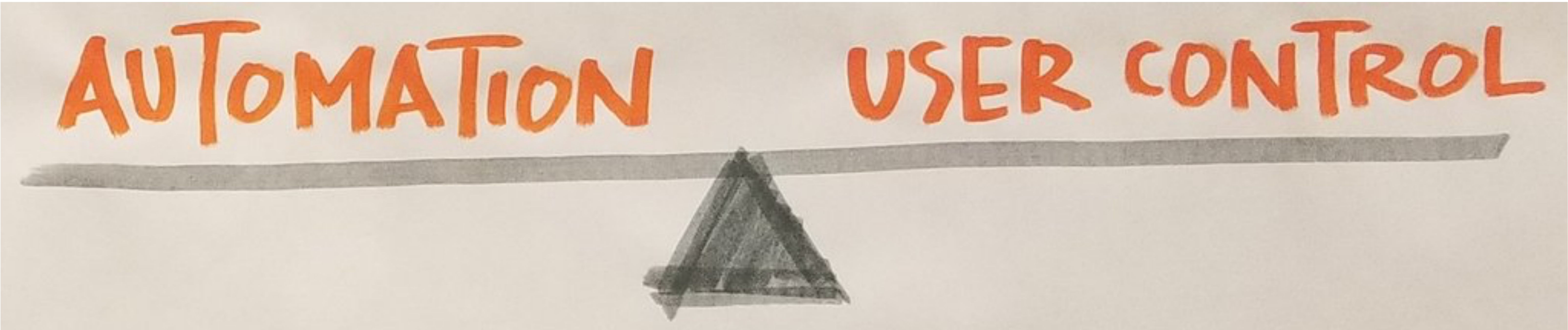
Agency + Automation

Jeffrey Heer @jeffrey_heer
U. Washington / Trifacta



A Balancing Act…

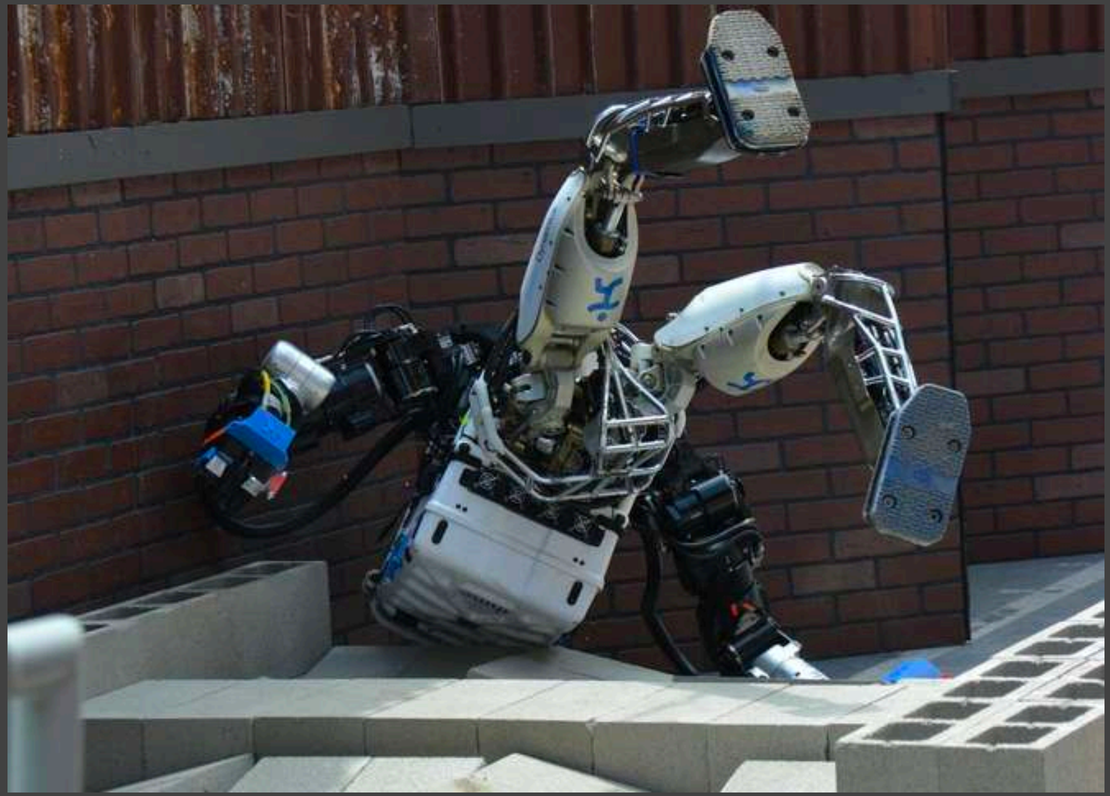
Balancing Automation and Control

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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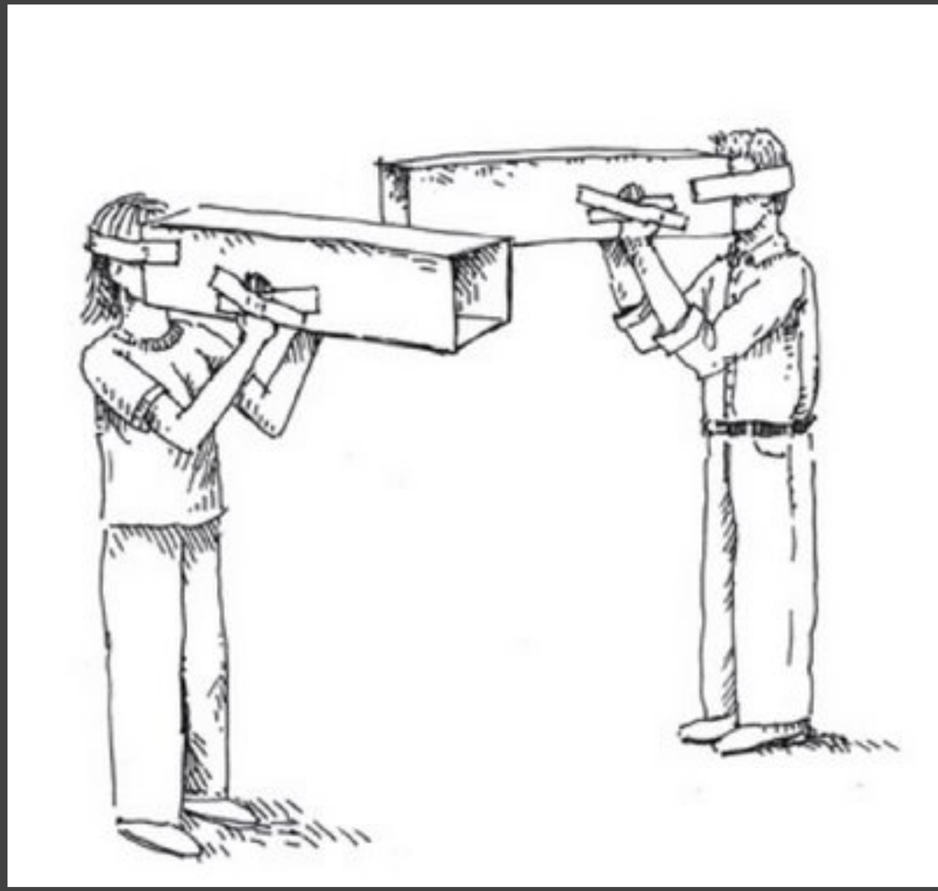
Lack of global view -> overweight local information.



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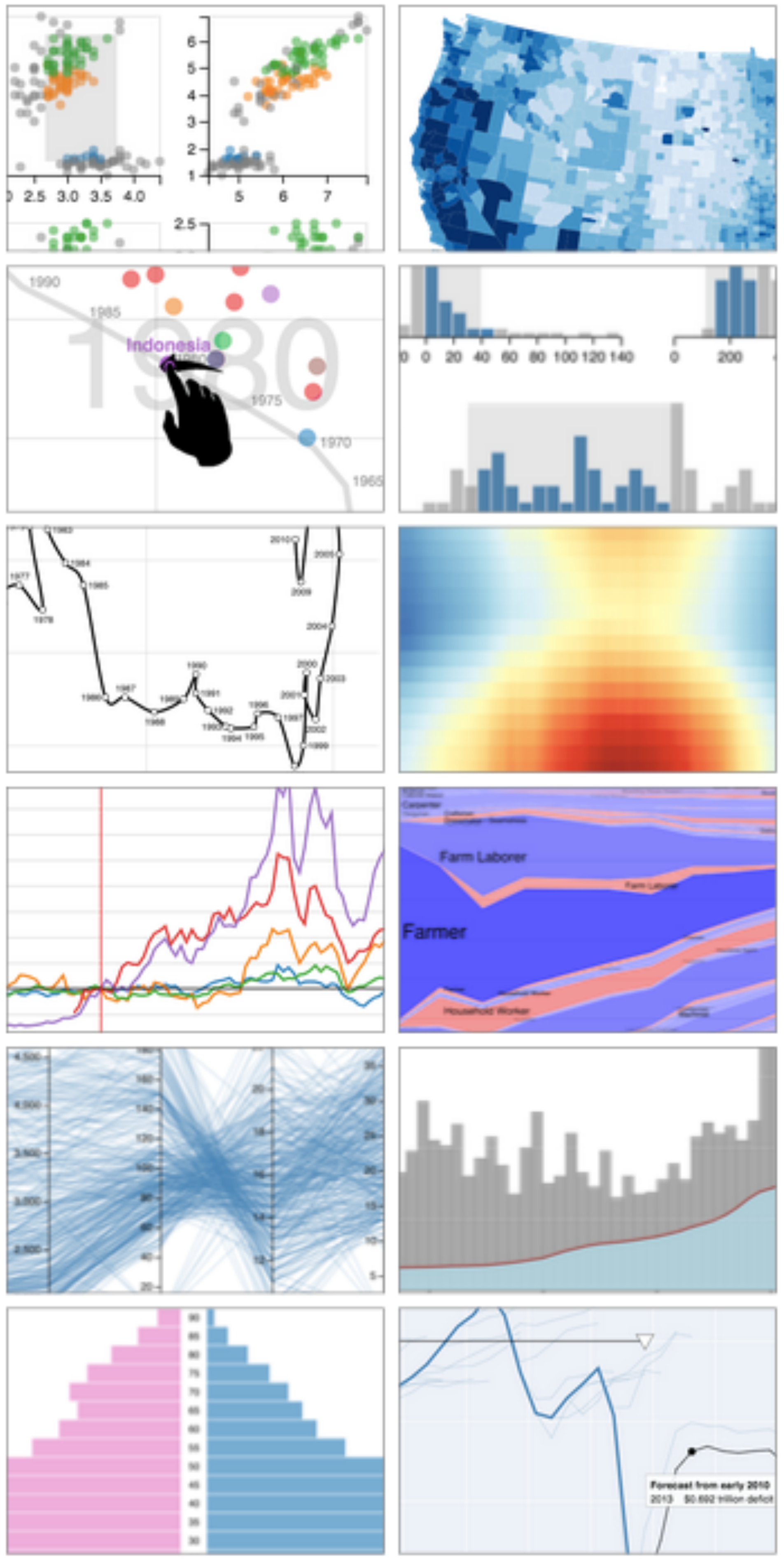
Strategy: Shared Representations
Enhance user interfaces with **models of capabilities, actions & goals** to reason about the task and enable principled human-AI collaboration.

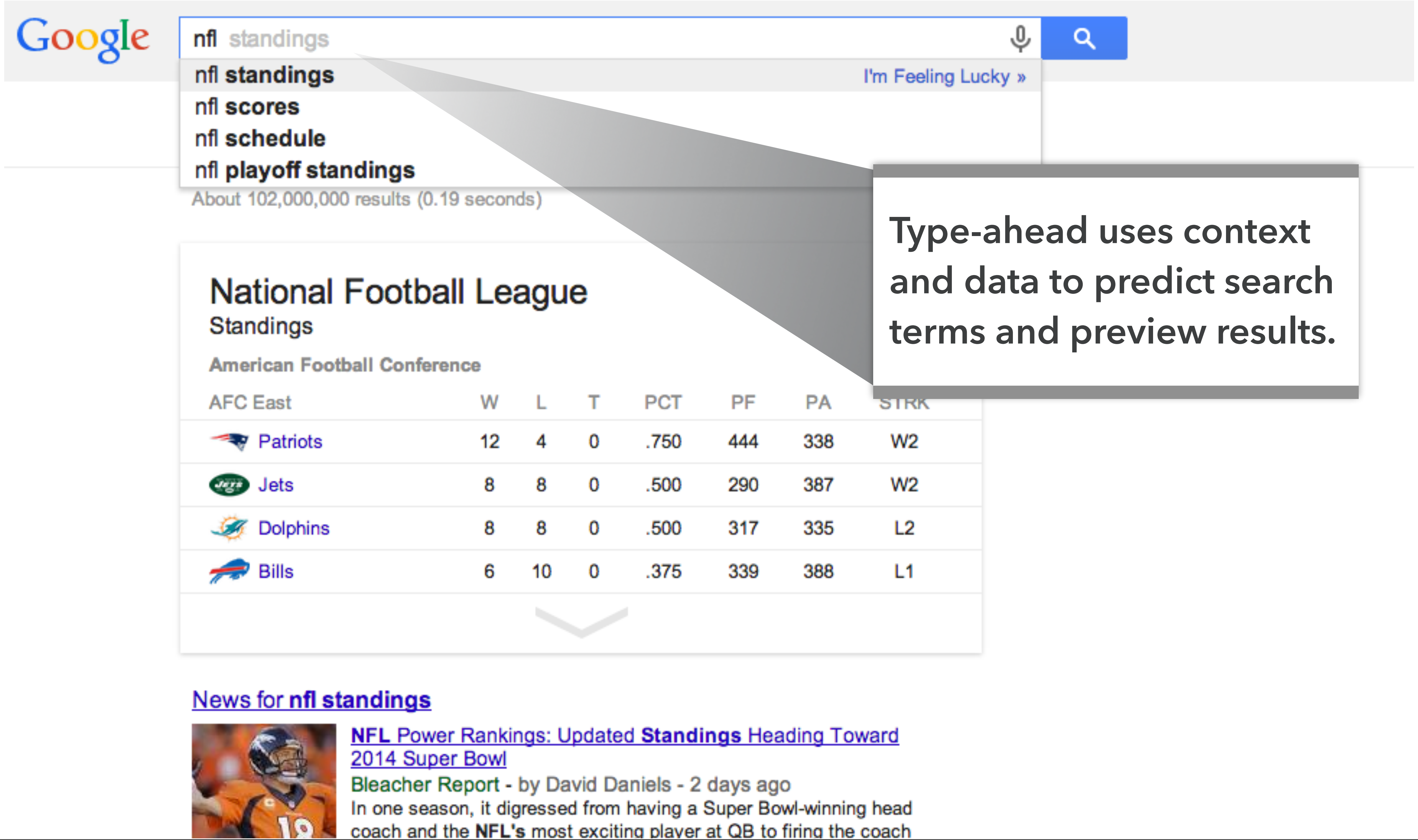


DESIGN CHALLENGE:

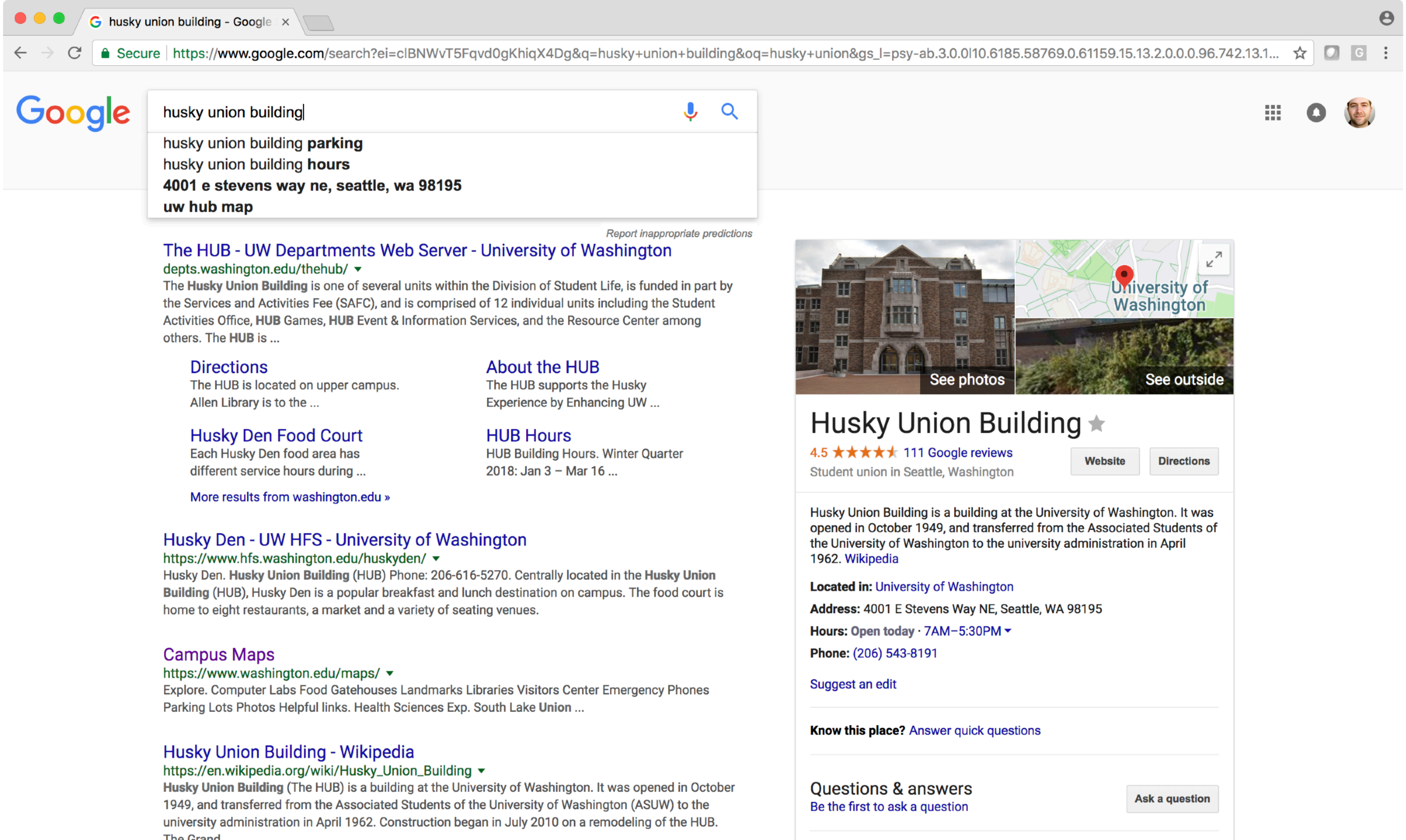
Determine "regions of optimality" in possible divisions of labor among directed and automated actions.

A Humble Starting Point

Search Query Auto-Complete



Type-ahead uses context and data to predict search terms and preview results.


husky union building - Google
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Google
husky union building
husky union building parking
husky union building hours
4001 e stevens way ne, seattle, wa 98195
uw hub map
Report inappropriate predictions
The HUB - UW Departments Web Server - University of Washington
depts.washington.edu/thehub/
The Husky Union Building is one of several units within the Division of Student Life, is funded in part by the Services and Activities Fee (SAFC), and is comprised of 12 individual units including the Student Activities Office, HUB Games, HUB Event & Information Services, and the Resource Center among others. The HUB is ...
Directions
The HUB is located on upper campus. Allen Library is to the ...
About the HUB
The HUB supports the Husky Experience by Enhancing UW ...
Husky Den Food Court
Each Husky Den food area has different service hours during ...
HUB Hours
HUB Building Hours. Winter Quarter 2018: Jan 3 – Mar 16 ...
More results from washington.edu »
Husky Den - UW HFS - University of Washington
https://www.hfs.washington.edu/huskyden/
Husky Den. Husky Union Building (HUB) Phone: 206-616-5270. Centrally located in the Husky Union Building (HUB), Husky Den is a popular breakfast and lunch destination on campus. The food court is home to eight restaurants, a market and a variety of seating venues.
Campus Maps
https://www.washington.edu/maps/
Explore. Computer Labs Food Gatehouses Landmarks Libraries Visitors Center Emergency Phones Parking Lots Photos Helpful links. Health Sciences Exp. South Lake Union ...
Husky Union Building - Wikipedia
https://en.wikipedia.org/wiki/Husky_Union_Building
Husky Union Building (The HUB) is a building at the University of Washington. It was opened in October 1949, and transferred from the Associated Students of the University of Washington (ASUW) to the university administration in April 1962. Construction began in July 2010 on a remodeling of the HUB.
The Grand
University of Washington
See photos
See outside
Husky Union Building
4.5 111 Google reviews
Student union in Seattle, Washington
Website
Directions
Husky Union Building is a building at the University of Washington. It was opened in October 1949, and transferred from the Associated Students of the University of Washington to the university administration in April 1962. Wikipedia
Located in: University of Washington
Address: 4001 E Stevens Way NE, Seattle, WA 98195
Hours: Open today · 7AM–5:30PM
Phone: (206) 543-8191
Suggest an edit
Know this place? Answer quick questions
Questions & answers
Be the first to ask a question
Ask a question

Design Characteristics

Provides significant value-added automation.

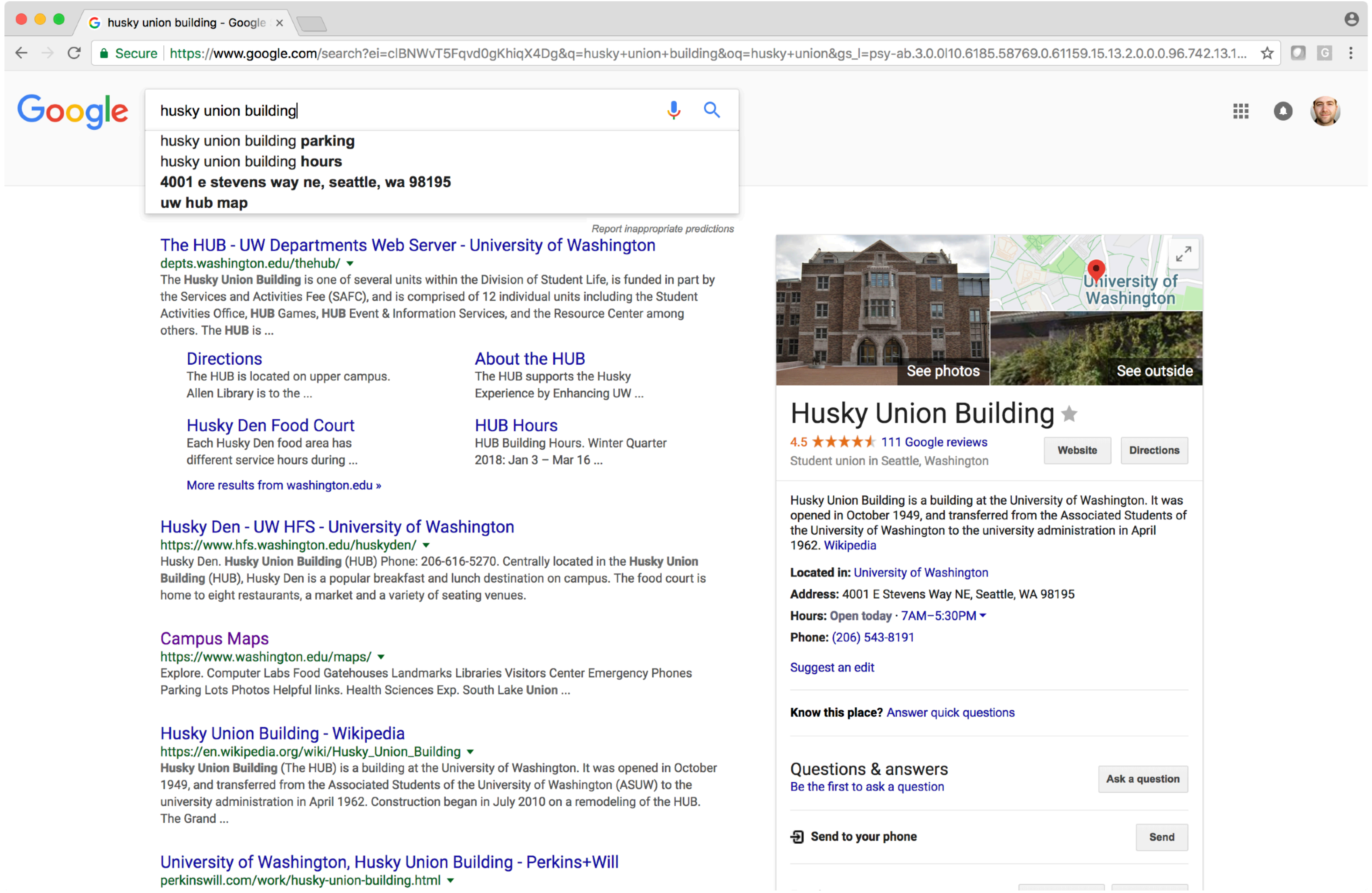
Supports uncertainty around user goals.

Employs dialog to resolve key uncertainties.

Allows efficient direct invocation and termination.

Provides mechanisms for agent–user collaboration to refine results.

Continues to learn by observing user actions.



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Principles of Mixed-Initiative User Interfaces

Eric Horvitz
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ABSTRACT
Recent debate has centered on the relative promise of focusing user-interface research on developing new metaphors and tools that enhance users' abilities to directly manipulate objects *versus* directing effort toward developing interface agents that provide automation. In this paper, we review principles that show promise for allowing engineers to enhance human—computer interaction through an elegant coupling of automated services with direct manipulation. Key ideas will be highlighted in terms of the LookOut system for scheduling and meeting management.

Keywords
Intelligent agents, direct manipulation, user modeling, probability, decision theory, UI design

INTRODUCTION
There has been debate among researchers about where great opportunities lay for innovating in the realm of human—computer interaction [10]. One group of researchers has expressed enthusiasm for the development and application of new kinds of automated services, often referred to as interface "agents." The efforts of this group center on building machinery for sensing a user's activity and taking automated actions [4,5,6,8,9]. Other researchers have suggested that effort focused on automation might be better expended on exploring new kinds of metaphors and conventions that enhance a user's ability to *directly manipulate* interfaces to access information and invoke services [1,13]. Innovations on both fronts have been fast paced. However, there has been a tendency for a divergence

wish to avoid limiting designs for human–computer interaction to direct manipulation when significant power and efficiencies can be gained with automated reasoning. There is great opportunity for designing innovative user interfaces, and new human–computer interaction modalities by considering, from the ground up, designs that take advantage of the power of direct manipulation and potentially valuable automated reasoning [2].

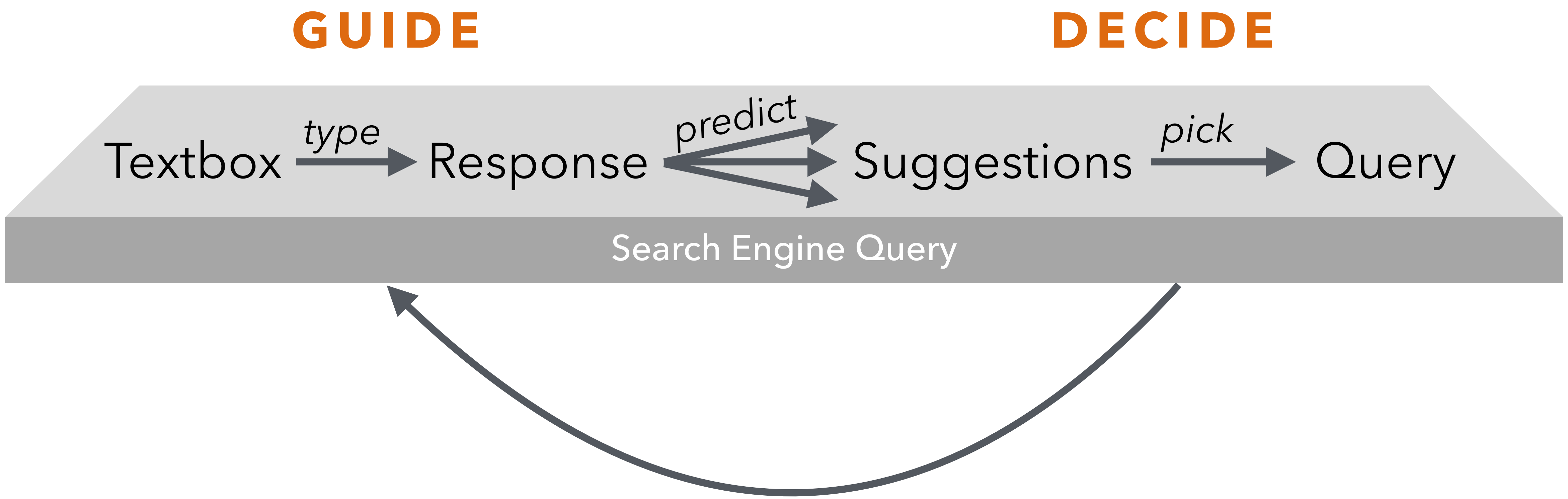
PRINCIPLES FOR MIXED-INITIATIVE UI
Key problems with the use of agents in interfaces include poor guessing about the goals and needs of users, inadequate consideration of the costs and benefits of automated action, poor timing of action, and inadequate attention to opportunities that allow a user to guide the invocation of automated services and to refine potentially suboptimal results of automated analyses. In particular, little effort has been expended on designing for a *mixed-initiative* approach to solving a user's problems—where we assume that intelligent services and users may often collaborate efficiently to achieve the user's goals.

Critical factors for the effective integration of automated services with direct manipulation interfaces include:

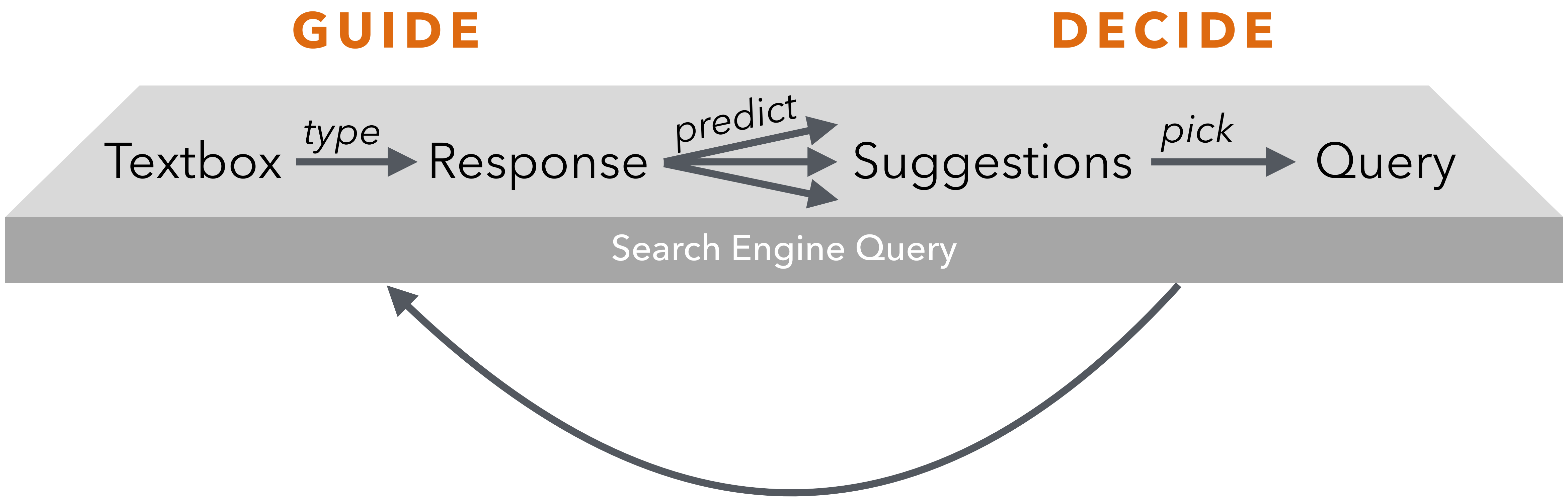
(1) **Developing significant value-added automation.** It is important to provide automated services that provide *genuine value* over solutions attainable with direct manipulation.

(2) **Considering uncertainty about a user's goals.** Computers are often uncertain about the goals and current the focus of attention of a user. In many cases,

Search Query Auto-Complete

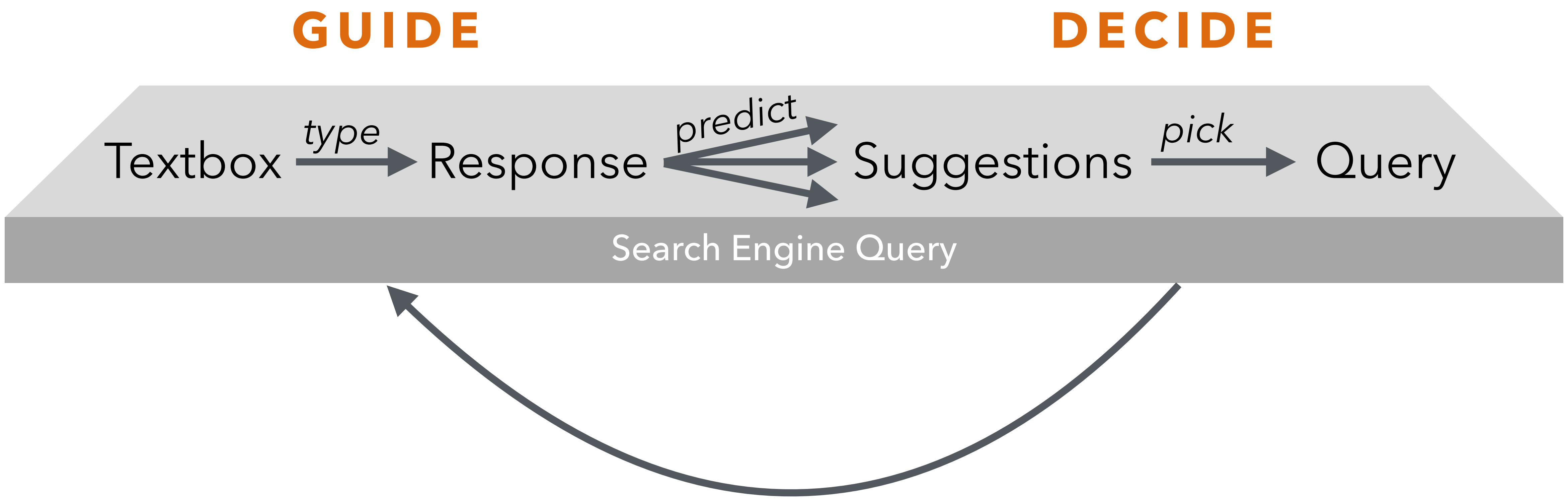


Search Query Auto-Complete



The input and output domains are the same: **text.**

Search Query Auto-Complete



What about more complex input/output relations?

EXAMPLES:

Data Cleaning & Transformation

Exploratory Data Visualization

Natural Language Translation

EXAMPLES:

Data Cleaning & Transformation

Exploratory Data Visualization

Natural Language Translation

I spend more than half of my time integrating, cleansing and transforming data without doing any actual analysis. Most of the time I’m lucky if I get to do any “analysis” at all.

Anonymous Data Scientist
from our 2012 interview study

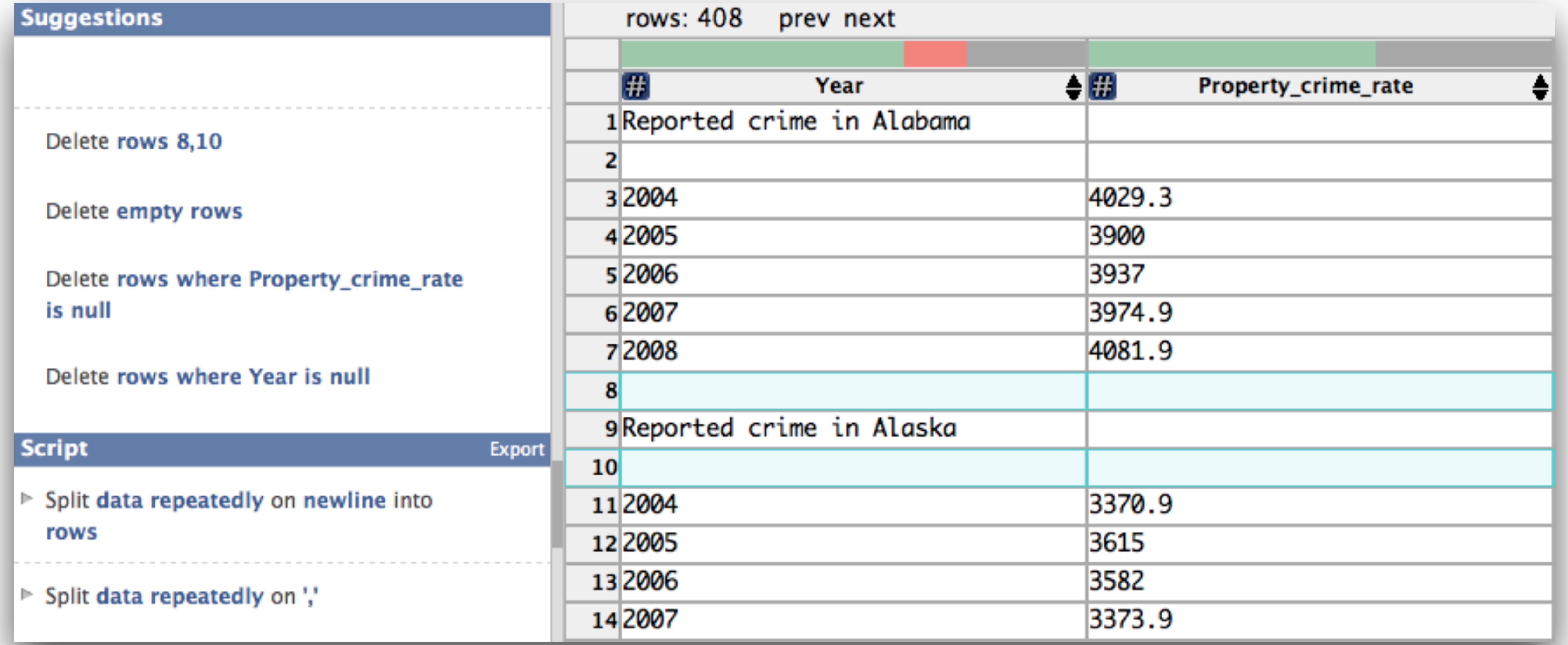
Big Data Borat

@BigDataBorat

Following

In Data Science, 80% of time spent prepare data, 20% of time spent complain about need for prepare data.

DataWrangler



Wrangler: Interactive Visual Specification of Data Transformation Scripts

Sean Kandel et al. *ACM CHI 2011*

DataWrangler

Reduces specification time, promotes the use of reusable, scalable transformations rather than idiosyncratic edits.

Agency: Users appreciated suggestions in response to an initiating interaction, but did not always act on *proactive* assistance, often preferring to maintain the initiative.

Complementarity: Suggestions good for tasks people found hard (extraction patterns, table reshaping). People good in cases where inference is less tractable (arbitrary formulas).

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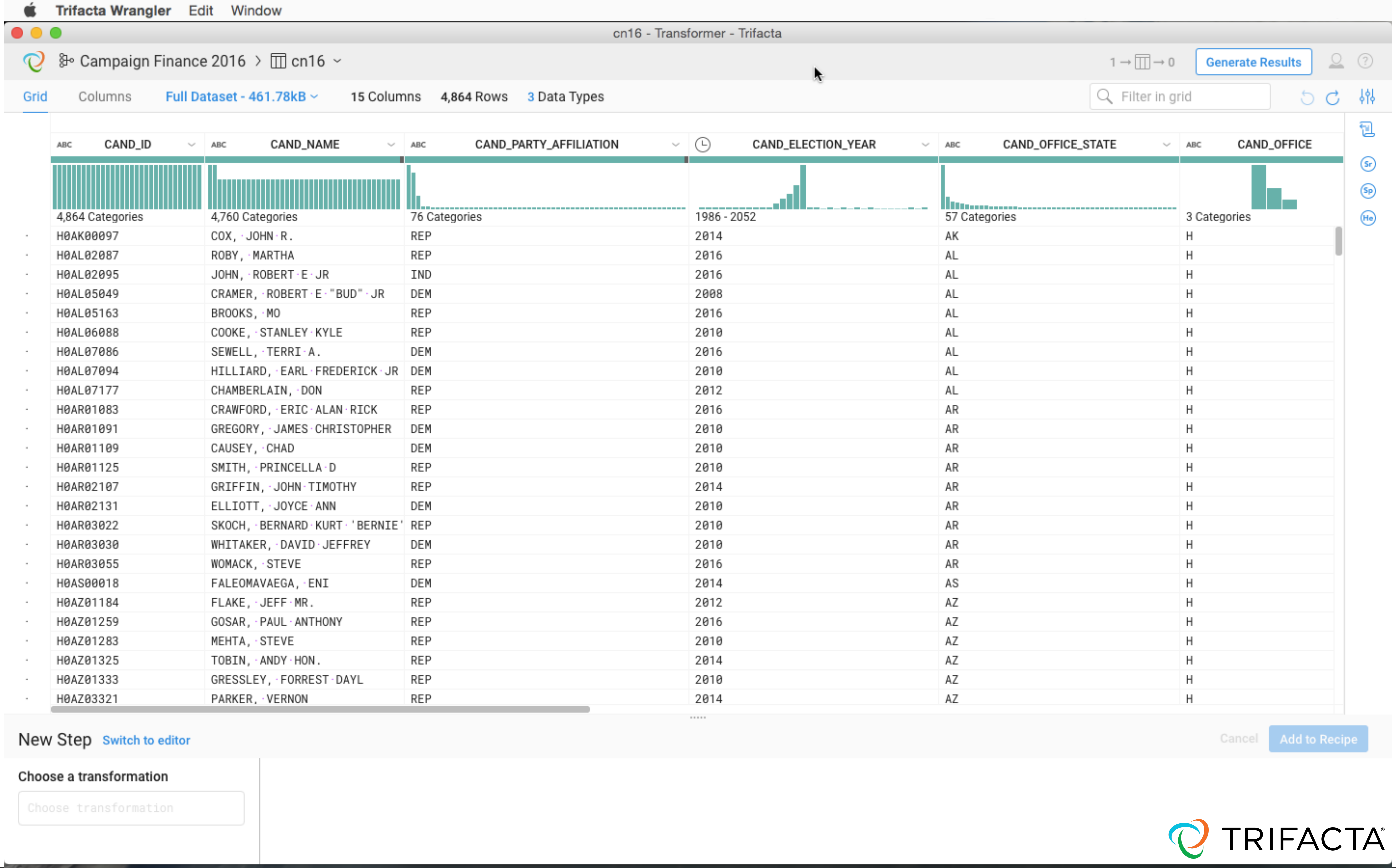
TRIFACTA®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Campaign Finance 2016 > cn16
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Grid Columns Full Dataset - 461.78kB 15 Columns 4,864 Rows 3 Data Types
Filter in grid
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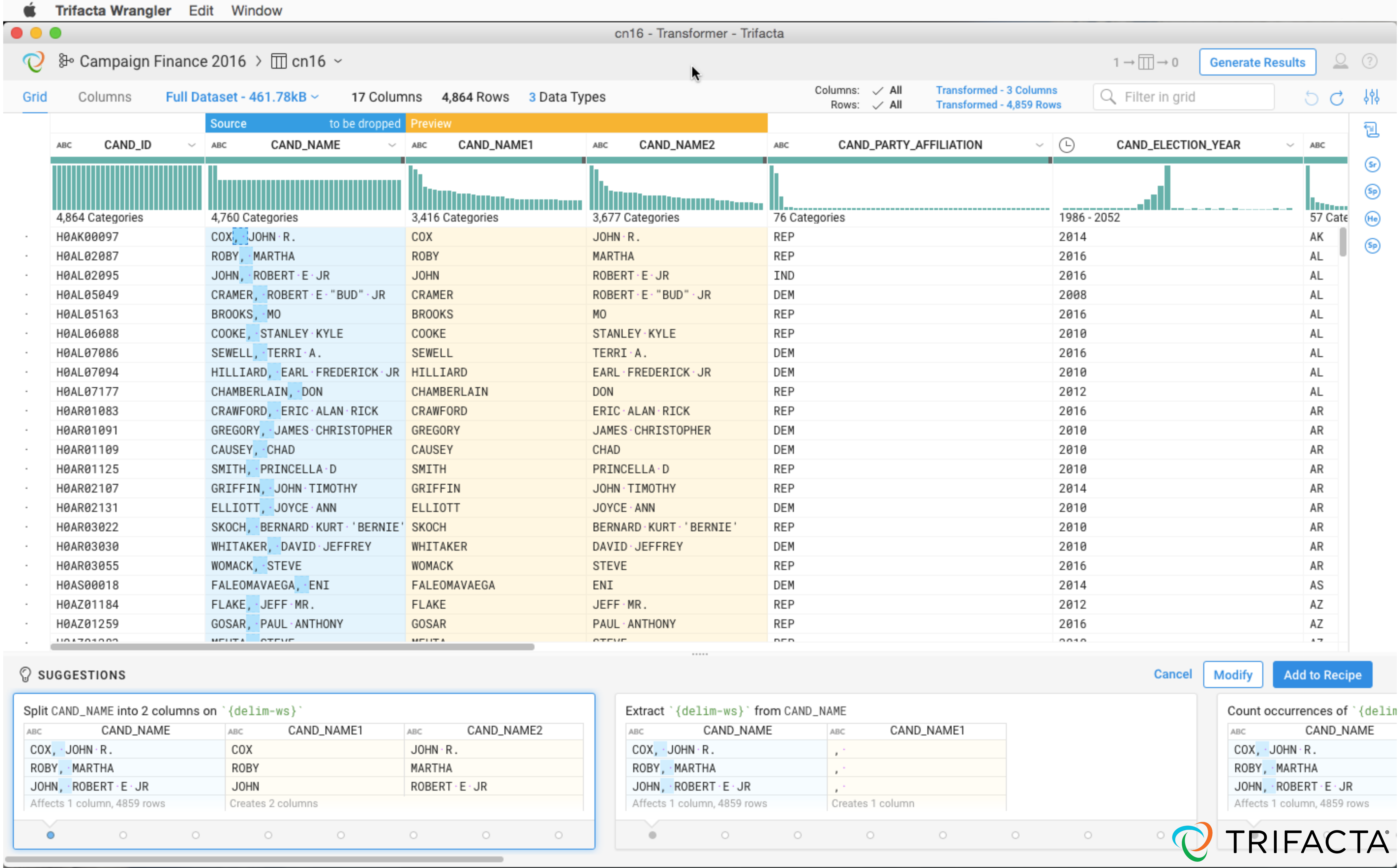
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Columns: All Rows: All
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Filter in grid
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Preview
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H0AZ01184 FLAKE, JEFF MR. FLAKE JEFF MR. REP 2012 AZ
H0AZ01259 GOSAR, PAUL ANTHONY GOSAR PAUL ANTHONY REP 2016 AZ
SUGGESTIONS
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Split CAND_NAME into 2 columns on `{delim-ws}`
CAND_NAME CAND_NAME1 CAND_NAME2
COX, JOHN R. COX JOHN R.
ROBY, MARTHA ROBY MARTHA
JOHN, ROBERT E JR JOHN ROBERT E JR
Affects 1 column, 4859 rows Creates 2 columns
Extract `{delim-ws}` from CAND_NAME
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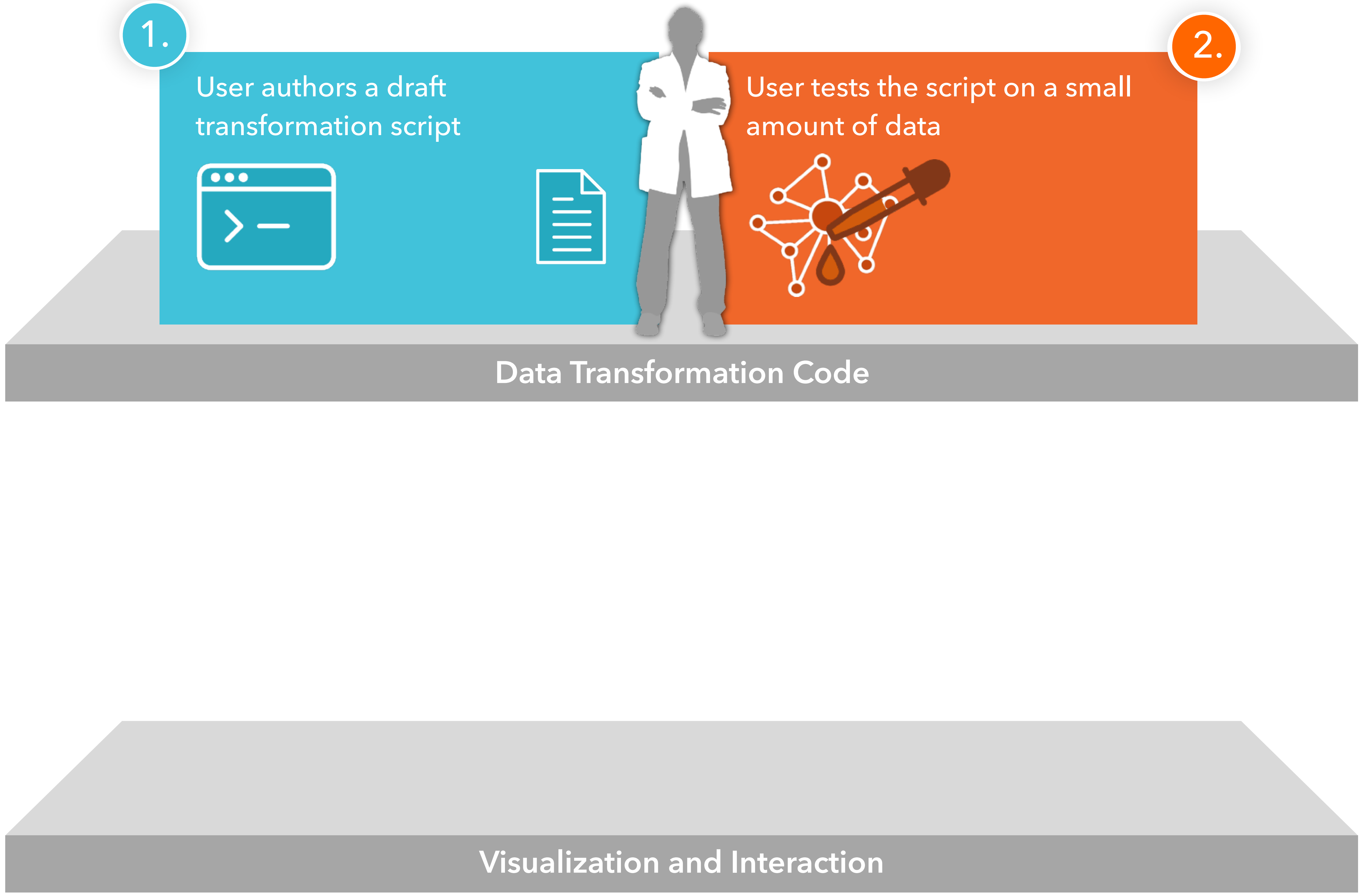
ROBY, MARTHA ,
JOHN, ROBERT E JR ,
Affects 1 column, 4859 rows Creates 1 column
Count occurrences of `{delim
CAND_NAME
COX, JOHN R.
ROBY, MARTHA
JOHN, ROBERT E JR
Affects 1 column, 4859 rows
TRIFACTA

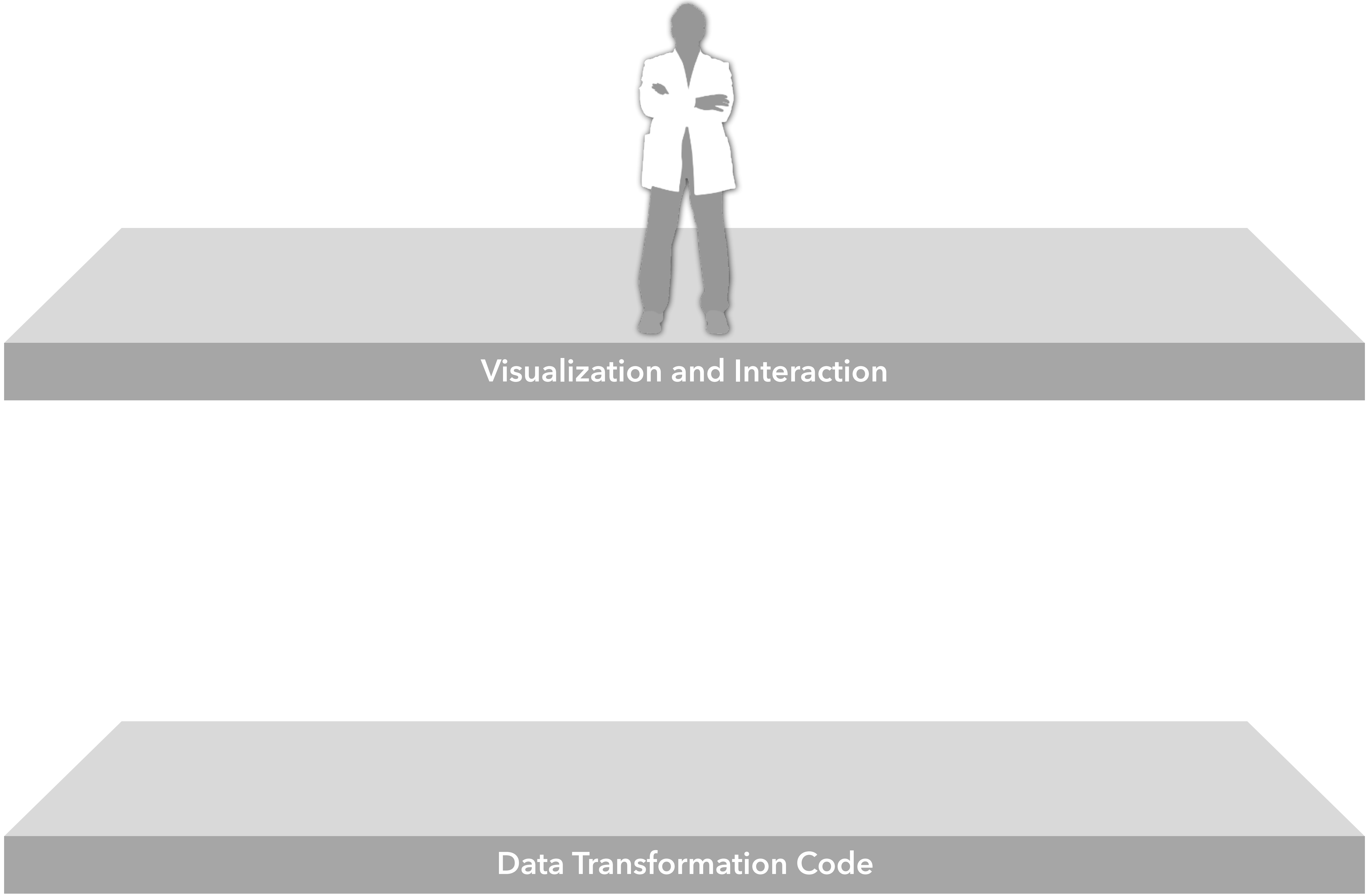
Traditional Specification

Traditional Specification

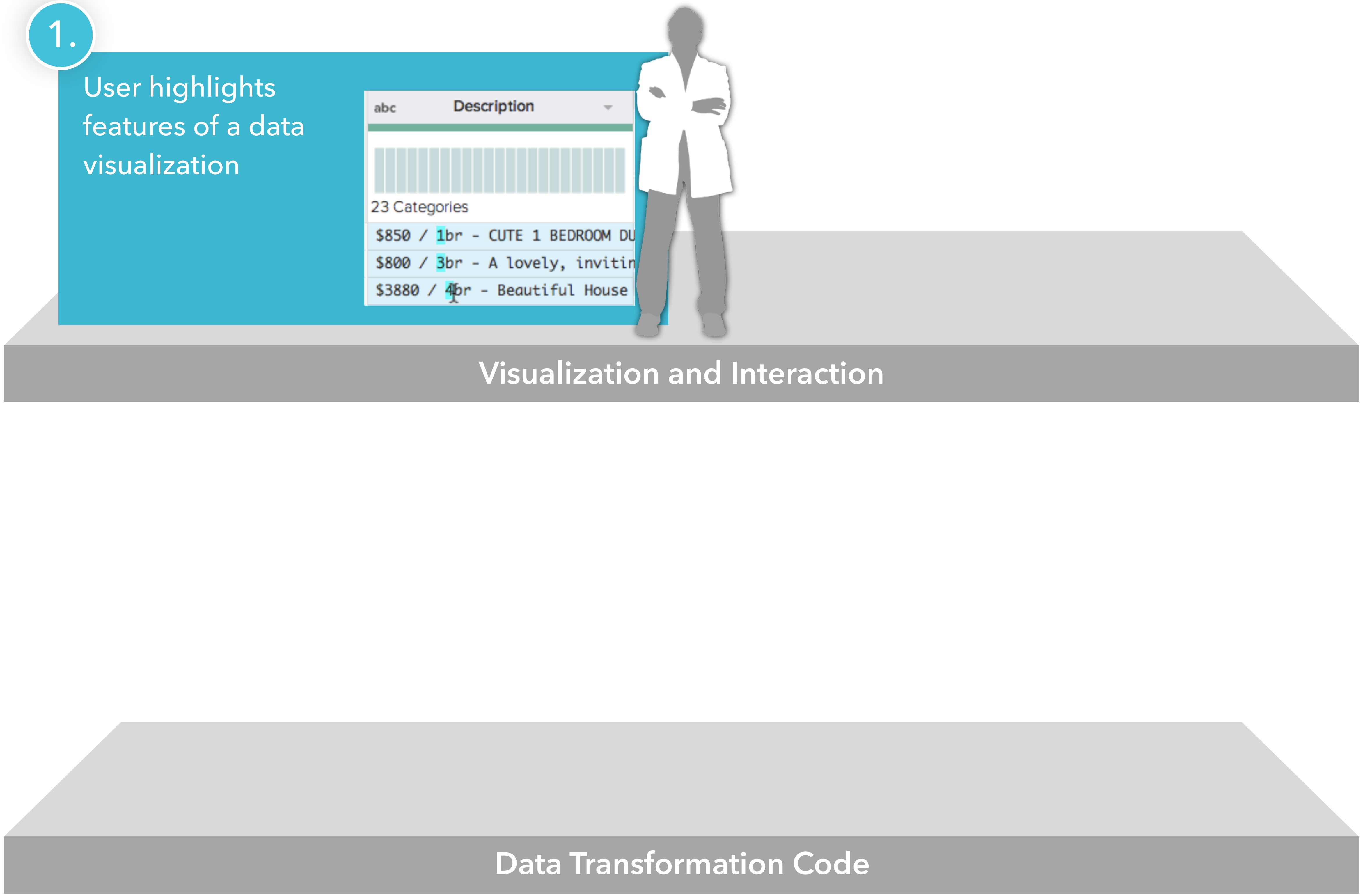


Traditional Specification

Predictive Interaction



Predictive Interaction



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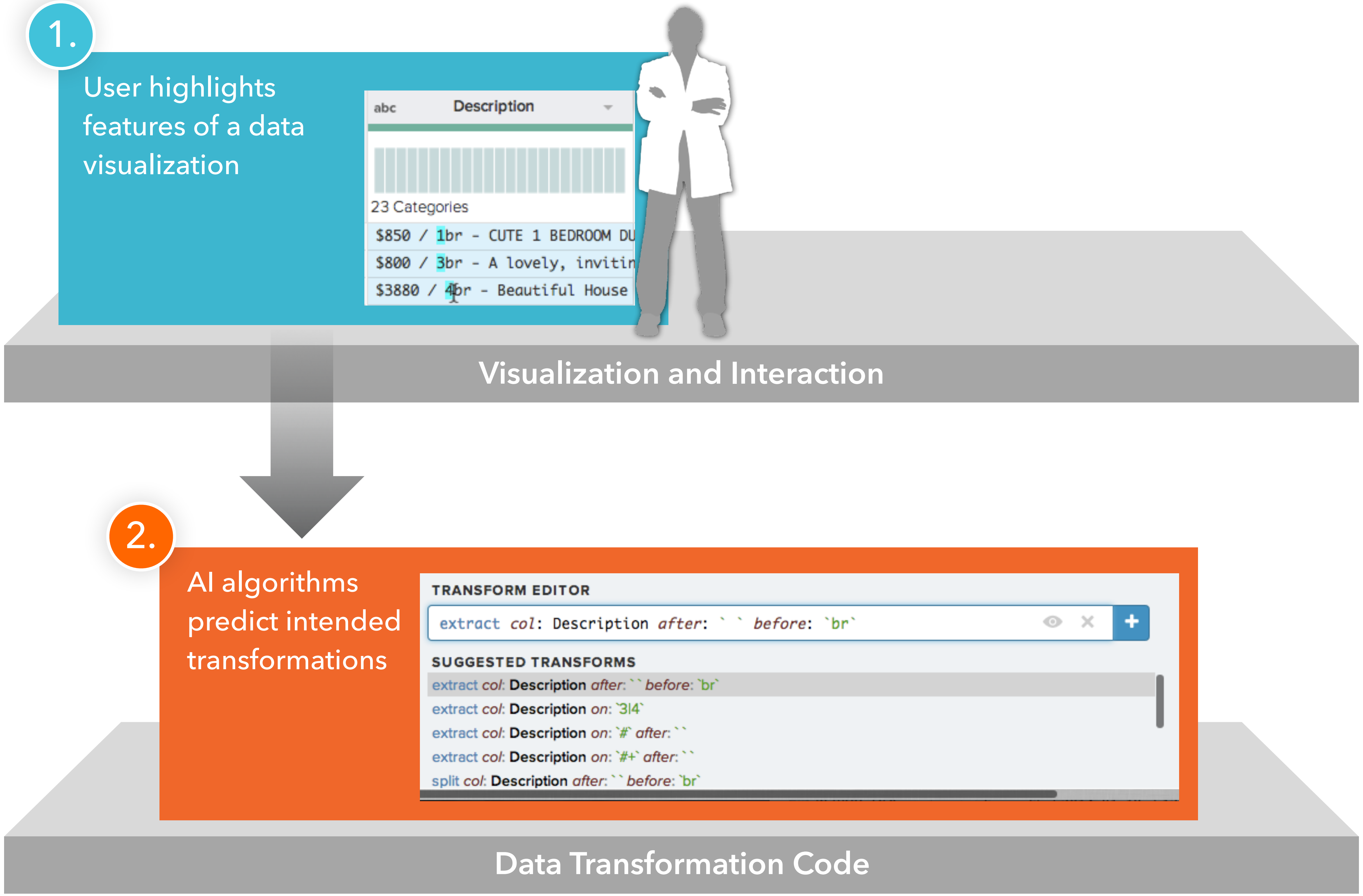
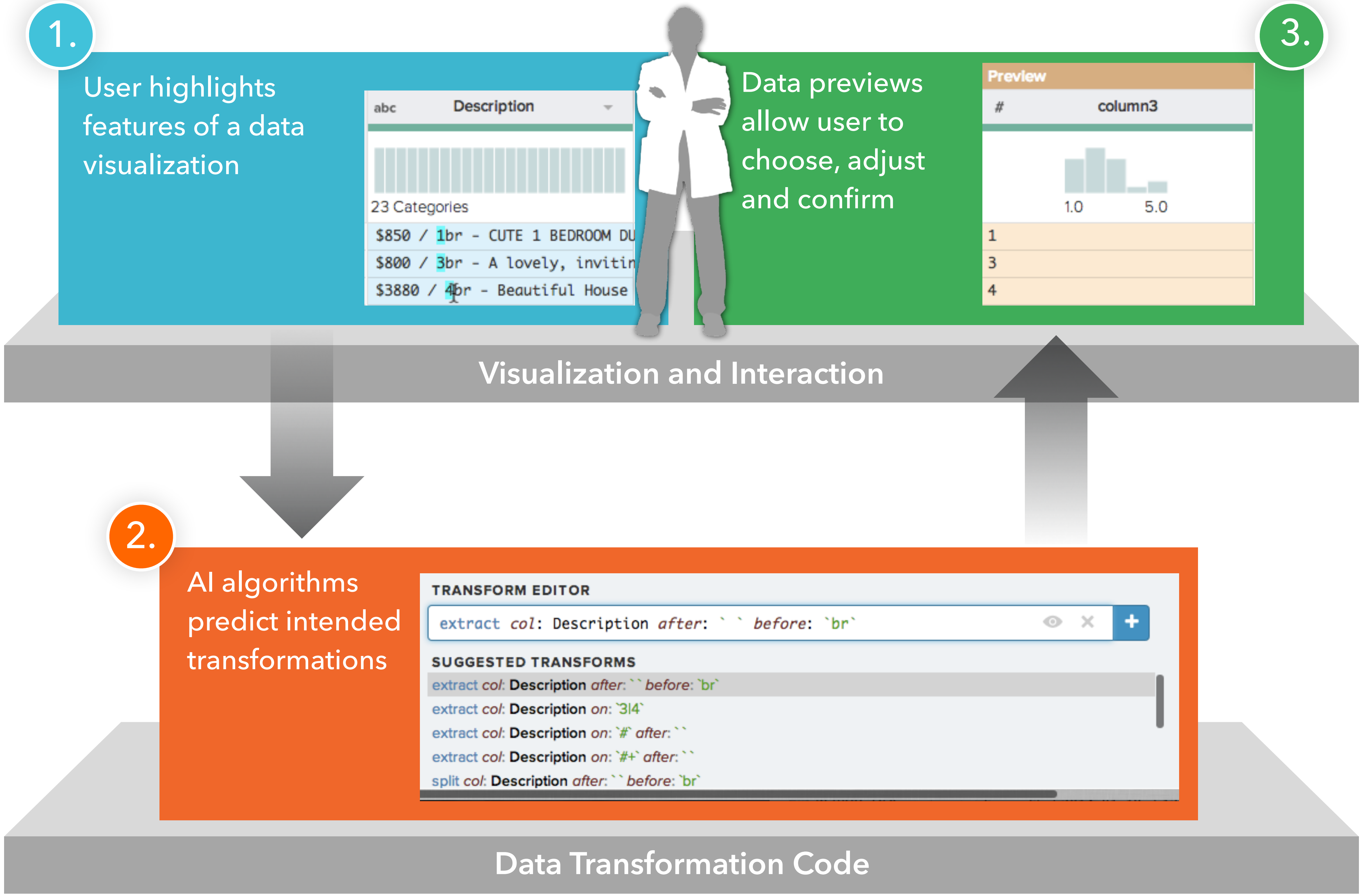


Predictive Interaction



Domain-Specific Language as Shared Representation

Model the task (often as a sequence).

Formalism for reasoning about actions.

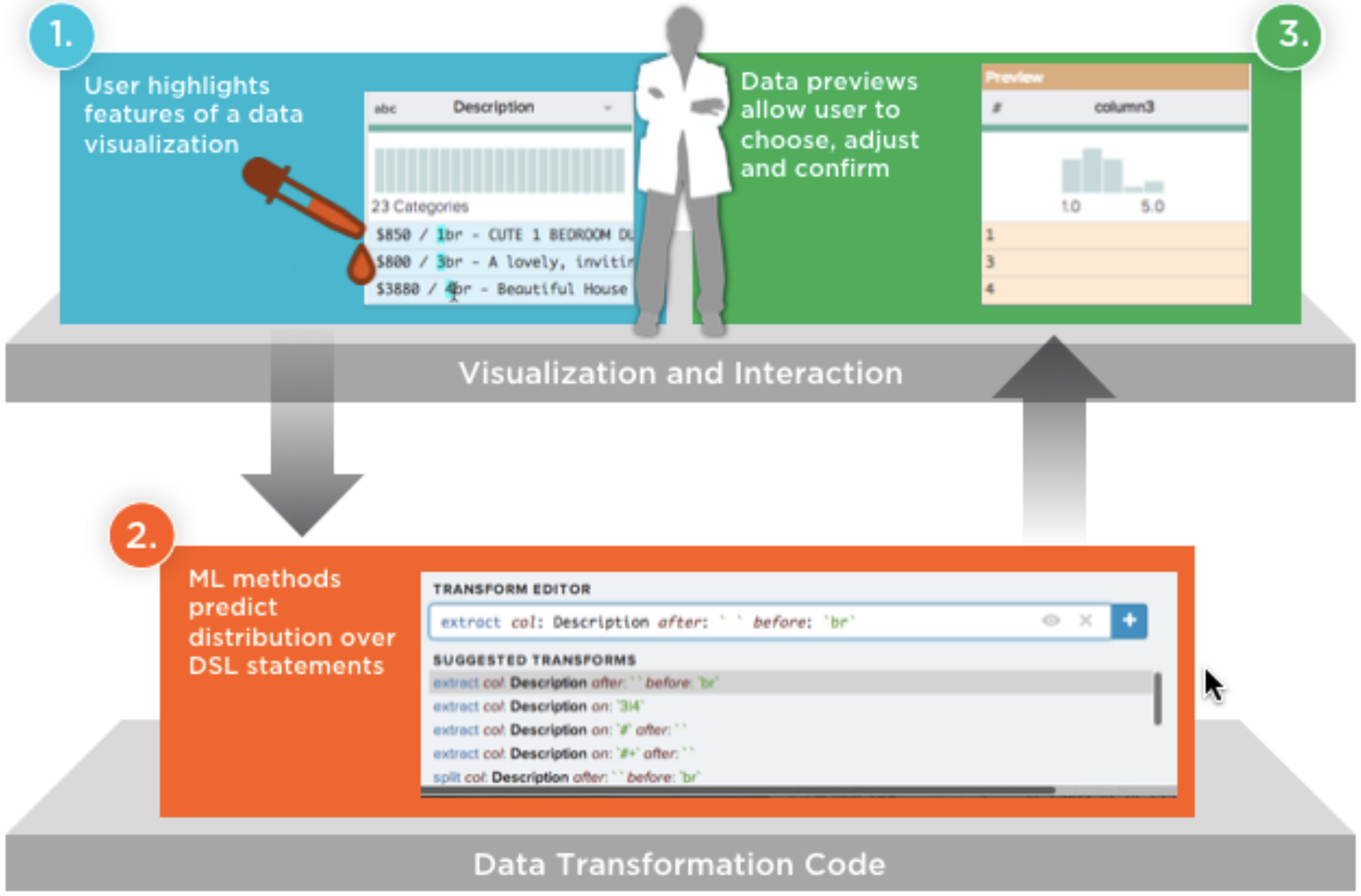
Provides means of learning from usage

Can be re-applied to new inputs.

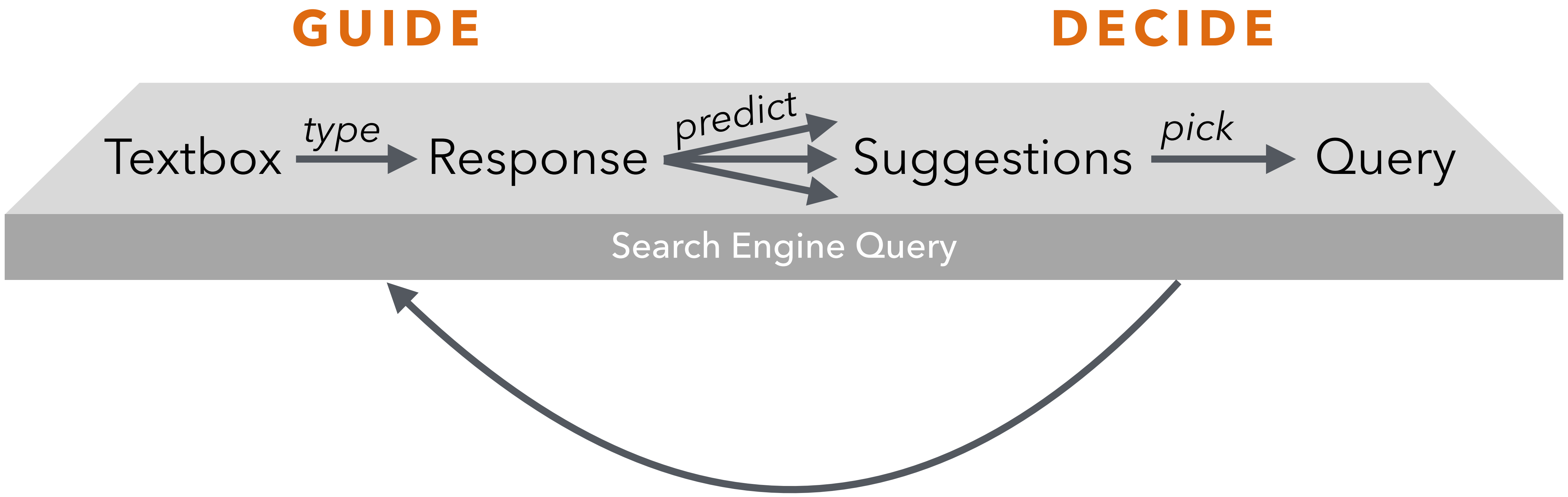
Cross-compile to different runtimes.

Necessary Components:

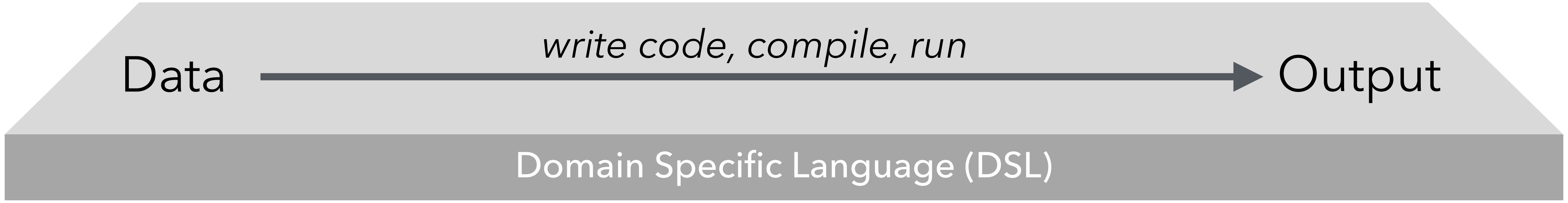
1. Content Representations
2. Language + Prediction Model
3. Preview Mechanisms



Auto-Complete



Predictive Interaction in Wrangler



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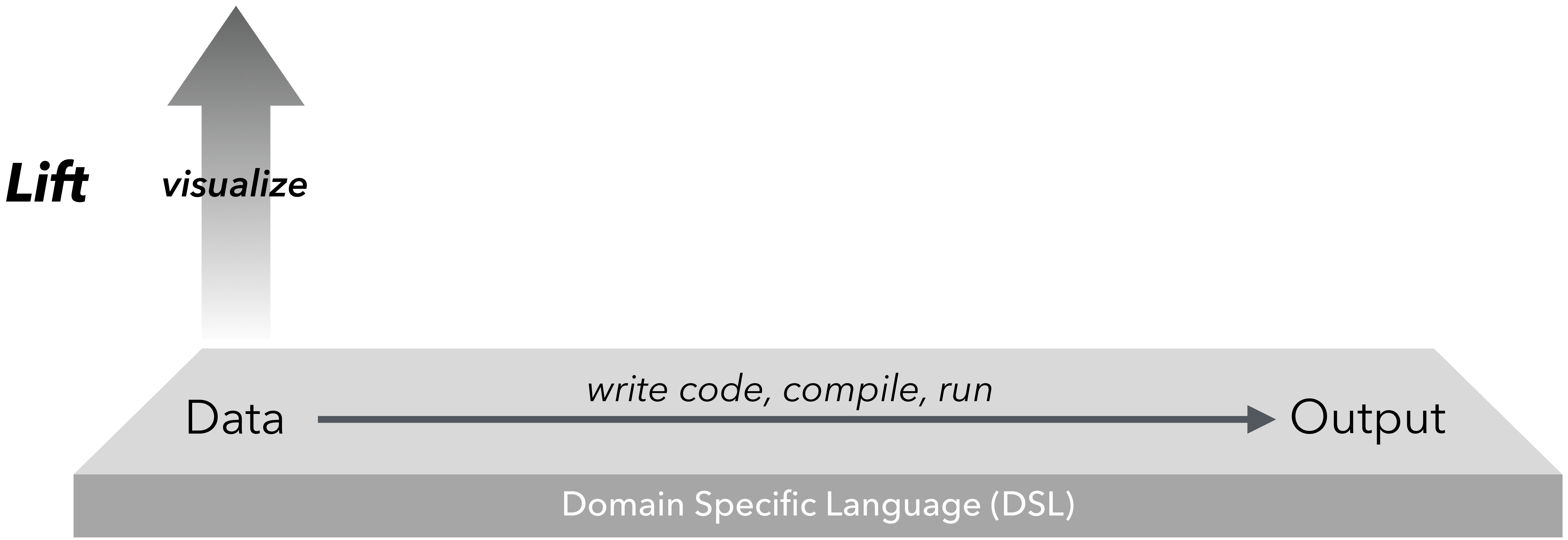
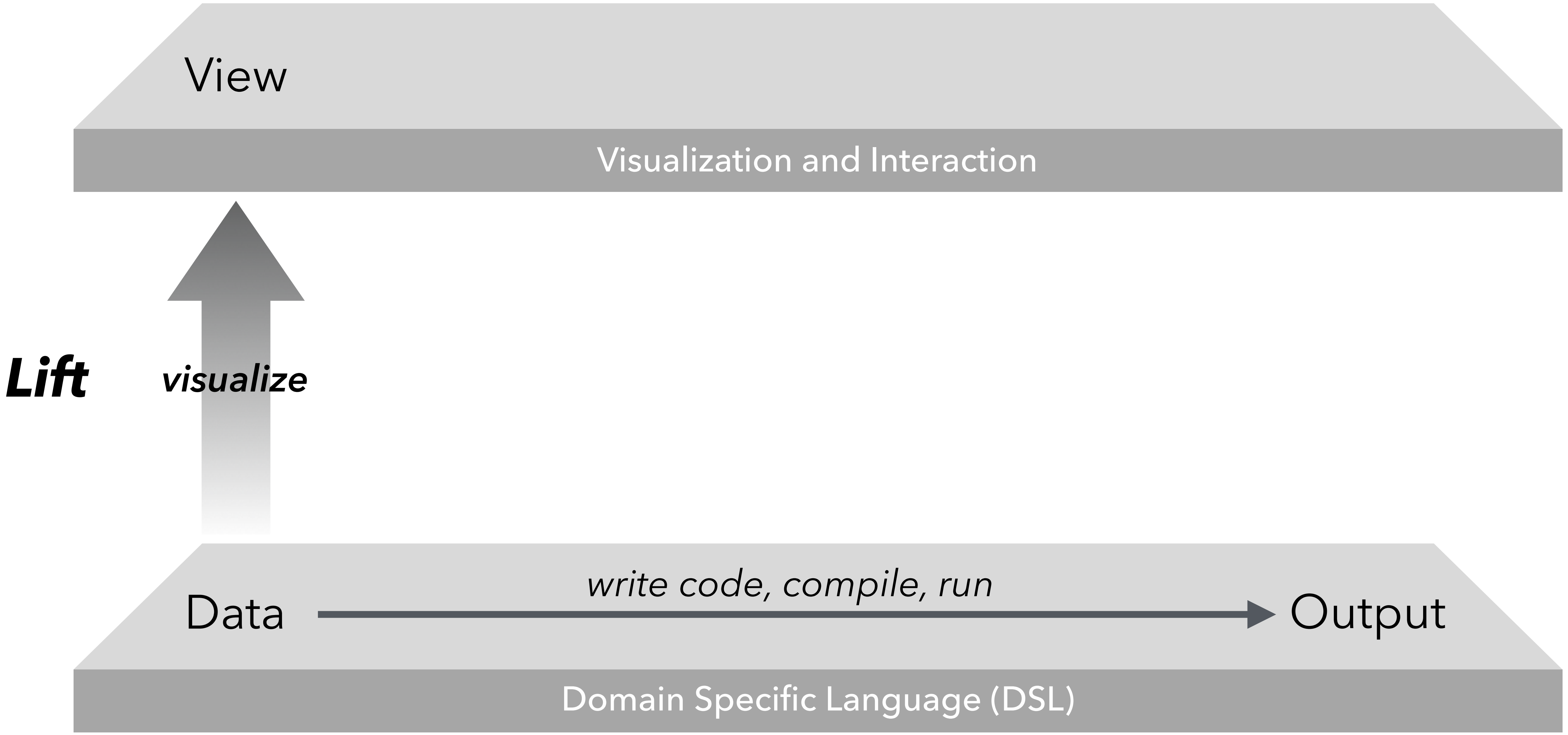


Predictive Interaction in Wrangler



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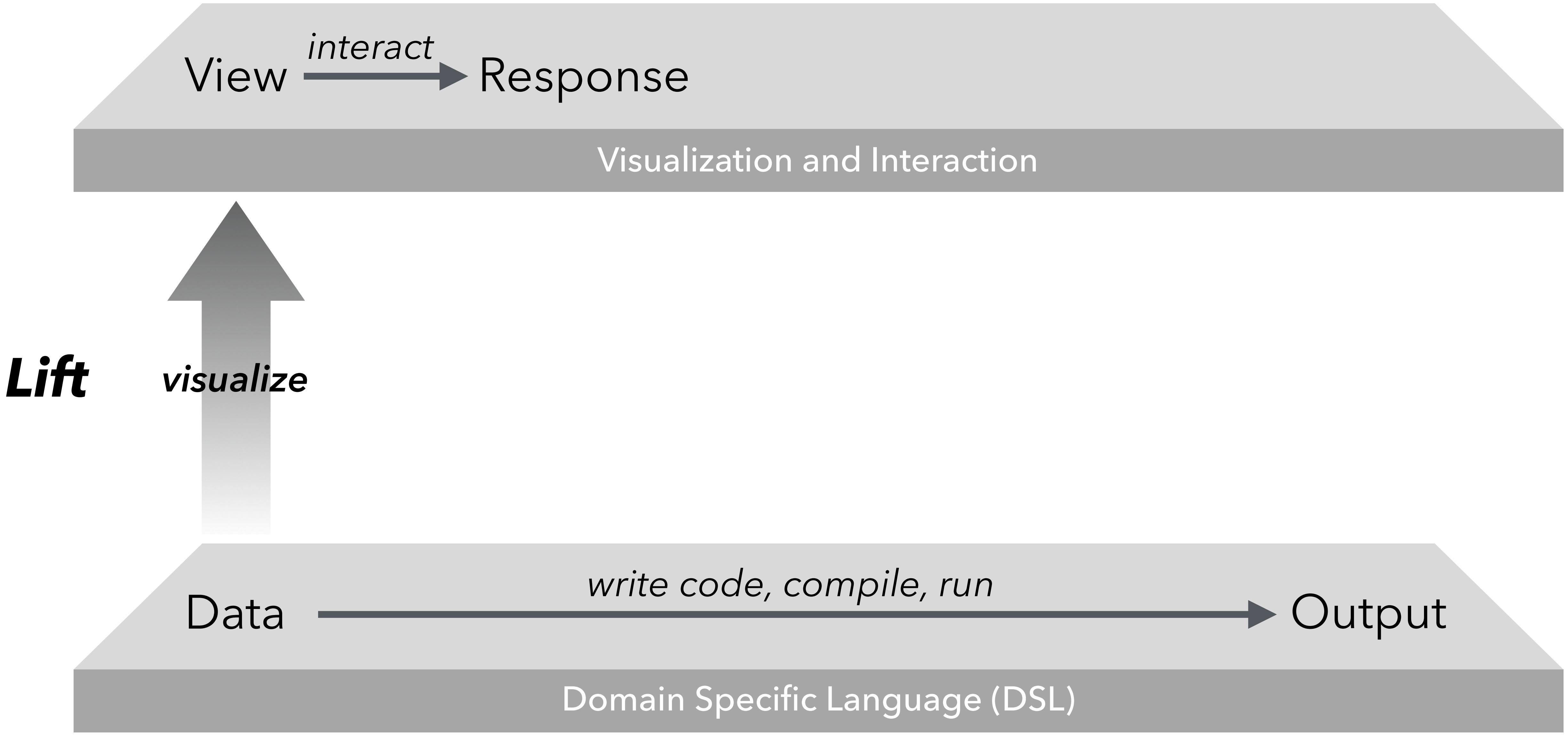
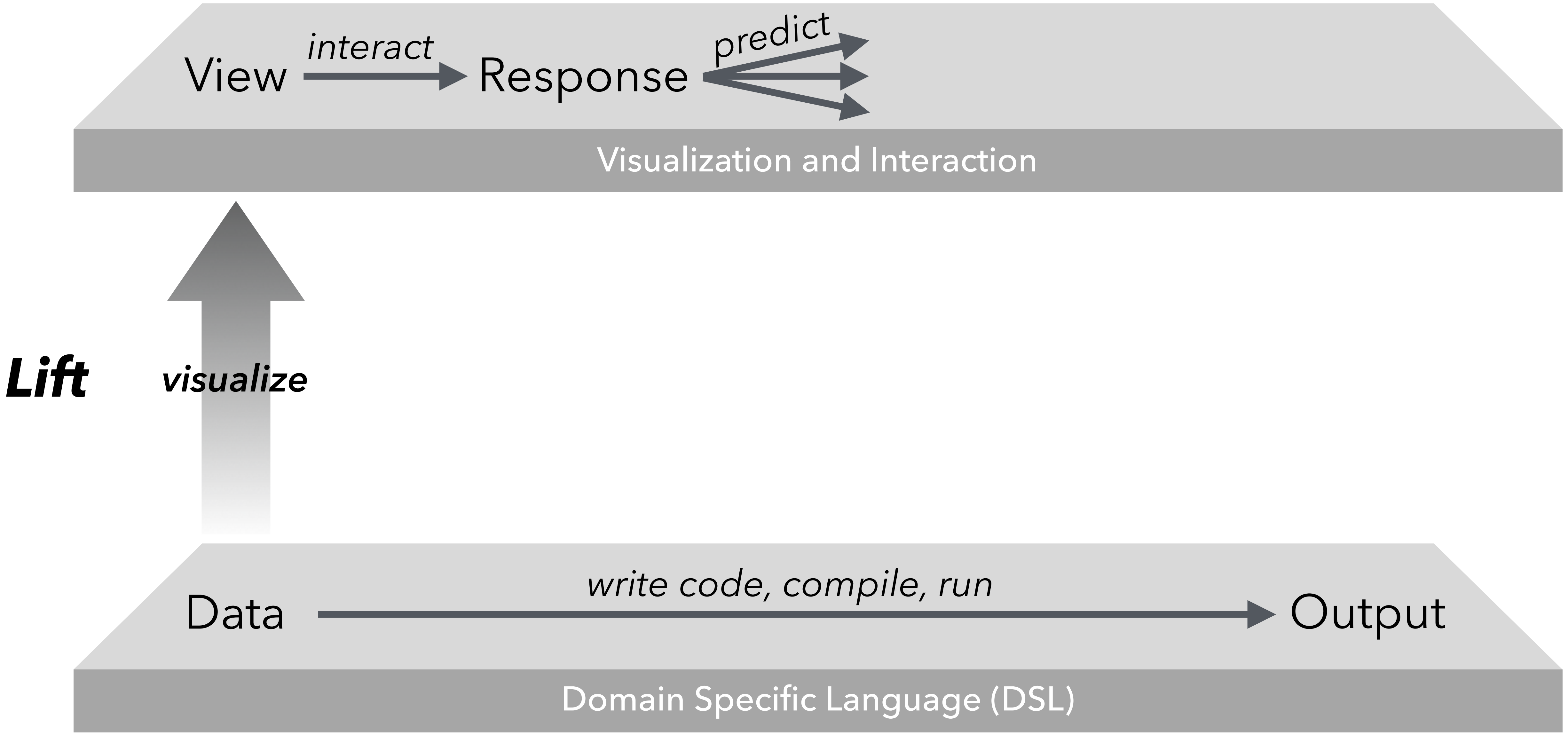


Predictive Interaction in Wrangler



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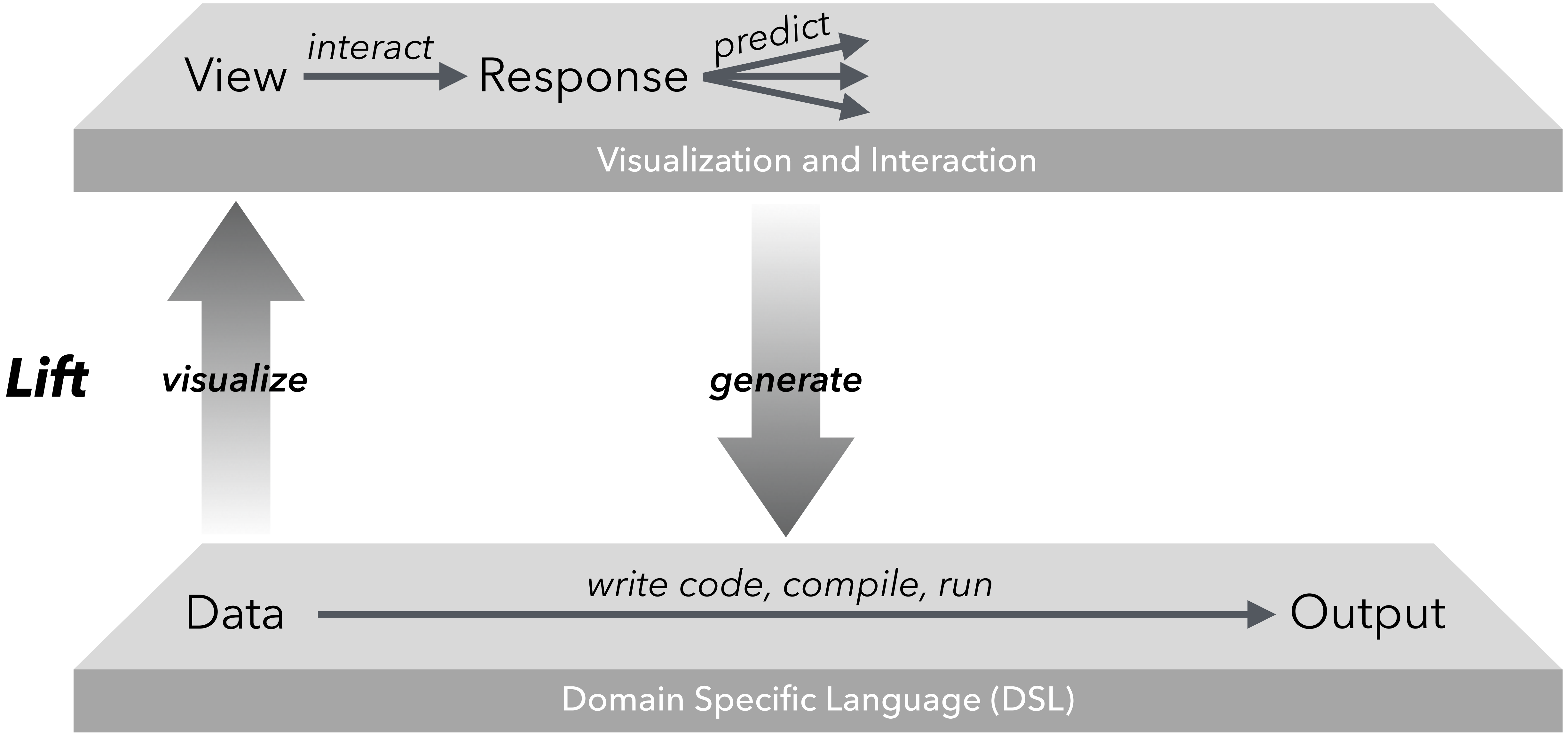
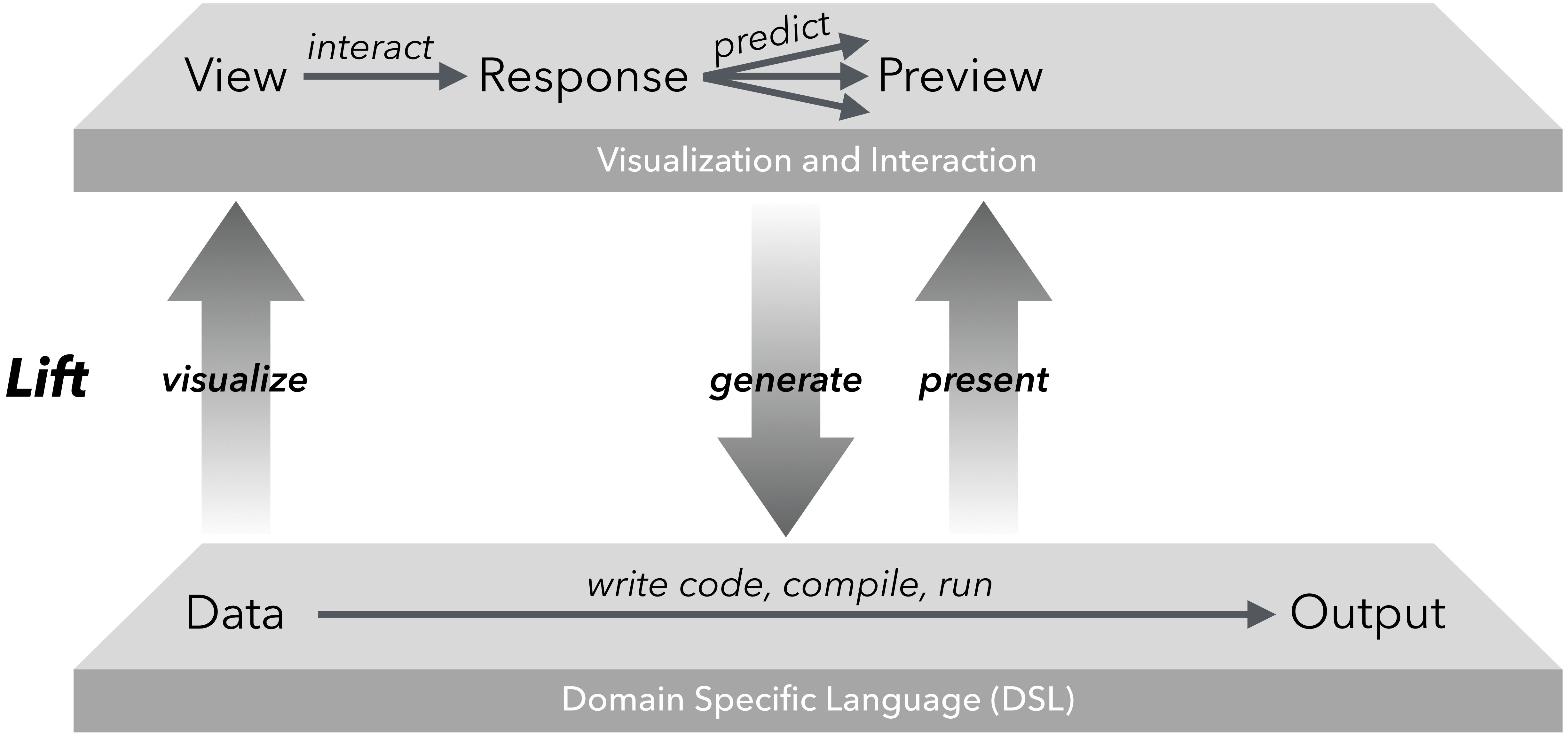


Predictive Interaction in Wrangler



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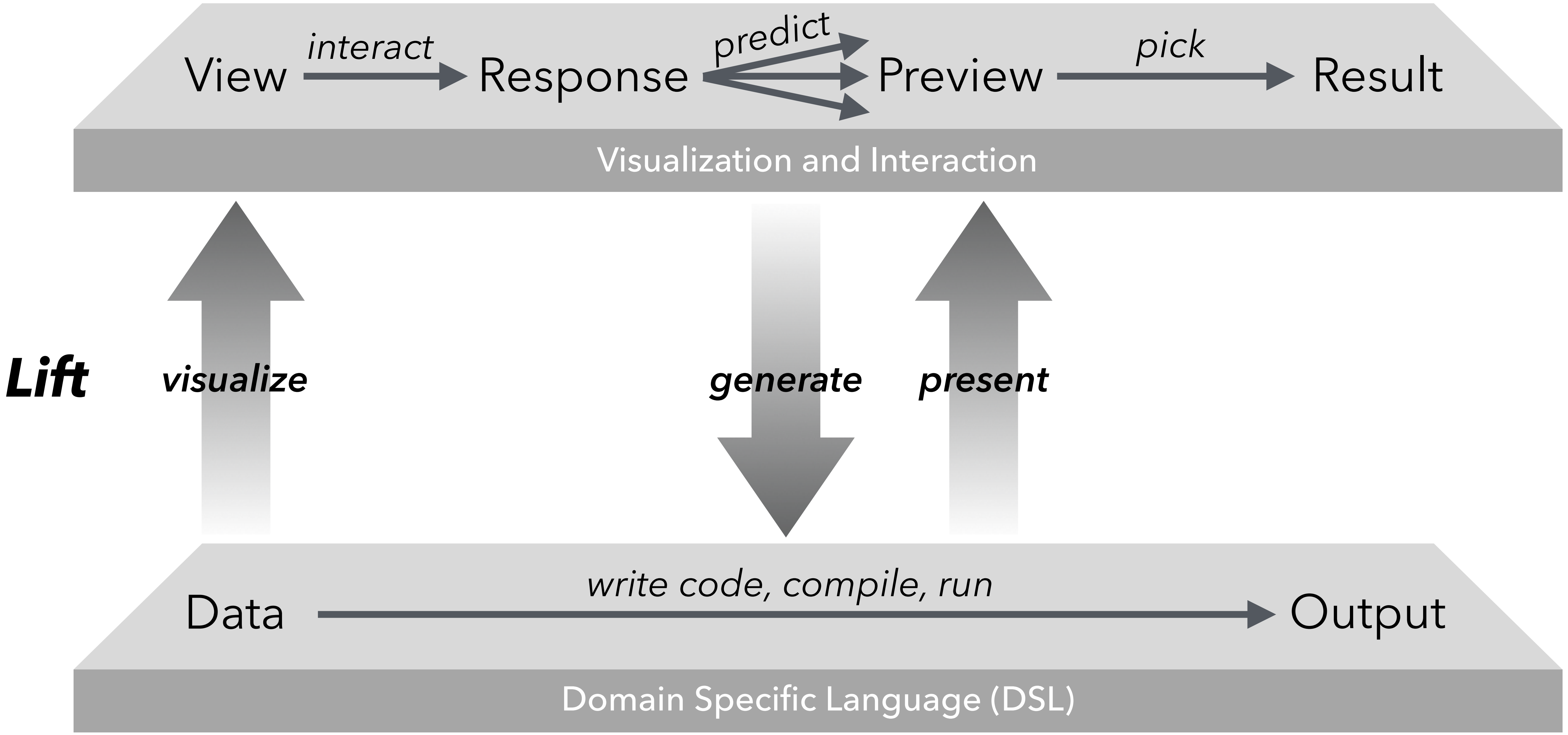
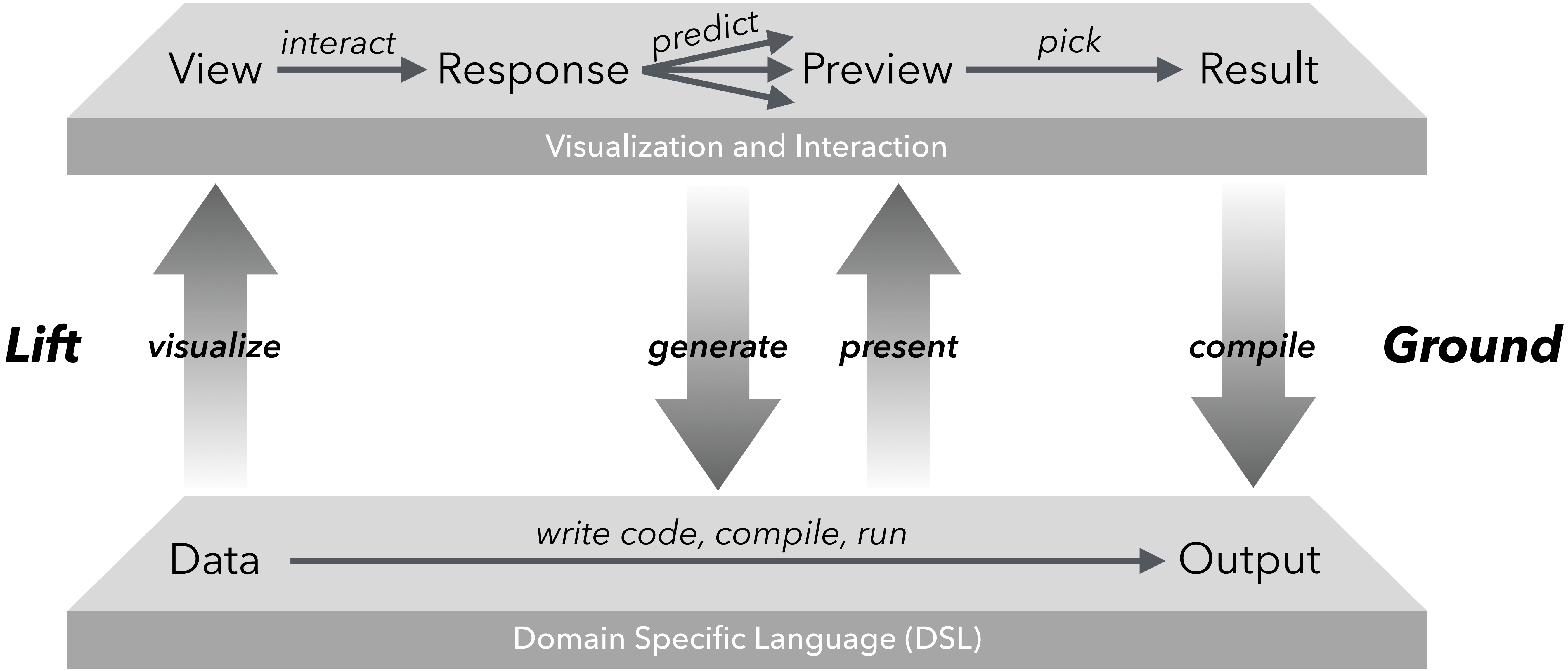
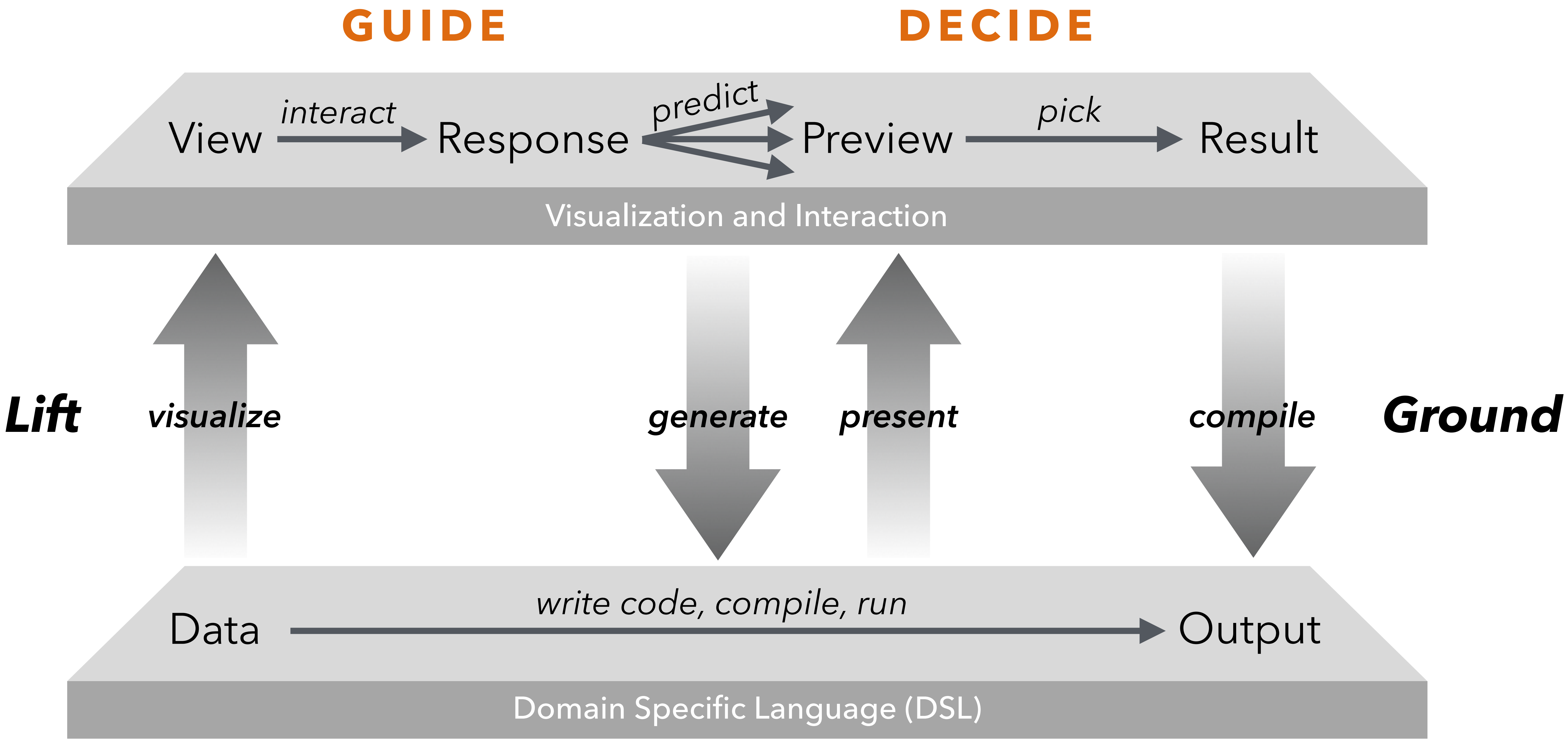


Predictive Interaction in Wrangler



Predictive Interaction in Wrangler

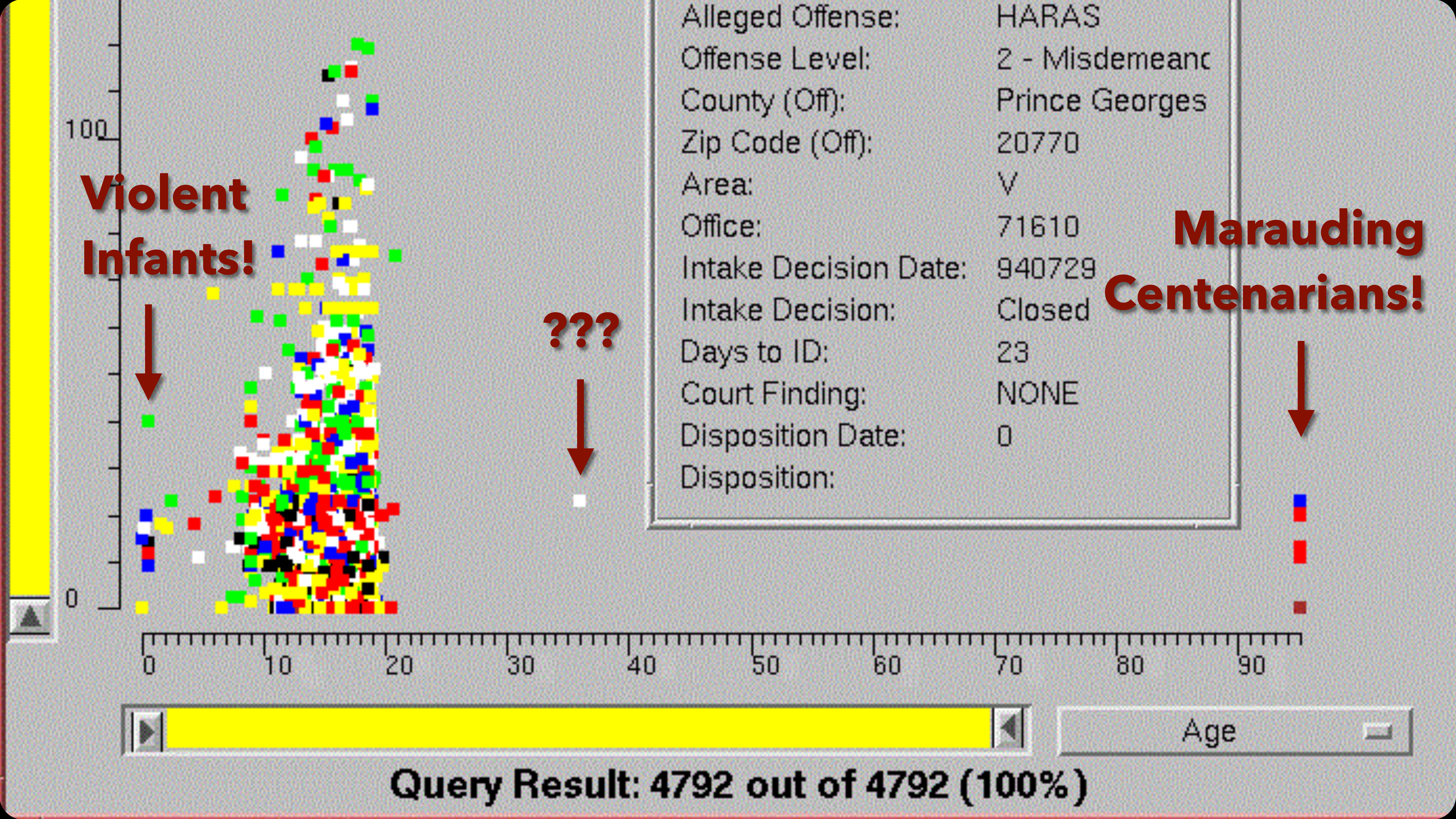


EXAMPLES:

Data Cleaning & Transformation

Exploratory Data Visualization

Natural Language Translation


Alleged Offense: HARAS
Offense Level: 2 - Misdemeanc
County (Off): Prince Georges
Zip Code (Off): 20770
Area: V
Office: 71610
Intake Decision Date: 940729
Intake Decision: Closed
Days to ID: 23
Court Finding: NONE
Disposition Date: 0
Disposition:
Violent Infants!
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Marauding Centenarians!
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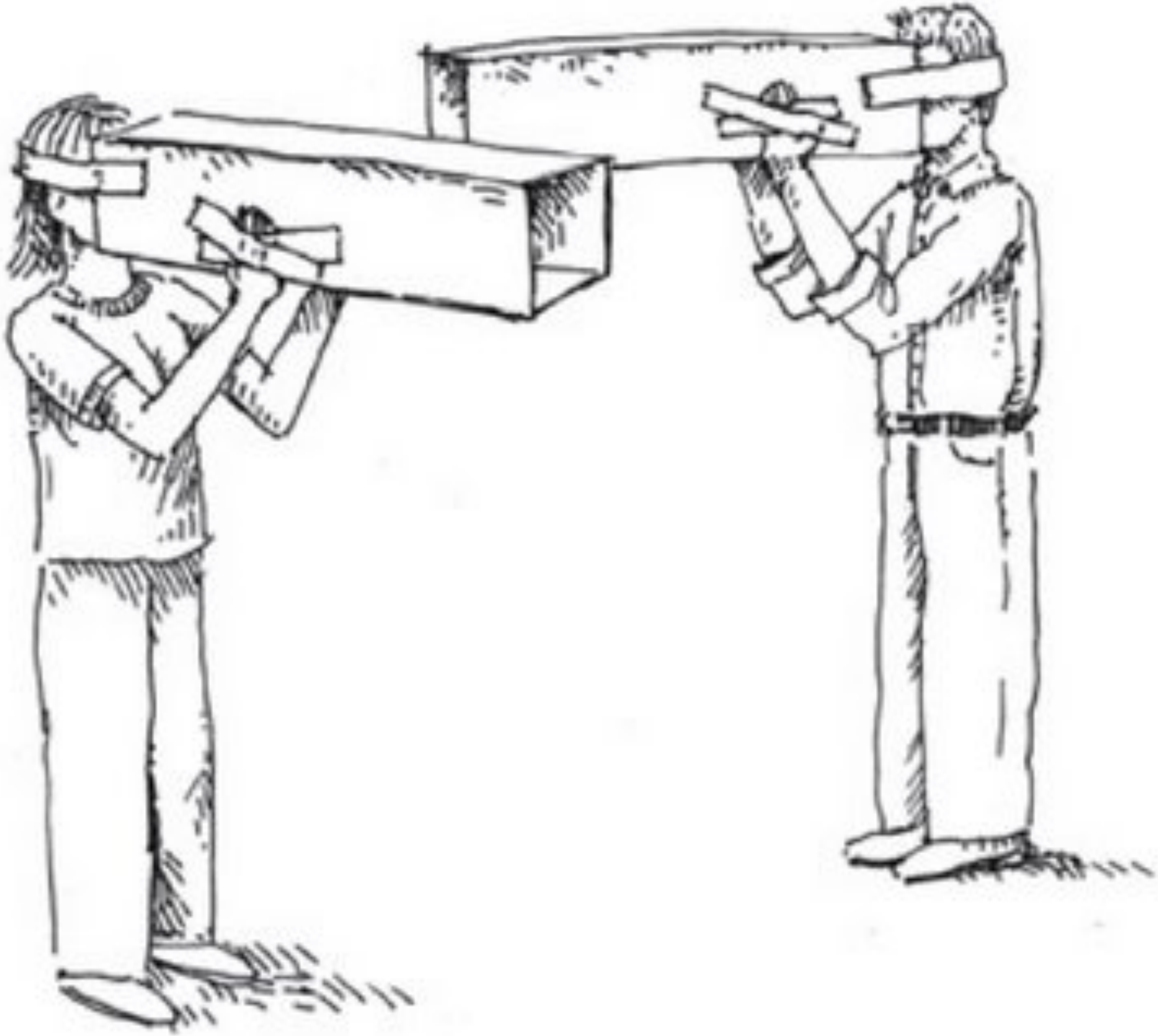
Age
Query Result: 4792 out of 4792 (100%)



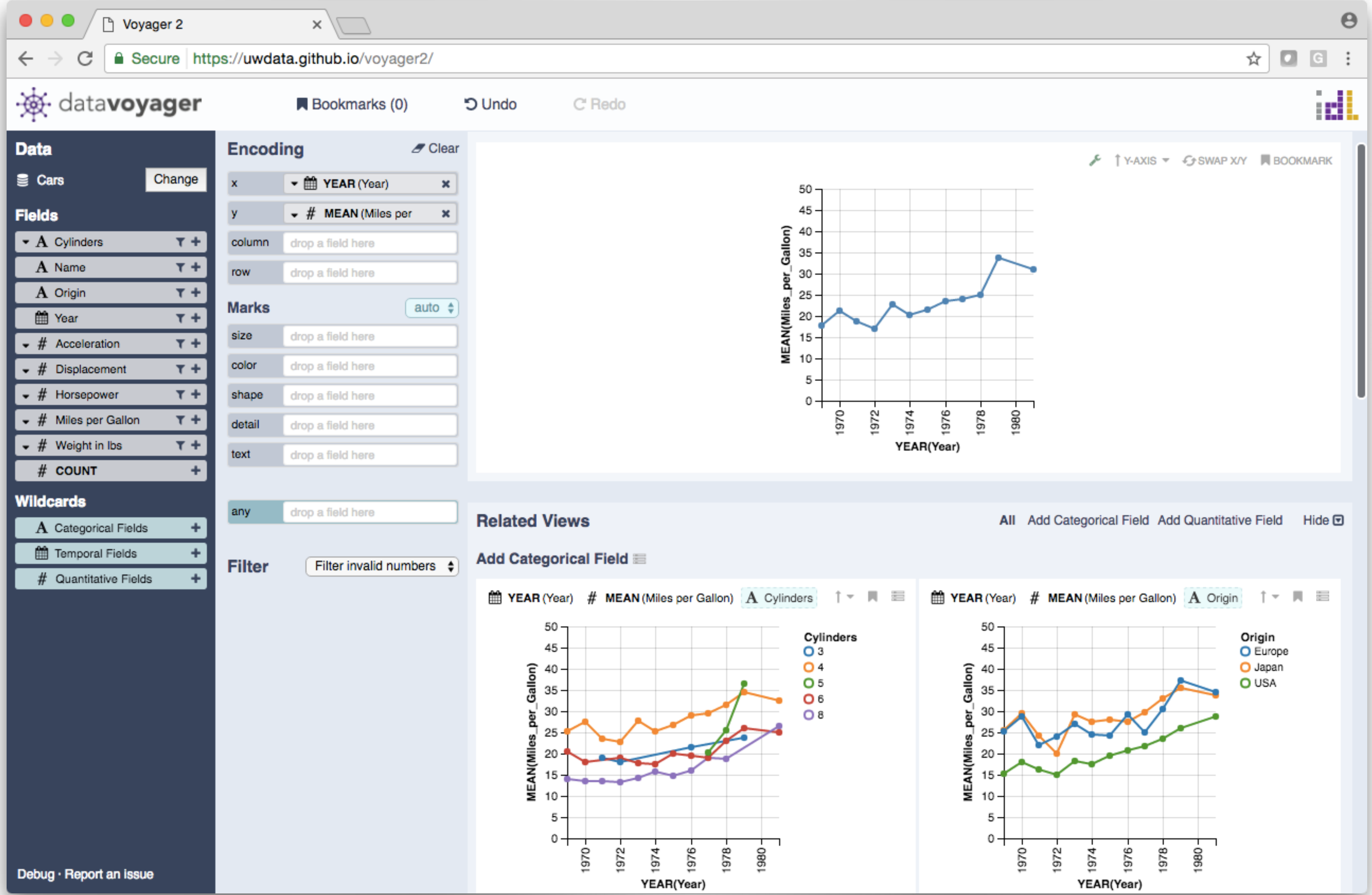
Common exploration pitfalls:

Overlook data quality issues

Fixate on specific relationships

Plus many other biases…

[Heuer 1999, Kahneman 2011, …]



Voyager: Combine Manual Specification with Visualization Recommenders

Key Idea: Augment manual exploration with visualization recommendations sensitive to the user's current focus.

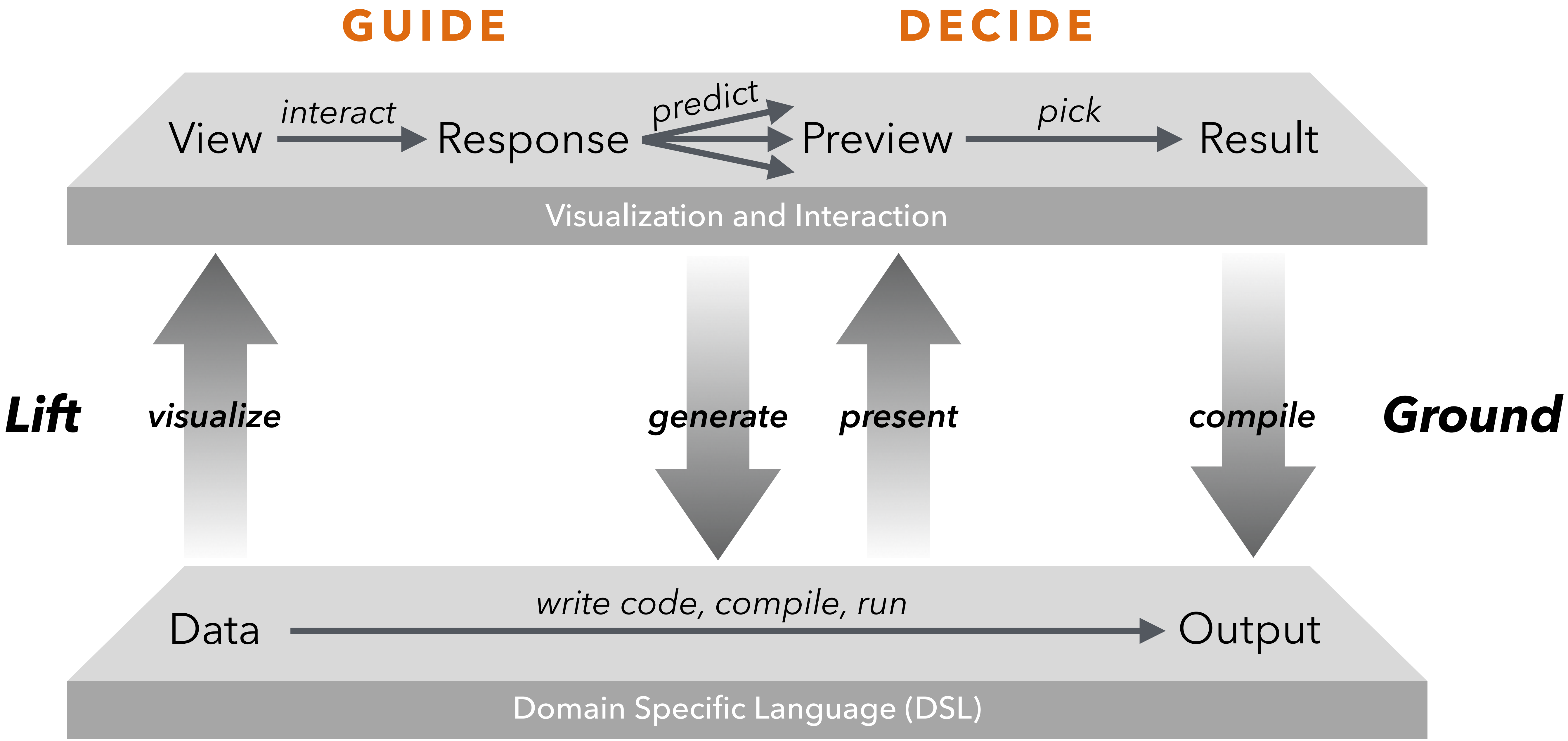
The ultimate goal is to support *systematic consideration* of the data, without exacerbating *false discovery*.

To model a user's search frontier, we *enumerate related Vega-Lite specifications*, seeded by the user's current focus.

Candidate charts are pruned and ranked using a formal model of *design guidelines* and *perceptual effectiveness*, which can be trained from perception experiment results.

Voyager: Combine Manual Specification with Visualization Recommenders

Predictive Interaction in Voyager



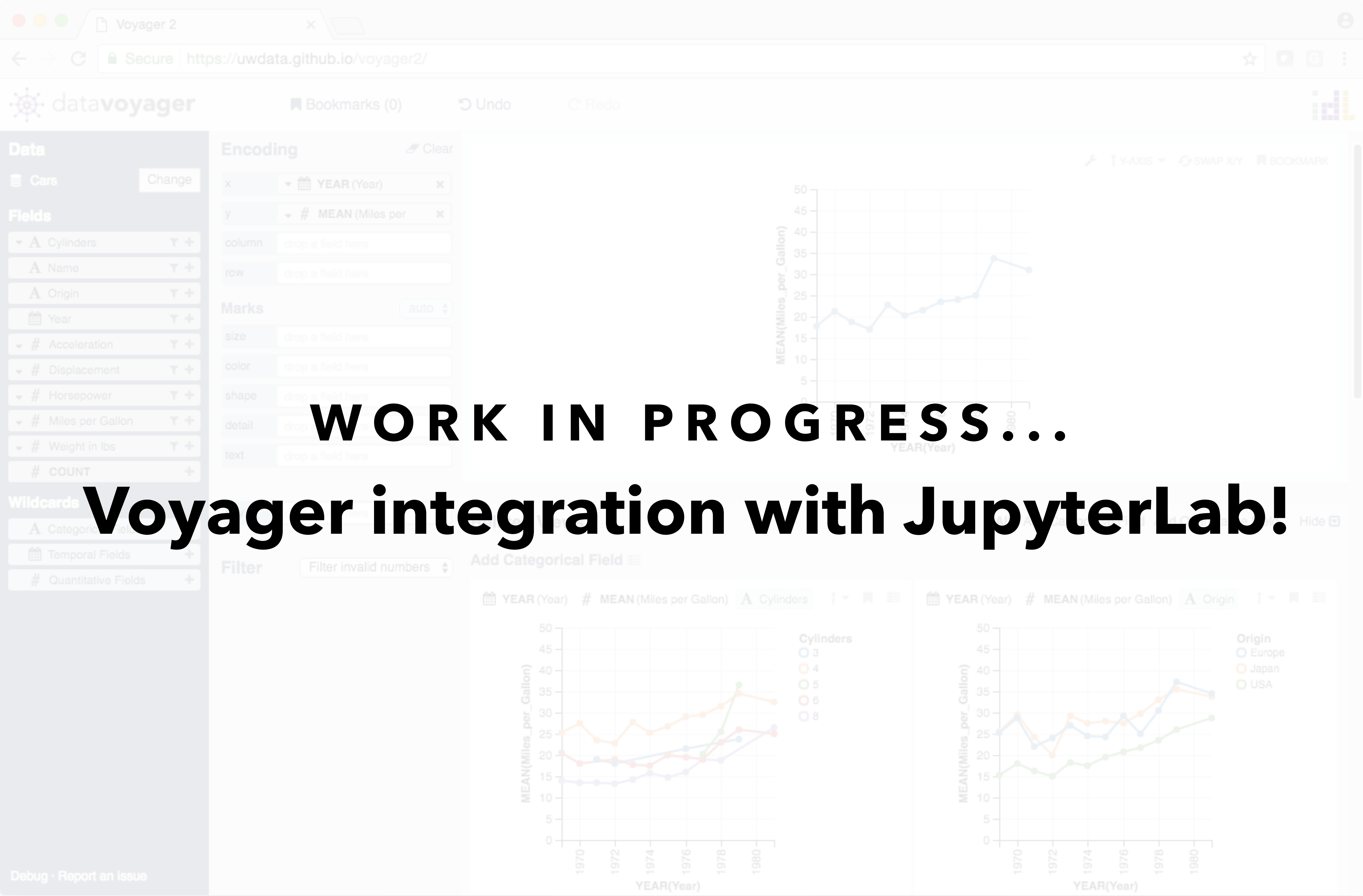
Compared to existing tools, leads to **over 4x more variable sets seen**, and **over 2x more variable sets interacted with**.

“The related view suggestion accelerates exploration a lot.”

“I like that it shows me what fields to include in order to see a specific graph. Otherwise, I have to do a lot of trial and error and can't express what I wanted to see.”

“These related views are so good but it’s also spoiling that I start thinking less. I’m not sure if that’s really a good thing.”

Voyager: Combine Manual Specification with Visualization Recommenders



WORK IN PROGRESS...

Voyager integration with JupyterLab!

Voyager: Combine Manual Specification with Visualization Recommenders

EXAMPLES:

Data Cleaning & Transformation

Exploratory Data Visualization

Natural Language Translation

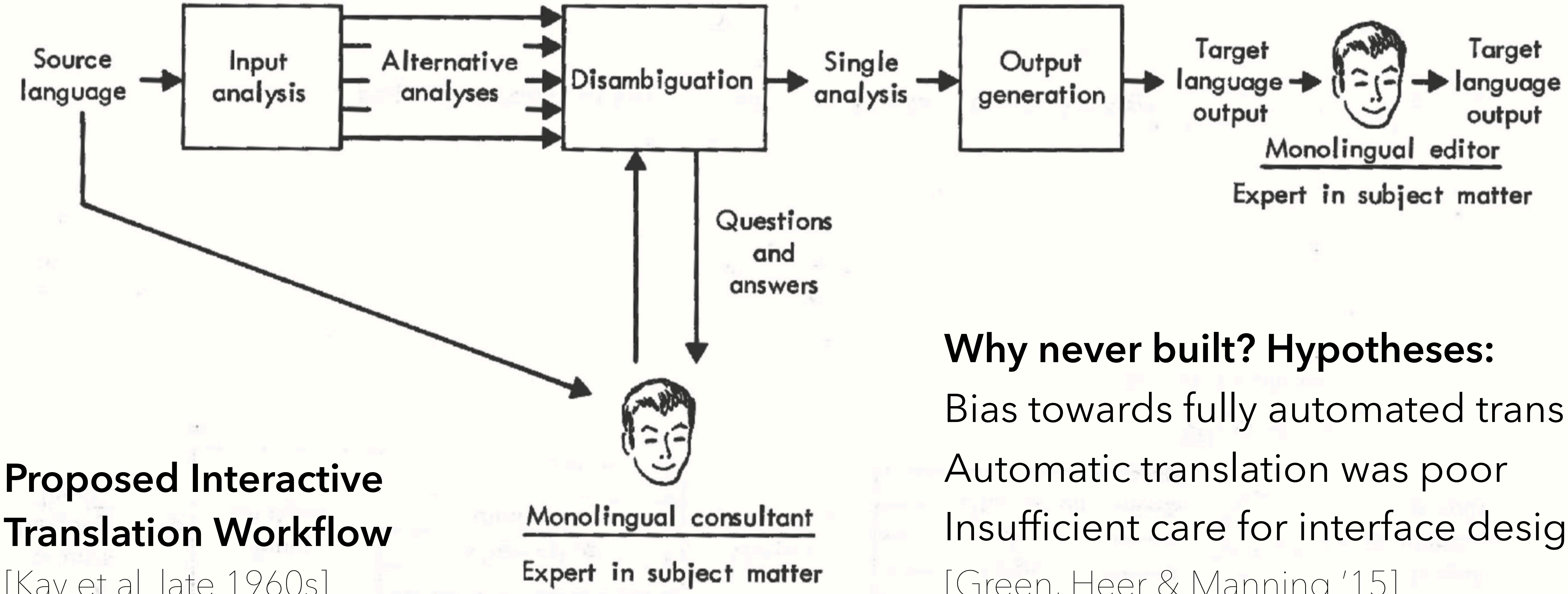
Mid-Century Prospects for Automated Language Translation

"Fully automatic, high quality translation is not a reasonable goal, not even for scientific texts. A human translator, in order to arrive at high quality output, is often obliged to make intelligent use of extra-linguistic knowledge which sometimes has to be of considerable breadth and depth."

"As soon as the aim of MT is lowered to that of high quality translation by a machine-posteditor partnership, the decisive problem becomes ***to determine the region of optimality in the continuum of possible divisions of labor***."

Yehoshua Bar-Hillel [Advances in Computers 1960]

Interactive Translation: An under-explored idea?



Proposed Interactive Translation Workflow
[Kay et al. late 1960s]

Why never built? Hypotheses:

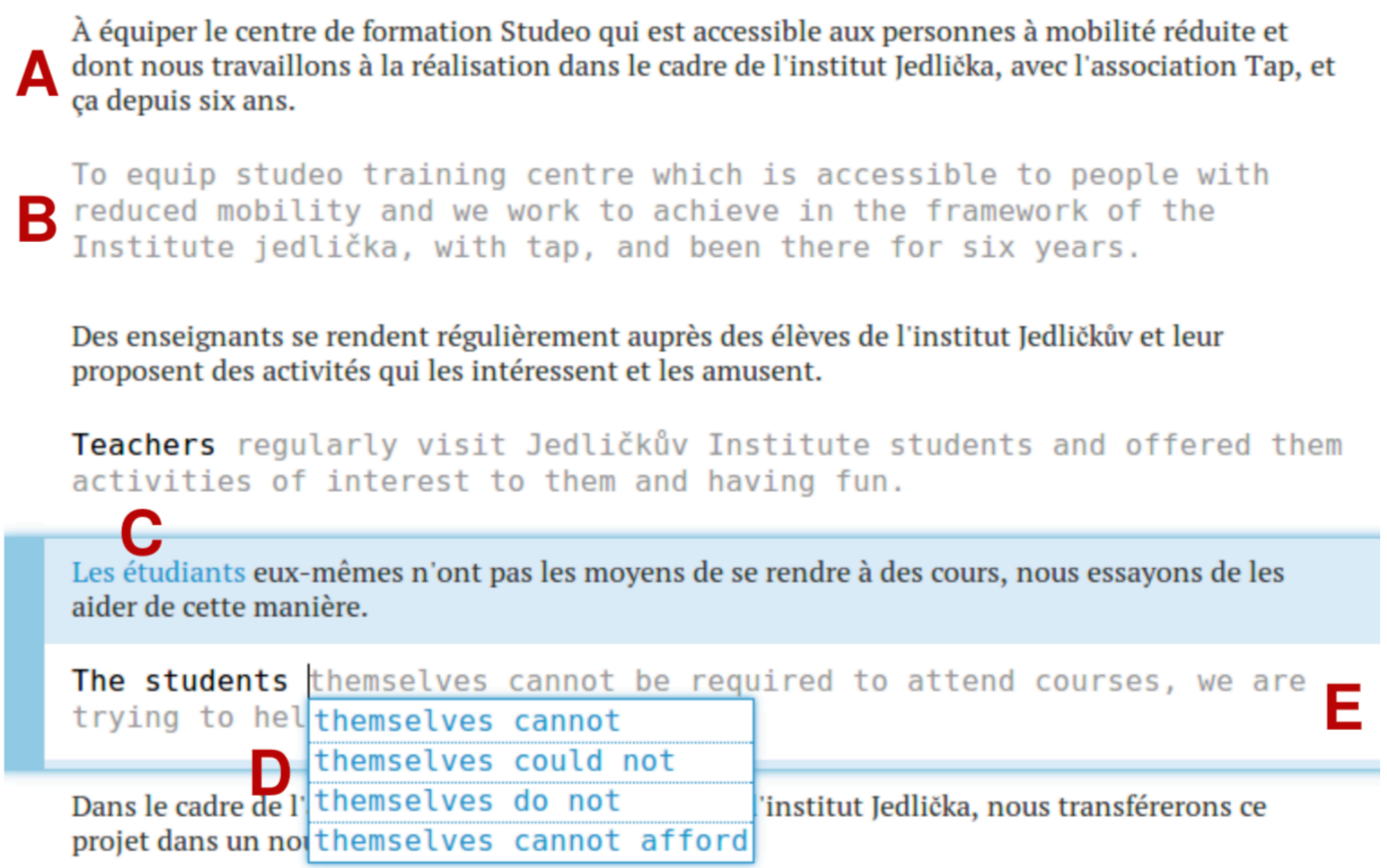
Bias towards fully automated translation

Automatic translation was poor

Insufficient care for interface design

[Green, Heer & Manning '15]

Predictive Translation Memory (PTM)



(A) Source text interleaved with (B) target text.

(C) Shaded words show coverage of translation.

(D) phrase auto-complete and (E) full translation suggestions.

Suggestions (D, E) adapt to user input in real-time.

On-the-fly retuning enables domain adaptation by the machine translation system.

Interactive Machine Translation Results

Experiments with **professional translators**, across **language pairs** (Arabic, French, German -> English) and **text genres** (software, medical, news).

Results

Post-editing of full machine translation leads to reduced time and improved quality over purely manual translation.

Interactive translation with PTM slightly slower than post-editing, but results in higher quality translations, over 99% of characters entered via interactive aids.

Re-tuning on interactive PTM input leads to significantly greater MT improvements than with post-editing, leading to fine-grained corrections.

Concerns over agency: *"less susceptible to be creative"*; MT *"distracts from my own original translation process by putting words in [my] head."*

The New Engine for Enterprise Translation Workflows

Increase quality and speed with the **neural feedback loop**, which combines human ingenuity and machine intelligence in a virtuous cycle

WATCH THE VIDEO LEARN MORE ABOUT LILT

EXAMPLES:

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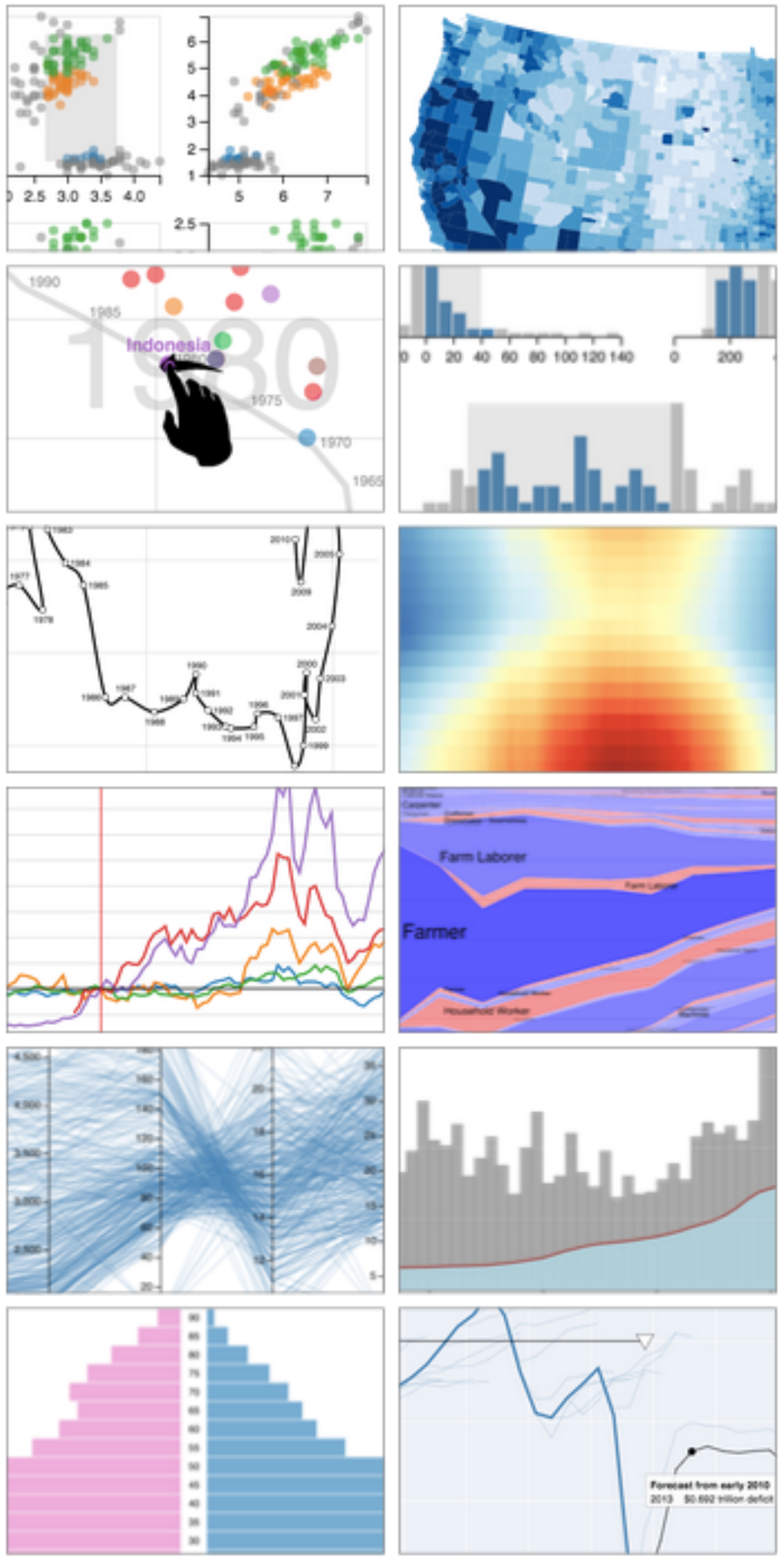
DESIGN CHALLENGE:

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

Future Challenges

Design Process, Tools, & Monitoring

How might we support productive prototyping, development, deployment, and monitoring of interactive systems using machine learning?



SPECTRUM OF SHARED REPRESENTATIONS

Hand-Engineered **Learned from Data**

SPECTRUM OF SHARED REPRESENTATIONS

Data Wrangler

Manually designed language (Wrangle).
Combinatorial search over possible actions.
Machine learning for ranking and inference.

Hand-Engineered **Learned from Data**

SPECTRUM OF SHARED REPRESENTATIONS

Data Wrangler

Increasing use of ML to infer actions & parameters. Enrichment of UI for direct specification of actions and interactive refinement of recommendations.

Hand-Engineered

Learned from Data

SPECTRUM OF SHARED REPRESENTATIONS

Data Wrangler

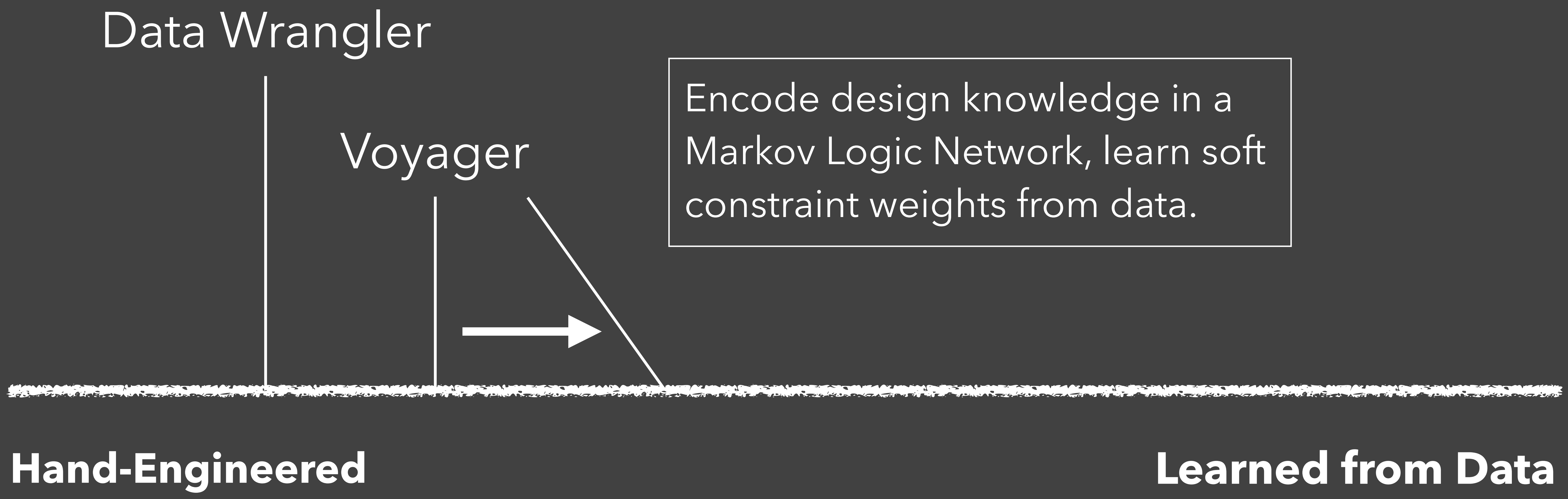
Voyager

Manually designed language (Vega-Lite).
Combinatorial search over possible charts.
Machine learning for ranking and inference.

Hand-Engineered

Learned from Data

SPECTRUM OF SHARED REPRESENTATIONS



SPECTRUM OF SHARED REPRESENTATIONS

Shared representation is digital text.
Beam search, trained on large linguistic corpus.

Data Wrangler

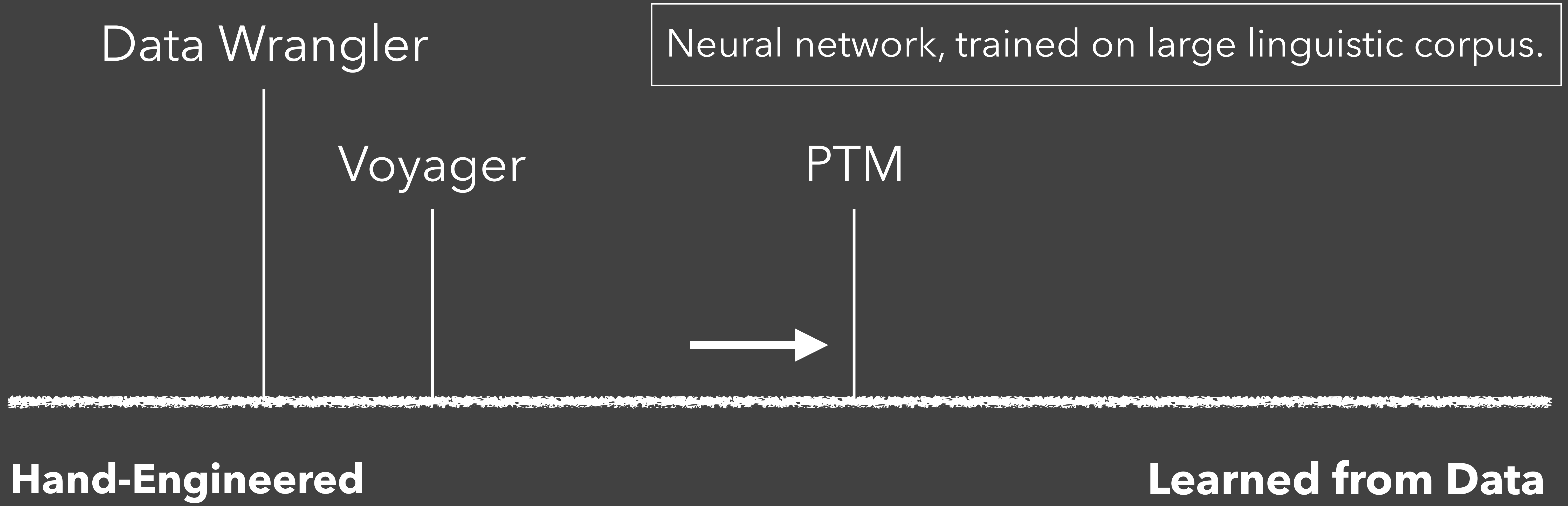
Voyager

PTM

Hand-Engineered

Learned from Data

SPECTRUM OF SHARED REPRESENTATIONS



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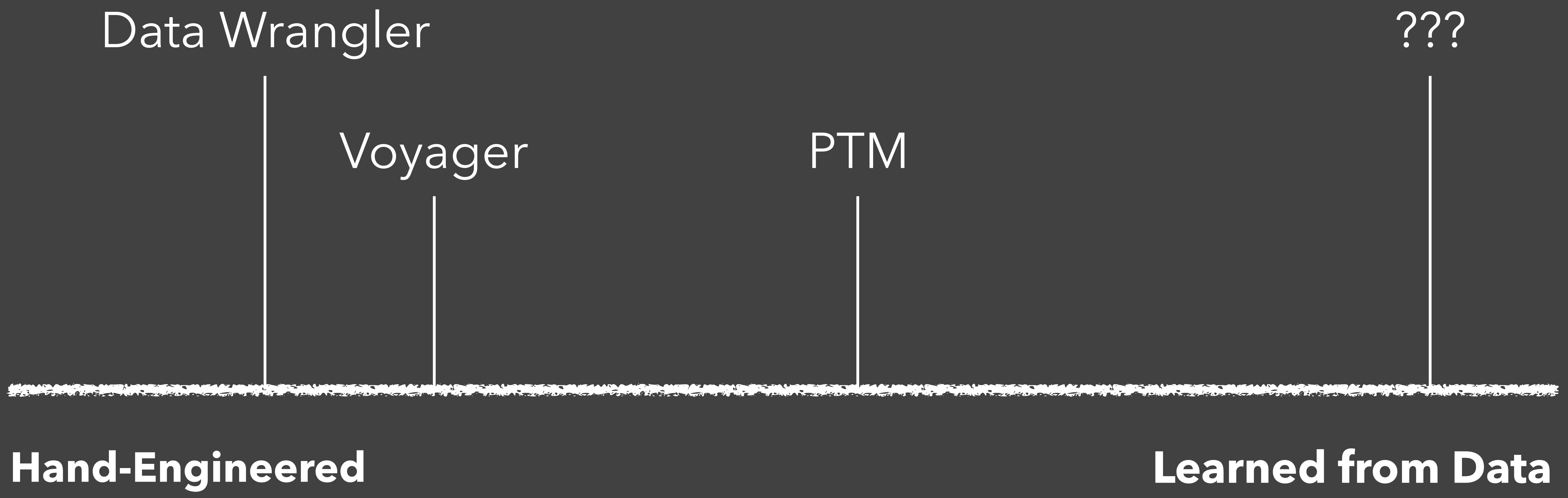
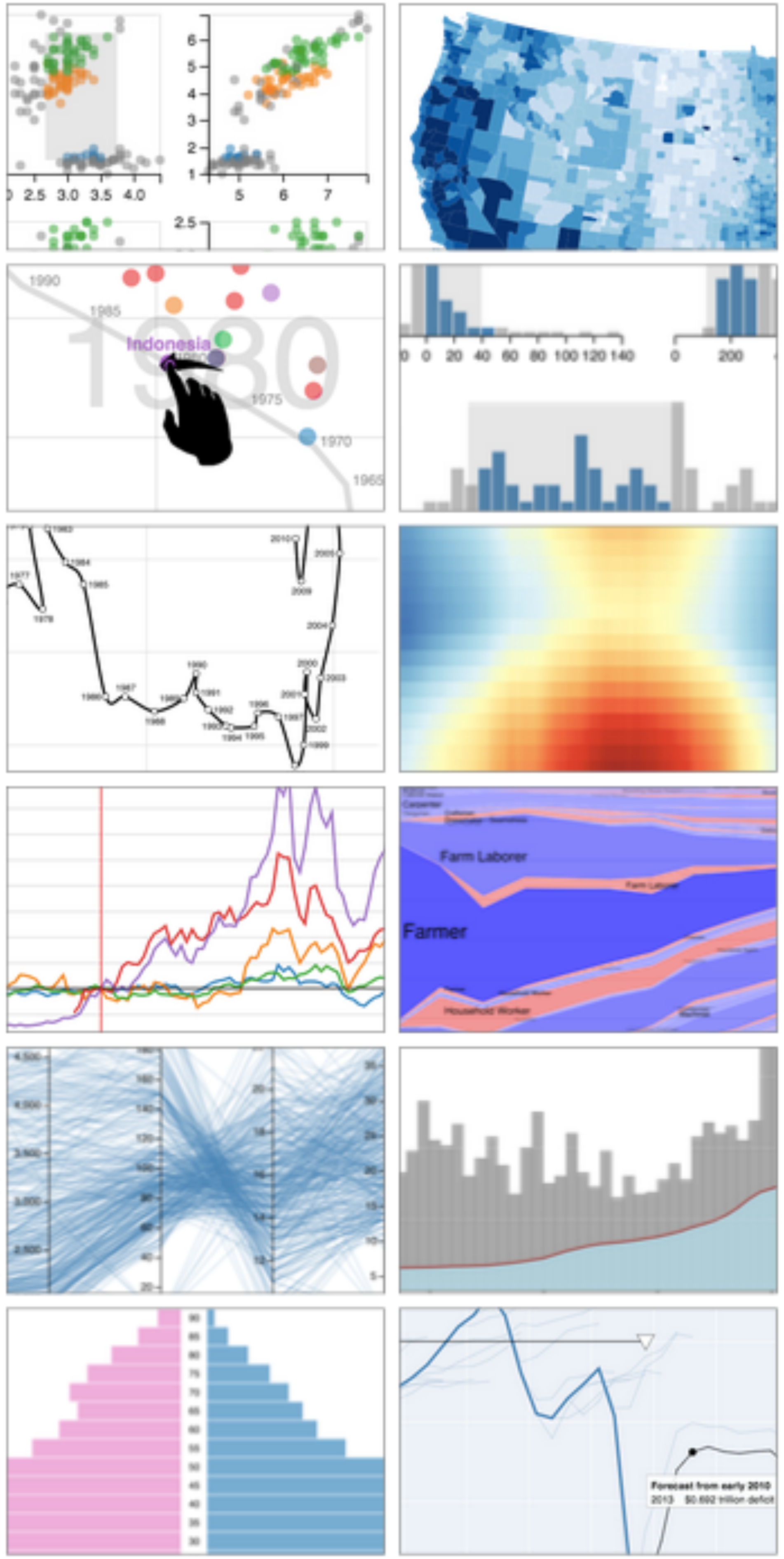


Future Challenges

Design Process, Tools, & Monitoring
How might we support productive prototyping, development, deployment, and monitoring of interactive systems using machine learning?

Mapping Machine-Learned Representations
Can people identify novel and useful features?
Can people help constrain / train these models?



Using Artificial Intelligence to Augment Human Intelligence

By creating user interfaces which let us work with the representations inside machine learning models, we can give people new tools for reasoning.

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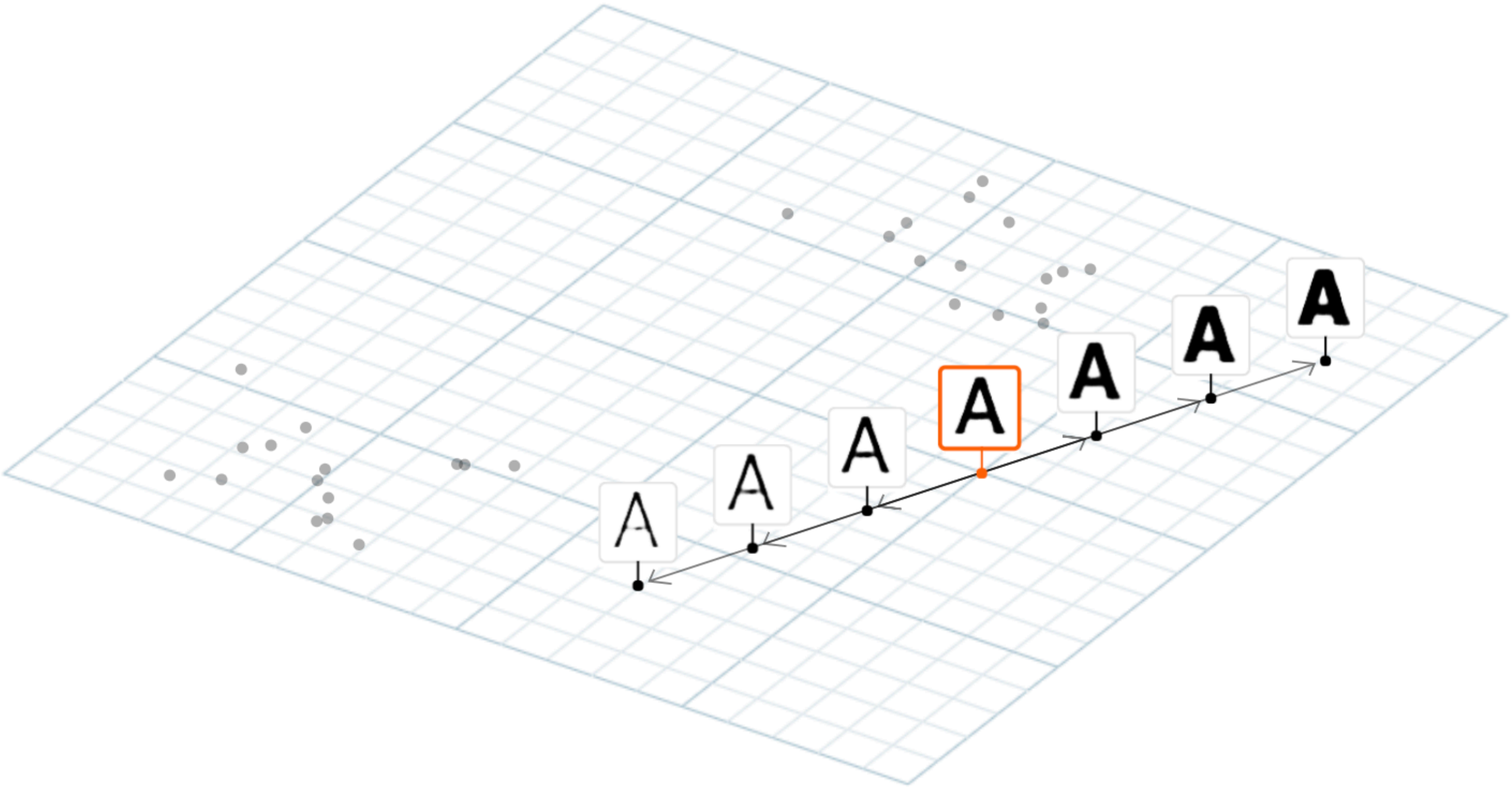

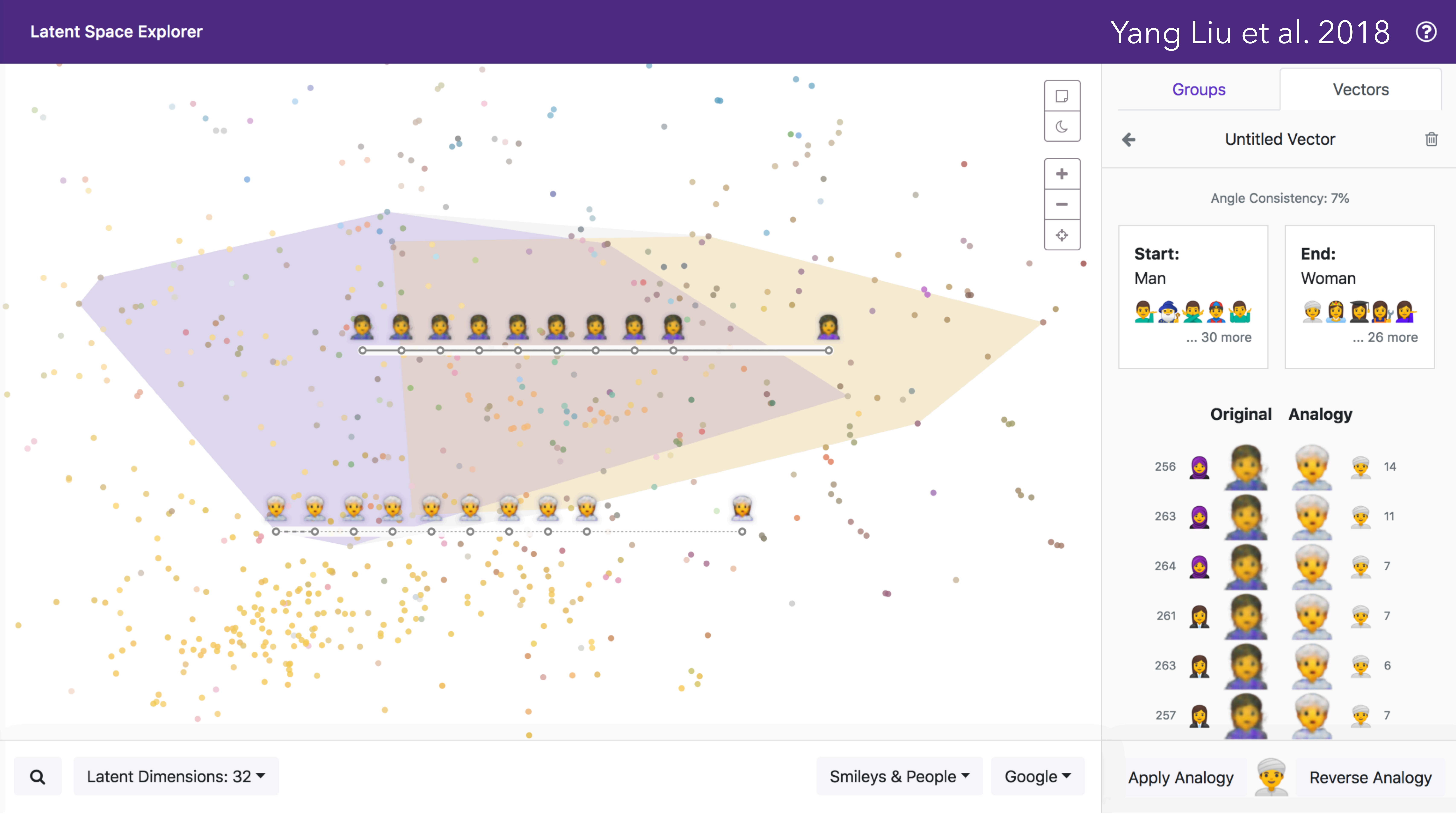

Latent Space Explorer
Yang Liu et al. 2018
Groups
Vectors
Untitled Vector
Angle Consistency: 7%
Start:
Man
... 30 more
End:
Woman
... 26 more
Original
Analogy
256
14
263
11
264
7
261
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263
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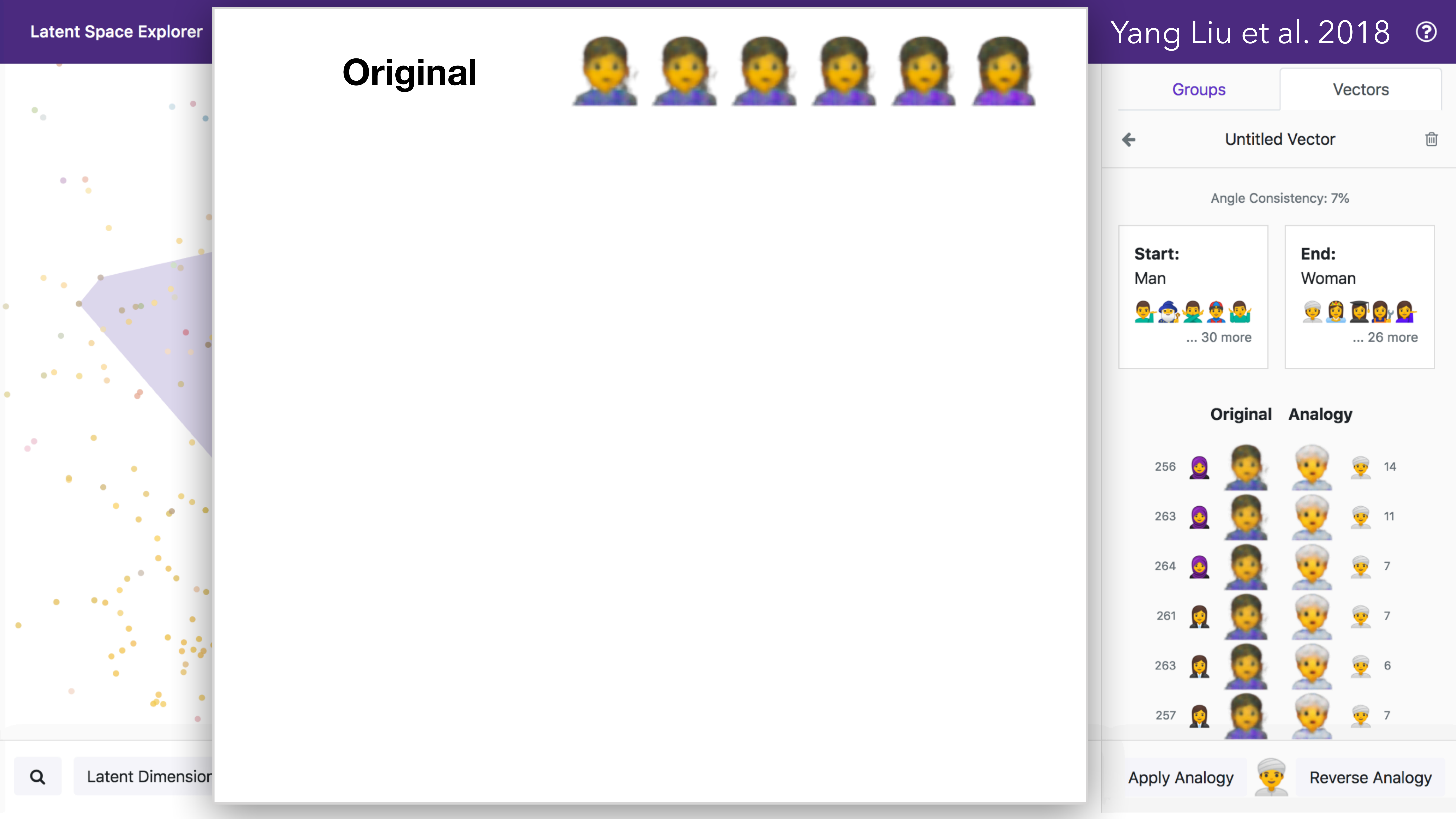
257
7
Latent Dimensions: 32
Smileys & People
Google
Apply Analogy
Reverse Analogy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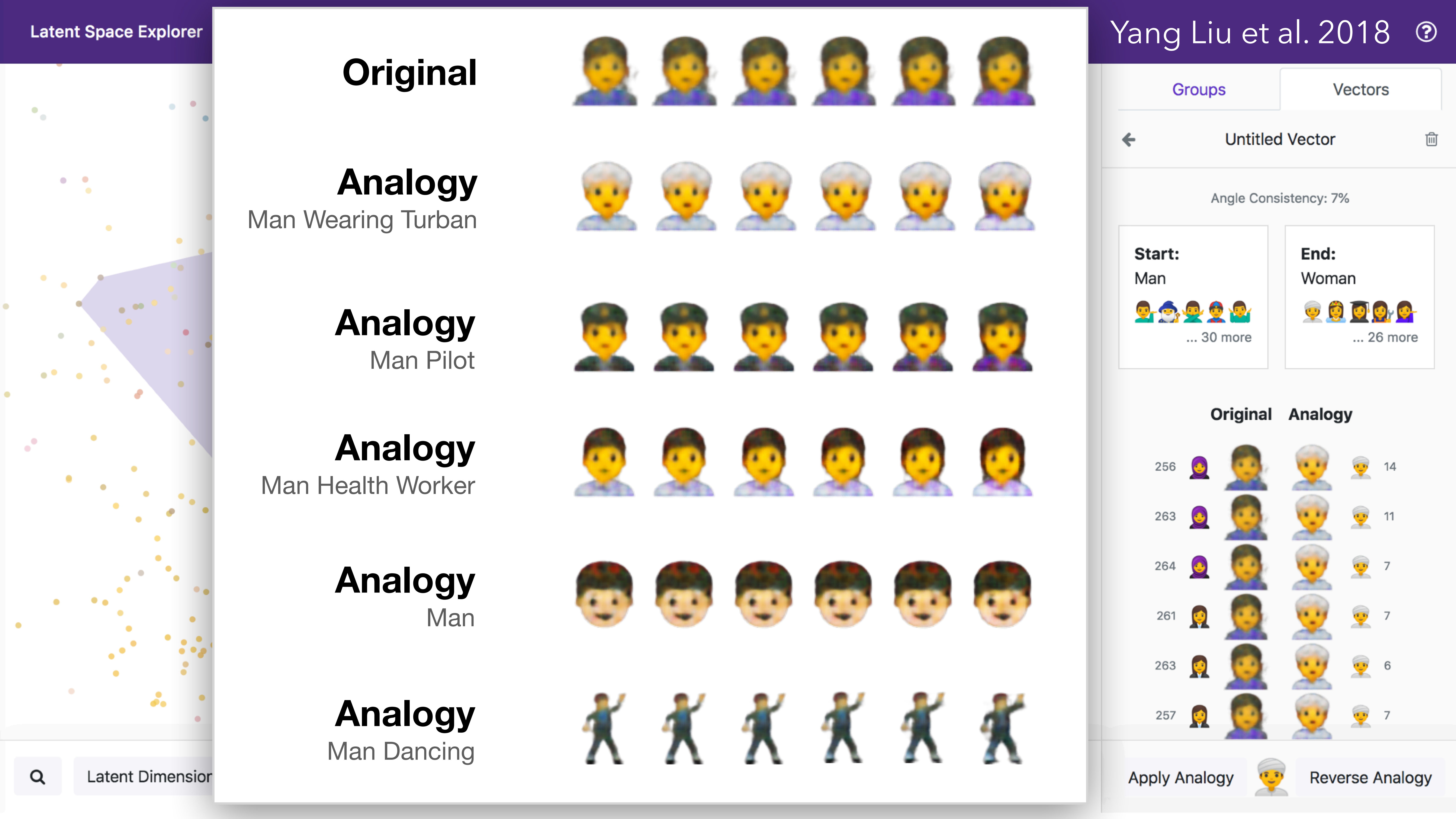

Latent Space Explorer
Yang Liu et al. 2018
Original
Analogy
Man Wearing Turban
Analogy
Man Pilot
Analogy
Man Health Worker
Analogy
Man
Analogy
Man Dancing
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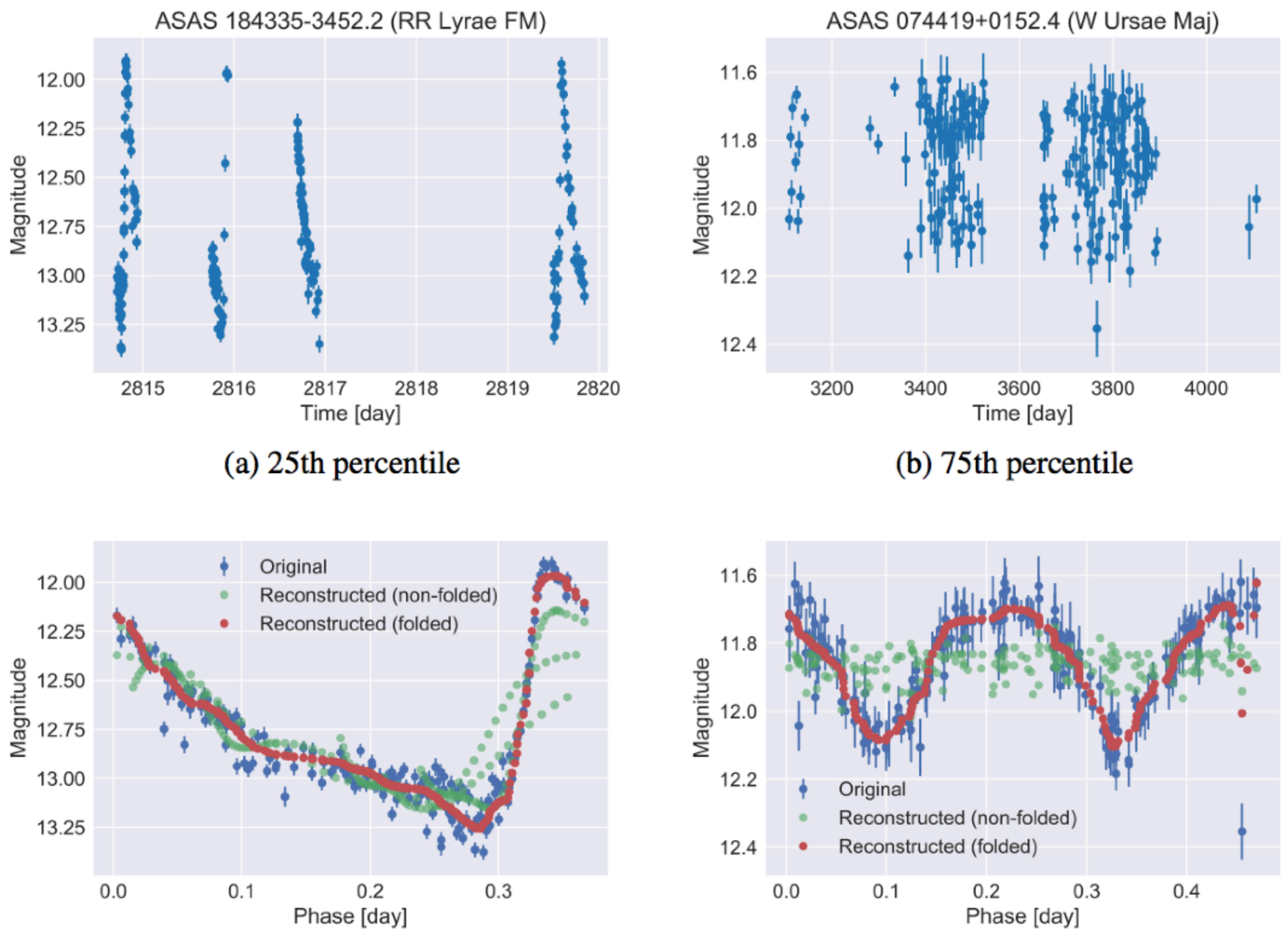
A recurrent neural network for classification of unevenly sampled variable stars

[Naul et al. 2017]

Extracting a biologically relevant latent space from cancer transcriptomes with variational autoencoders

[Way & Greene 2018]

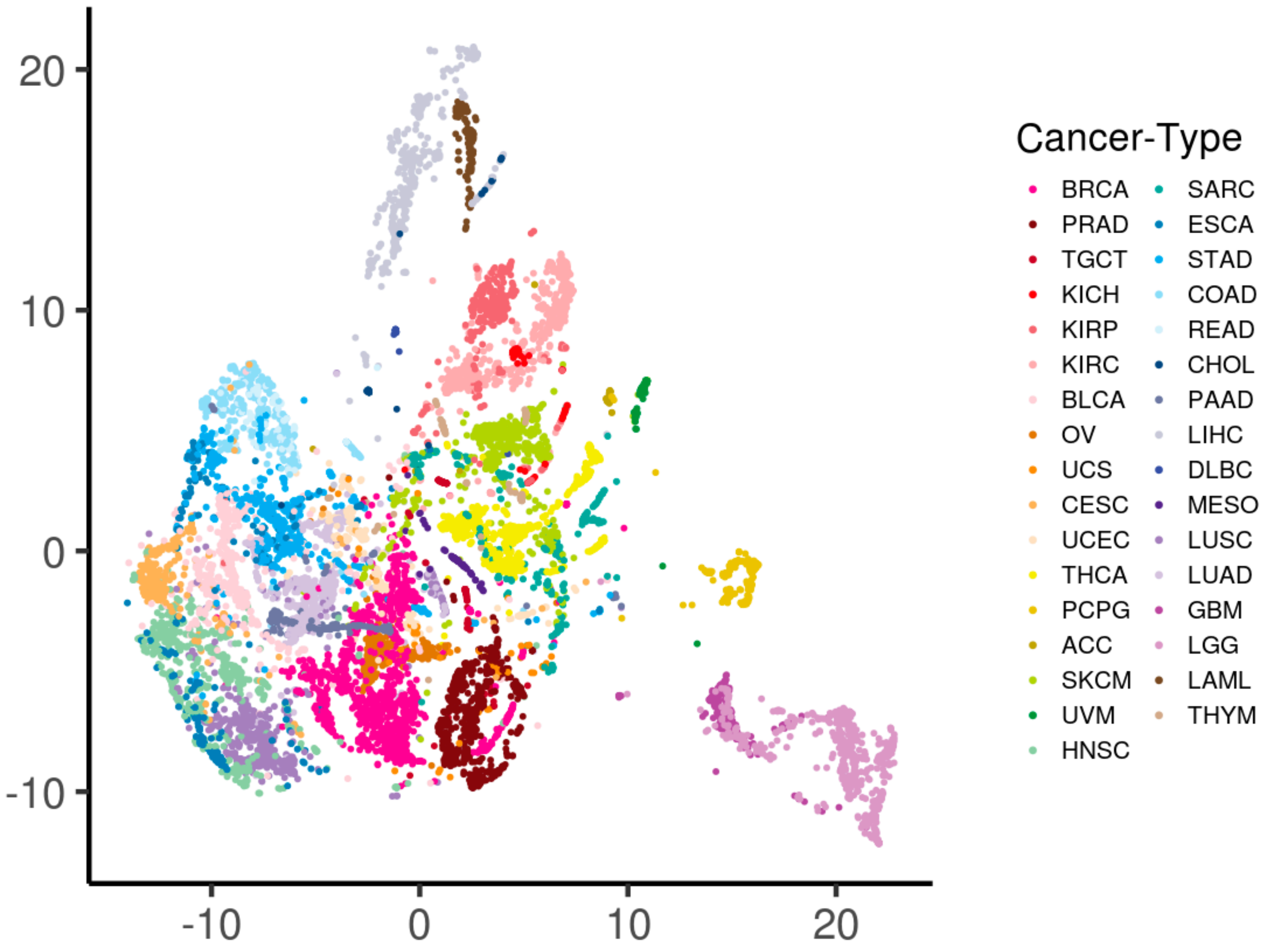


(a) 25th percentile

(b) 75th percentile

(c) 25th percentile (folded)

(d) 75th percentile (folded)



Future Challenges

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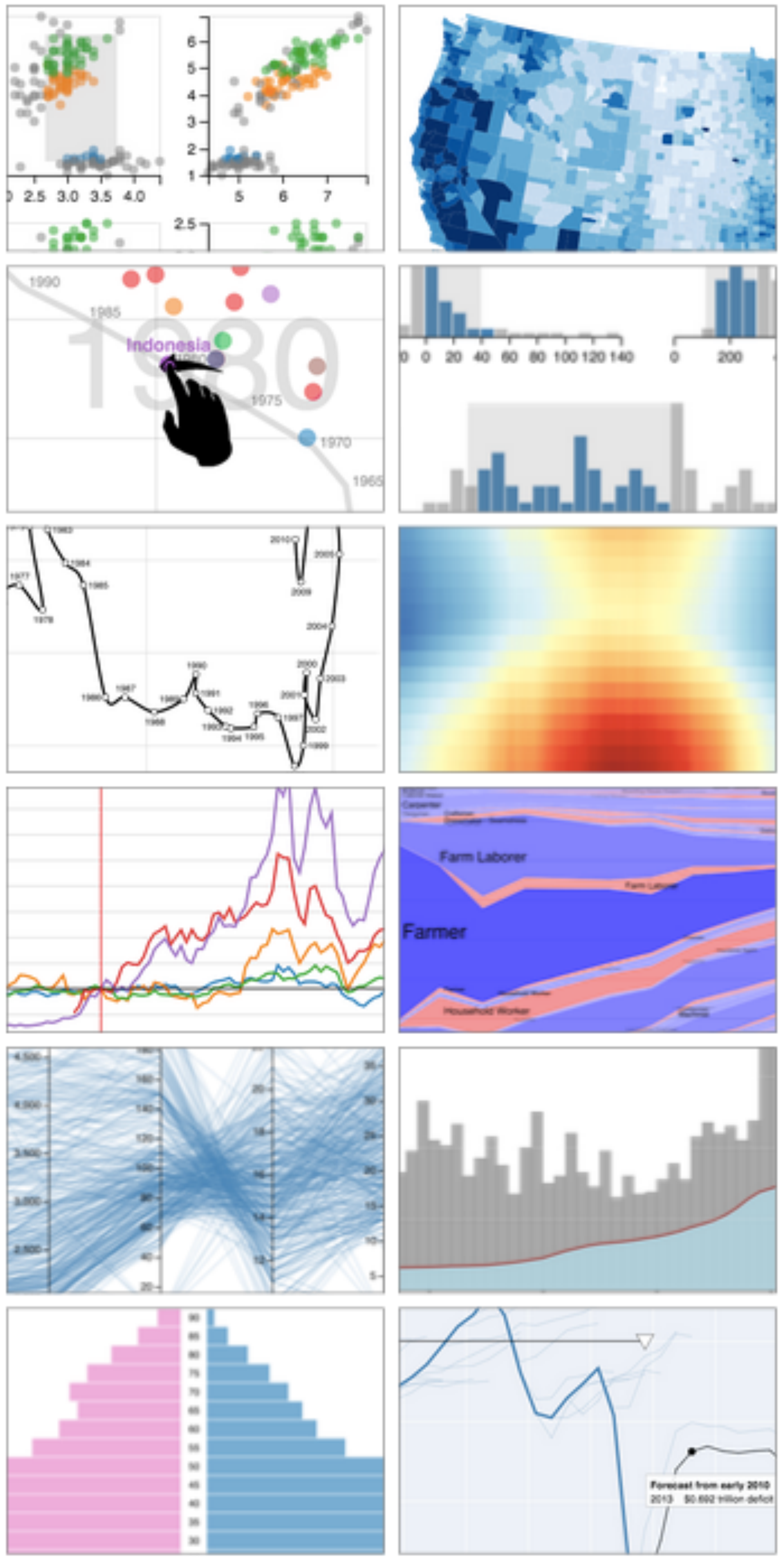
Evaluating Trade-Offs of Agency & Automation

Must go beyond result quality and productivity.

Locus of control, agency vs. passive acceptance?

Training and skill acquisition vs. de-skilled labor?

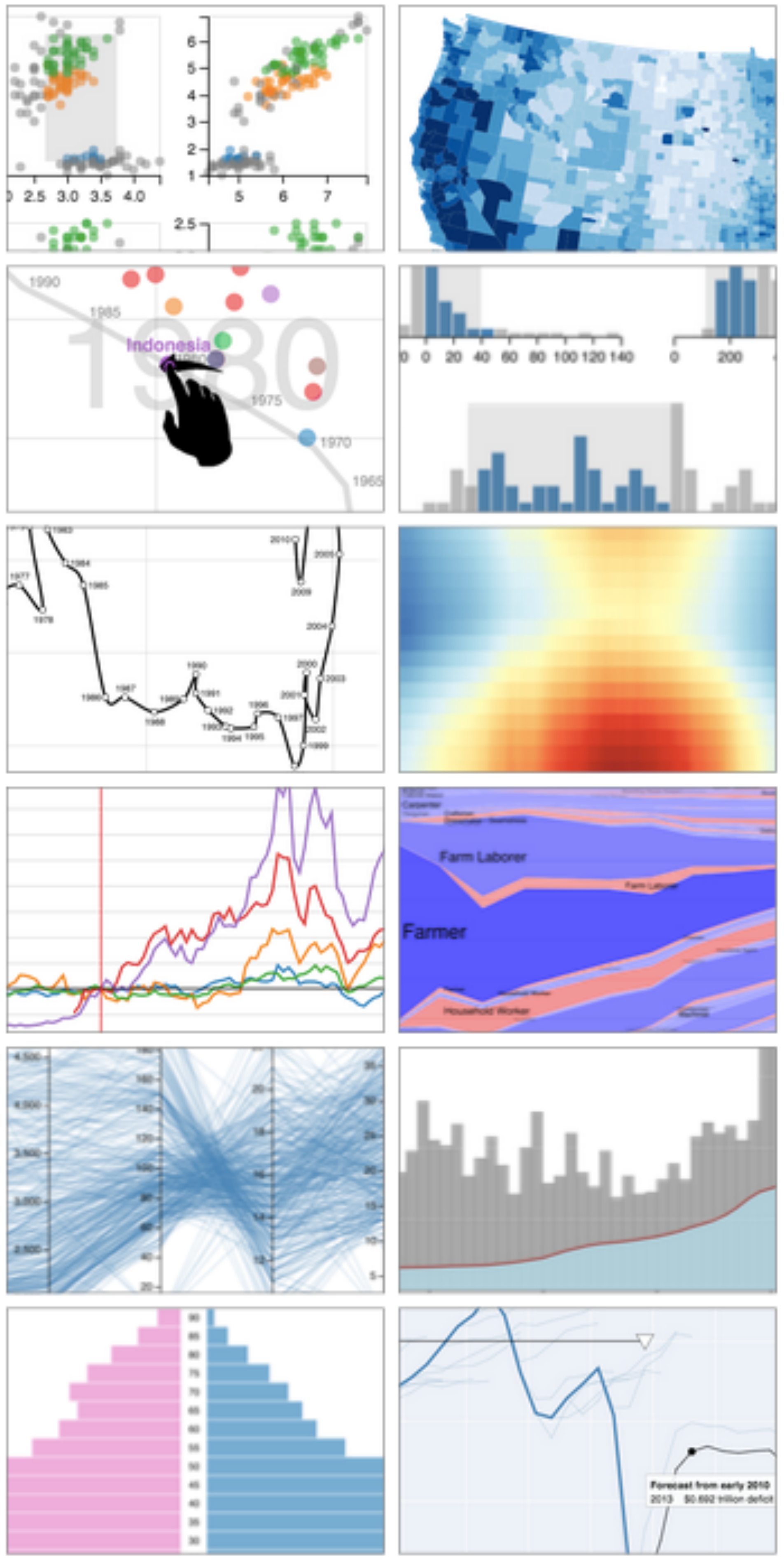


Related Reading

Agency + Automation. (2018). J Heer, in submission to *Proc. of the National Academy of Sciences (PNAS).*
https://homes.cs.washington.edu/~jheer/Agency+Automation.pdf

Predictive Interaction. (2015). J Heer, JH Hellerstein, S Kandel. *Conf. Innovative Data Systems Research (CIDR).*
http://idl.cs.washington.edu/papers/predictive-interaction

Natural Language Translation at the Intersection of AI and HCI. (2015). S Green, J Heer, CM Manning. *Communications of the ACM*, 58(9).
http://idl.cs.washington.edu/papers/translation-ai-hci



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GORDON AND BETTY MOORE FOUNDATION

THE PAUL G. ALLEN FAMILY FOUNDATION

Agency + Automation

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