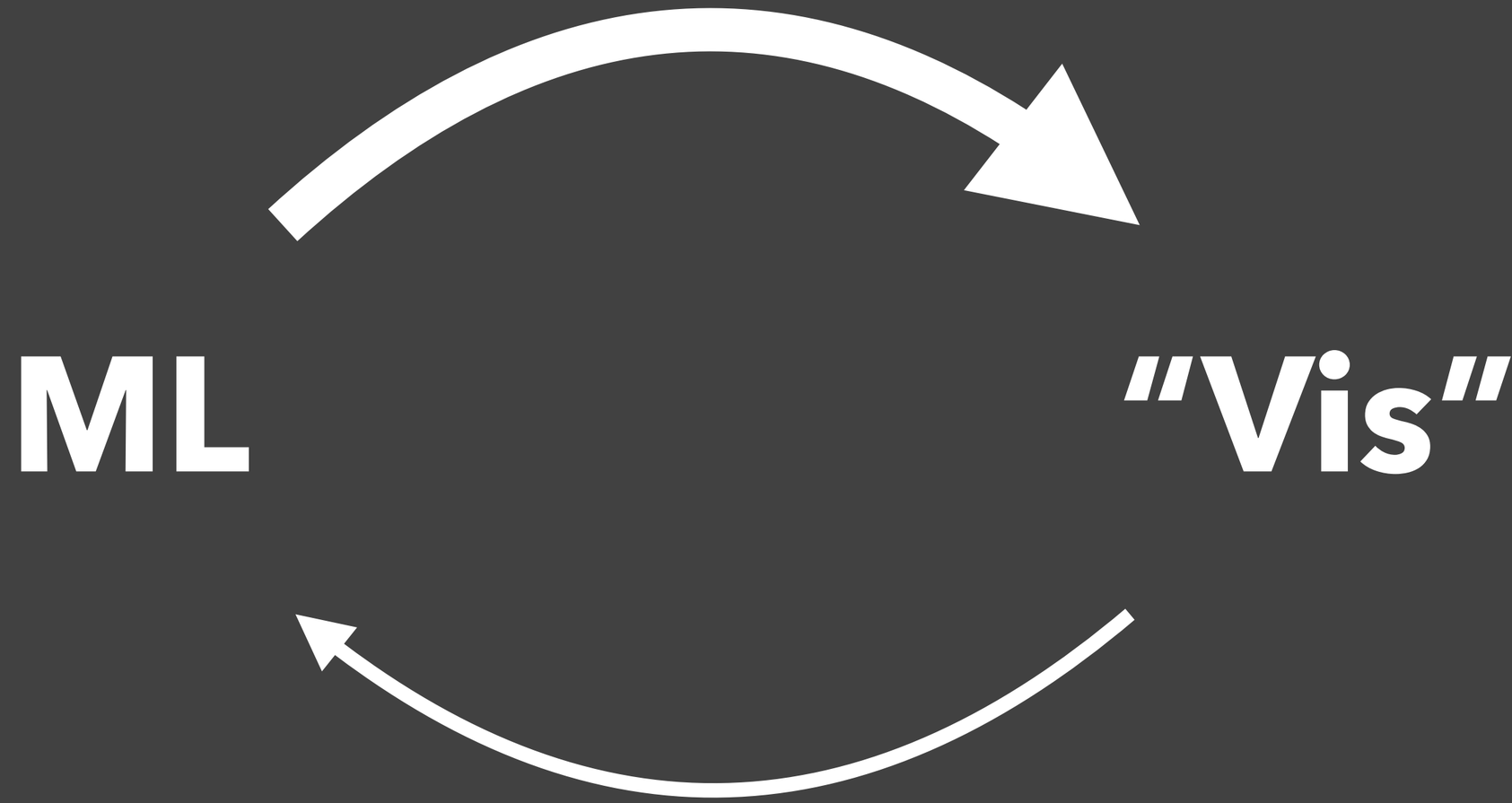


Seq2Seq-Vis for Model Debugging [Strobelt et al. 2018]



Visual analysis to debug RNN machine translation models.

Concepts, Theory, & Methods



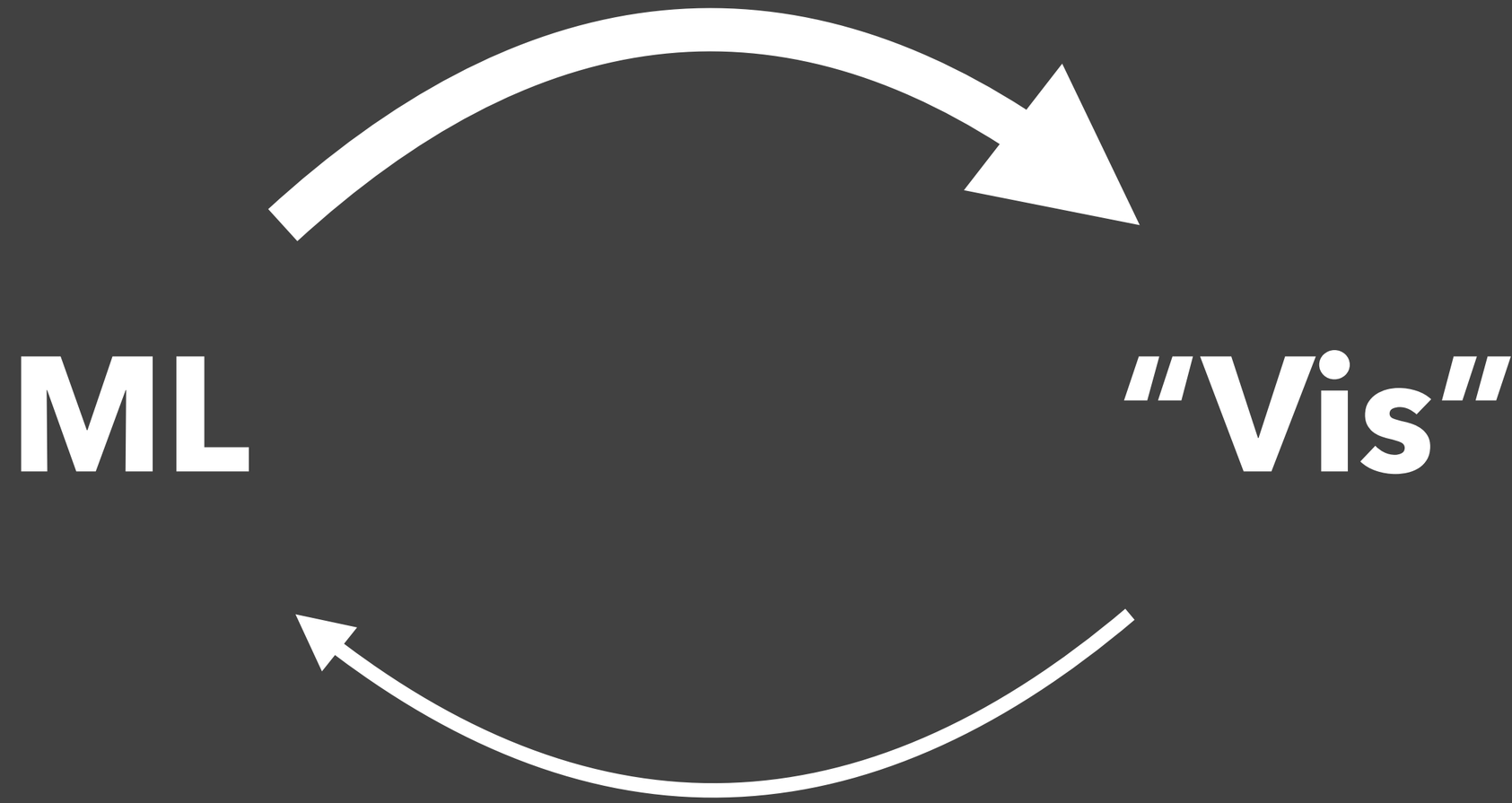
Inspection Tools

Model Visualization

Model Visualization

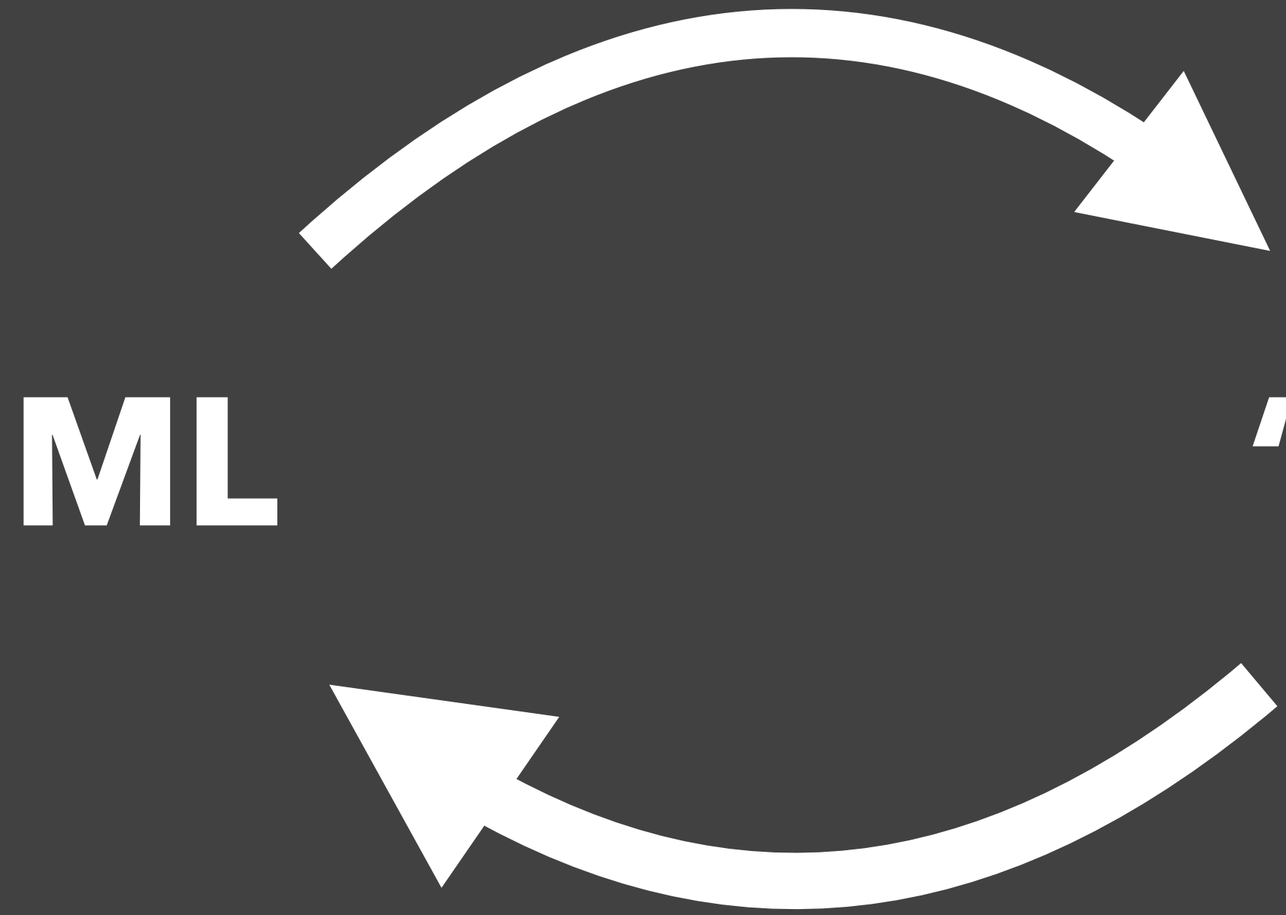
…is not enough!

Concepts, Theory, & Methods



Inspection Tools

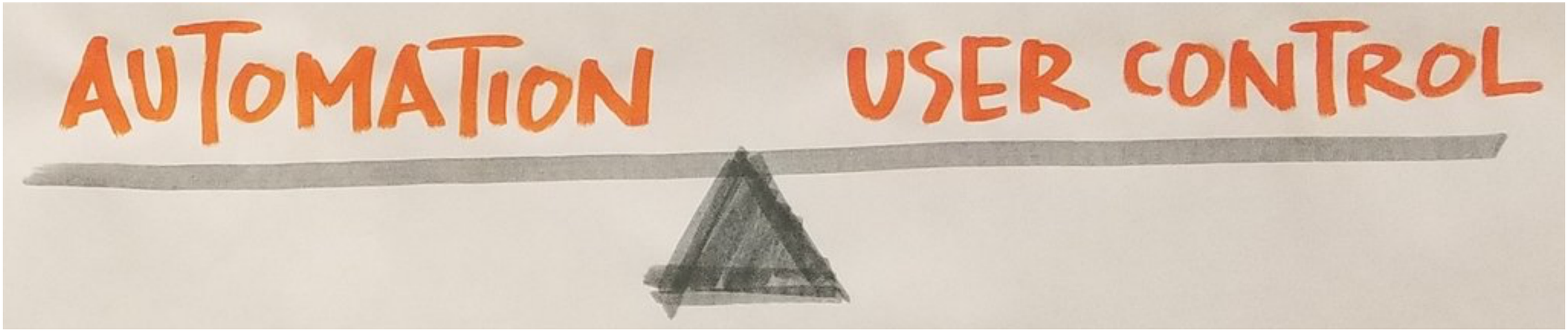
Concepts, Theory, & Methods



Human-Centered Concepts & Interaction Paradigms

DESIGN CHALLENGE:

Determine “regions of optimality” in possible divisions of labor among directed and automated actions.



A Balancing Act…

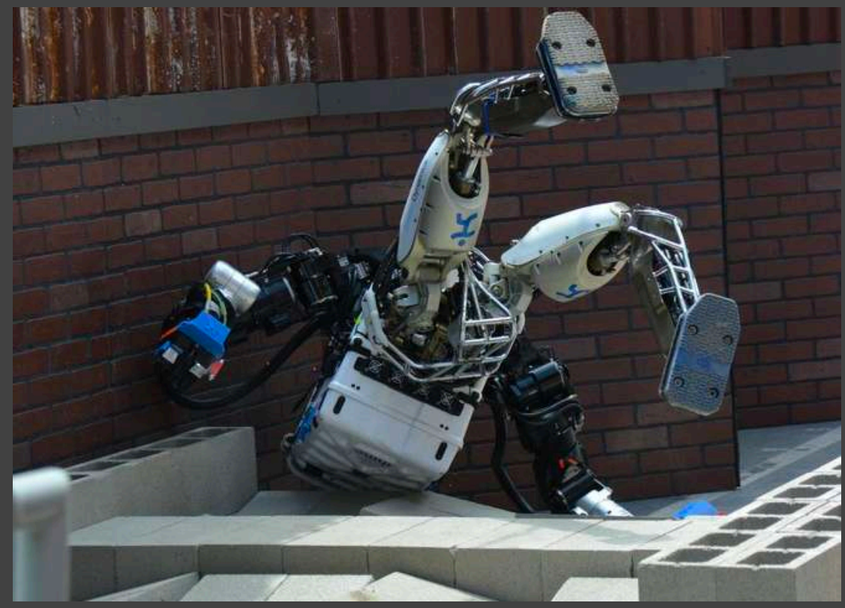
Balancing Automation and Control

Challenges of Automation:

Loss of critical engagement & domain expertise.

Automated methods may not be sufficiently accurate.

Consequences of poor models let loose in the world.



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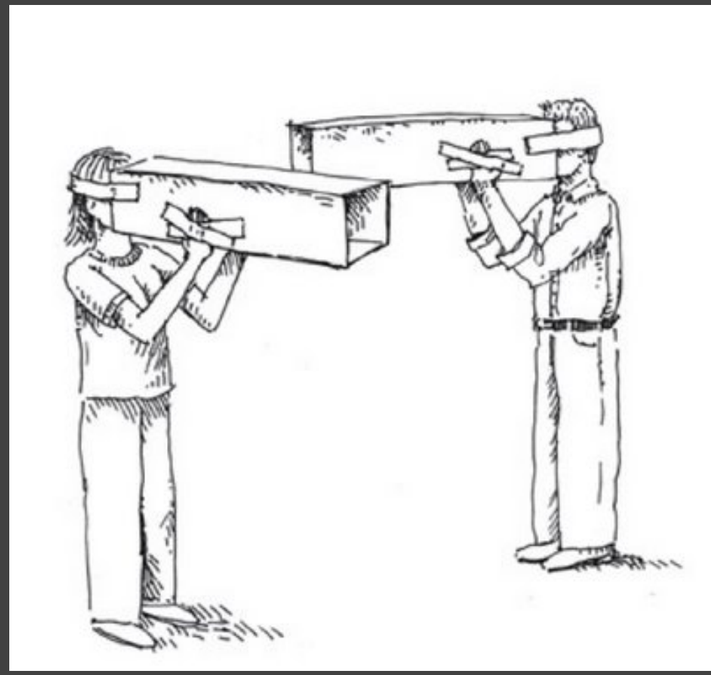
Ambiguity of intent. Scale. Cognitive biases, mistakes.

Lack of global view -> overweight local information.



Balancing Automation and Control

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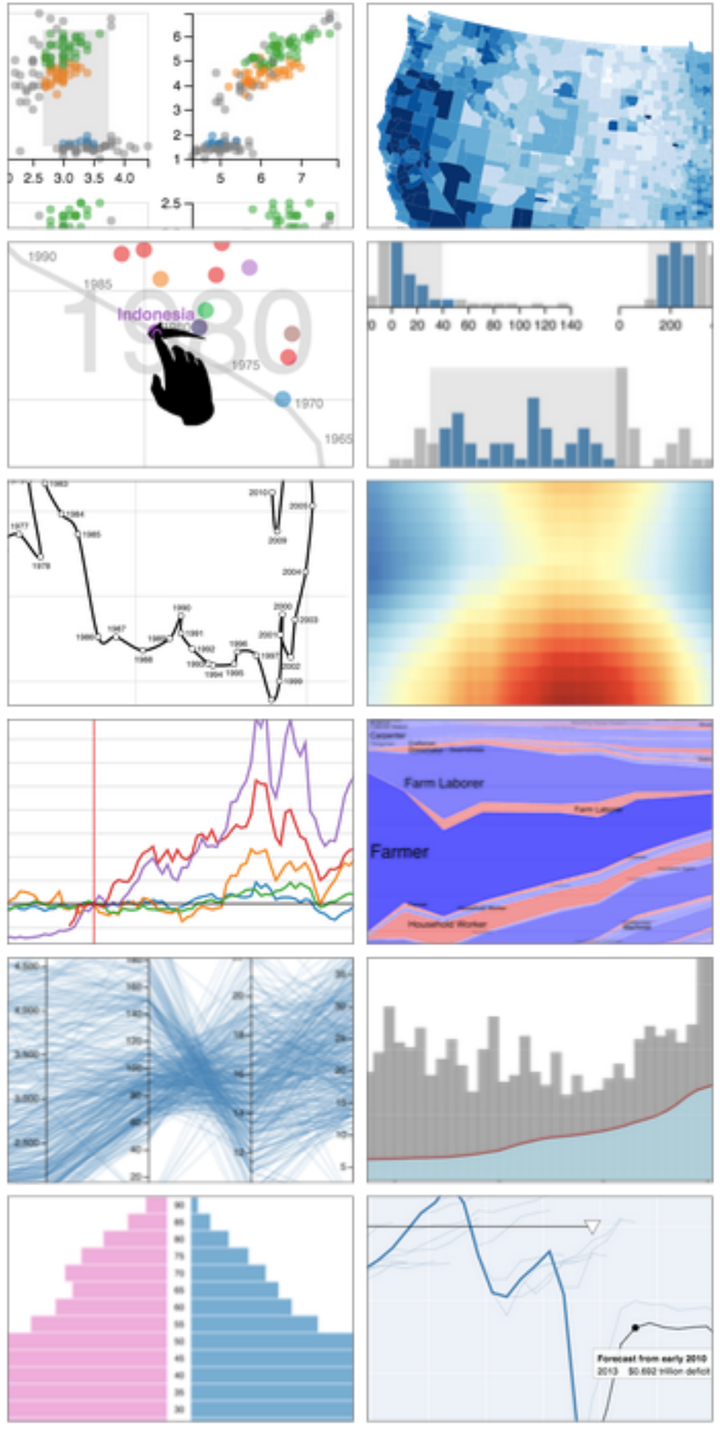
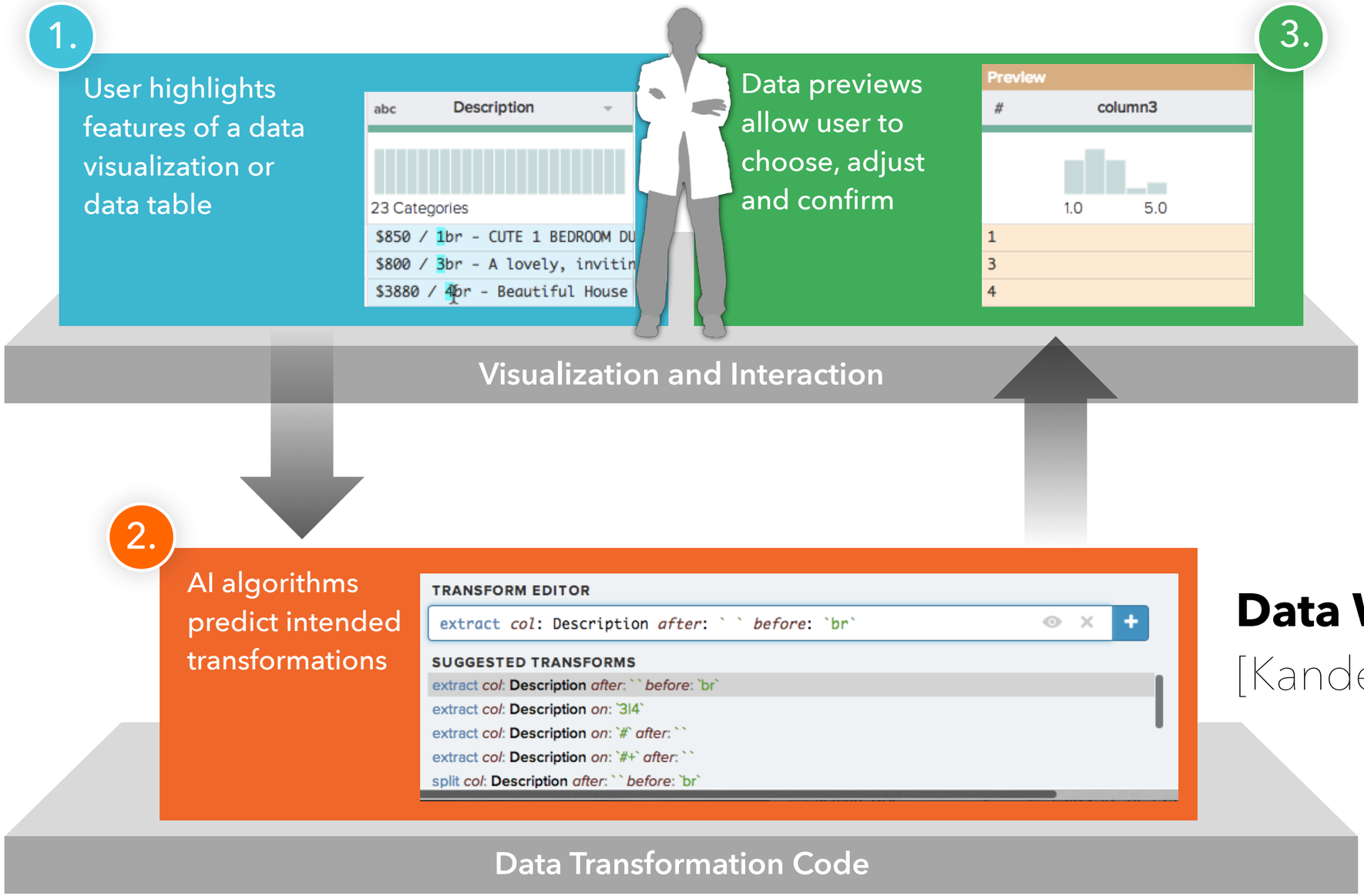
Lack of global view -> overweight local information.

Strategy: Shared Representations
Enhance user interfaces with **models of capabilities, actions & goals** to reason about the task and enable principled human-AI interaction.



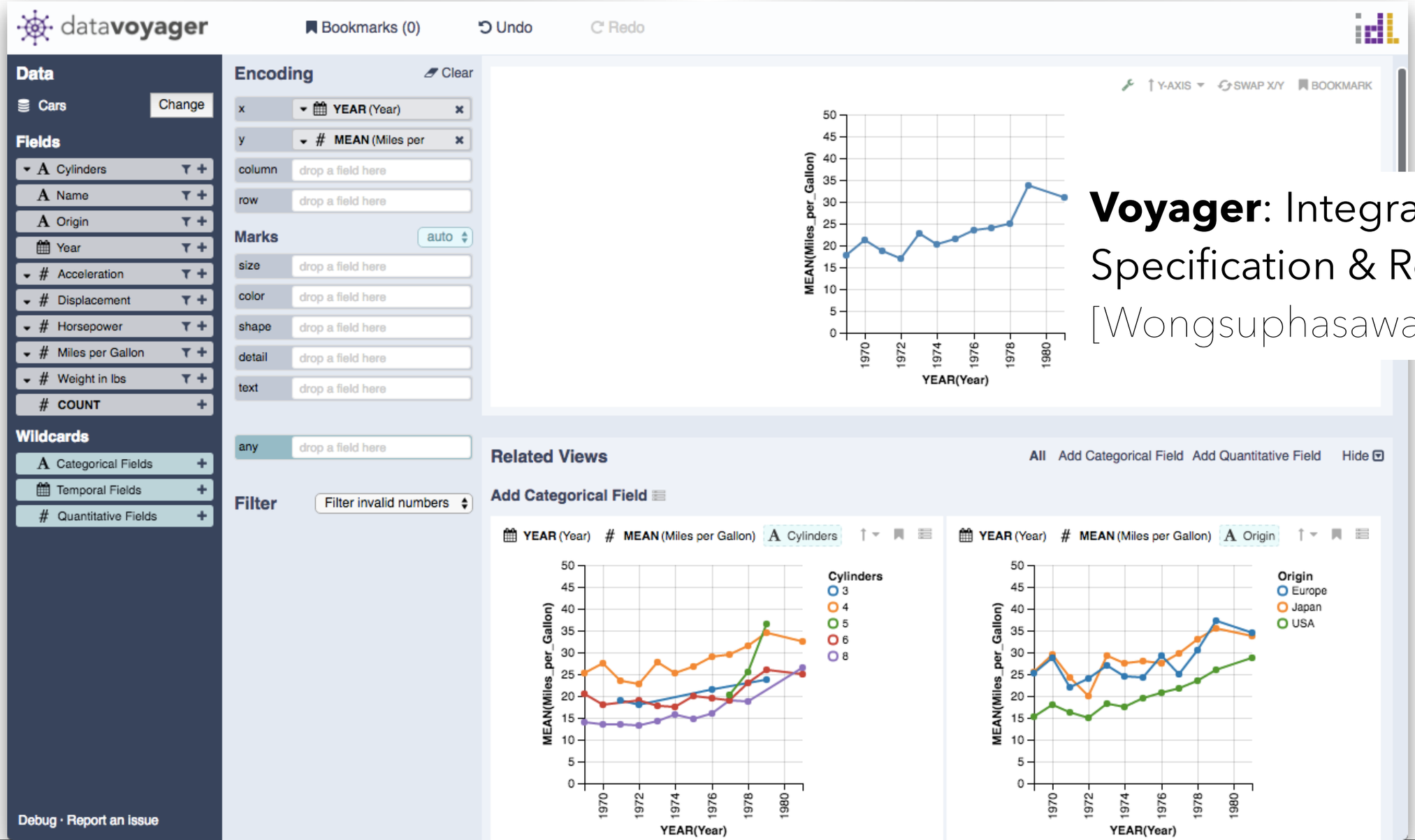
Predictive Interaction for **Data Wrangling**



Data Wrangler

[Kandel et al. 2011]

Predictive Interaction for **Exploratory Analysis**



Voyager: Integrate Visualization Specification & Recommendation [Wongsuphasawat et al. 2016, 17]

Predictive Interaction for **Error Analysis**

How many people are in this picture?

groundtruth:**3** *(* 10)*

saaa:**2** vqacounting:**3**

How many brownish peaks are there?

groundtruth:**2** *(* 10)*

saaa:**4** vqacounting:**5**

DID YOU MEAN TO FILTER INSTANCES THAT ARE... Close Now

```
starts_with(question, pattern="how many ADJ")
starts_with(question, pattern="ADV ADJ ADJ")
attr:question_type == "how many"
```

A

See more general suggestions?

	saaa		vqacounting	
all_instances	121512	43% 57%	121512	39% 61%
how_many_noun	11471	62% 38%	11471	51% 49%
how_many_adj	788	66% 34%	788	63% 37%

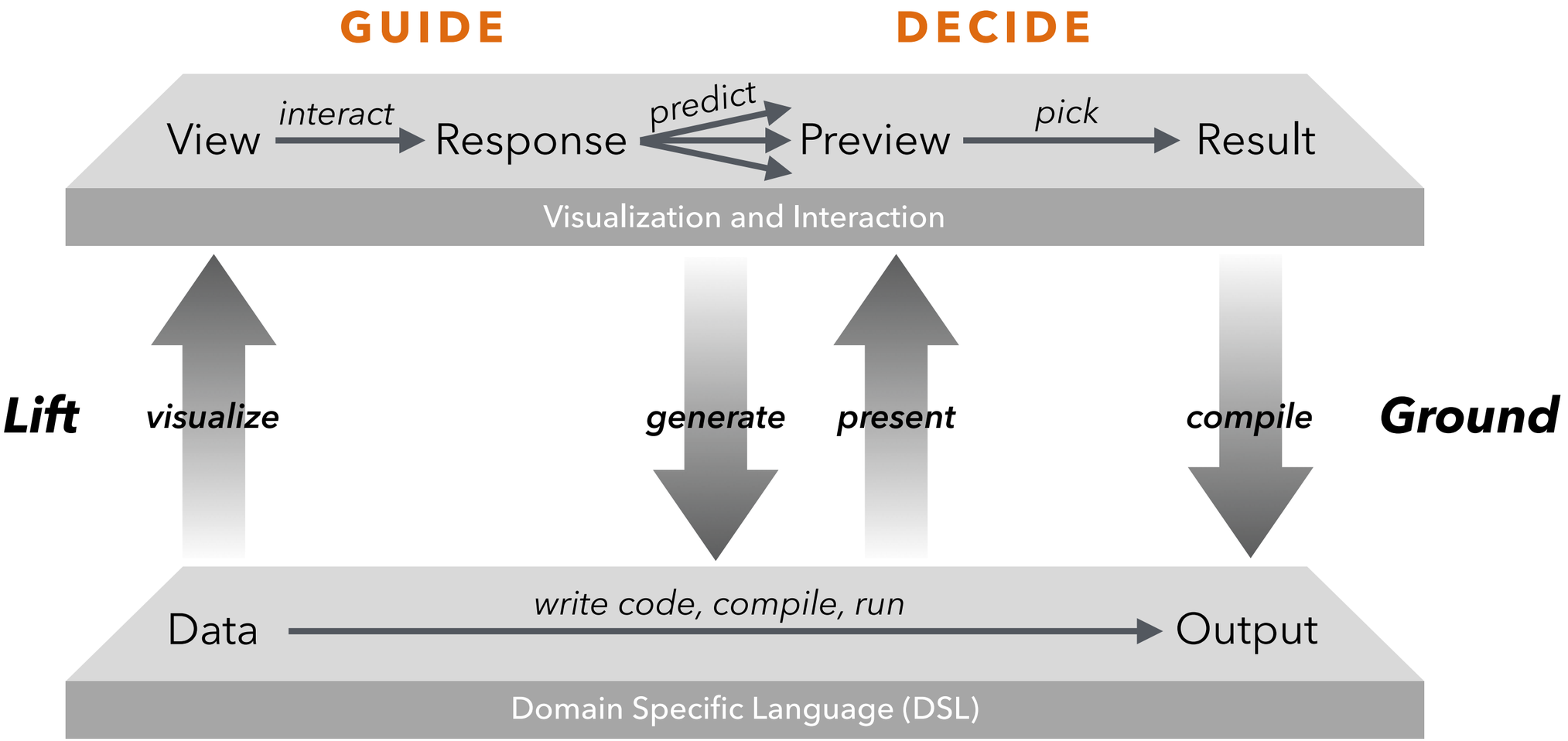
How many ~~brownish~~ peaks are there?

DID YOU WANT TO GENERALIZE TO...

brownish →	☐ keep
brownish peaks → **peaks**	☐ keep
brownish NOUN → NOUN	☐ keep
ADJ NOUN → NOUN	☐ keep
how many ADJ → **how many** ADJ	☐ keep
how many ADJ NOUN → **how many** NOUN	☑ keep

Errudite: Reproducible & Testable Error Analysis of NLP Models [Wu et al. ACL 2019]

Predictive Interaction [Heer, Hellerstein, Kandel CIDR'15]



Research Opportunities

Effective AI-Infused Interactive Systems

Challenge “fully automated” assumptions.

New interaction paradigms and prototyping tools.

Virtuous cycle of human *and* machine learning.

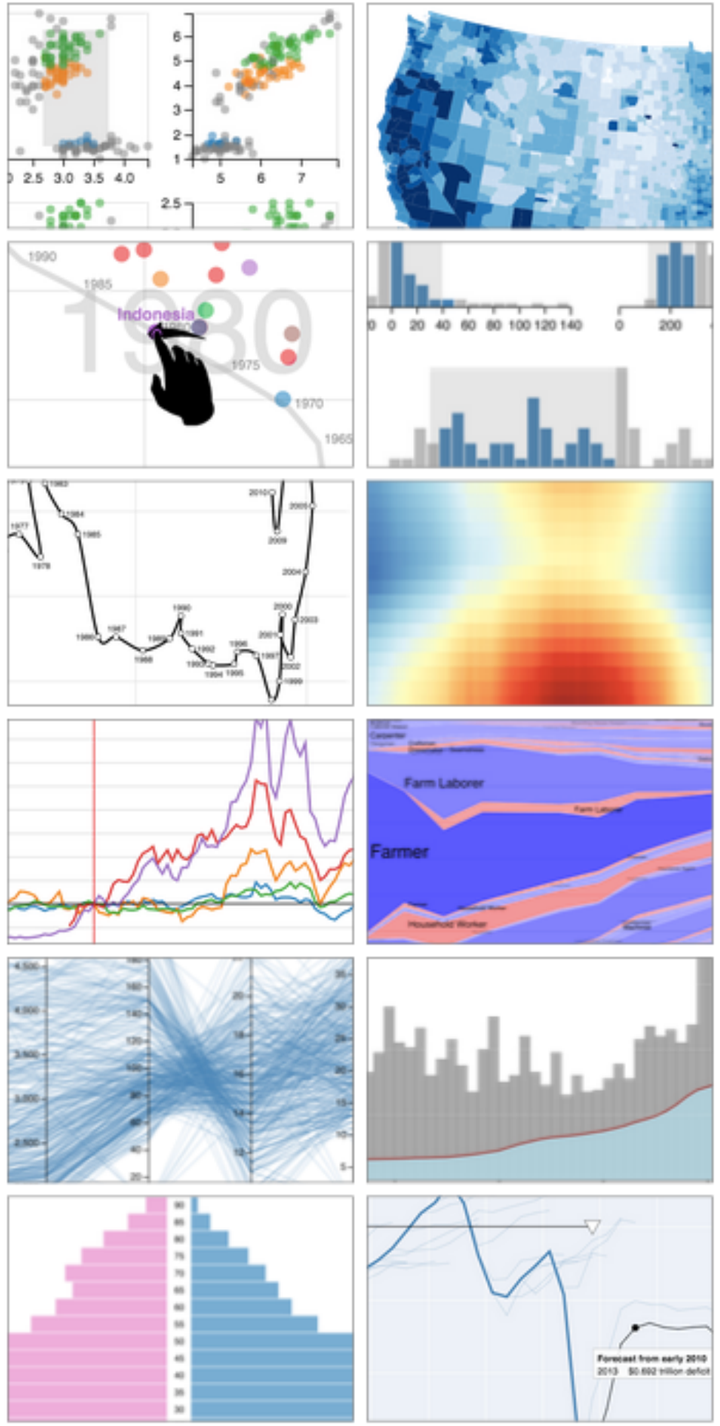
Data analysis is an exciting petri dish for this…

…to develop theory with broader applicability!

Evaluate Trade-offs in Agency + Automation

Under what conditions do we become complacent consumers of machine recommendations?

How do we promote critical engagement?



EPILOGUE:

Accessibility (a11y)

John A Guerra Gómez
@duto_guerra

. @benbendc: "My strong way of promoting information visualization is to declare that it is such a powerful amplifier of human abilities that it should be illegal, unprofessional, and unethical to do data analysis using only statistical and algorithmic processes." 👏

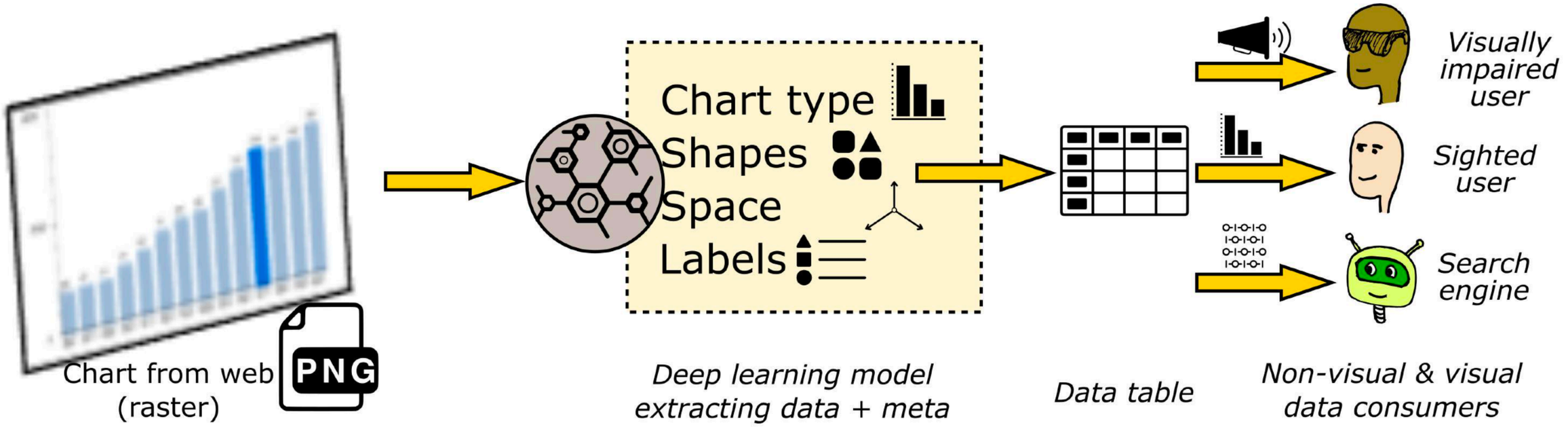
Jeffrey Heer @jeffrey_heer · Mar 13

Though I appreciate the underlying sentiment, this position seems to imply blatant violations of the Americans with Disabilities Act. With the exception of color vision deficiency, visualization is overdue in seriously attending to accessibility -- my own work very much included!

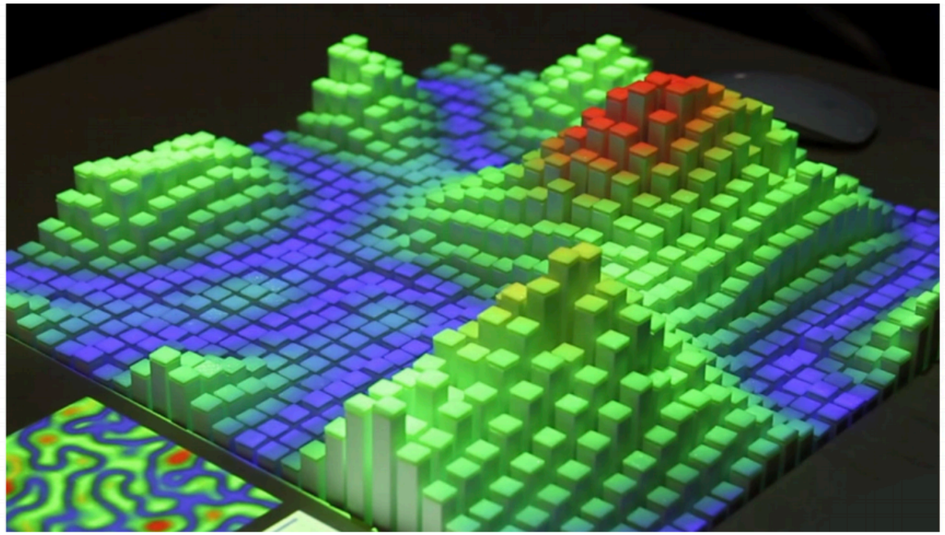
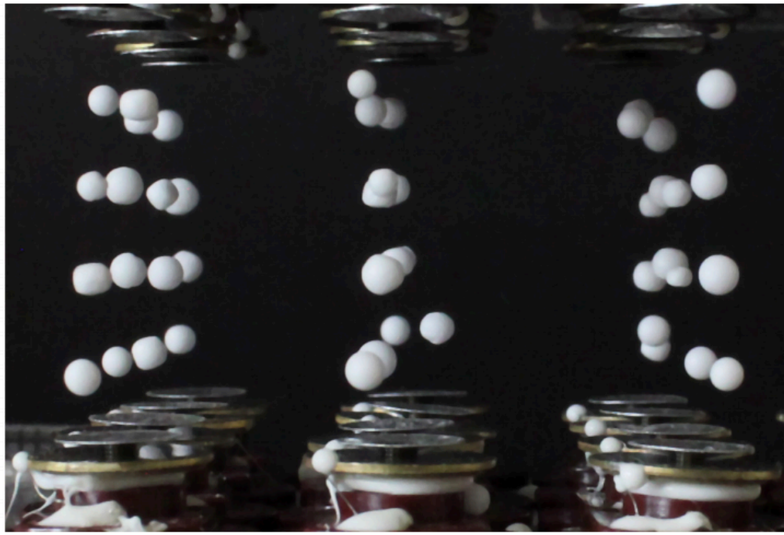
> 
>
> **John A Guerra Gómez** @duto_guerra · Mar 13
>
> . @benbendc: "My strong way of promoting information visualization is to declare that it is such a powerful amplifier of human abilities that it should be illegal, unprofessional, and unethical to do data analysis using only statistical and algorithmic processes." 👏 twitter.com/JessicaHullman...

Not all of us can see.

Reverse Engineering of Visualizations



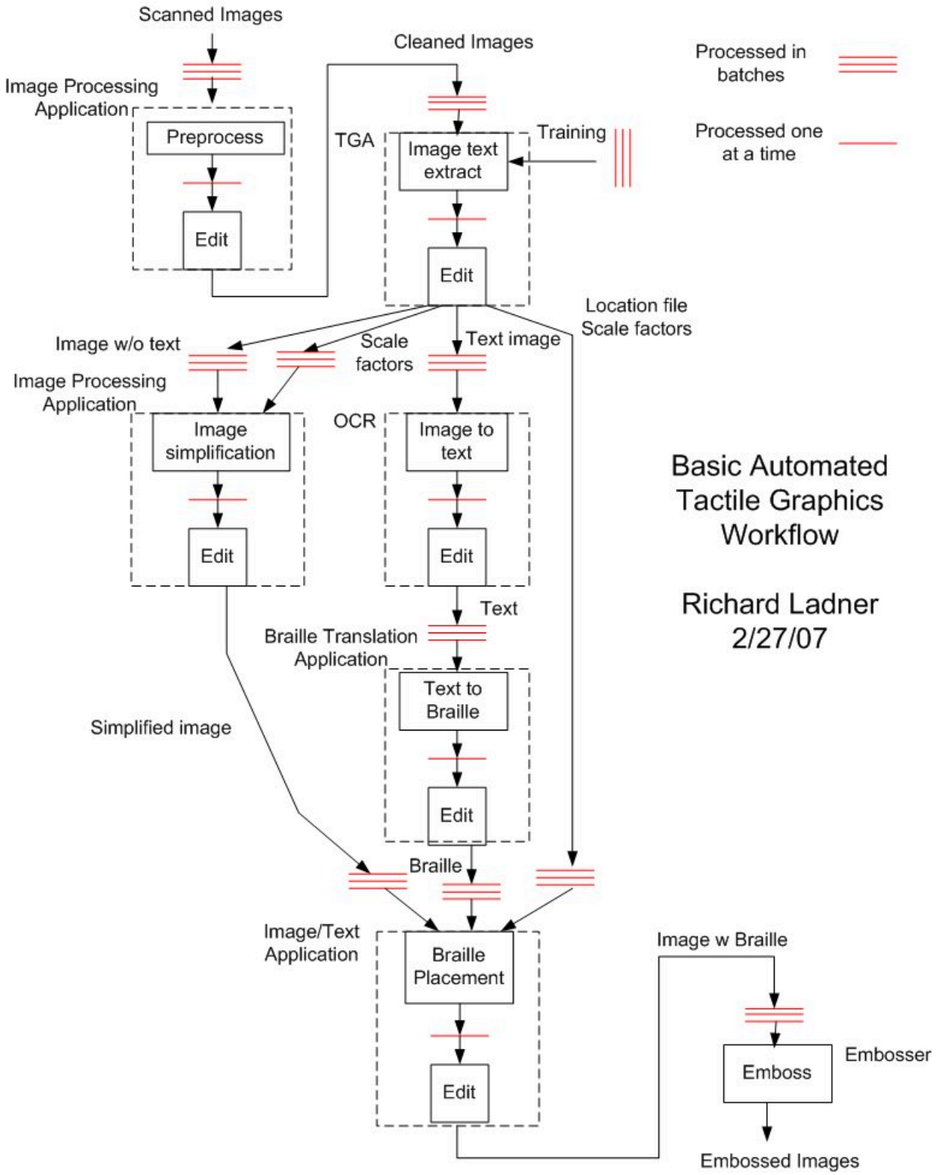
[ReVision, Savva et al. 2011; REV, Poco et al. 2017, **Choi et al. 2019**]

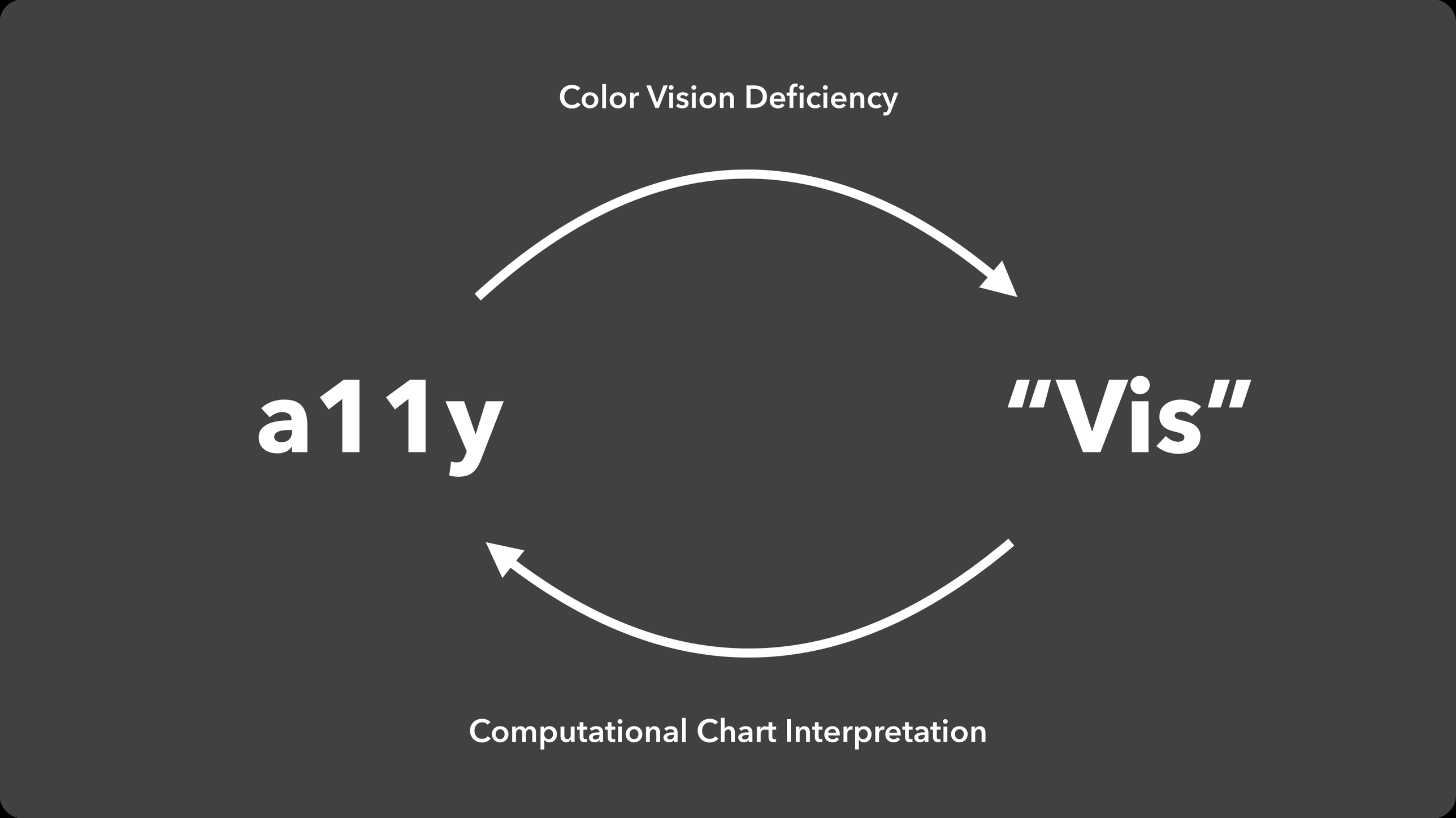




Opportunities and Challenges for Data Physicalization

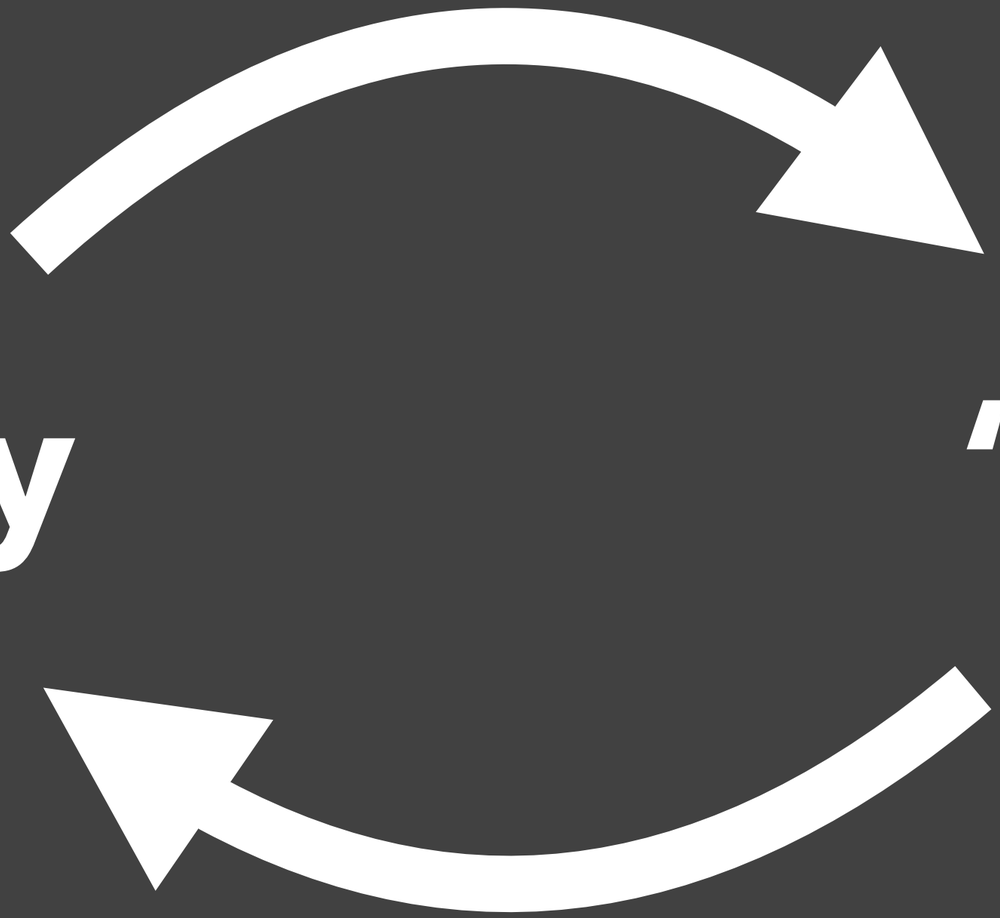
Yvonne Jansen[1], Pierre Dragicevic[2], Petra Isenberg[2], Jason Alexander[3], Abhijit Karnik[3], Johan Kildal[4], Sriram Subramanian[5], Kasper Hornbæk[1]

Tactile Graphics




Color Vision Deficiency
a11y
"Vis"
Computational Chart Interpretation

Accessible Output, Annotation, Captioning
Richer Individual Differences, Aesthetics



Perception Models, Modality Translation, Perceptualization Tools

Research Opportunities

More Accessible Graphics

Reader-friendly annotation, captioning.

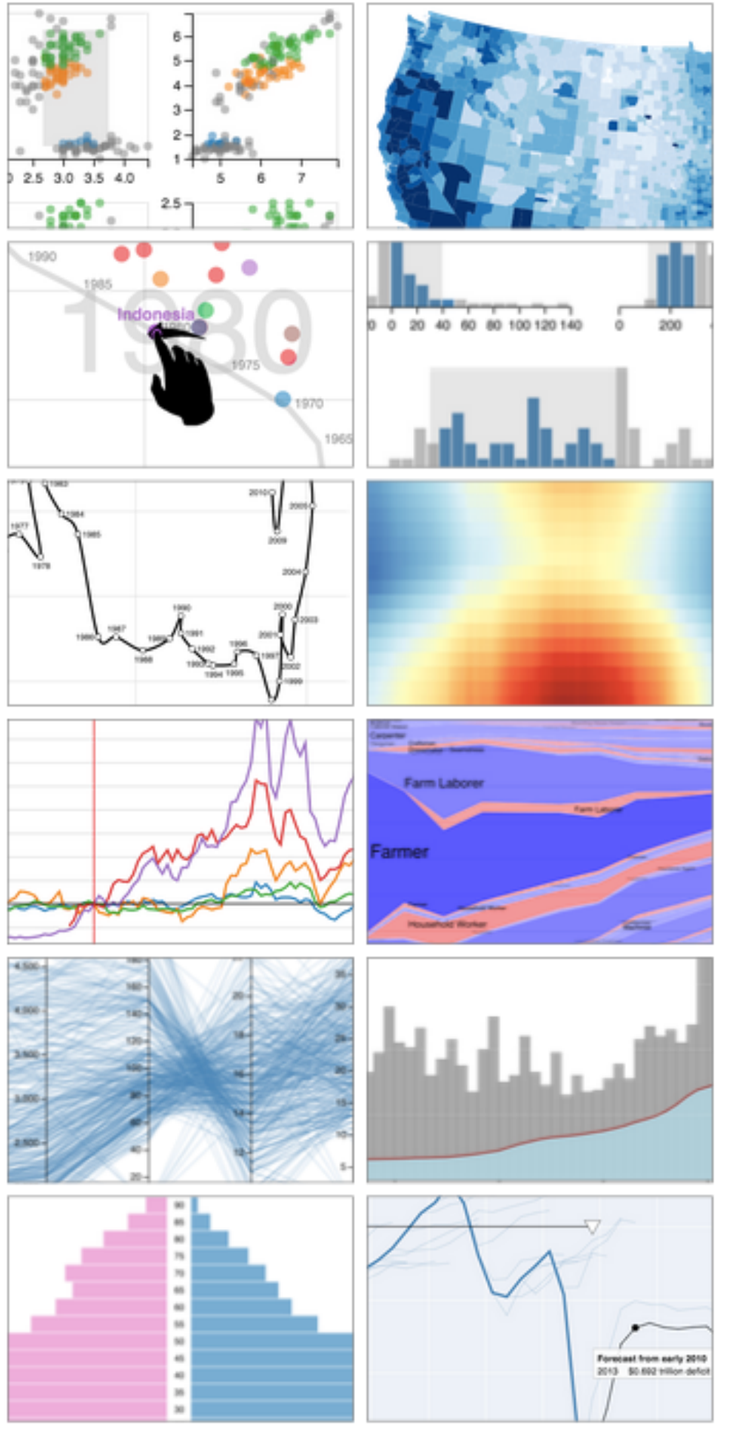
Augmenting Models of "Graphical" Perception

Perceptual effectiveness for non-visual or multi-modal displays. Challenge existing approaches & models?

- (Musical) aesthetics critical to sonification?
- Individual differences (e.g., sighted vs. blind)?

Modality Translation of Data "Perceptualizations"

Given a formal visualization specification, how might we re-target a design to other modalities?



Visualization

… is not enough!

Visualization
… is **necessary**,
but not **sufficient**.

We are capable of **more**.

“The purpose of computing
is **insight**, not **numbers**.”

- Richard Hamming

“The purpose of visualization is **insight**, not **pictures**.”

- Ben Shneiderman

The ultimate subject of the visualization research community is **people**, not **pictures**.

Visualization is Not Enough

Jeffrey Heer @jeffrey_heer
U. Washington / Trifacta