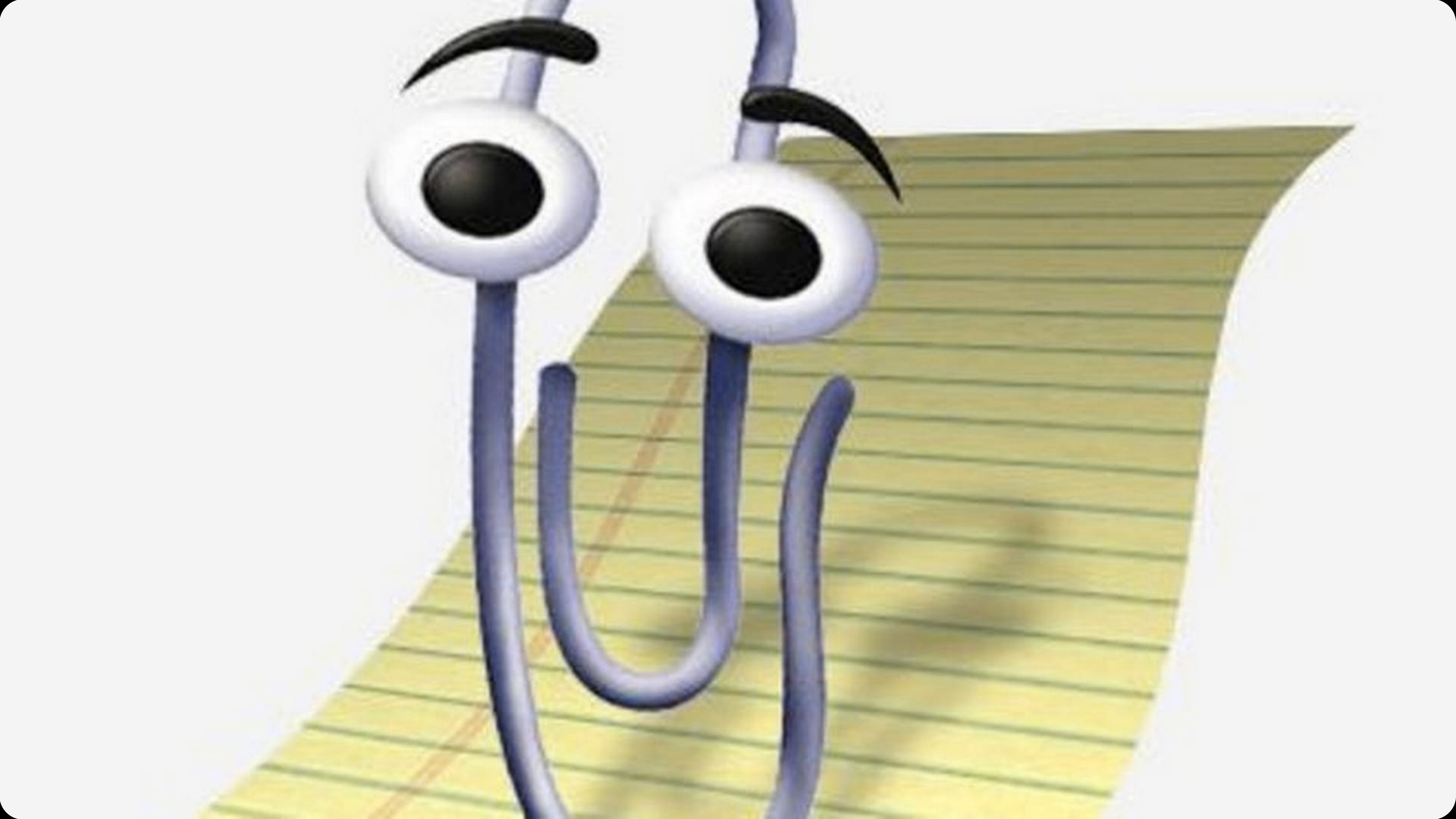
Predictive Interaction

Jeffrey Heer @jeffrey_heer
U. Washington / Trifacta

My software doesn’t know
what I’m trying to do.

What if it did?



Demo document

For years I have been driving an old used car with a lot of mileage and I hate it. It gets me where I need to go, but I'm tired of fixing leaks and broken parts all the time. Its annoying every times I need to take it to the mechanic. Even when they take care of everything, I know I'll just end up going back there in a few weeks.

years,

Possibly confused word: *Its*

every ~~times~~ → every time

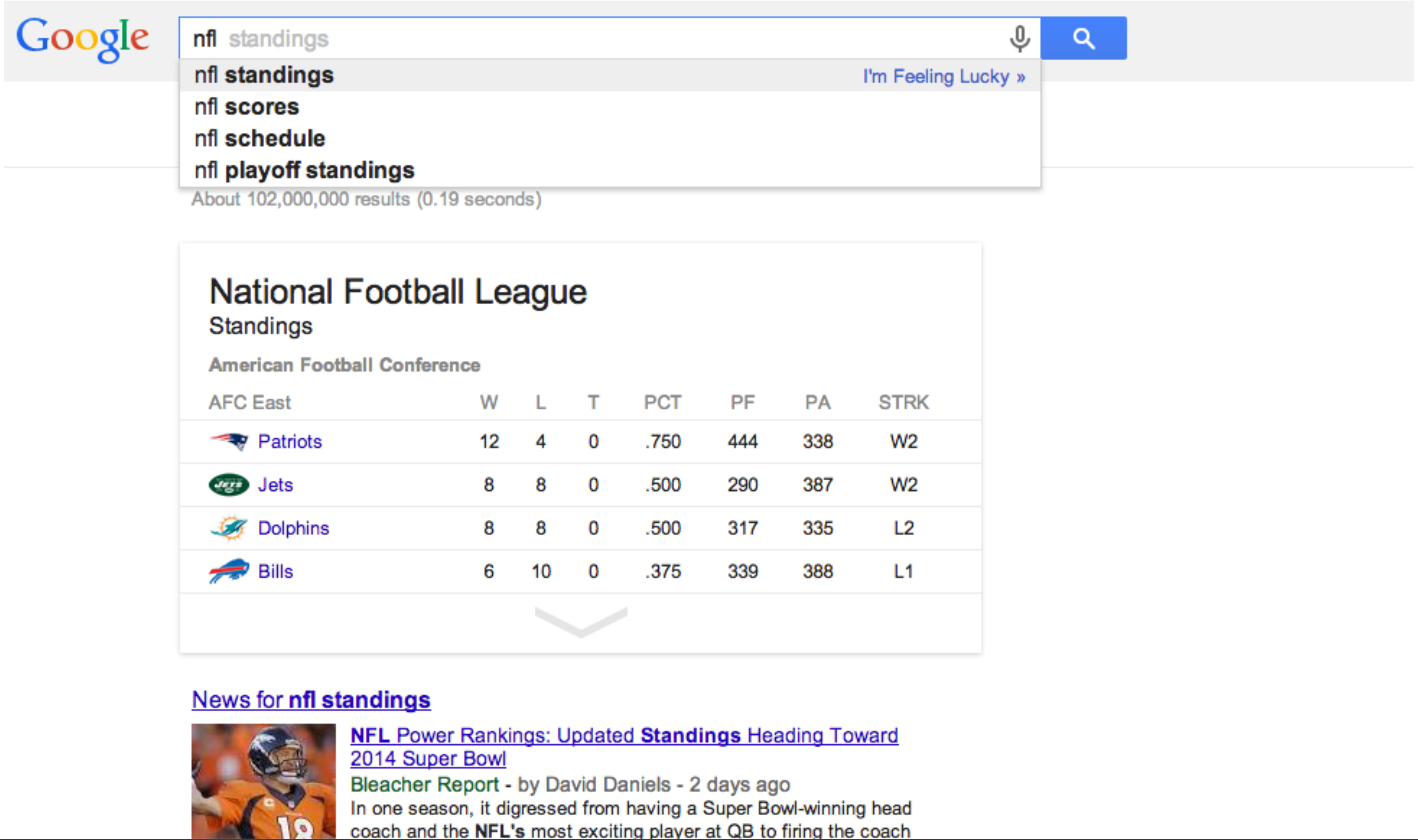
I have finally decided that I am not going to do it anymore. I have decided to buy a new car! Unfortunately, I have a problem. I have no idea what car to get. Do I want something fast? Do I want something big? Do I want something stylish? Something economical? I have so many choices that I don't even know where to begin. I am not sure if I will be able to make the decision on my own. I don't have not a lot of money, either, so I probably don't have many options.

~~not~~

After I did some research, I knew that I would need some expert advice. Eventually, I went to a local dealership to check out some new models. I

~~did~~ → had done

Hints of Intelligent Interaction



Google

nfl standings

nfl **standings** I'm Feeling Lucky »
nfl **scores**
nfl **schedule**
nfl **playoff standings**

About 102,000,000 results (0.19 seconds)

National Football League
Standings

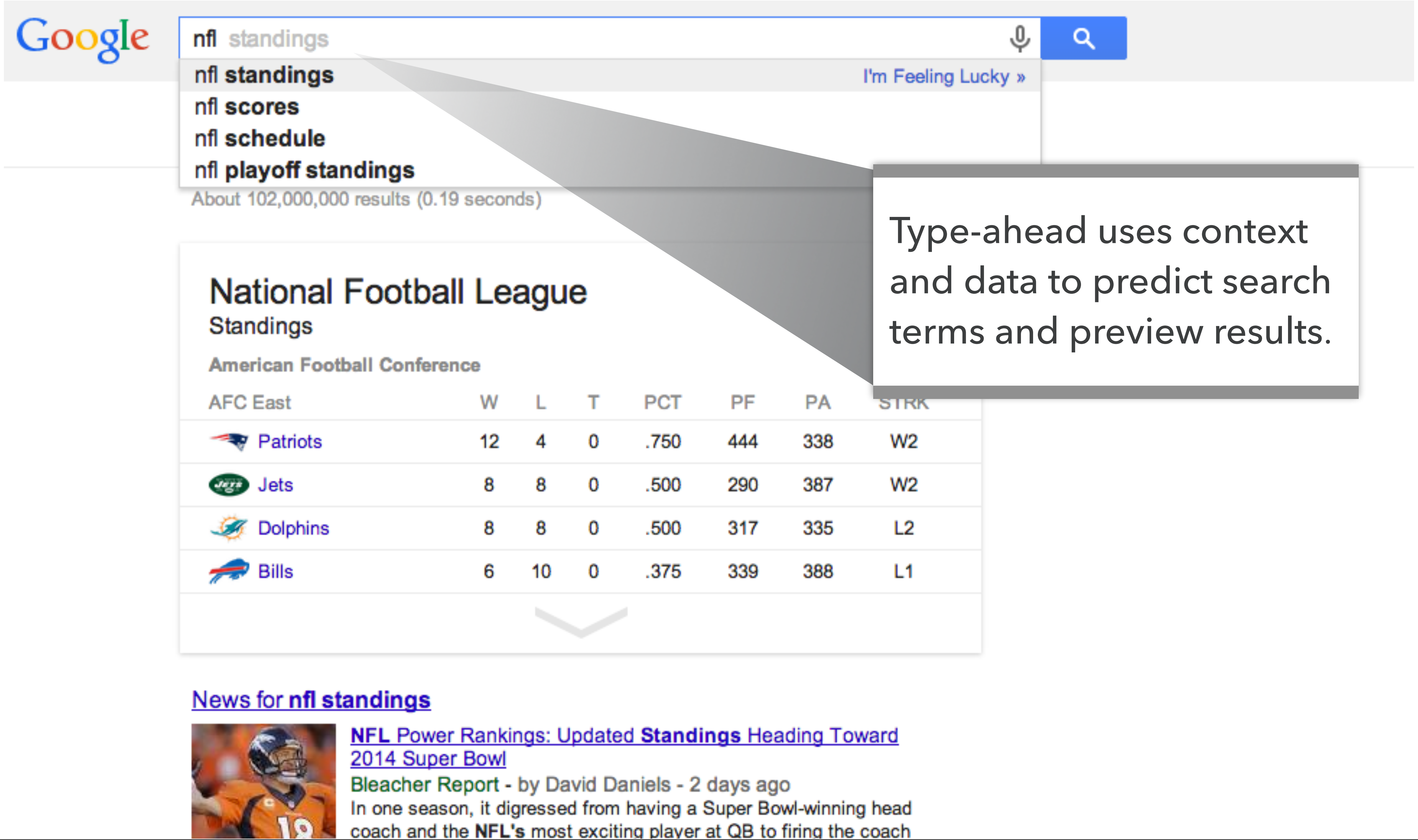
American Football Conference

AFC East	W	L	T	PCT	PF	PA	STRK
Patriots	12	4	0	.750	444	338	W2
Jets	8	8	0	.500	290	387	W2
Dolphins	8	8	0	.500	317	335	L2
Bills	6	10	0	.375	339	388	L1

News for **nfl standings**

NFL Power Rankings: Updated **Standings** Heading Toward 2014 Super Bowl
Bleacher Report - by David Daniels - 2 days ago
In one season, it digressed from having a Super Bowl-winning head coach and the **NFL's** most exciting player at QB to firing the coach

Hints of Intelligent Interaction



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

kdd idea

kdd **2014**
kdd **2017**
kdd **2016 registration**
kdd **2015 accepted papers**

About 553,000 results (1.18 seconds)

Interactive Data Exploration and Analytics (IDEA 2016) - Workshop at ...
poloclub.gatech.edu/**idea**2016/ ▾ Georgia Institute of Technology ▾
IDEA will be a full-day workshop on Sunday, Aug 14, at **KDD** 2016 in the Embarcadero room in Hotel Parc 55 (just across the street from the main conference ...

Interactive Data Exploration and Analytics (IDEA 2015) - Workshop at ...
poloclub.gatech.edu/**idea**2015/ ▾ Georgia Institute of Technology ▾
The **Interactive Data Exploration and** Analytics (**IDEA**) workshop addresses the ... **IDEA** will be a full-day workshop on Monday, Aug 10, at **KDD** 2015 at the Hilton ...
The IDEA · Dates · Call · Submission

Interactive Data Exploration and Analytics (IDEA 2014) - Workshop at ...
poloclub.gatech.edu/**idea**2014/ ▾ Georgia Institute of Technology ▾
Aug 24, 2014 - The **Interactive Data Exploration and** Analytics (**IDEA**) workshop addresses ... Last year's **IDEA** at **KDD** 2013 in Chicago was a great success. ‹ › ...
The IDEA · Program · Keynotes · Dates

IDEA 2016 : KDD 2016 Workshop on Interactive Data Exploration and ...
wikicfp.com/cfp/servlet/event.showcfp?eventid=53928&copyownerid=50759 ▾
Call for Papers - **IDEA** @ **KDD** 2016. **KDD** 2016 Workshop on **Interactive Data Exploration and** Analysis. Sunday, August 14. San Francisco **IDEA** is a full-day ...
Fri, Oct 14 IDEA 2016

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More images for kdd idea

polo chau

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polo chau **google scholar**
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polo chau**ssure**

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Duen Horng (Polo) Chau - Georgia Tech
www.cc.gatech.edu/~**dchau**/ ▾ Georgia Institute of Technology College of Computing ▾
U Kang, Leman Akoglu, **Polo Chau**. The 7th ACM International Conference on Web Search and Data Mining (WSDM2014). New York City. February 24, 2014.

Polo Chau | Georgia Tech - College of Computing
www.cc.gatech.edu/.../**polo-ch**... ▾ Georgia Institute of Technology College of Computing ▾
Polo Chau. **Polo Chau**. Assistant Professor. Email: polo@gatech.edu. Personal webpage: http://www.cc.gatech.edu/~dchau ...

Data and Visual Analytics - Polo Club of Data Science - Georgia Tech
poloclub.gatech.edu/cse6242/ ▾ Georgia Institute of Technology ▾
Polo Chau, Tue, 3:30-4:00pm (+ 30min after Tue's class at Clough Starbucks), Klaus 1324. Gopi Krishnan Nambiar, Mon, 9-10 AM, common area between Klaus ...

Duen Horng (Polo) Chau - Google Scholar Citations
https://scholar.google.com/citations?user=YON32W4AAAAJ ▾ Google Scholar ▾
Assistant Professor, College of Computing, Georgia Tech - gatech.edu
Parallel crawling for online social networks. DH **Chau**, S Pandit, S Wang, C Faloutsos. Proceedings of the 16th international conference on World Wide Web, ...

Polo Chau | LinkedIn
https://www.linkedin.com/in/**polochau** ▾
Atlanta, Georgia - Assistant Professor at Georgia Tech - Georgia Institute of Technology
Assistant Professor at Georgia Tech. ... Georgia Institute of Technology. ... Associate Director, MS in Analytics.

[PDF] Duen Horng (Polo) Chau - Georgia Tech - Carnegie Mellon School of ...
www.cs.cmu.edu/~**dchau**/**polo**_cv.pdf ▾ Carnegie Mellon University ▾
Jul 3, 2013 - RESEARCH INTERESTS. **POLO CHAU** Legal name: Duen Horng Chau. Assistant Professor, School of Computational Science & Engineering.

Polo Chau's Talk is Now Live - Science of Networks in Communities polo chaussure

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Découvrez les **Chaussures** Hommes sur Ralph Lauren France, le site officiel de ... Mocassins Workington cuir vachetta - **Polo** Ralph Lauren Mocassins - Ralph ...

Chaussures Polo Ralph Lauren homme - le meilleur de la chaussure ...
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★★★★★ Rating: 4.5 - 24,298 votes
Toute la nouvelle collection **Polo** Ralph Lauren homme est sur Sarenza. Faites votre choix parmi notre sélection de modèles. Livraison et retour toujours gratuits ...

Chaussures POLO Ralph Lauren Homme, Collection 2016 | Menlook
www.menlook.com › ... › Mode › Chaussures › polo ralph lauren ▾ Translate this page
Découvrez la collection de **Chaussures POLO** Ralph Lauren Homme & Commandez en ligne ✅ Satisfait ou Remboursé ✅Livraison Gratuite ✅Retour 30J ...

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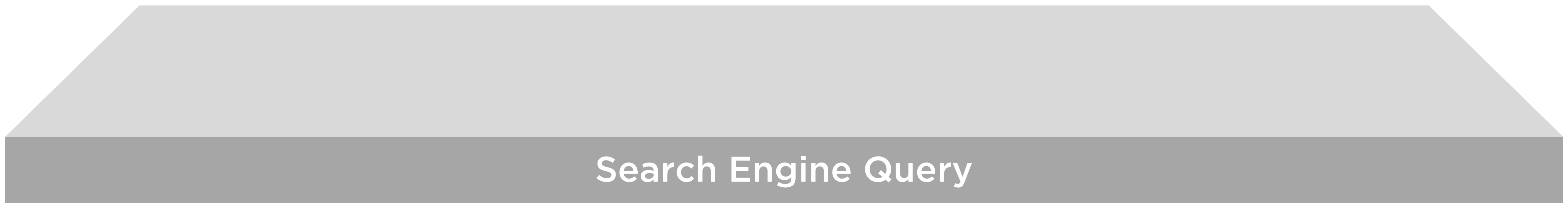
fr.marc-o-polo.com › Femme › Chaussures & Accessoires ▾ Translate this page

Search Query Auto-Complete



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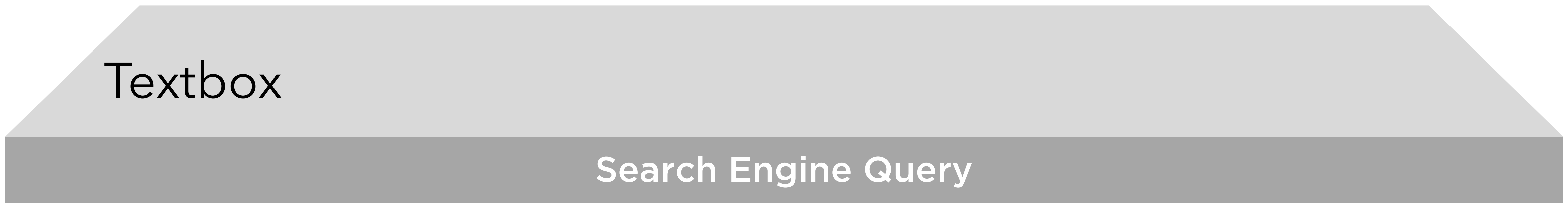

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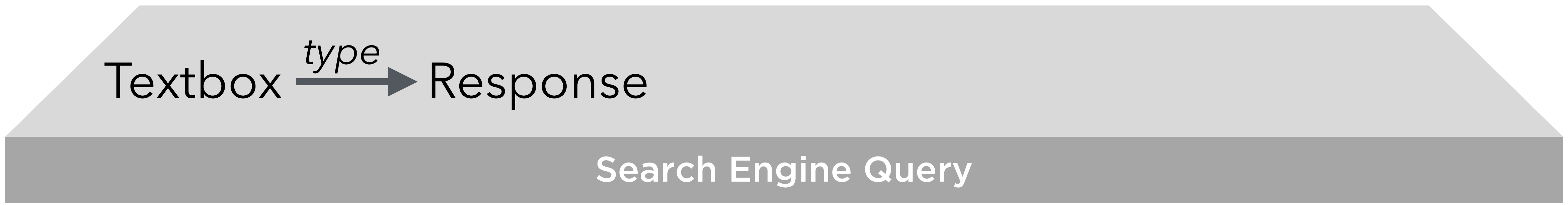

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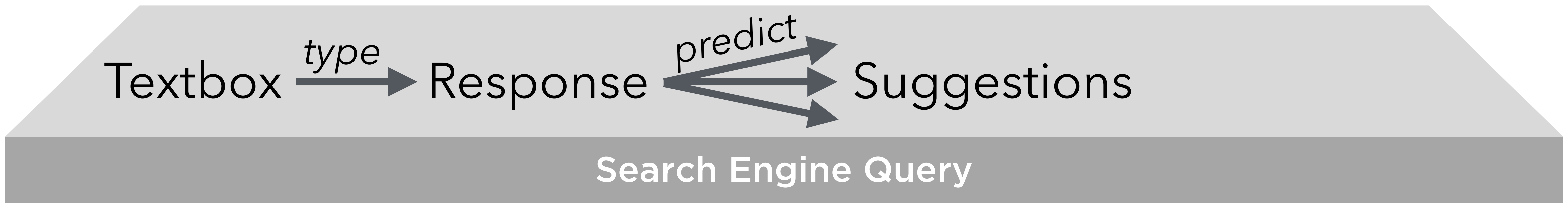

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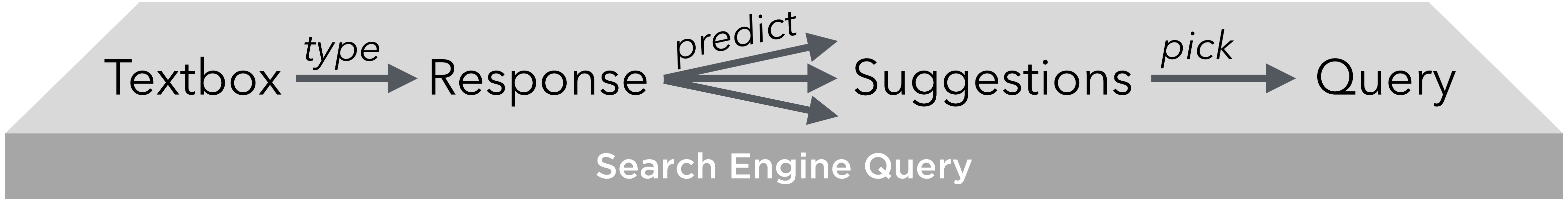

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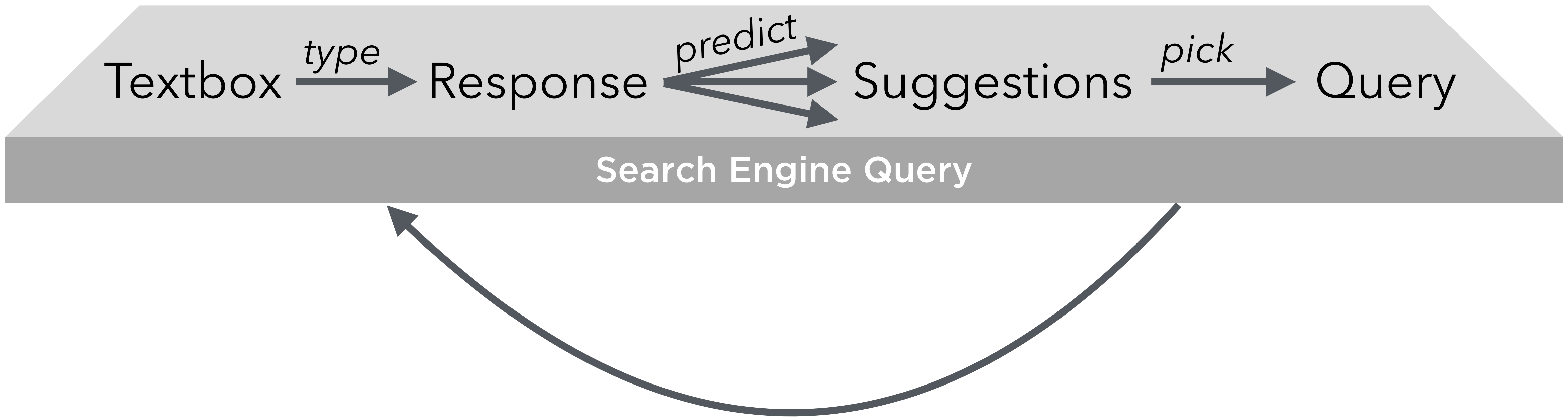

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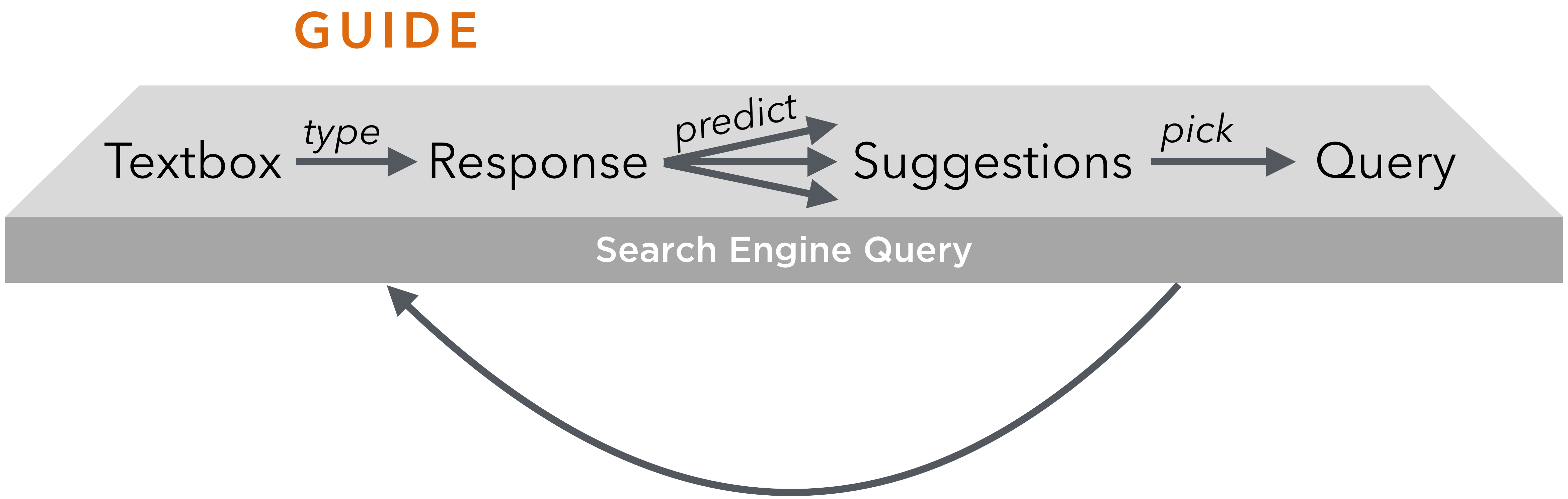

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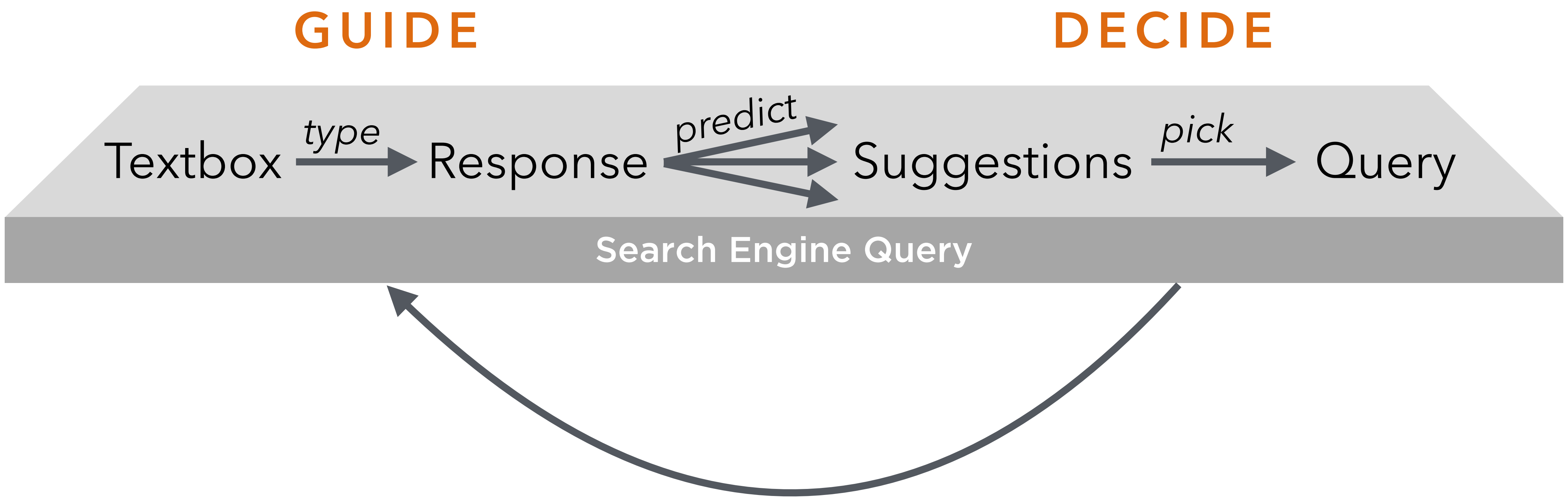

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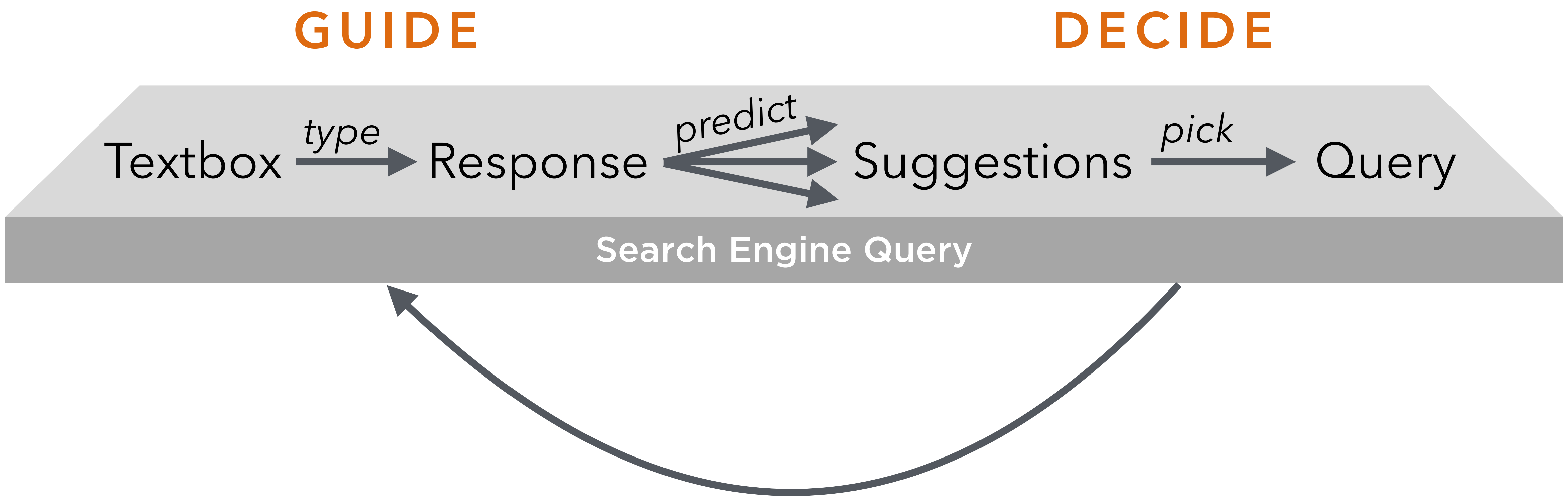
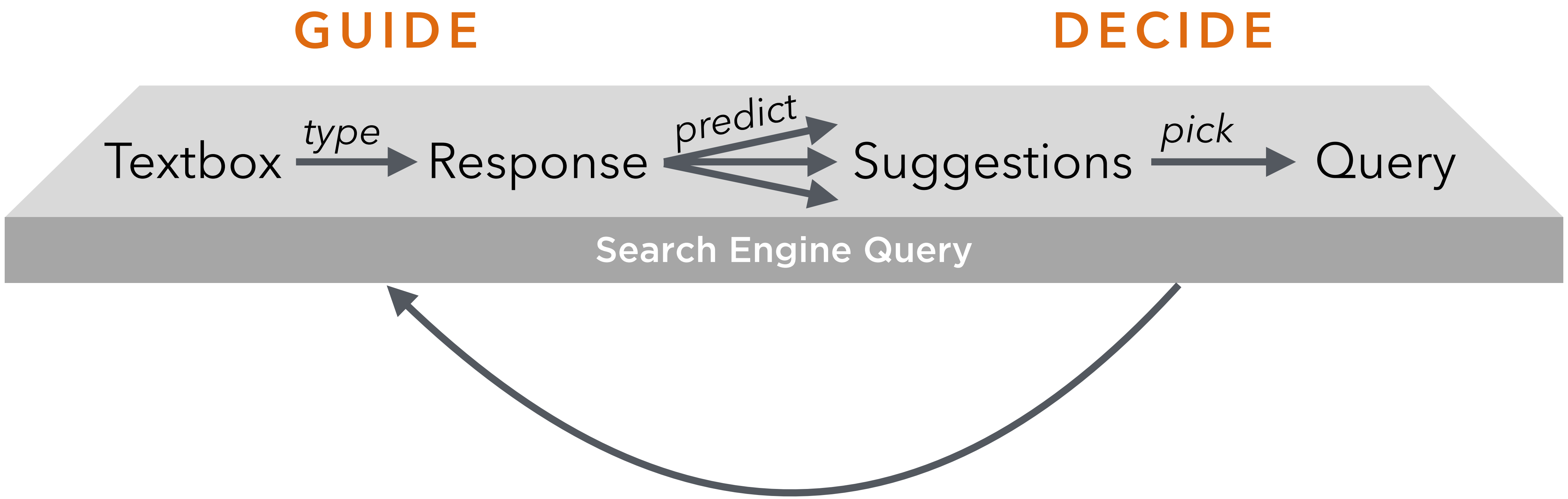


The input and output domains are the same: **text.**

Search Query Auto-Complete



What about more complex input/output relations?

Objectives

Accelerate successful task completion.

Scale to large data or batch repetition.

Support discovery and ambiguous intent.

Long-term learning and improvement.

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Model user interface actions in a **domain-specific language (DSL)**. Leverage the language to

(1) predict potential actions, and

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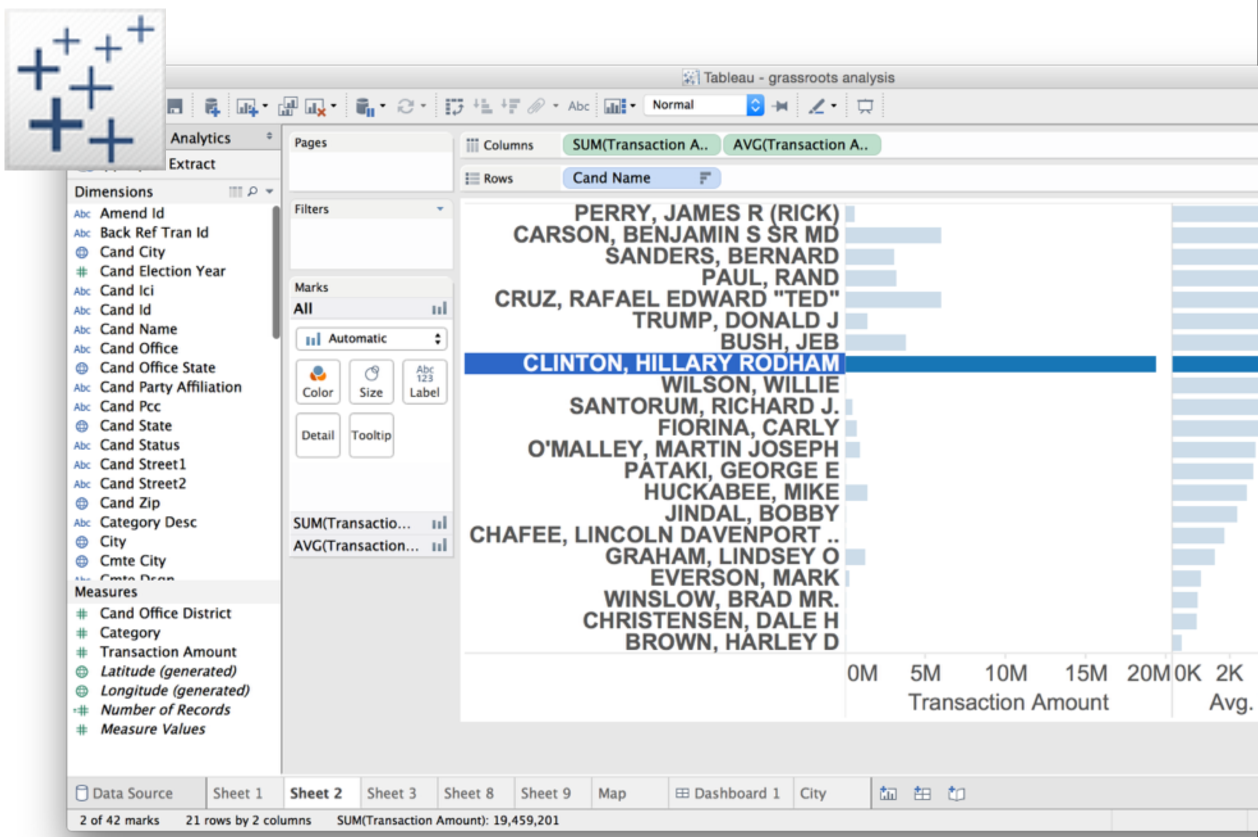

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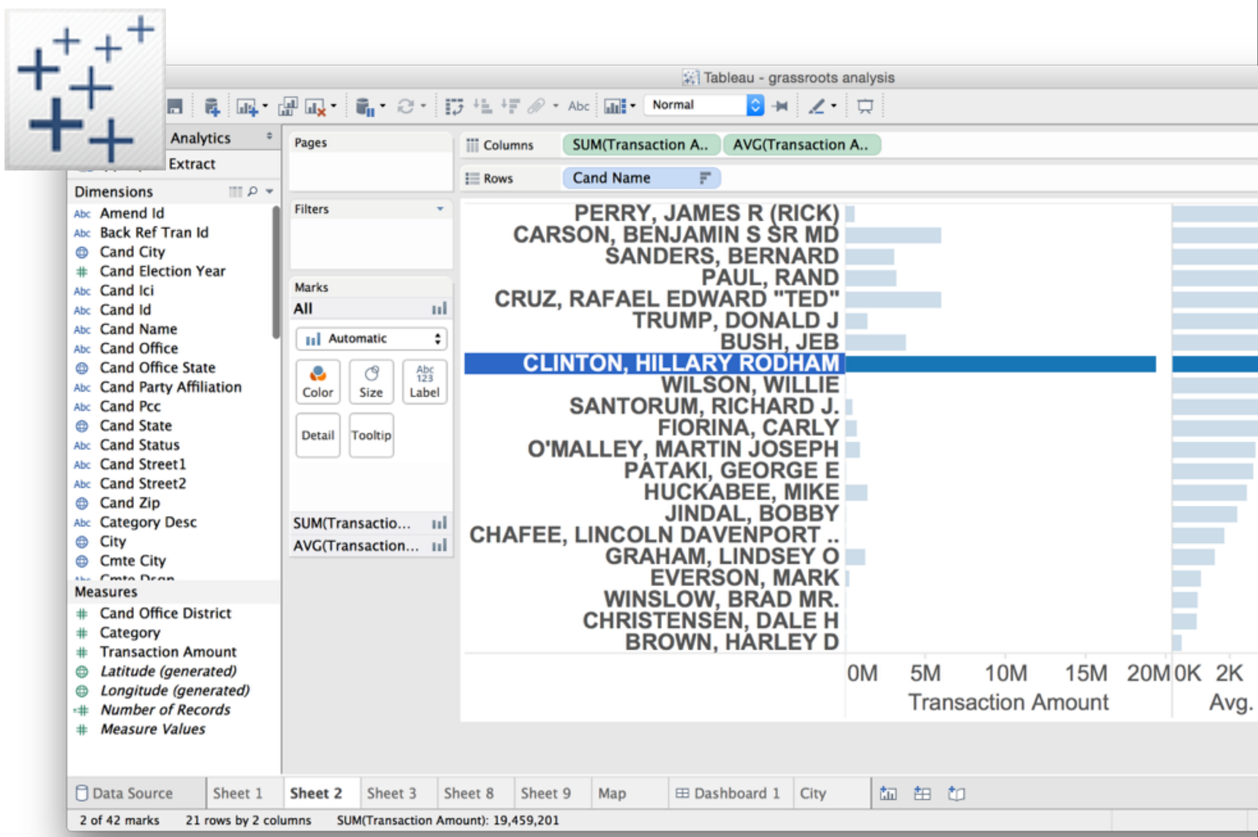

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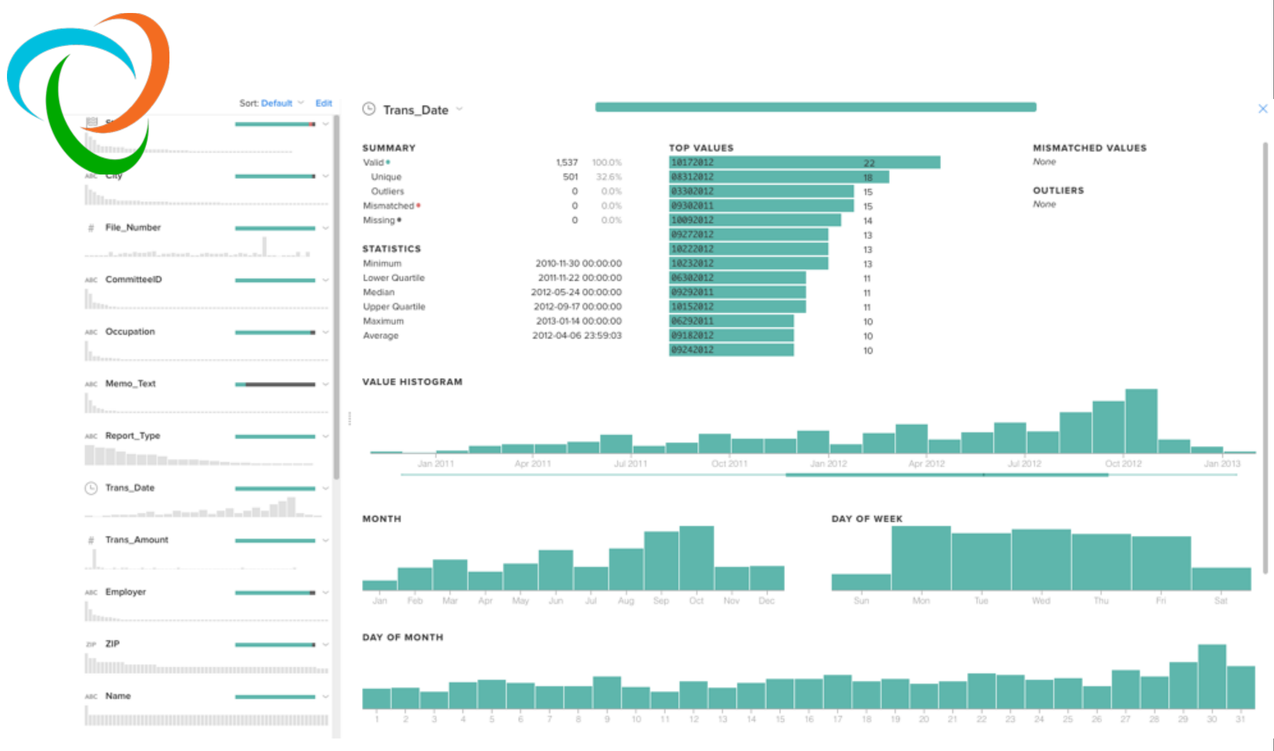

Why Domain-Specific Languages?

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Model the task as a program (often a sequence).

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Can be re-applied to new inputs.

Cross-compile to different runtimes.

EXAMPLE:

Data Visualization

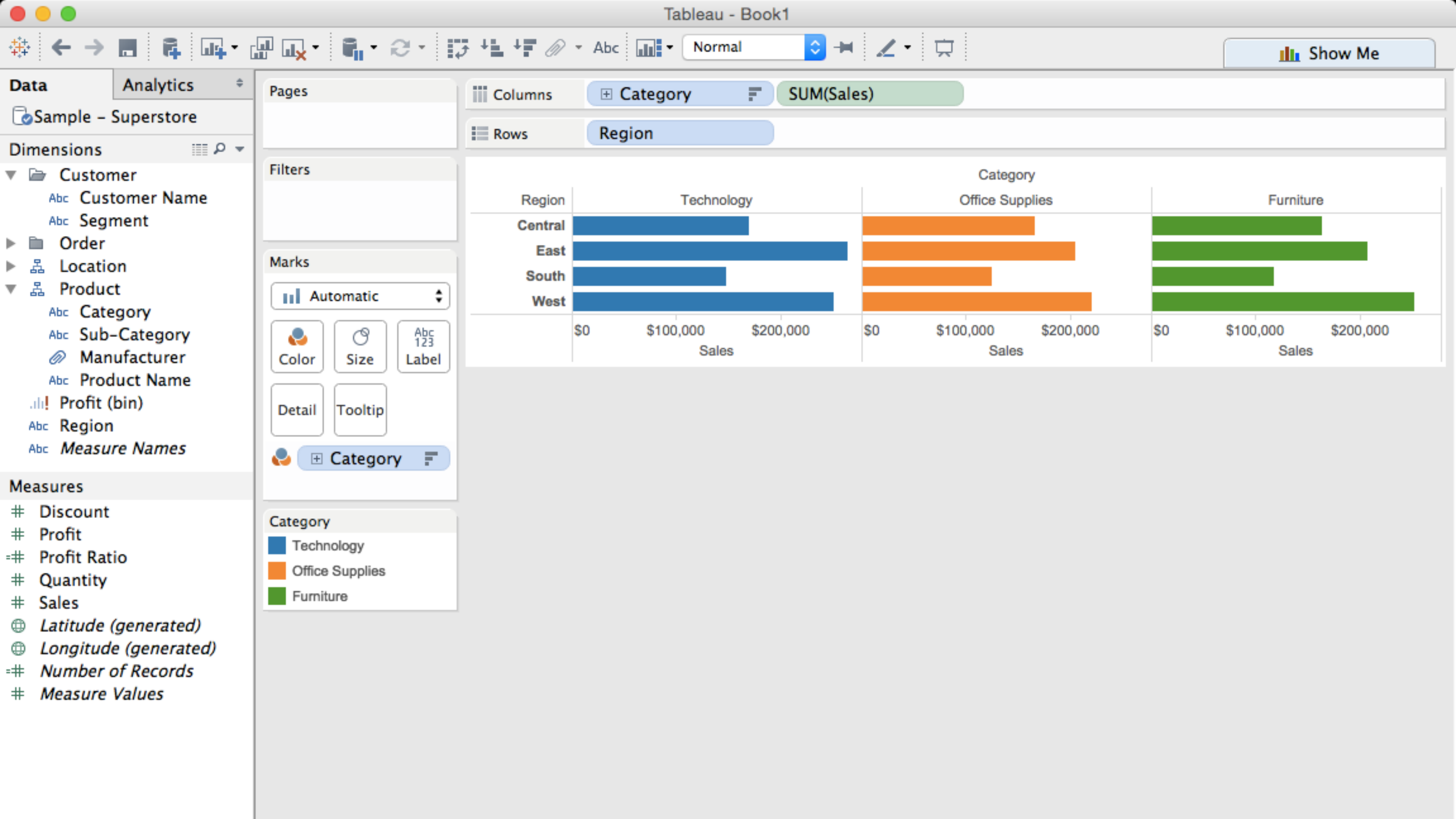
Tableau - Book1
Normal
Show Me
Data
Analytics
Sample – Superstore
Dimensions
Customer
Customer Name
Segment
Order
Location
Product
Category
Sub-Category
Manufacturer
Product Name
Profit (bin)
Region
Measure Names
Measures
Discount
Profit
Profit Ratio
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Sales
Latitude (generated)
Longitude (generated)
Number of Records
Measure Values
Pages
Filters
Marks
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Category
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Technology
Office Supplies
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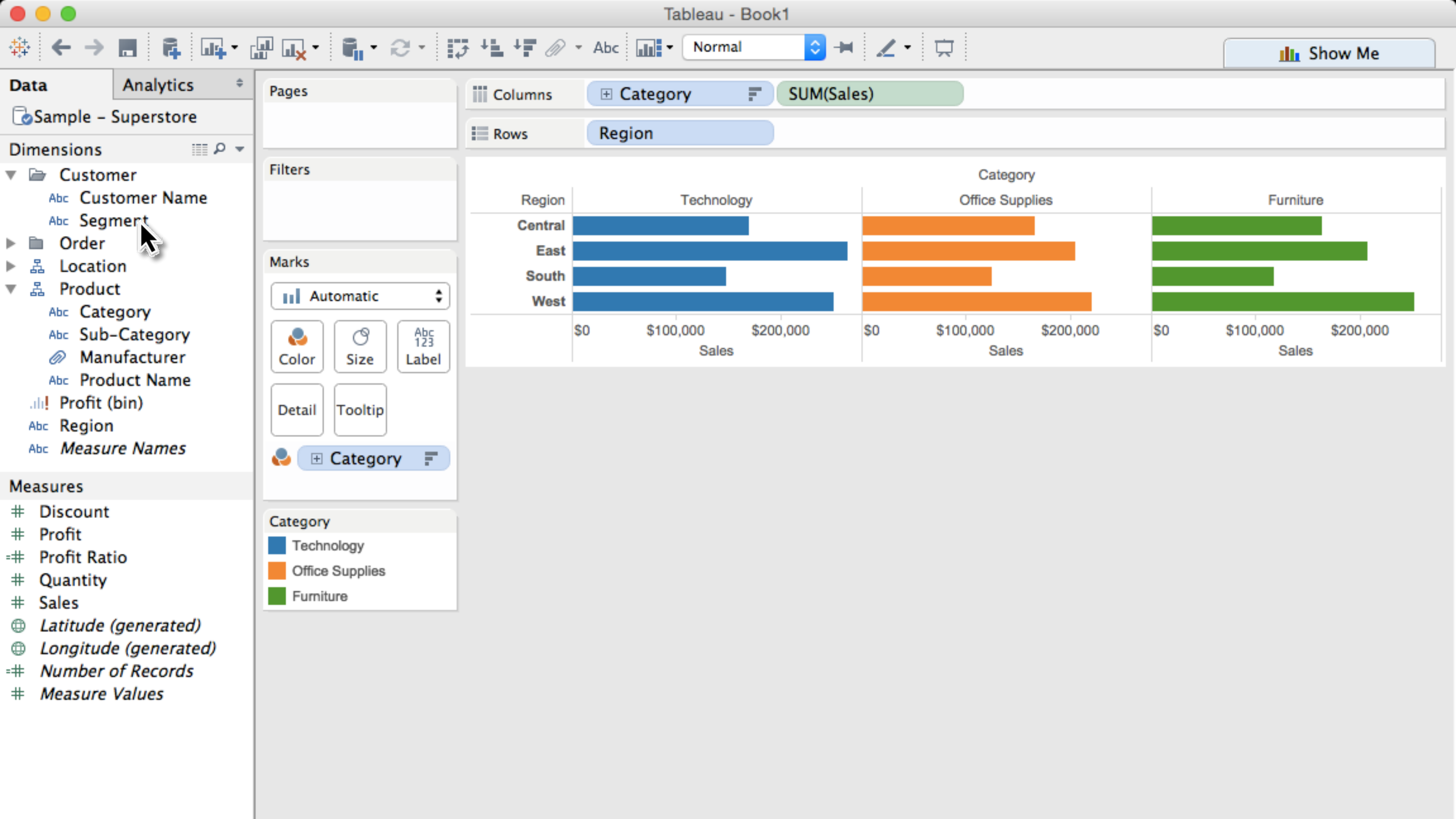
$200,000
Sales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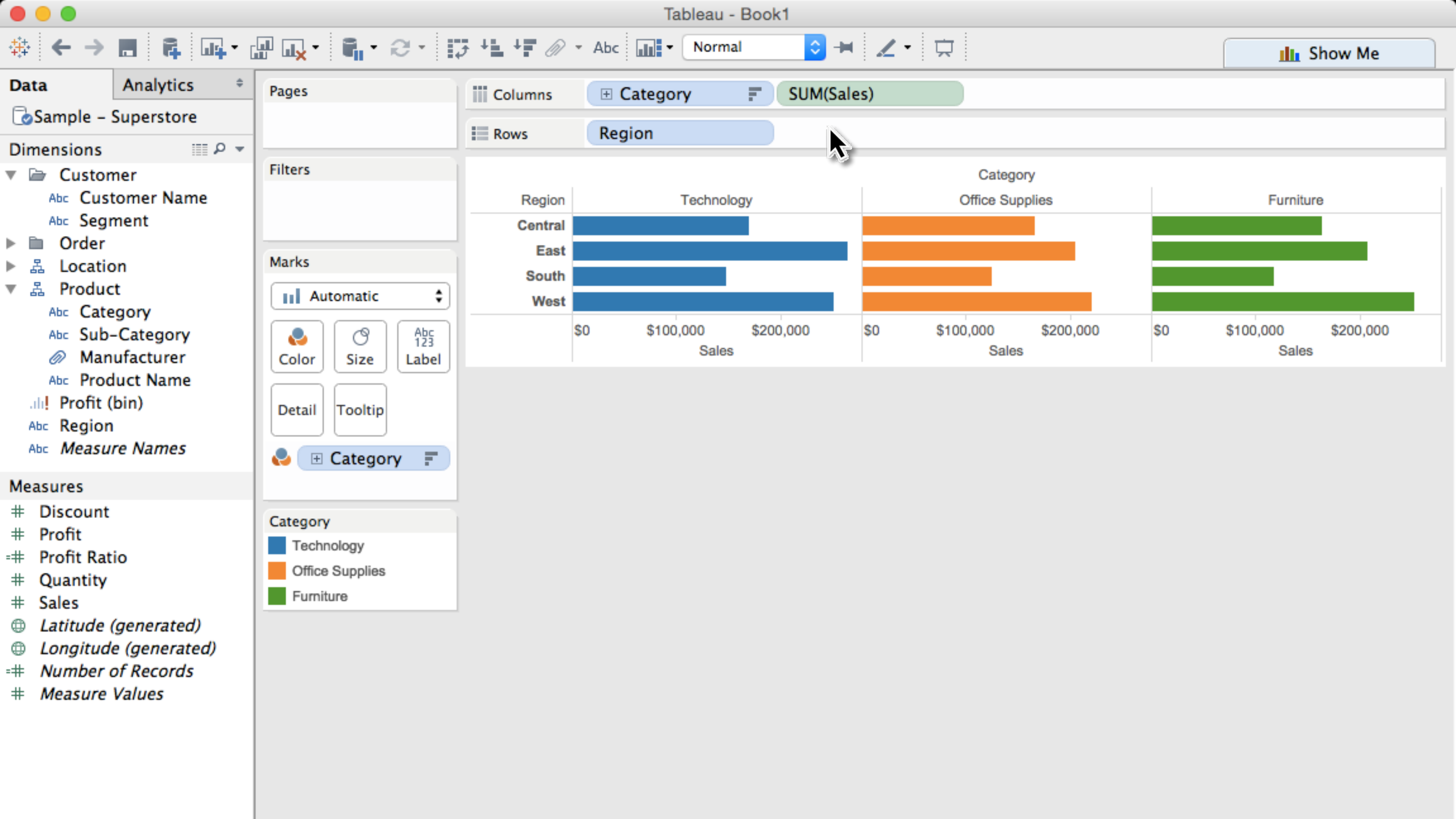

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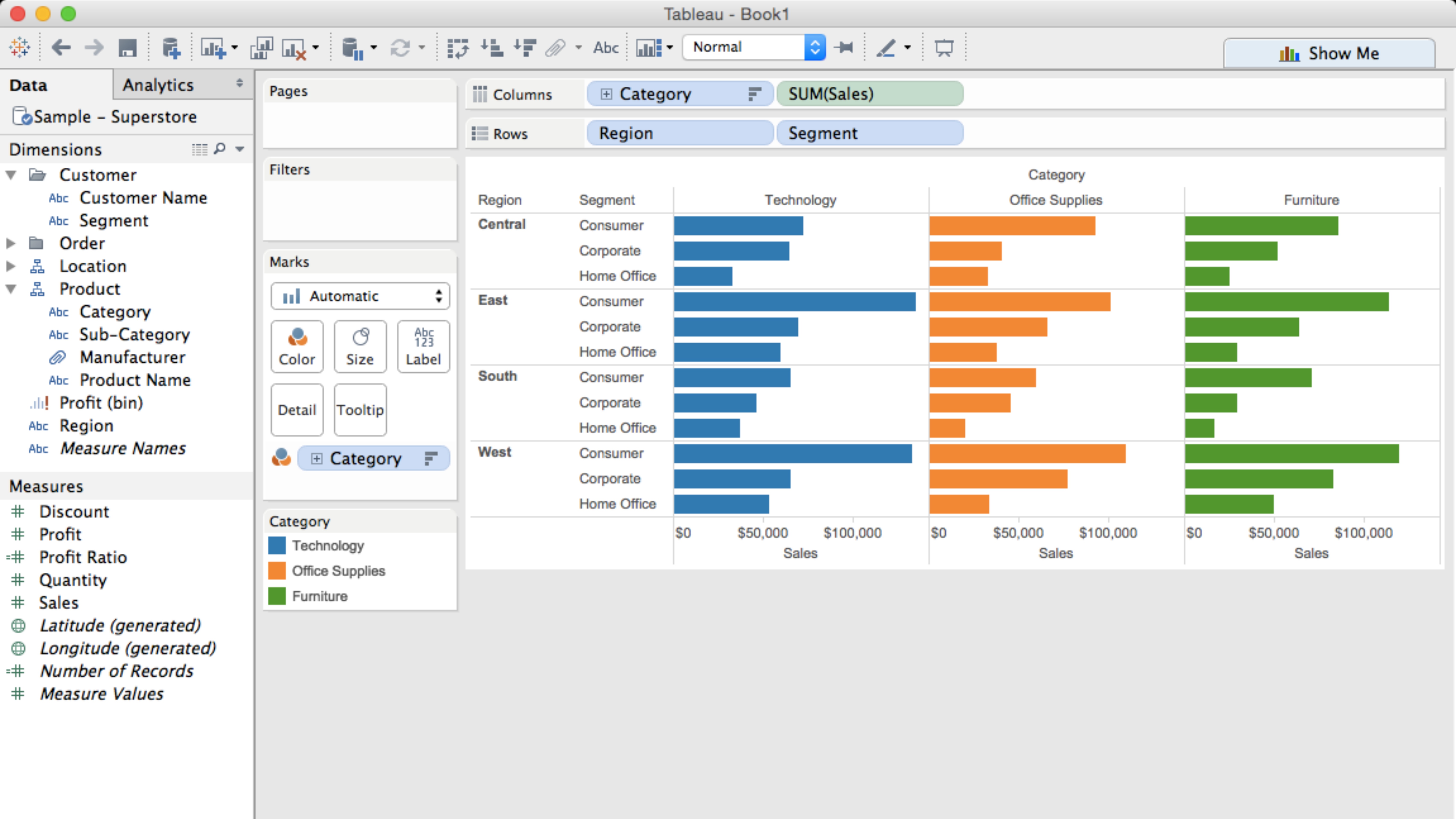
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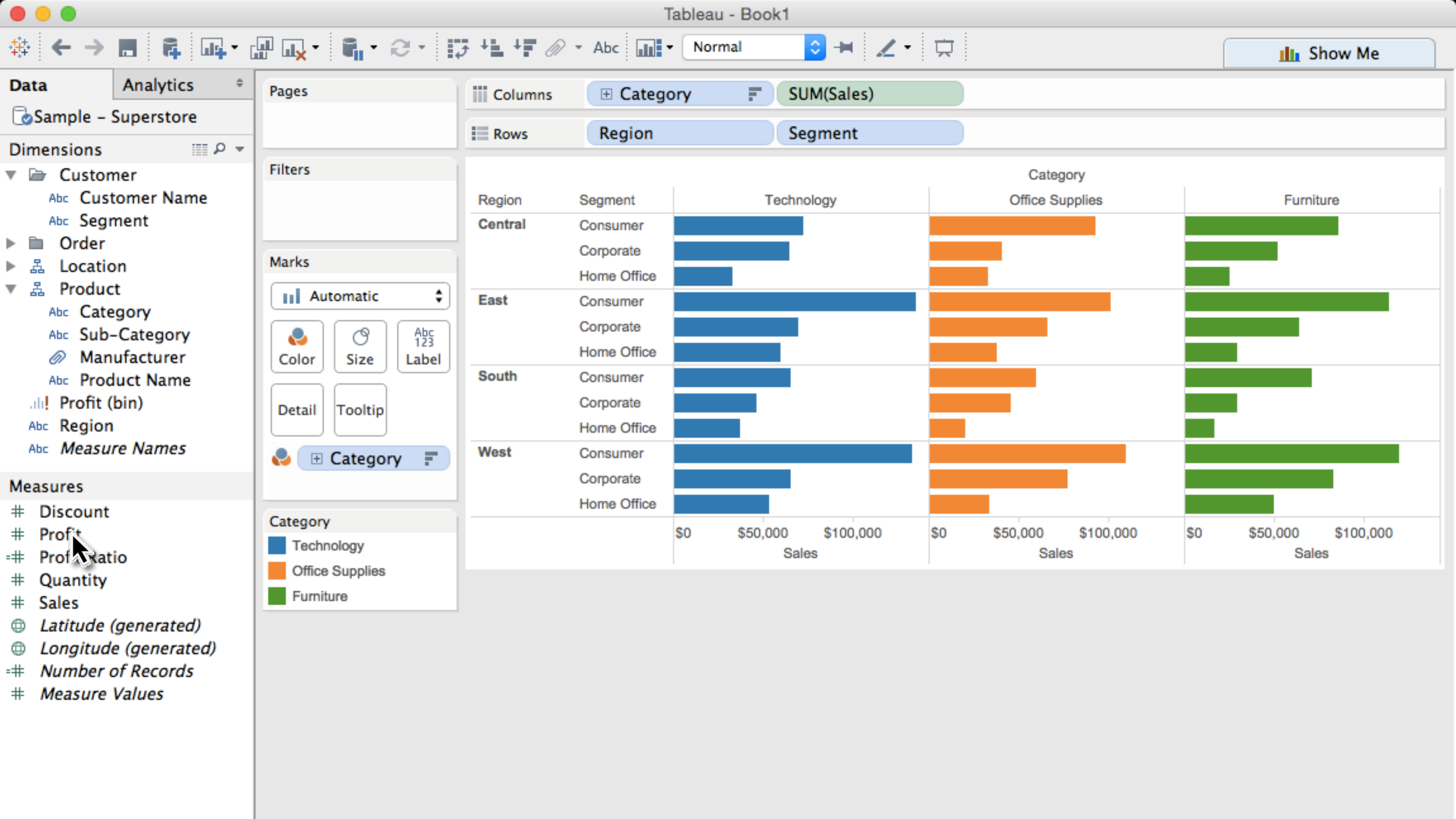

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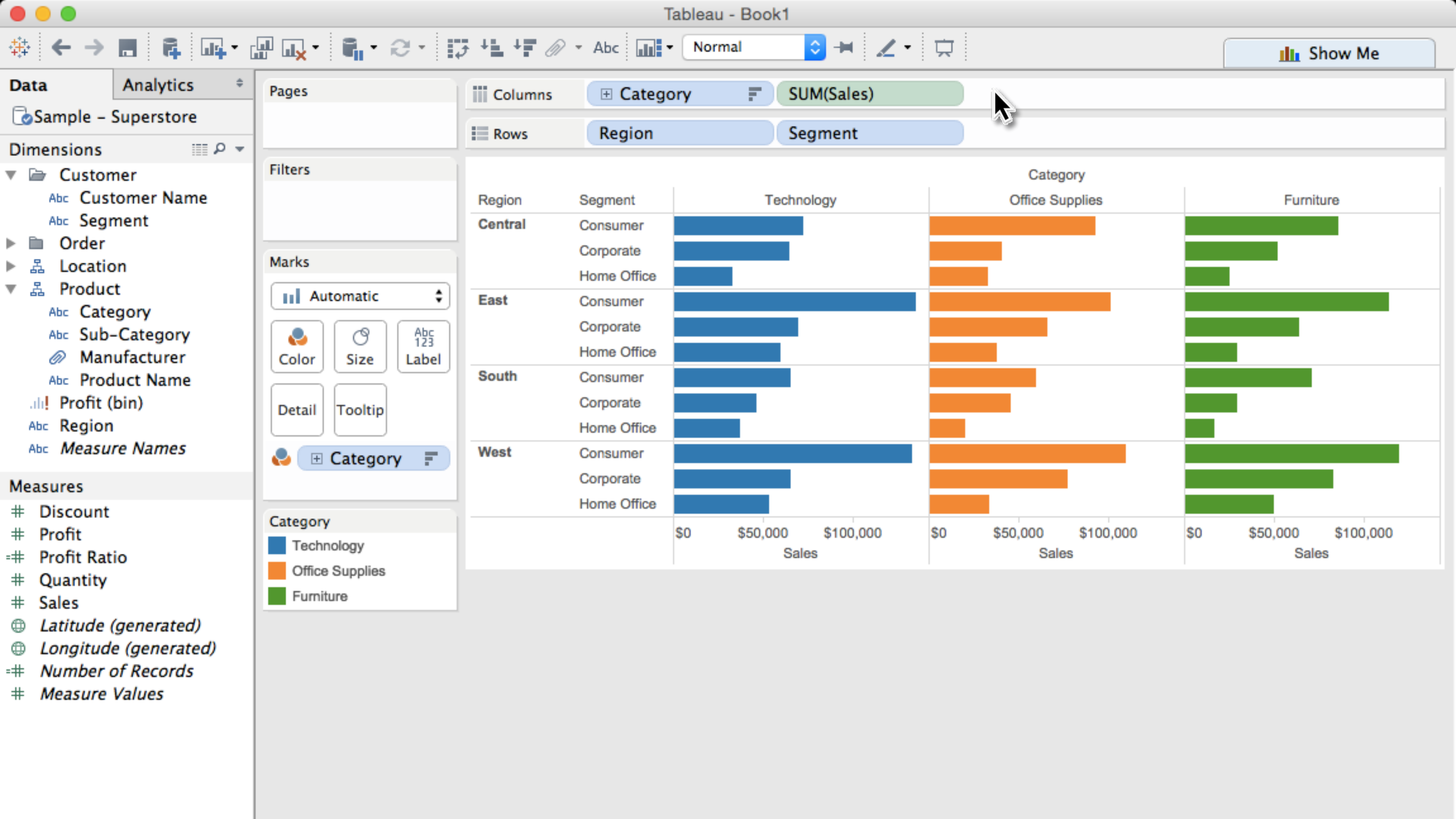
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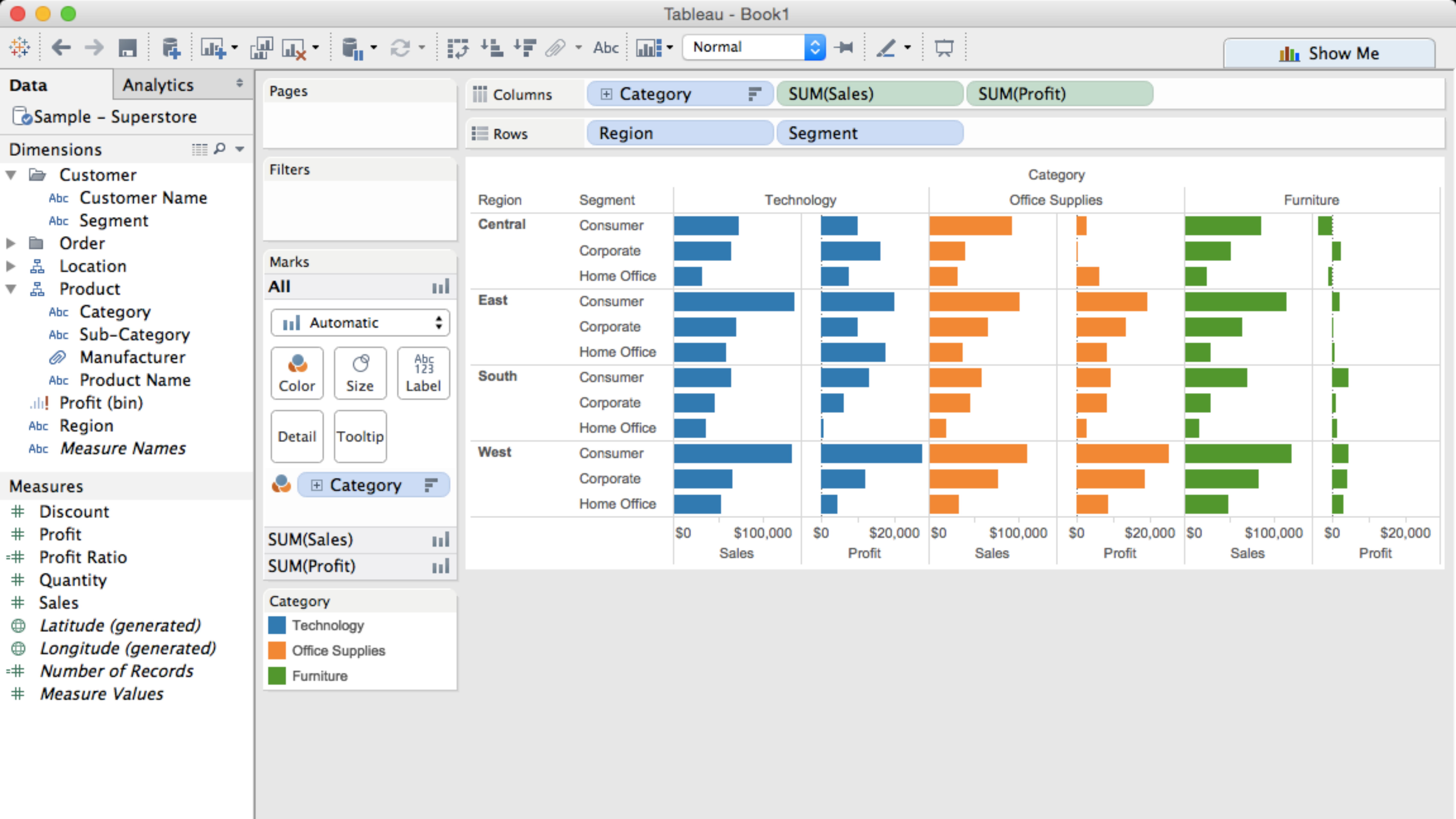
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Sales
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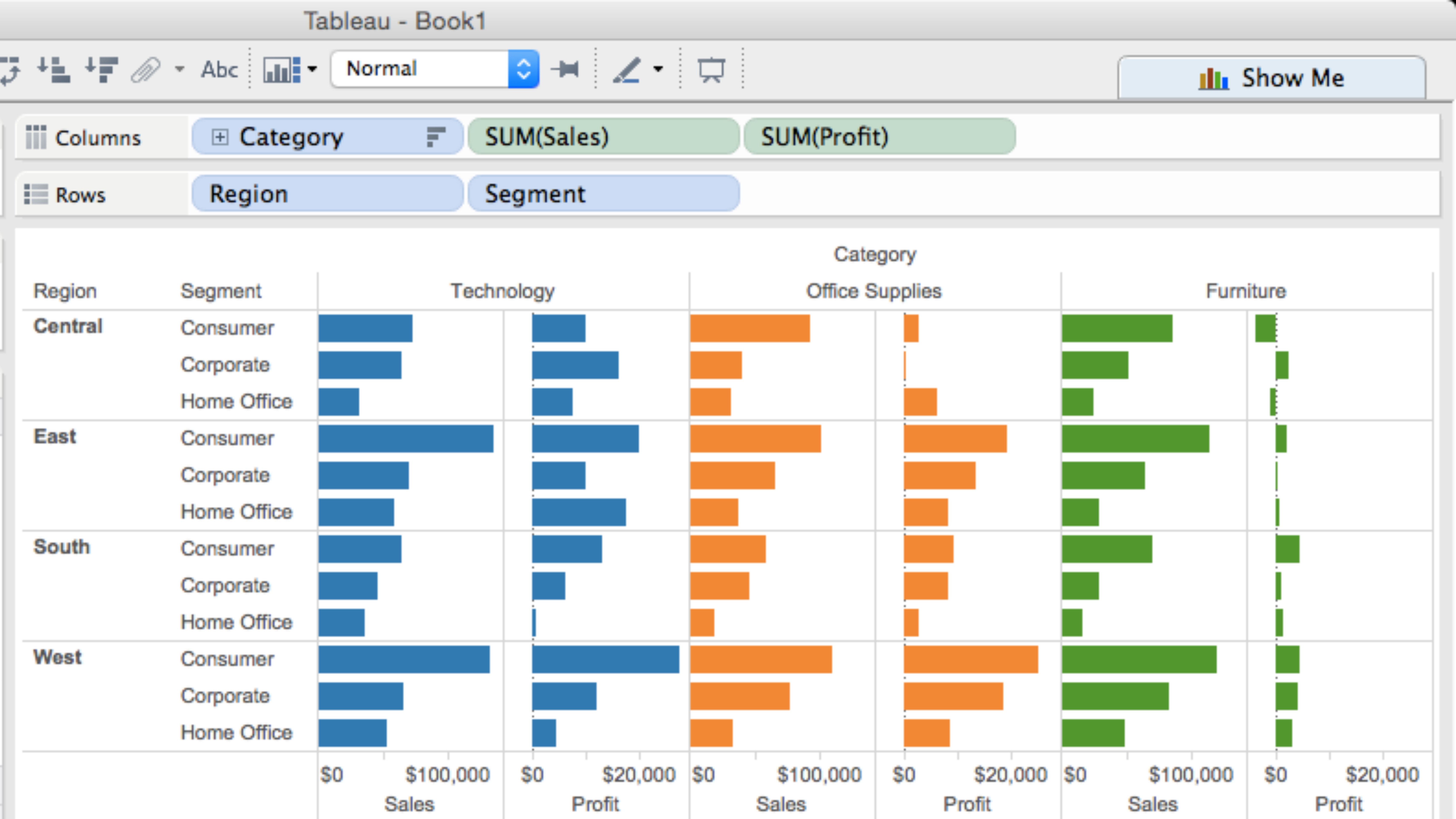
Profit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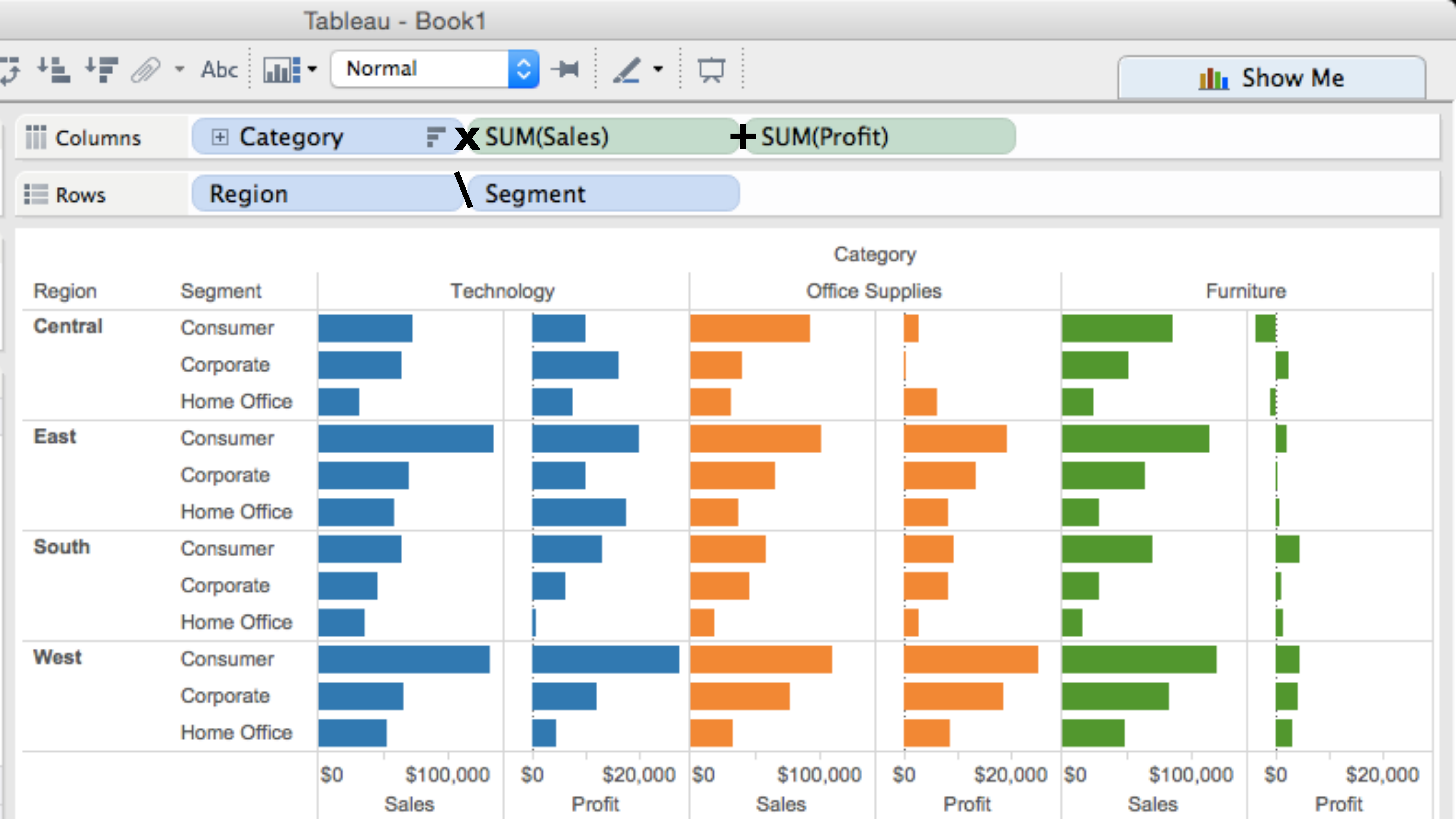

Tableau - Book1
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Columns
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SUM(Sales)
+
SUM(Profit)
Rows
Region
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Segment
Category
Region
Segment
Technology
Office Supplies
Furniture
Central
Consumer
Corporate
Home Office
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Sales
$0
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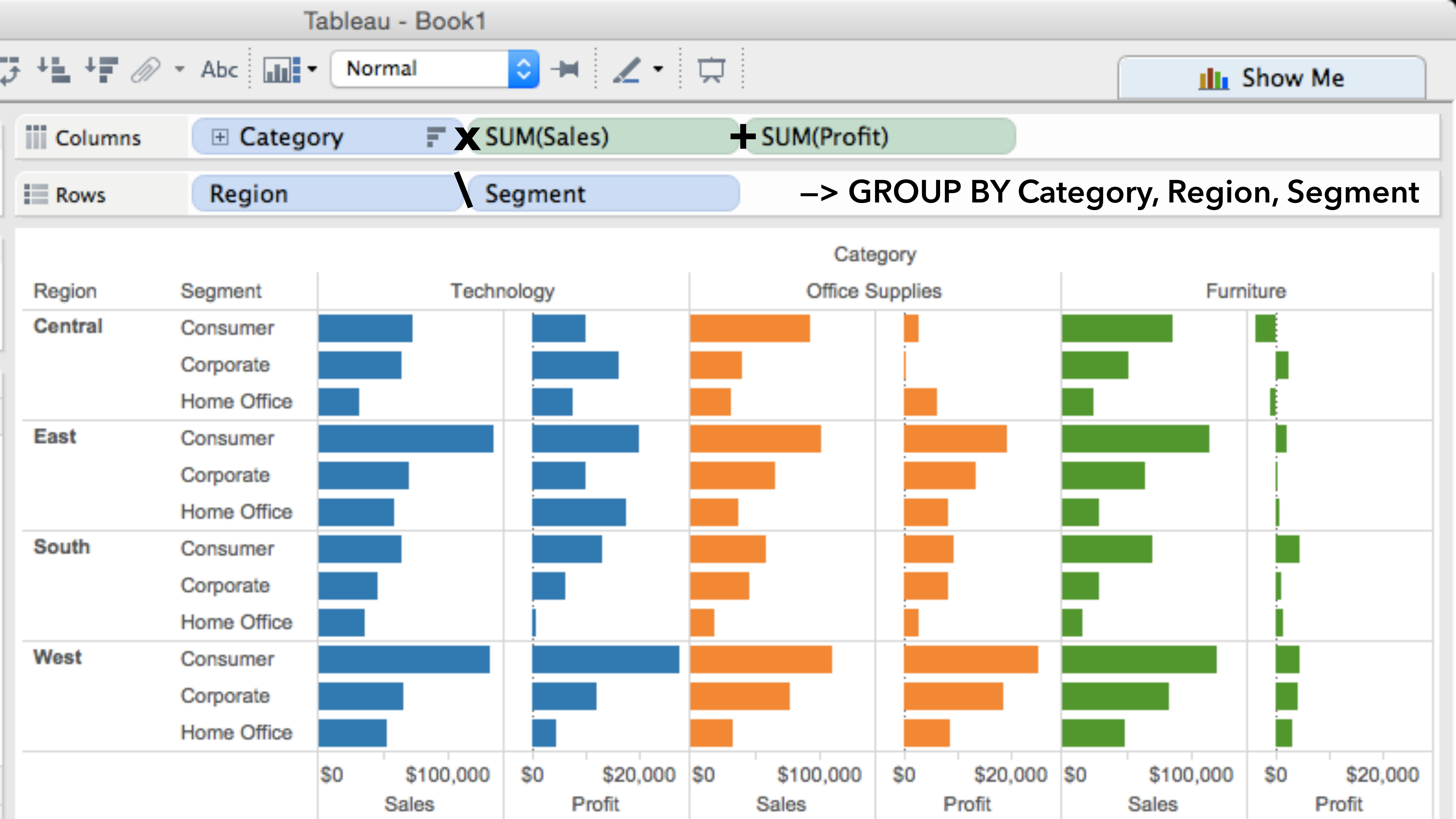


Tableau - Book1
Abc
Normal
Show Me
Columns
Category
x SUM(Sales)
+ SUM(Profit)
Rows
Region
\ Segment
–> GROUP BY Category, Region, Segment
Category
Region
Segment
Technology
Office Supplies
Furniture
Central
East
South
West
Consumer
Corporate
Home Office
$0
$100,000
$20,000
Sales
Profit

VizQL: A DSL for Tabular Visualization

Operators:
concatenation (+)
cross product (x)
nest (\)

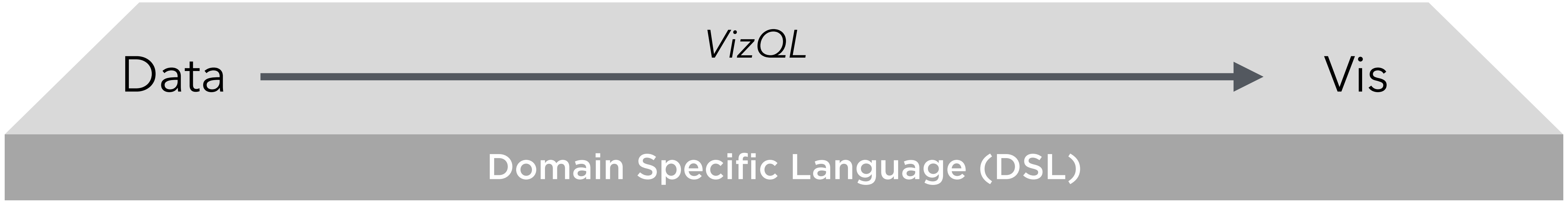
Operands:
Ordinal fields
Quantitative fields

The operators (+, x, \) and operands (O, Q)
provide an **algebra for tabular visualization**.

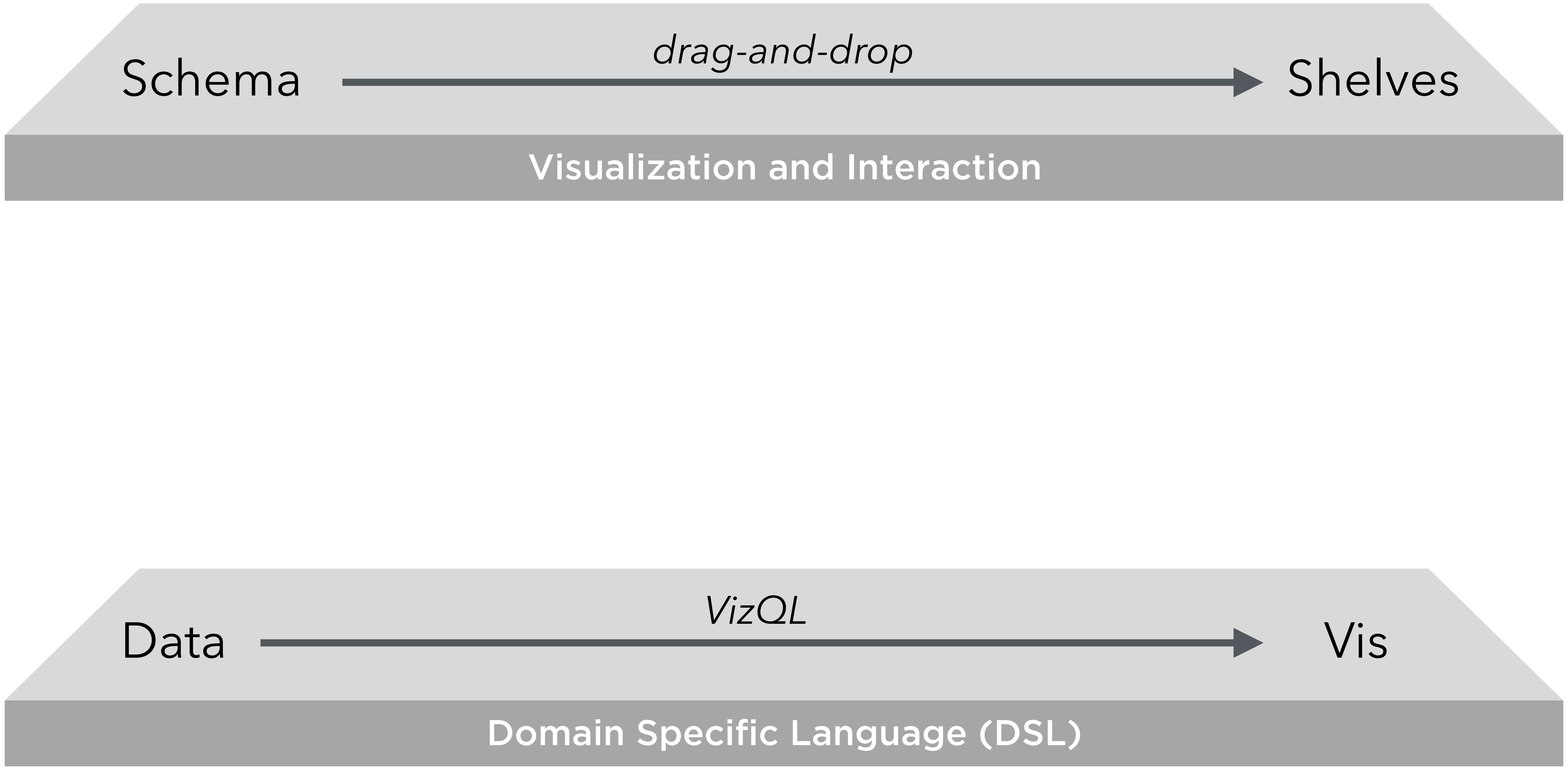
Algebraic statements are then **compiled** to:
Visualizations: partitions, visual encodings
Queries: selection, projection, group-by…

Users make statements via **drag-and-drop**
This specifies parameters, *not* operators!
Operators inferred by data type (O, Q)

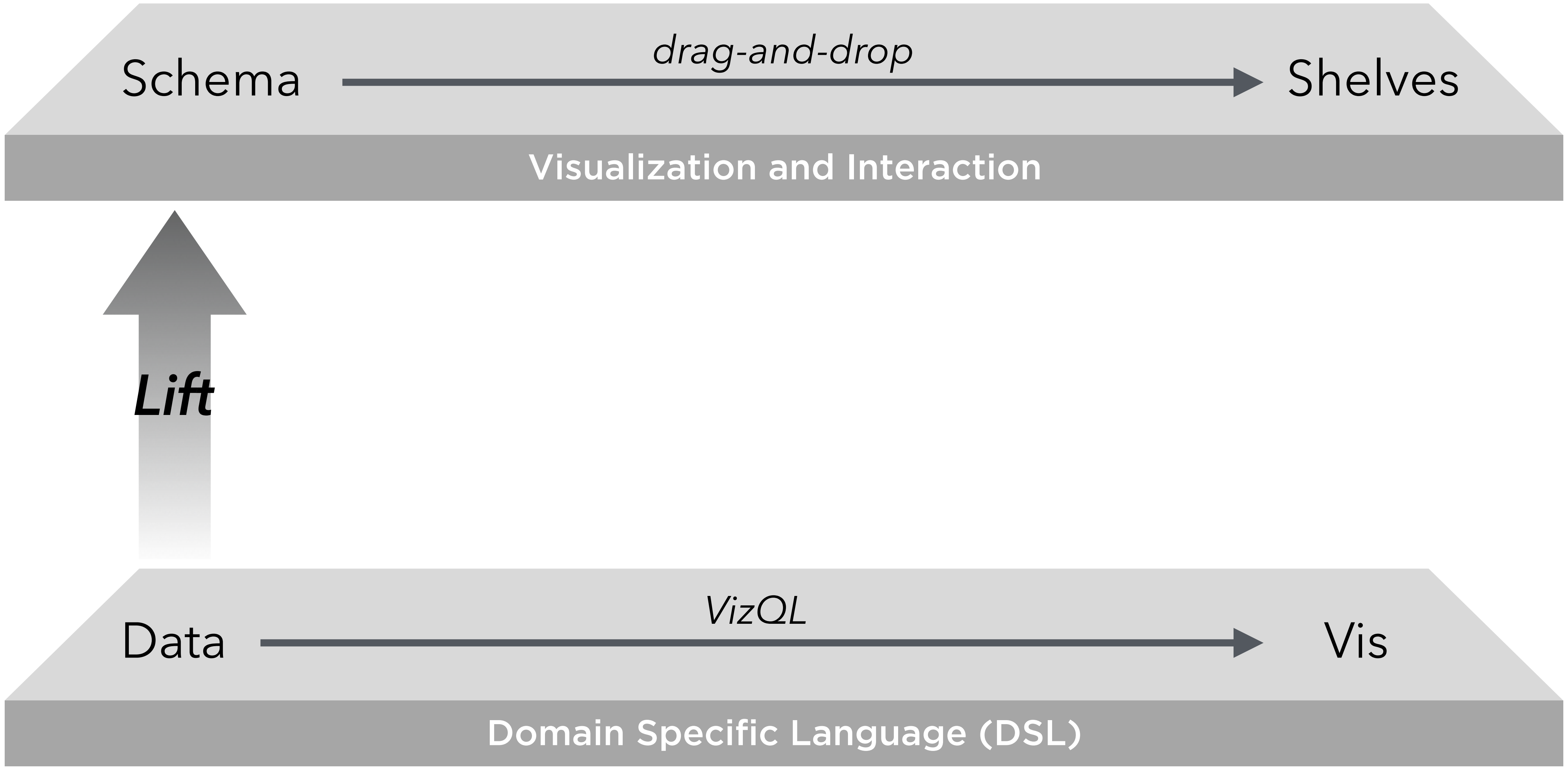
Mapping from Textual to Visual Languages



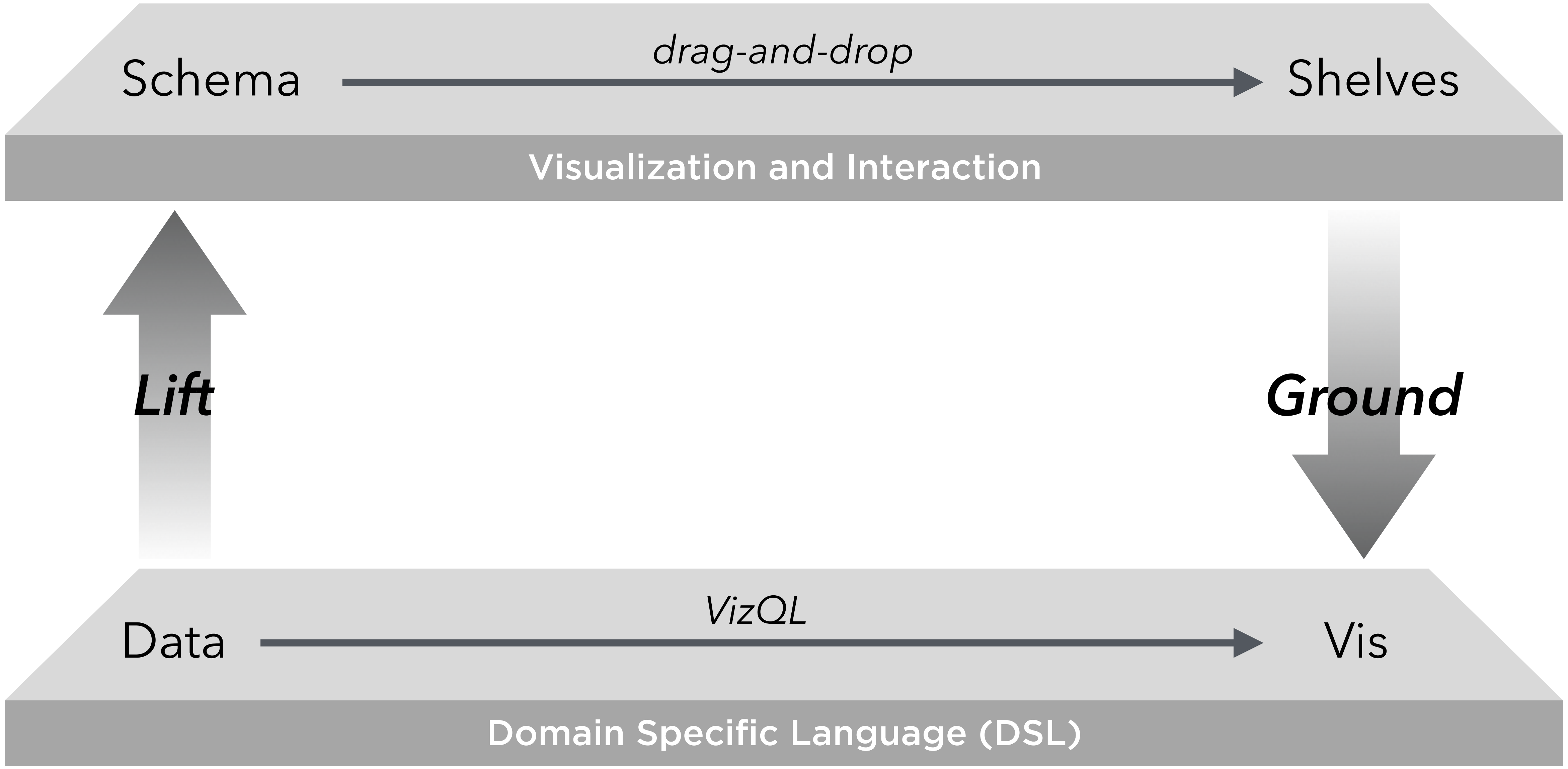
Mapping from Textual to Visual Languages



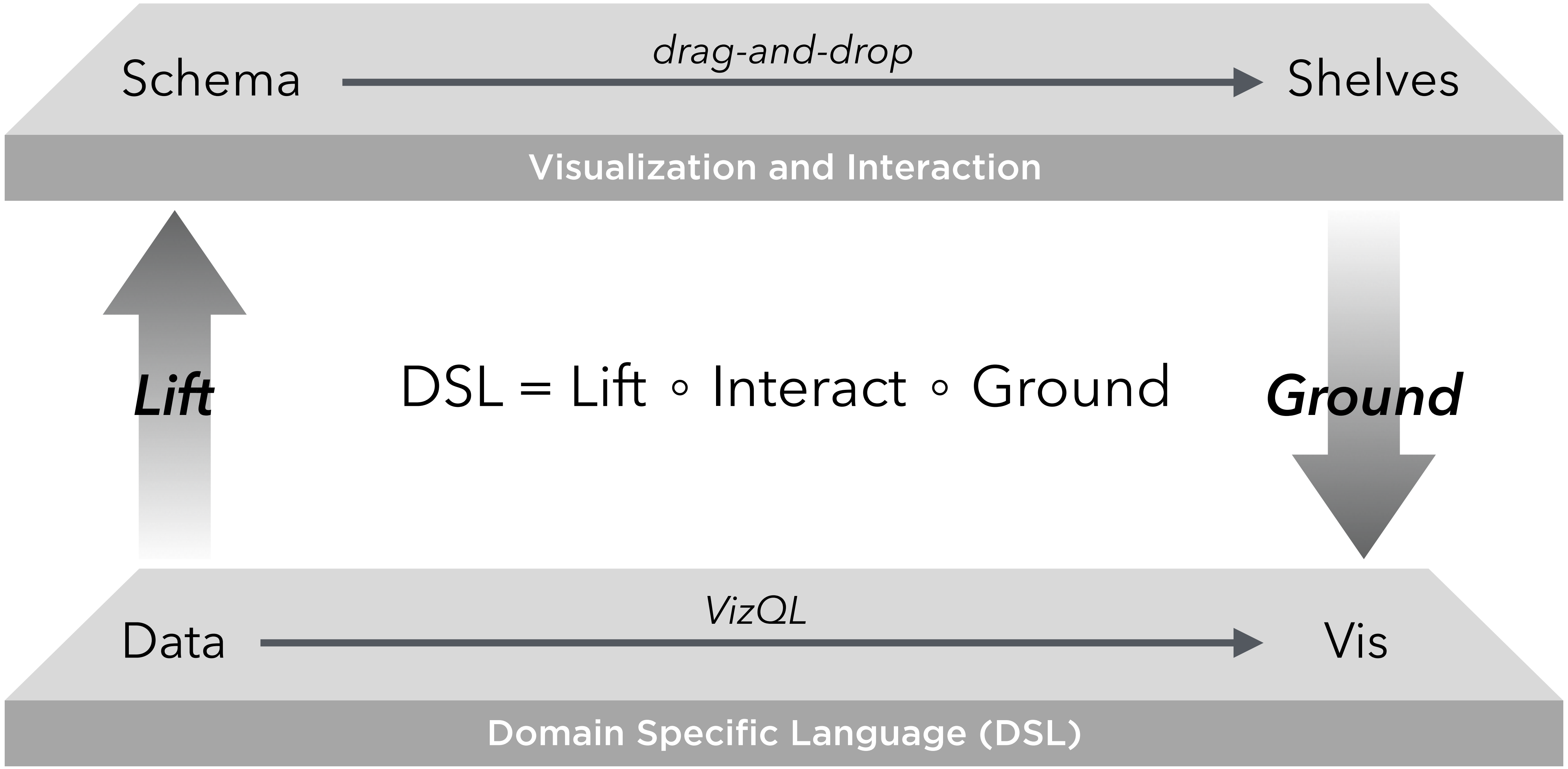
Mapping from Textual to Visual Languages



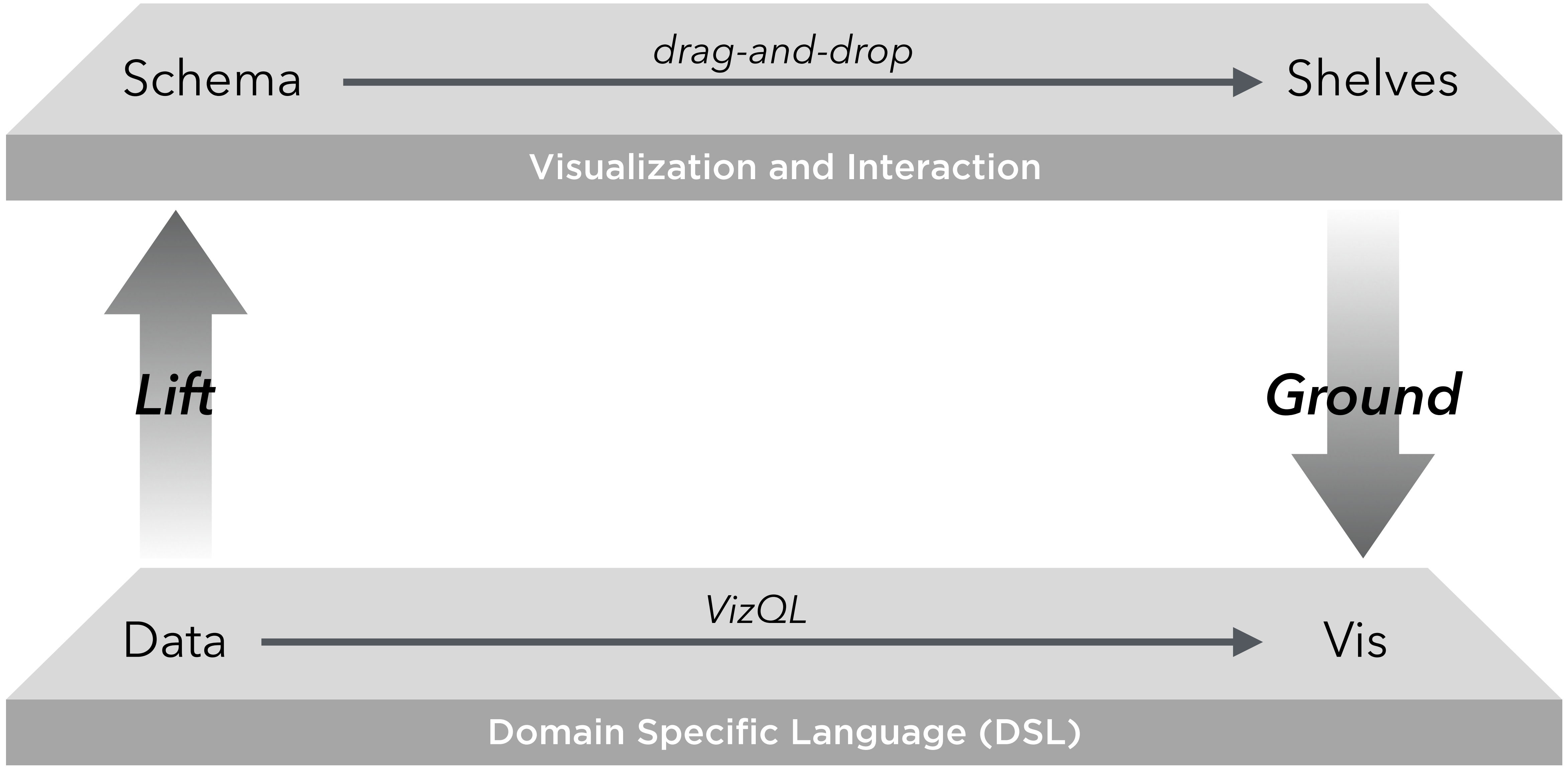
Mapping from Textual to Visual Languages



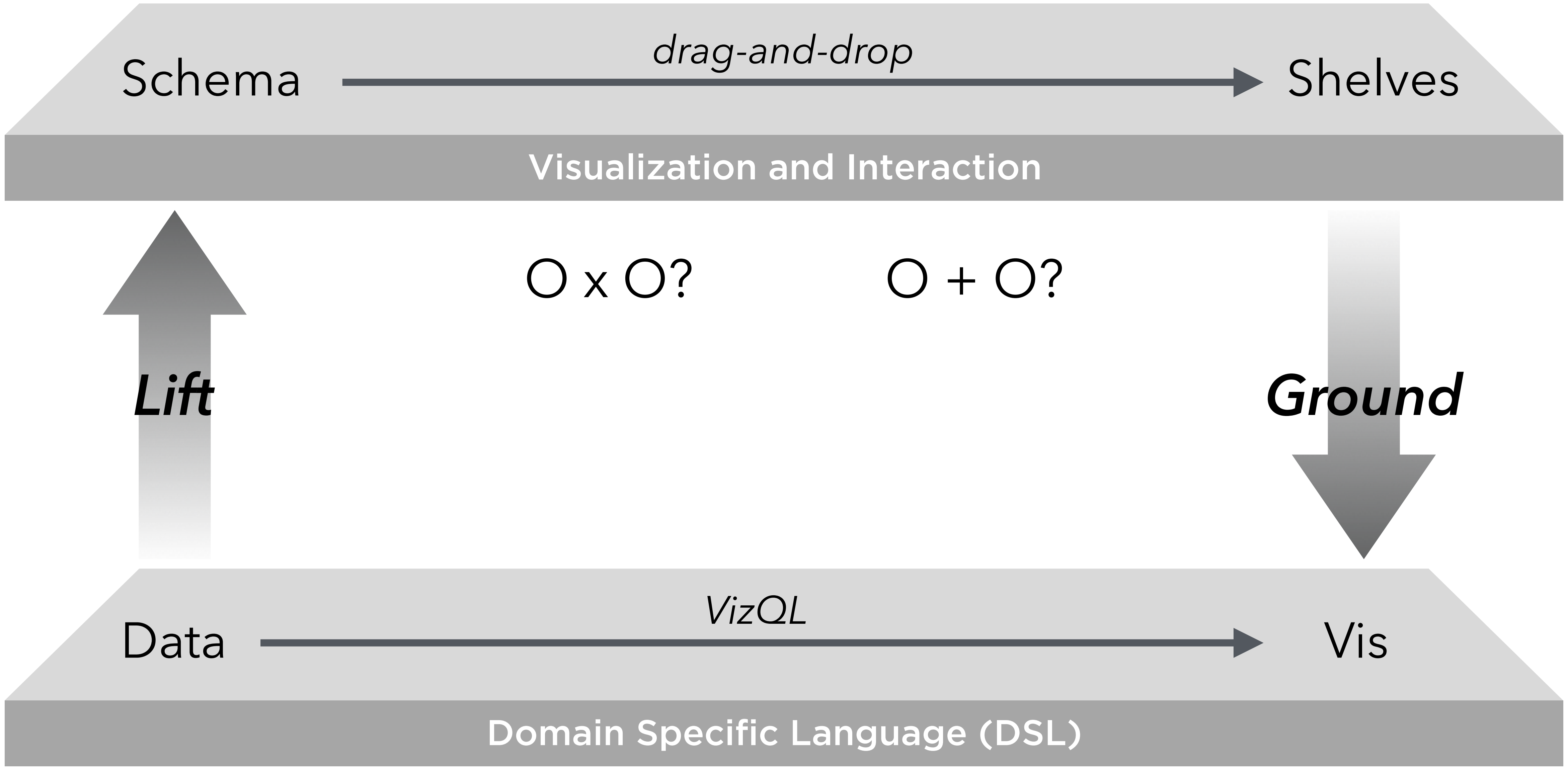
Mapping from Textual to Visual Languages



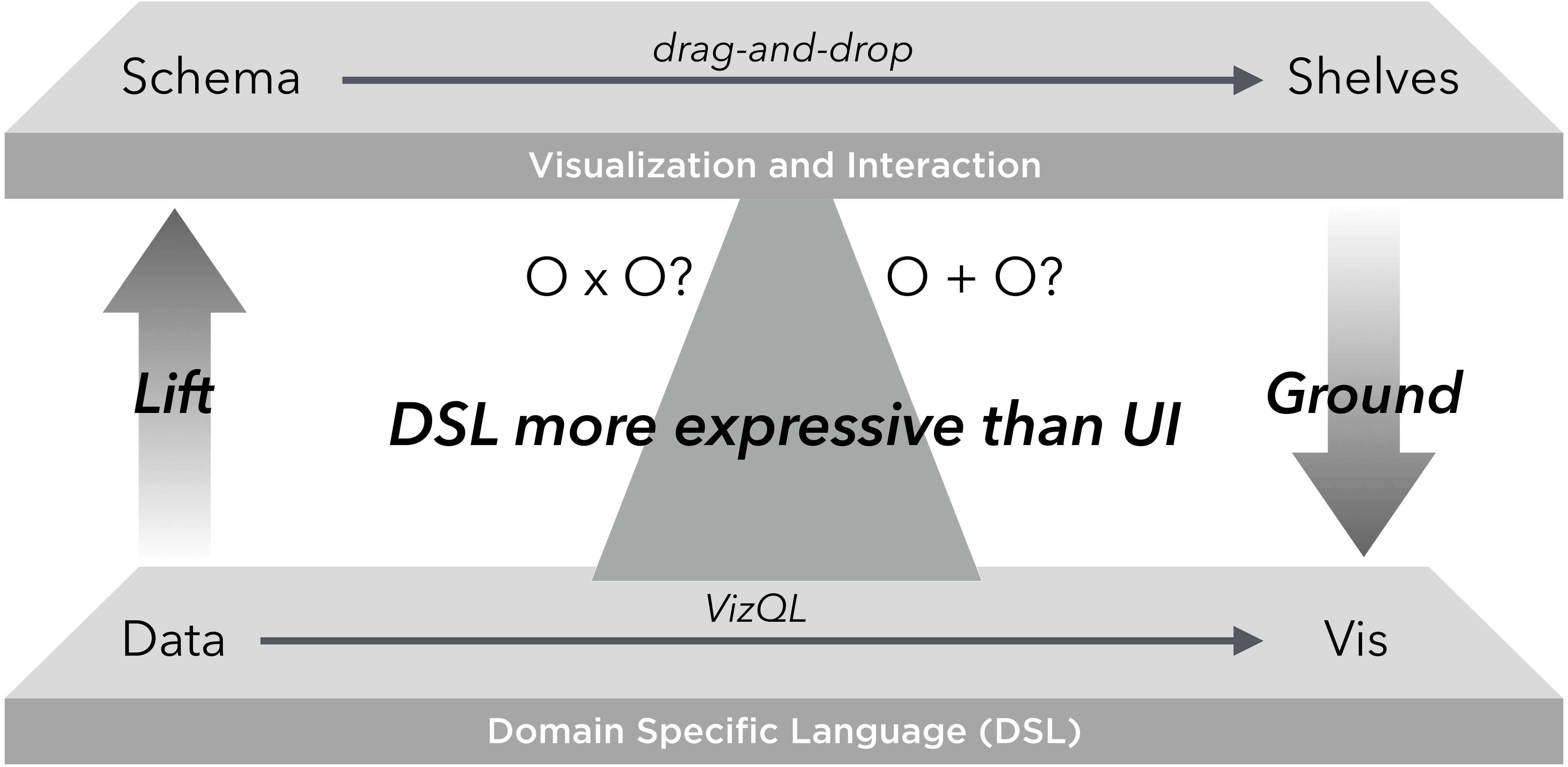
Are the Languages Isomorphic?



Are the Languages Isomorphic?



Are the Languages Isomorphic?



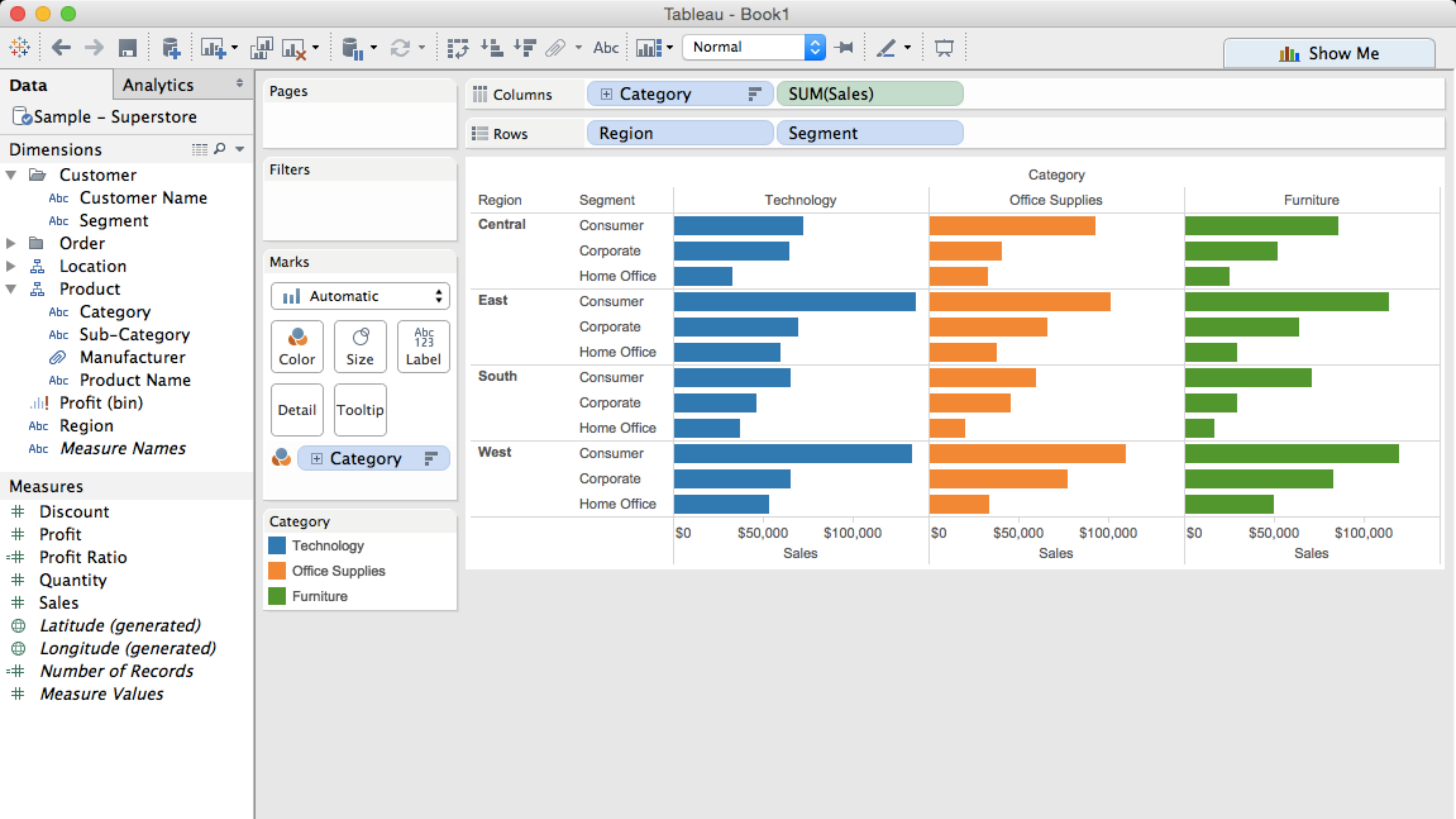


Tableau - Book1
Normal
Show Me
Data
Analytics
Sample - Superstore
Dimensions
Customer
Customer Name
Segment
Order
Location
Product
Category
Sub-Category
Manufacturer
Product Name
Profit (bin)
Region
Measure Names
Measures
Discount
Profit
Profit Ratio
Quantity
Sales
Latitude (generated)
Longitude (generated)
Number of Records
Measure Values
Pages
Filters
Marks
Automatic
Color
Size
Label
Detail
Tooltip
Category
Category
Technology
Office Supplies
Furniture
Columns
Category
SUM(Sales)
Rows
Region
Segment
Category
Region
Segment
Technology
Office Supplies
Furniture
Central
Consumer
Corporate
Home Office
East
Consumer
Corporate
Home Office
South
Consumer
Corporate
Home Office
West
Consumer
Corporate
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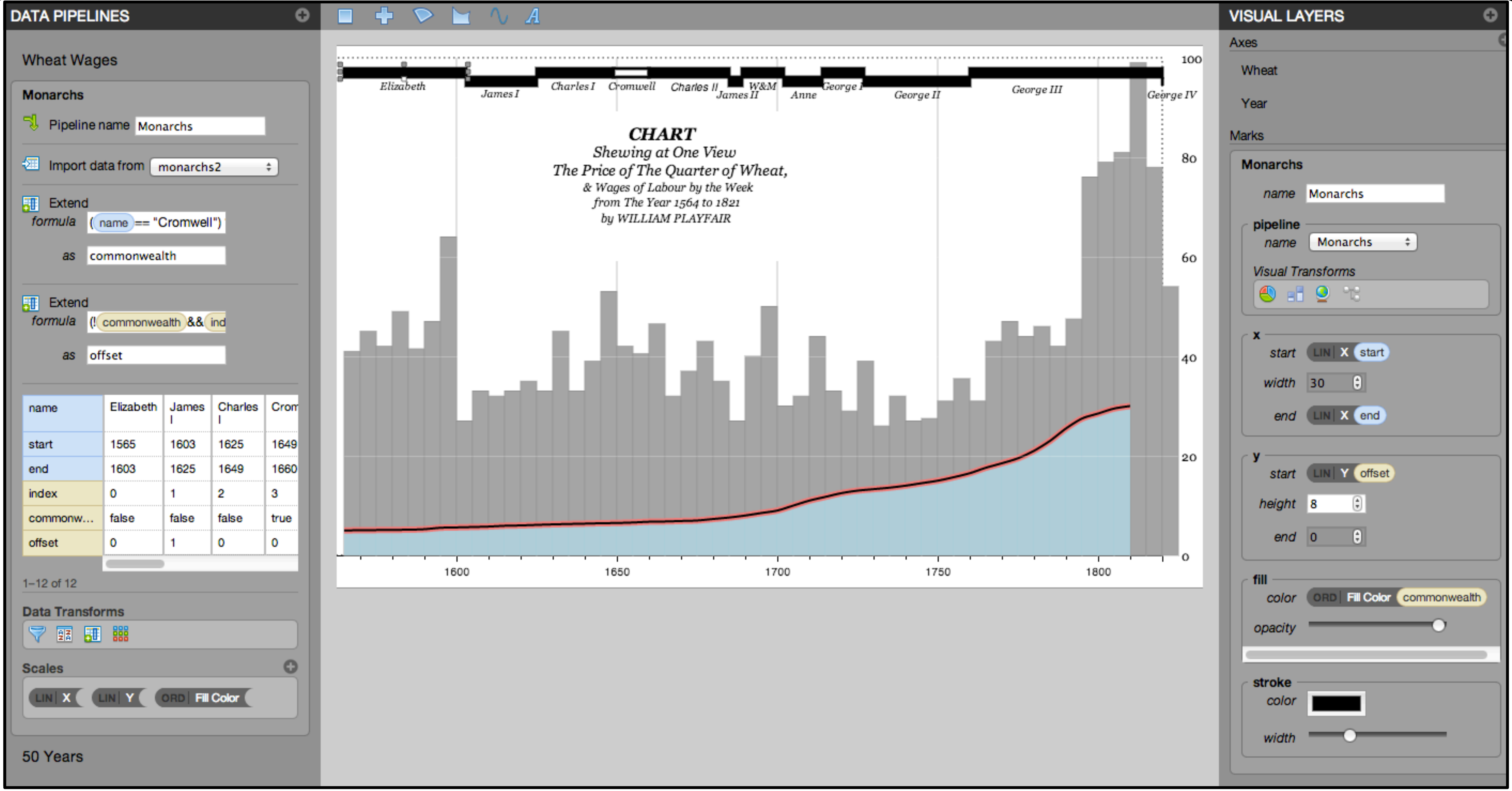
$50,000
$100,000
Sales



Lyra: A Visualization Design Environment. Arvind Satyanarayan & J. Heer. *EuroVis'14*

EXAMPLE:

Data Wrangling

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.

Bureau of Justice Statistics - Data Online
http://bjs.ojp.usdoj.gov/

Reported crime in Alabama

Year	Population	Property crime rate	Burglary rate	Larceny-theft rate	Motor vehicle theft rate
2004	4525375	4029.3	987	2732.4	309.9
2005	4548327	3900	955.8	2656	289
2006	4599030	3937	968.9	2645.1	322.9
2007	4627851	3974.9	980.2	2687	307.7
2008	4661900	4081.9	1080.7	2712.6	288.6

Reported crime in Alaska

Year	Population	Property crime rate	Burglary rate	Larceny-theft rate	Motor vehicle theft rate
2004	657755	3370.9	573.6	2456.7	340.6
2005	663253	3615	622.8	2601	391
2006	670053	3582	615.2	2588.5	378.3
2007	683478	3373.9	538.9	2480	355.1
2008	686293	2928.3	470.9	2219.9	237.5

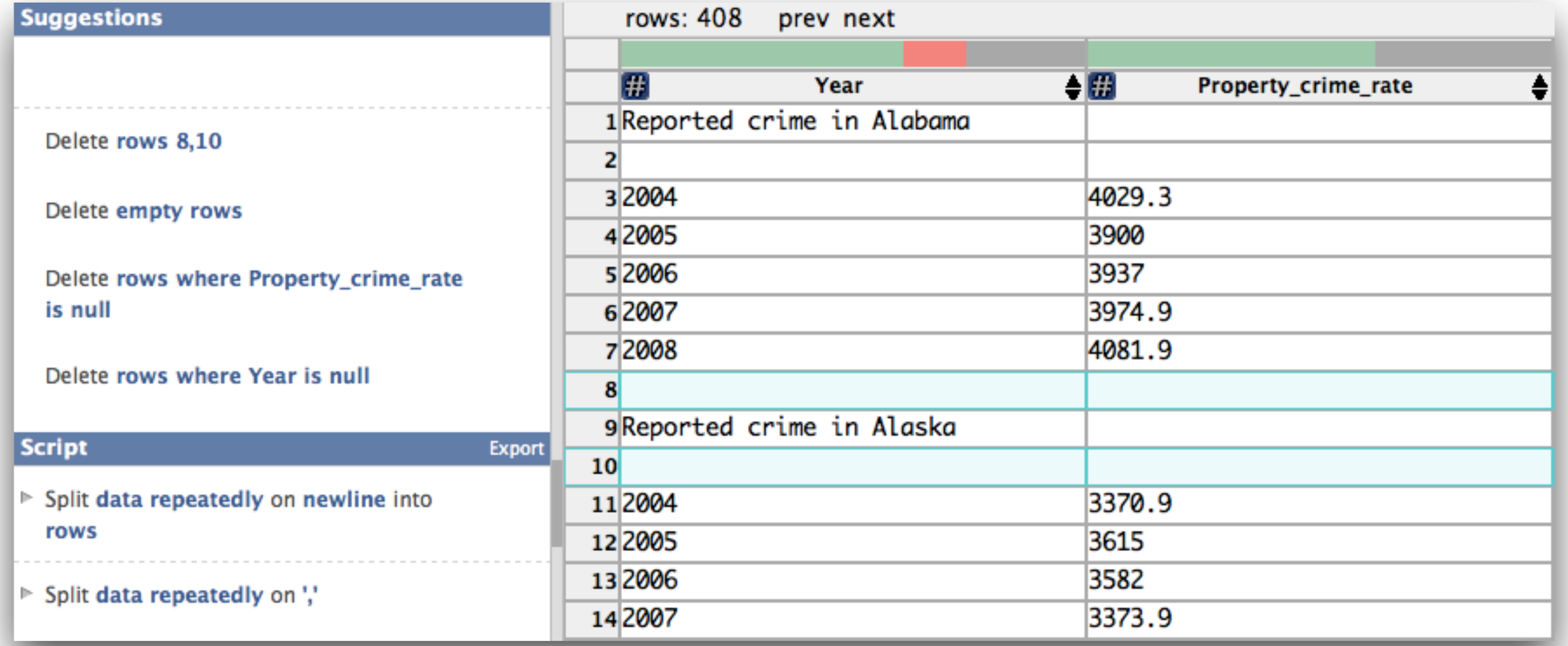
Reported crime in Arizona

Year	Population	Property crime rate	Burglary rate	Larceny-theft rate	Motor vehicle theft rate
2004	5739879	5073.3	991	3118.7	963.5
2005	5953007	4827	946.2	2958	922
2006	6166318	4741.6	953	2874.1	914.4
2007	6338755	4502.6	935.4	2780.5	786.7
2008	6500180	4087.3	894.2	2605.3	587.8

Reported crime in Arkansas

Year	Population	Property crime rate	Burglary rate	Larceny-theft rate	Motor vehicle theft rate
2004	2750000	4033.1	1096.4	2699.7	237
2005	2775708	4068	1085.1	2720	262
2006	2810872	4021.6	1154.4	2596.7	270.4
2007	2834797	3945.5	1124.4	2574.6	246.5
2008	2855390	3843.7	1182.7	2433.4	227.6

DataWrangler

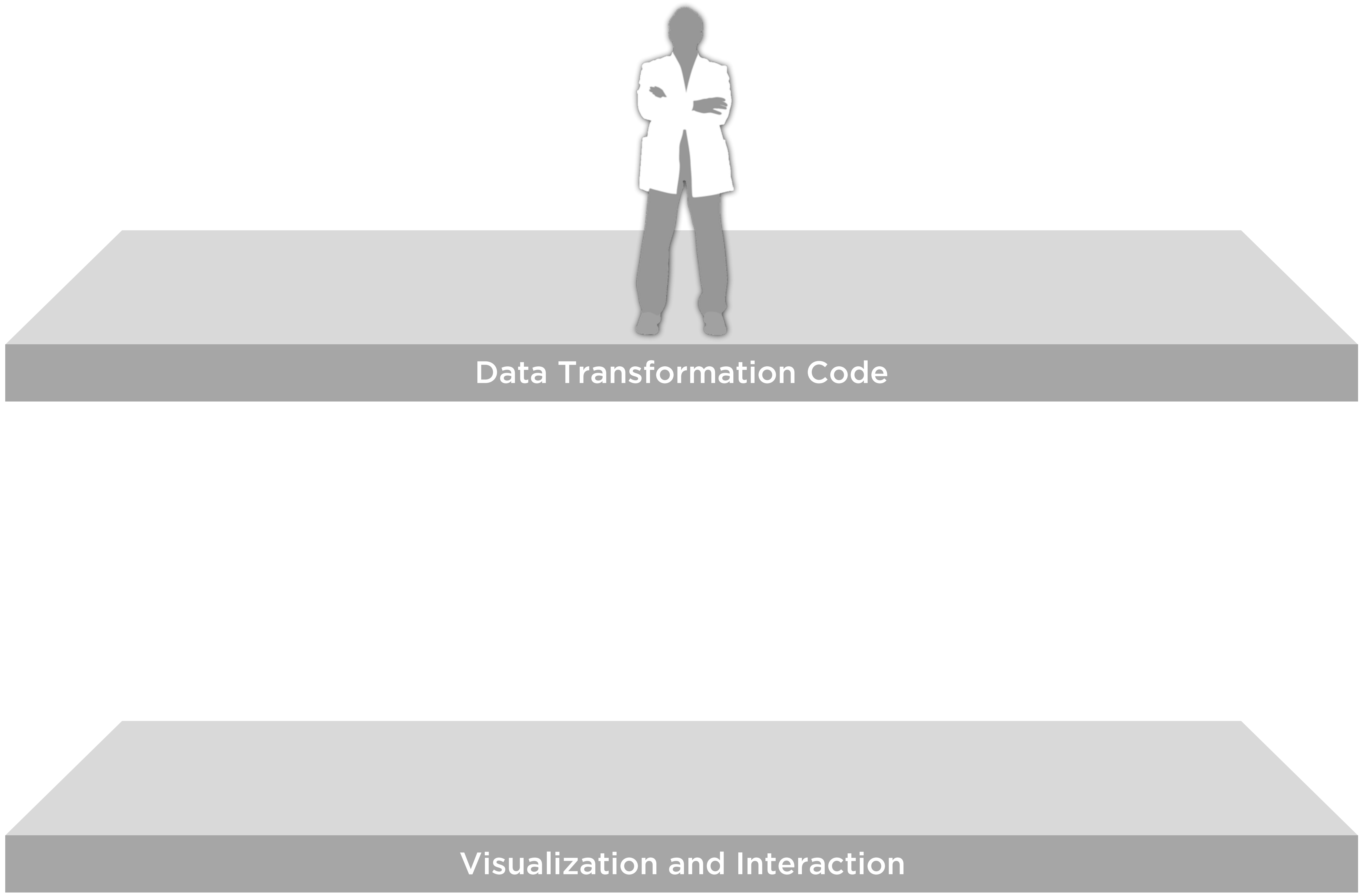


Wrangler: Interactive Visual Specification of Data Transformation Scripts

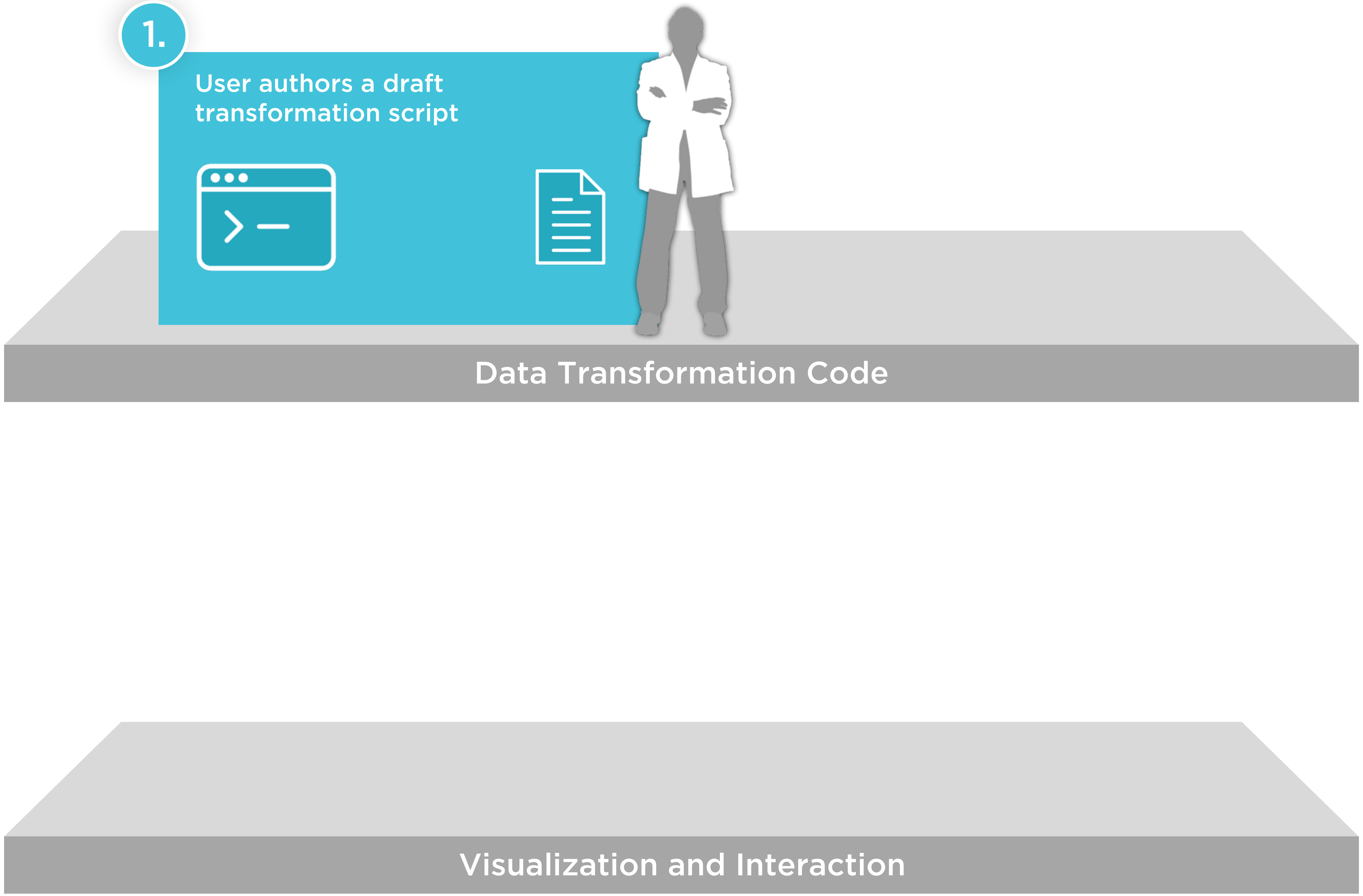
Sean Kandel et al. *CHI'11*

TRIFACTA

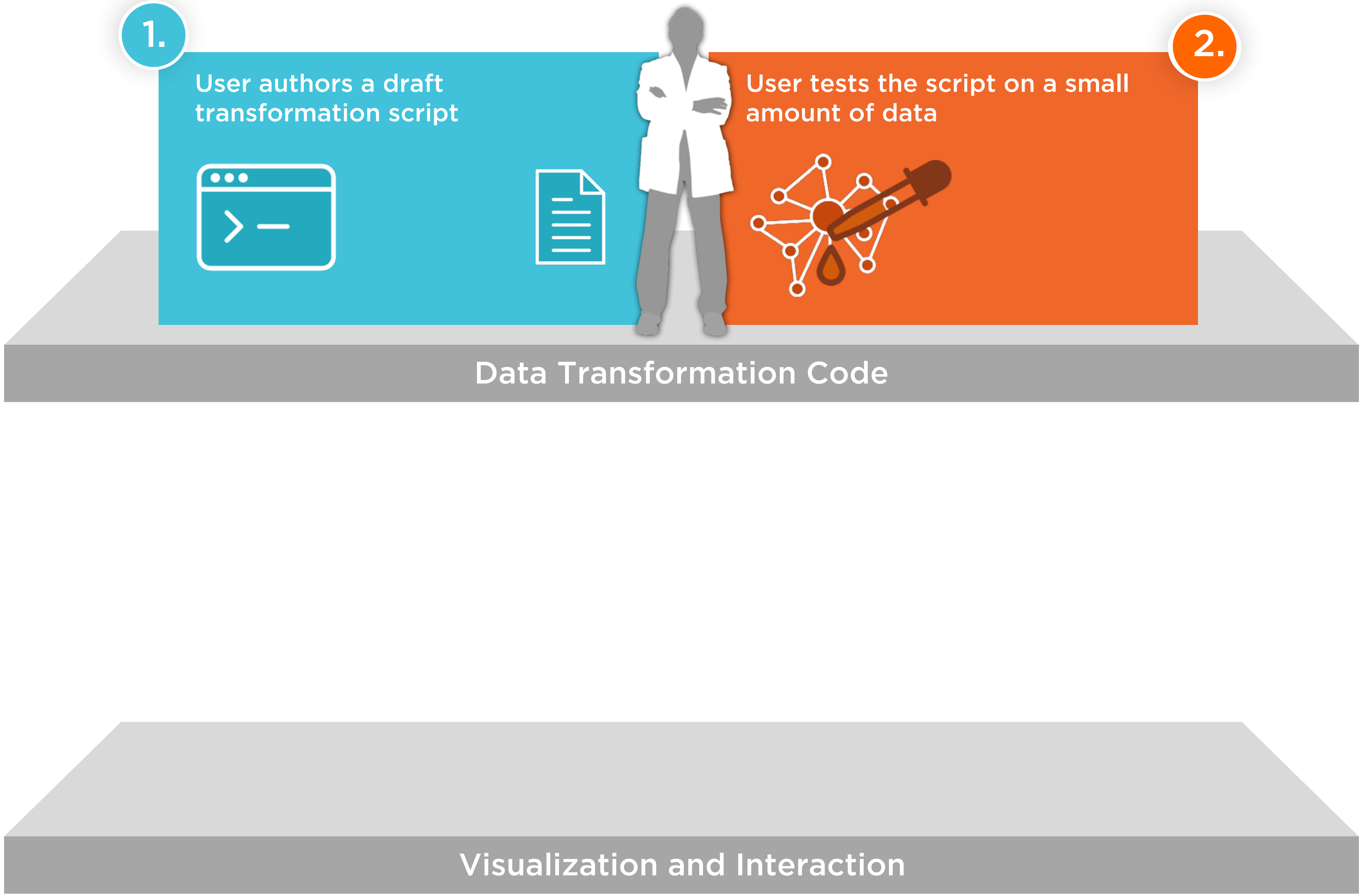
Traditional Specification



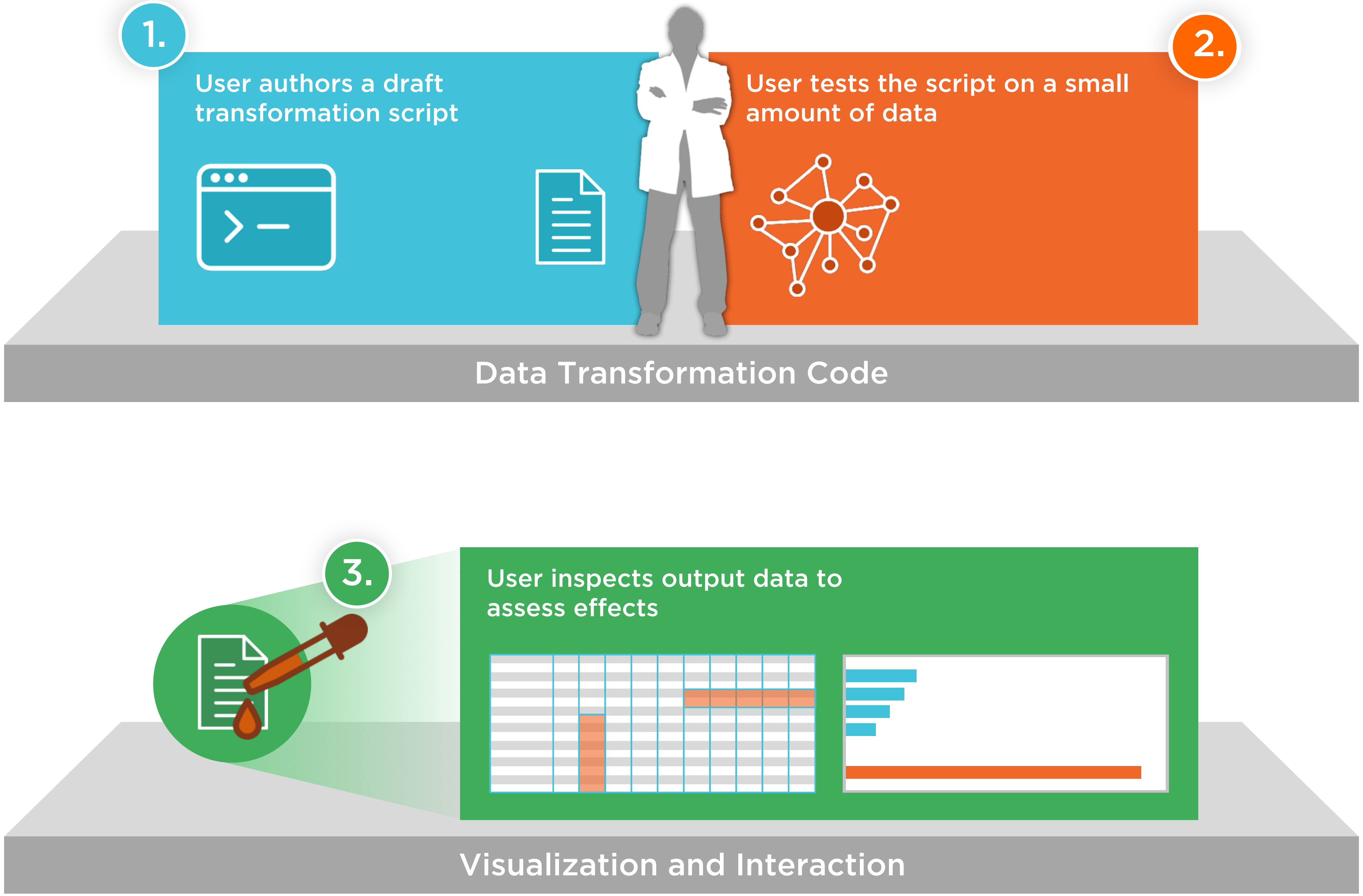
Traditional Specification



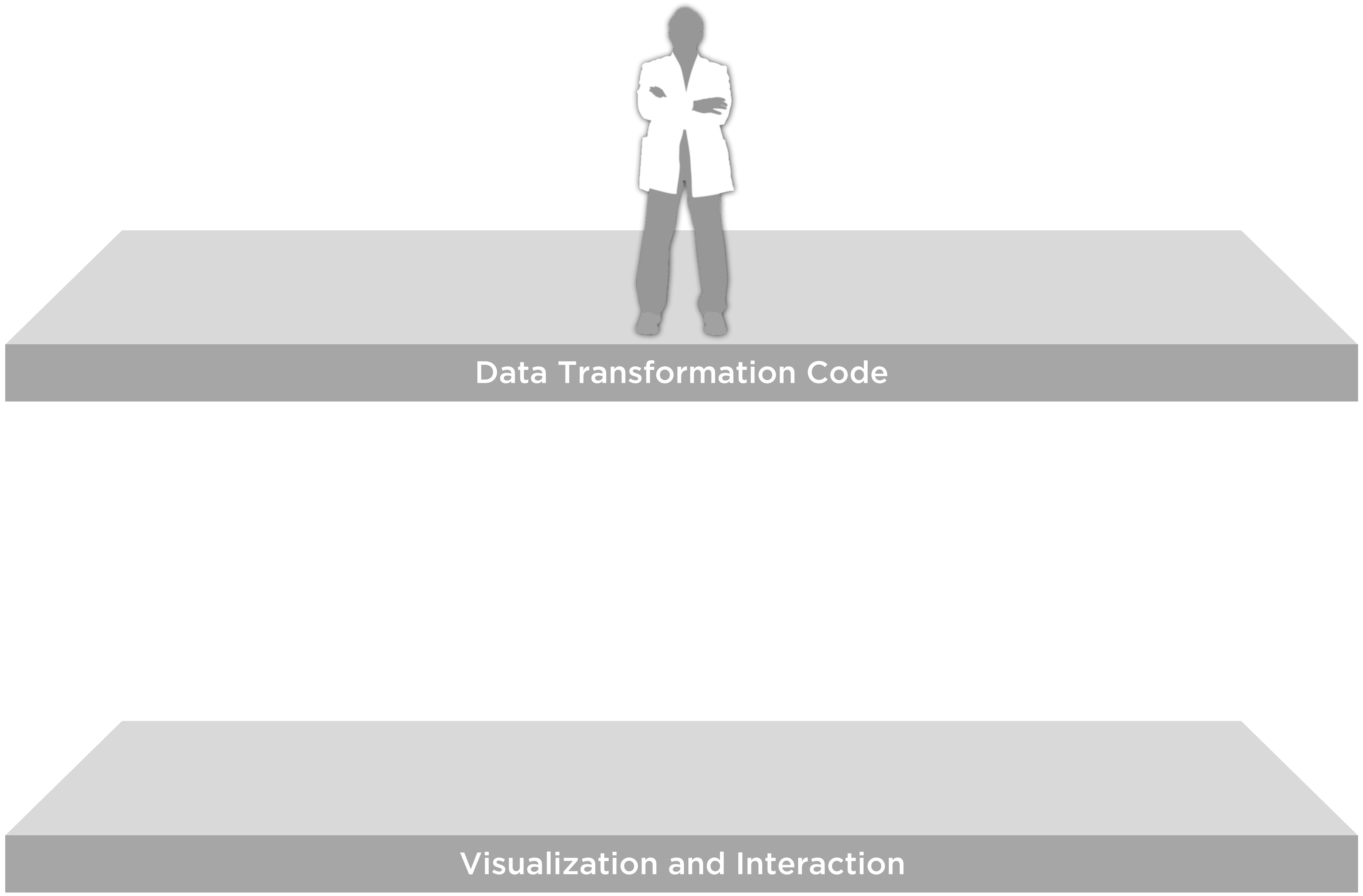
Traditional Specification



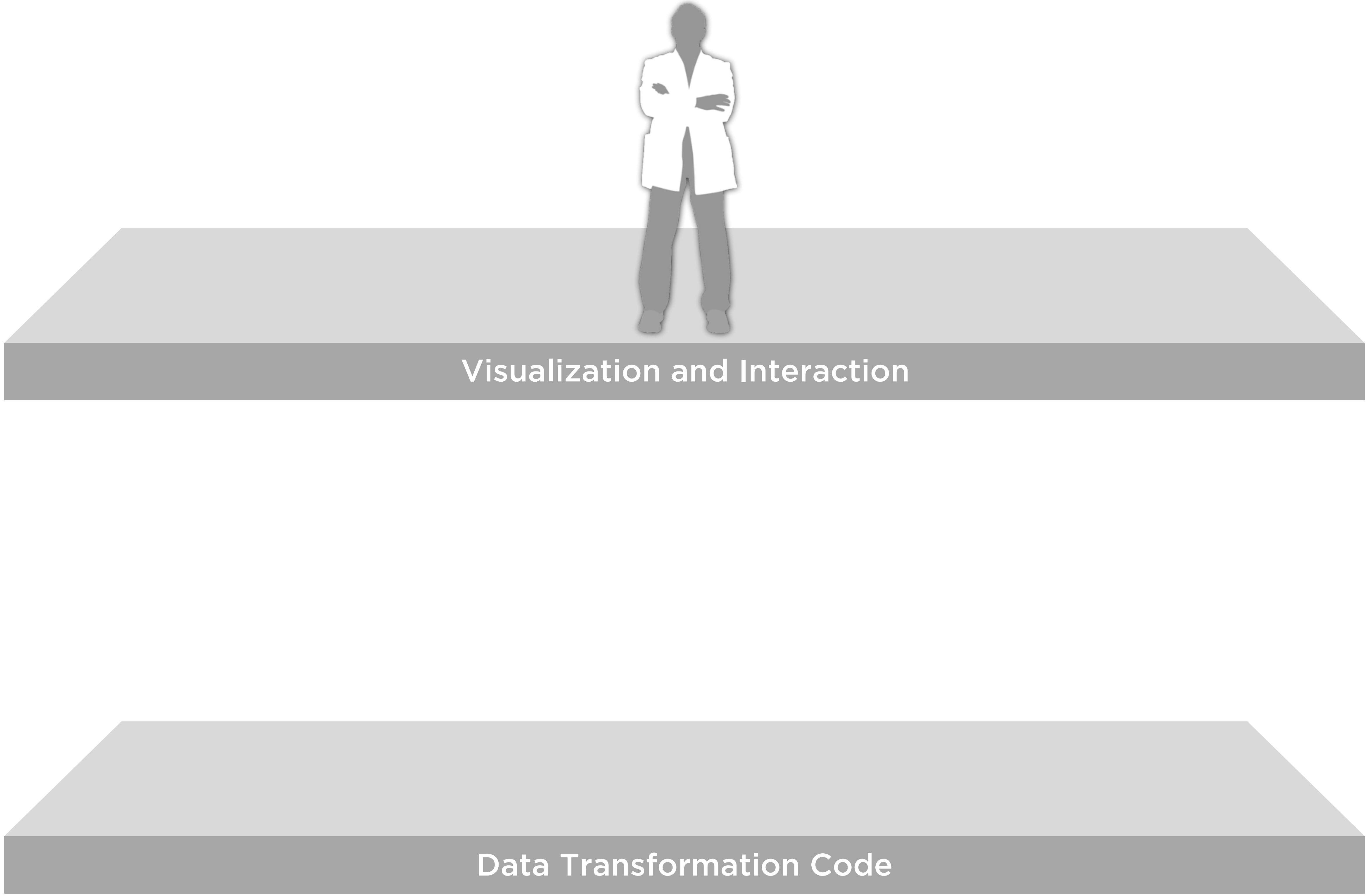
Traditional Specification



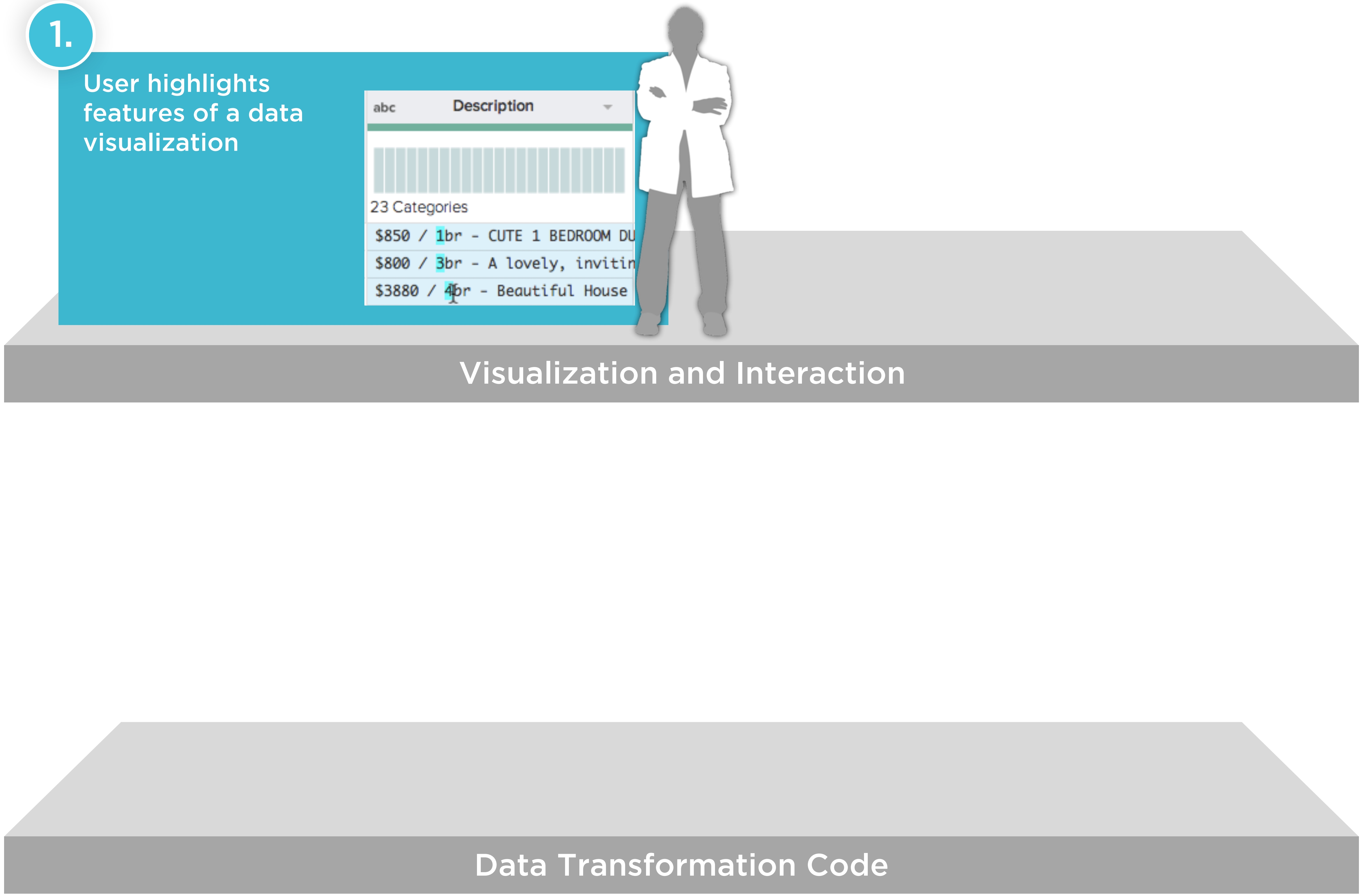
Predictive Interaction



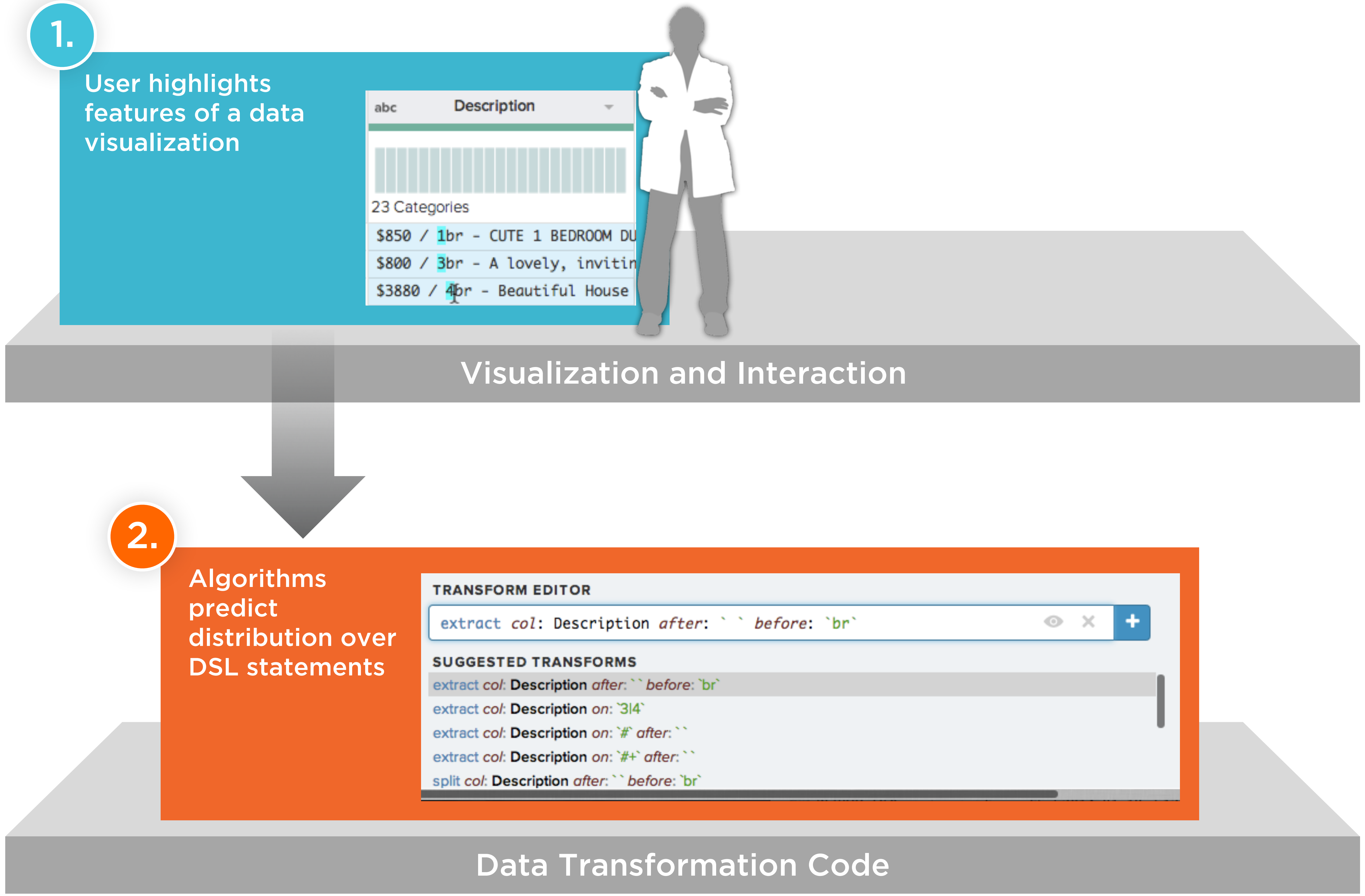
Predictive Interaction



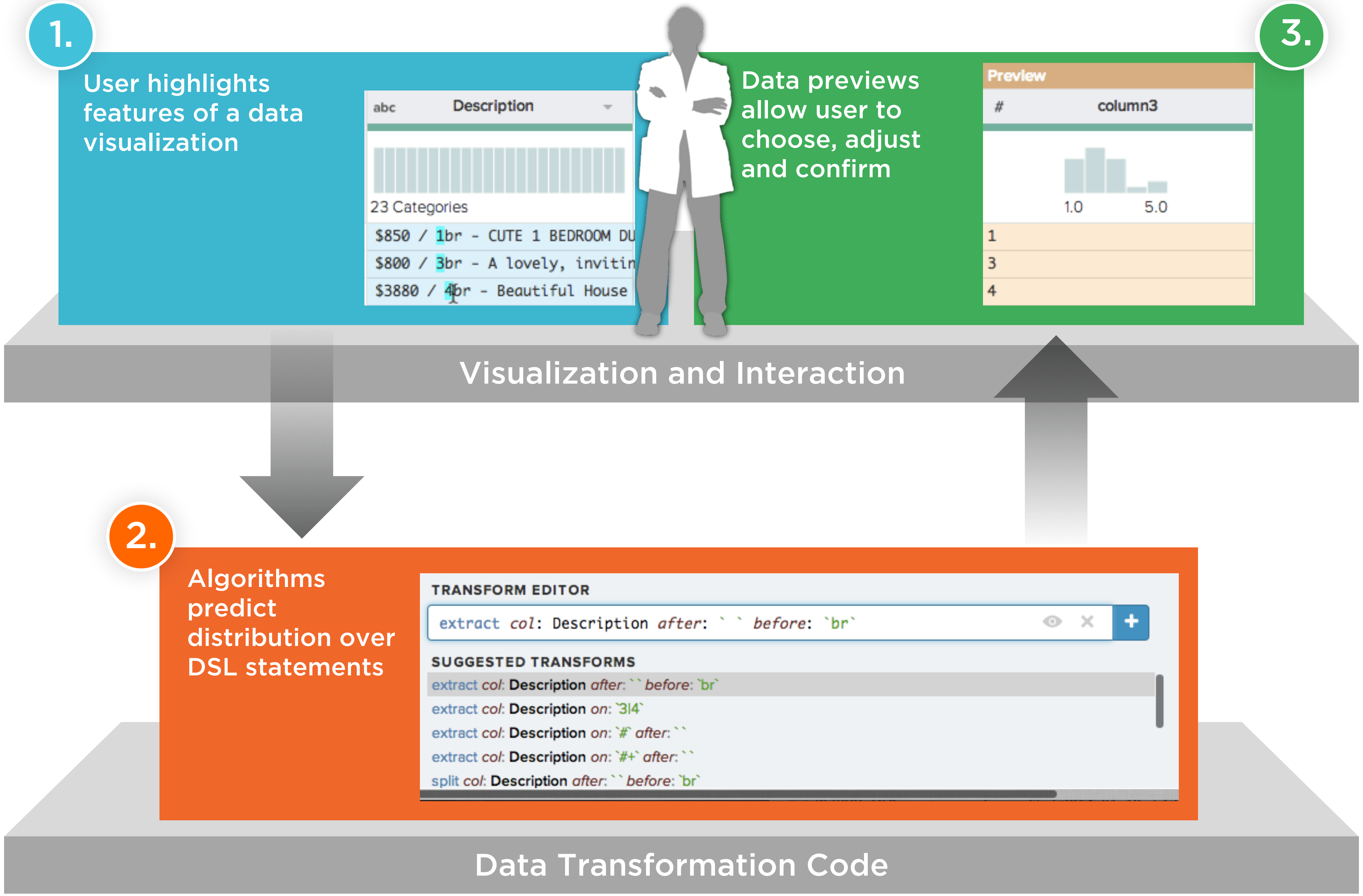
Predictive Interaction



Predictive Interaction



Predictive Interaction



Wrangle Language Building Blocks

Transforms

Split

Extract

Filter

Derive

Header

Pivot

Aggregate

Join

Union

…

Wrangle Language Building Blocks

Transforms	**Parameter Types**
Split	Text Selection
Extract	Column Selection
Filter	Row Selection
Derive	Formula
Header	Enumeration
Pivot	Number
Aggregate	String
Join	Boolean
Union	
…	

Text Selection: A Language within a Language

Transforms	**Parameter Types**
Split	***Text Selection***
Extract	Column Selection
Filter	Row Selection
Derive	Formula
Header	Enumeration
Pivot	Number
Aggregate	String
Join	Boolean
Union	
…	

SUGGESTED TRANSFORMS

	Source	Preview	
	abc Screen_Detail	abc Screen...	abc De
	6 Categories	2 Categories	8 Catego
31	adtam_name=utarget1&adtam_source=dynamic&adtam_size=180x150	dynamic	Nokia
32	adtam_name=holidaypromo1&adtam_source=dynamic&adtam_size=300x250	dynamic	Nokia
33	adtam_name=utarget1&adtam_source=dynamic&adtam_size=180x150	dynamic	samsung
34	adtam_name=holidaypromo2&adtam_source=mobile&adtam_size=240x400	mobile	Nokia

SUGGESTED TRANSFORMS

```
extract col: Screen_Detail on: /(?<=adtam_source\=)[^\&]*(?=\&)/
extract col: Screen_Detail on: /(?<=\=)[^\&]*(?=\&)/ limit: 2
extract col: Screen_Detail on: /(?<=\=)[a-z]+/ limit: 2
```

	Source	Preview	
	abc Screen_Detail	abc Screen...	abc De
	6 Categories	2 Categories	8 Catego
31	adtam_name=utarget1&adtam_source=dynamic&adtam_size=180x150	dynamic	Nokia
32	adtam_name=holidaypromo1&adtam_source=dynamic&adtam_size=300x250	dynamic	Nokia
33	adtam_name=utarget1&adtam_source=dynamic&adtam_size=180x150	dynamic	samsung
34	adtam_name=holidaypromo2&adtam_source=mobile&adtam_size=240x400	mobile	Nokia

```
/(?<=adtam_source\=)[^\&]*(?=\&)/
```

What (not) to match

```
/(?<=adtam_source\=)[^\&]*(?=\&)/
```

Look-behind **Look-ahead**

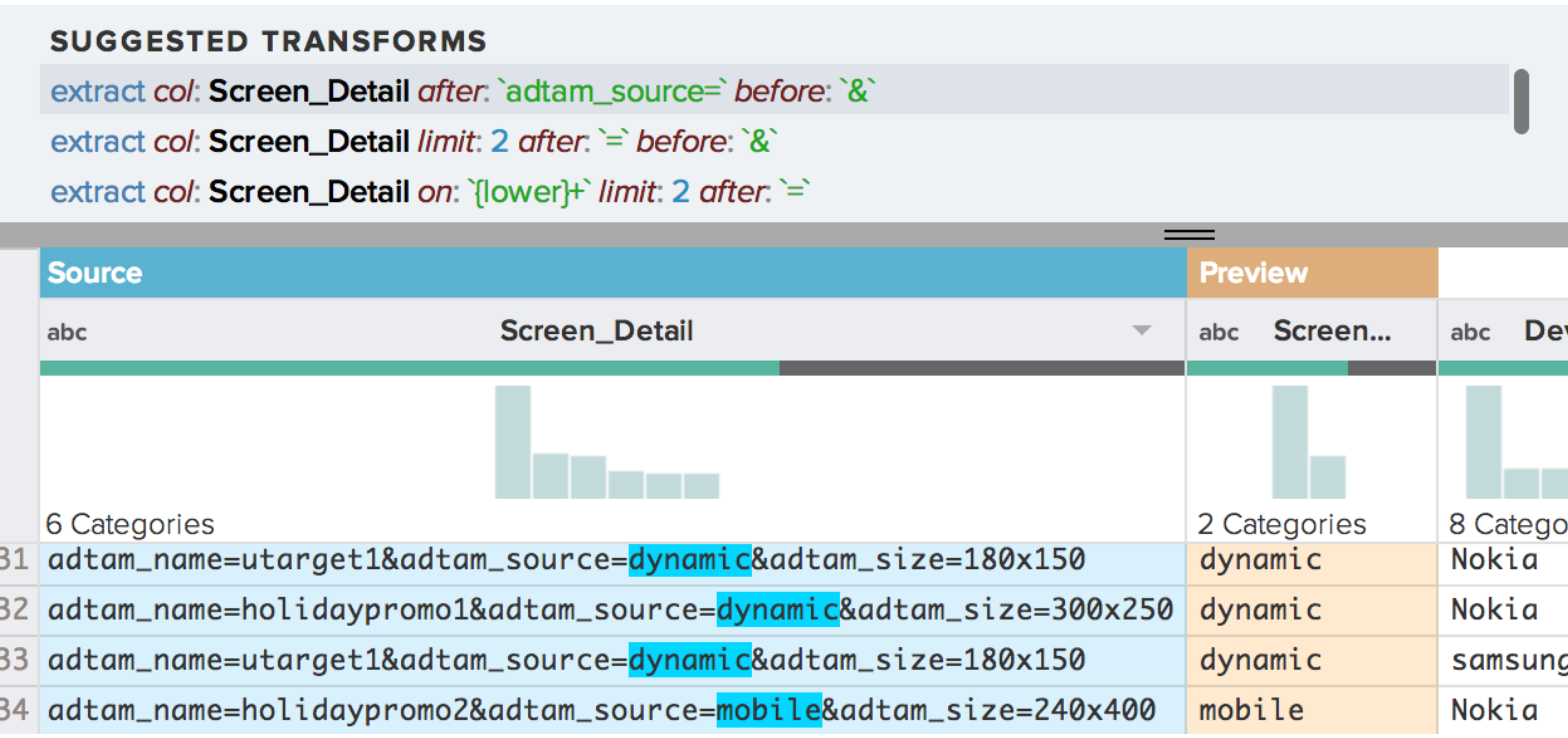
Control Characters

```
/(?<=adtam_source\=)[^\&]*(?=\&)/
```

Escaped Literal Characters

Write **once**, read **never.**

after: 'adtam_source=' *before:* '&'


SUGGESTED TRANSFORMS
extract col: Screen_Detail after: `adtam_source=` before: `&`
extract col: Screen_Detail limit: 2 after: `=` before: `&`
extract col: Screen_Detail on: `{lower}+` limit: 2 after: `=`
Source
Preview
abc Screen_Detail
abc Screen...
abc De
6 Categories
2 Categories
8 Catego
31 adtam_name=utarget1&adtam_source=dynamic&adtam_size=180x150 dynamic Nokia
32 adtam_name=holidaypromo1&adtam_source=dynamic&adtam_size=300x250 dynamic Nokia
33 adtam_name=utarget1&adtam_source=dynamic&adtam_size=180x150 dynamic samsung
34 adtam_name=holidaypromo2&adtam_source=mobile&adtam_size=240x400 mobile Nokia

Text Selection: A Language within a Language

Transforms	**Parameter Types**
Split	***Text Selection***
Extract	Column Selection
Filter	Row Selection
Derive	Formula
Header	Enumeration
Pivot	Number
Aggregate	String
Join	Boolean
Union	
…	

Text Selection: A Language within a Language

Transforms	Parameter Types	Text Selection Prepositions
Split	***Text Selection***	on
Extract	Column Selection	from / to
Filter	Row Selection	after / before
Derive	Formula	
Header	Enumeration	
Pivot	Number	
Aggregate	String	
Join	Boolean	
Union		
…		

Text Selection: A Language within a Language

Transforms

Split
Extract
Filter
Derive
Header
Pivot
Aggregate
Join
Union
…

Parameter Types

Text Selection
Column Selection
Row Selection
Formula
Enumeration
Number
String
Boolean

Text Selection Prepositions

on
from / to
after / before

Inference Procedure

Text Selection: A Language within a Language

Transforms

Split

Extract

Filter

Derive

Header

Pivot

Aggregate

Join

Union

…

Parameter Types

Text Selection

Column Selection

Row Selection

Formula

Enumeration

Number

String

Boolean

Text Selection Prepositions

on

from / to

after / before

Inference Procedure

1. User Selects Text(s)

Text Selection: A Language within a Language

Transforms

Split

Extract

Filter

Derive

Header

Pivot

Aggregate

Join

Union

…

Parameter Types

Text Selection

Column Selection

Row Selection

Formula

Enumeration

Number

String

Boolean

Text Selection Prepositions

on

from / to

after / before

Inference Procedure

1. User Selects Text(s)
2. Tokenize / Generalize

Text Selection: A Language within a Language

Transforms

Split
Extract
Filter
Derive
Header
Pivot
Aggregate
Join
Union
…

Parameter Types

Text Selection
Column Selection
Row Selection
Formula
Enumeration
Number
String
Boolean

Text Selection Prepositions

on
from / to
after / before

Inference Procedure

1. User Selects Text(s)
2. Tokenize / Generalize
3. Generate Clauses

Text Selection: A Language within a Language

Transforms

Split
Extract
Filter
Derive
Header
Pivot
Aggregate
Join
Union
…

Parameter Types

Text Selection
Column Selection
Row Selection
Formula
Enumeration
Number
String
Boolean

Text Selection Prepositions

on
from / to
after / before

Inference Procedure

1. User Selects Text(s)
2. Tokenize / Generalize
3. Generate Clauses
4. Combine Clauses

Text Selection: A Language within a Language

Transforms

Split
Extract
Filter
Derive
Header
Pivot
Aggregate
Join
Union
…

Parameter Types

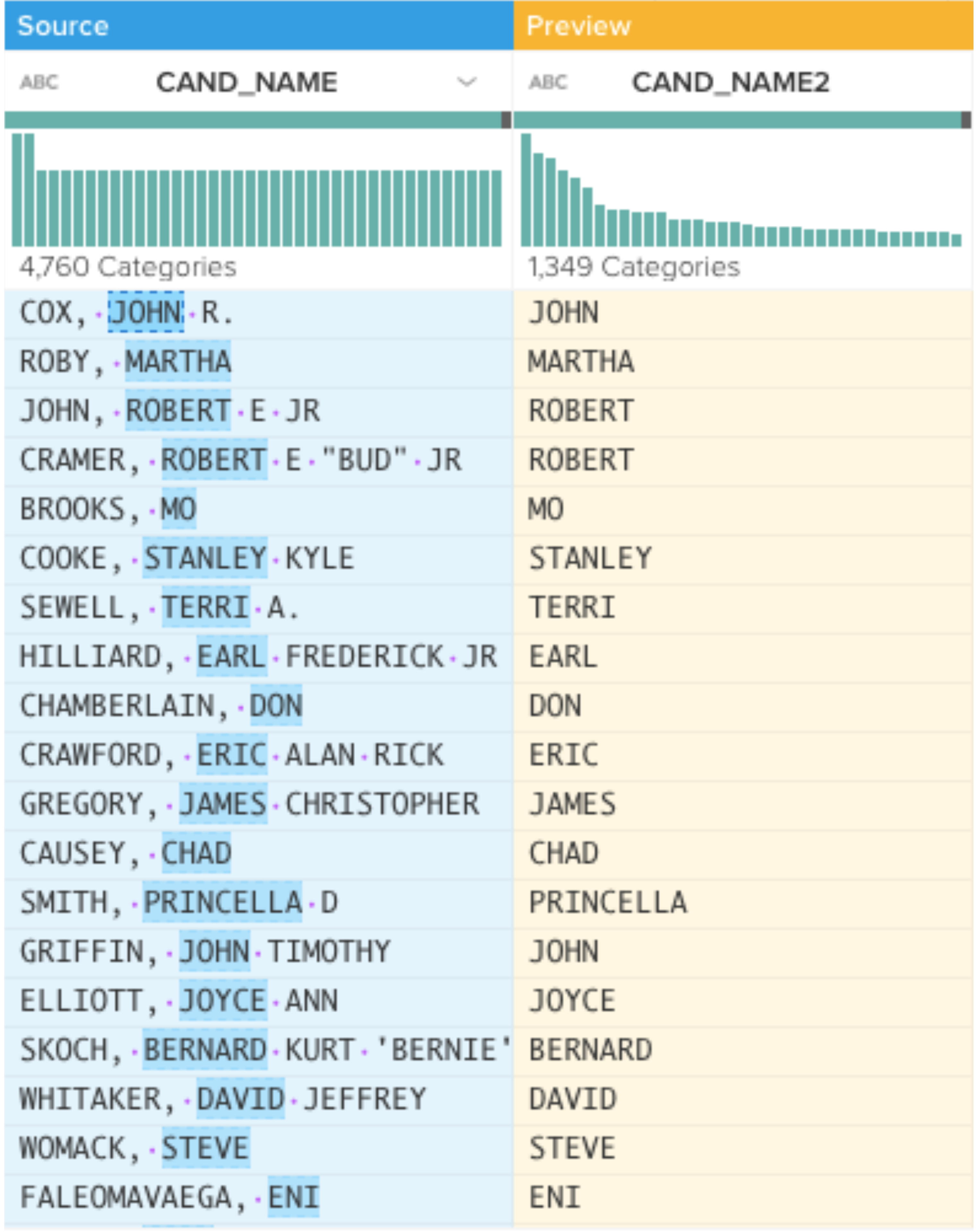
Text Selection
Column Selection
Row Selection
Formula
Enumeration
Number
String
Boolean

Text Selection Prepositions

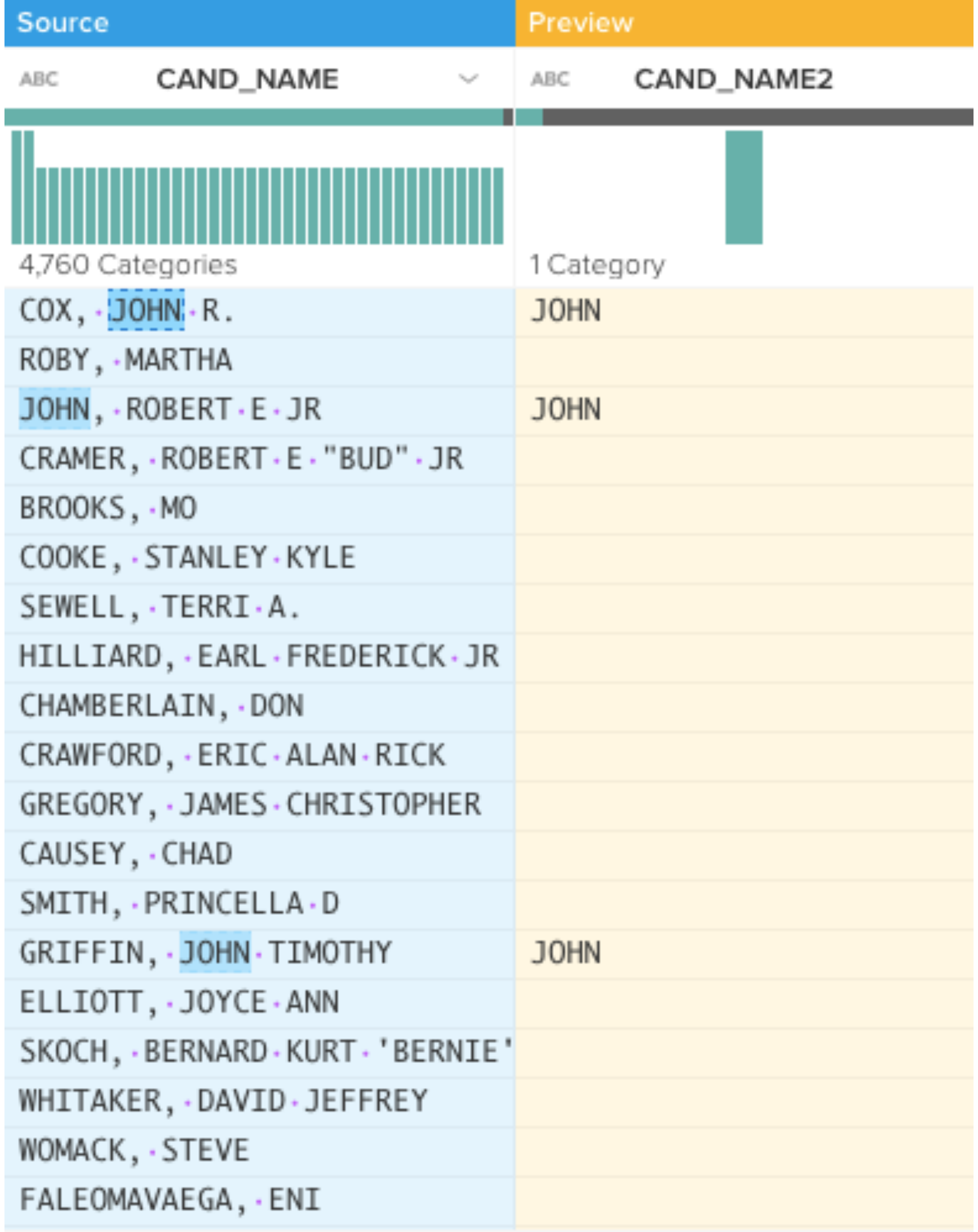
on
from / to
after / before

Inference Procedure

1. User Selects Text(s)
2. Tokenize / Generalize
3. Generate Clauses
4. Combine Clauses
5. Filter & Rank Patterns


Source
Preview
ABC CAND_NAME
ABC CAND_NAME2
4,760 Categories
1,349 Categories
COX, JOHN R. | JOHN
ROBY, MARTHA | MARTHA
JOHN, ROBERT E JR | ROBERT
CRAMER, ROBERT E "BUD" JR | ROBERT
BROOKS, MO | MO
COOKE, STANLEY KYLE | STANLEY
SEWELL, TERRI A. | TERRI
HILLIARD, EARL FREDERICK JR | EARL
CHAMBERLAIN, DON | DON
CRAWFORD, ERIC ALAN RICK | ERIC
GREGORY, JAMES CHRISTOPHER | JAMES
CAUSEY, CHAD | CHAD
SMITH, PRINCELLA D | PRINCELLA
GRIFFIN, JOHN TIMOTHY | JOHN
ELLIOTT, JOYCE ANN | JOYCE
SKOCH, BERNARD KURT 'BERNIE' | BERNARD
WHITAKER, DAVID JEFFREY | DAVID
WOMACK, STEVE | STEVE
FALEOMAVAEGA, ENI | ENI

vs.


Source
Preview
ABC CAND_NAME
ABC CAND_NAME2
4,760 Categories
1 Category
COX, JOHN R. | JOHN
ROBY, MARTHA
JOHN, ROBERT E JR | JOHN
CRAMER, ROBERT E "BUD" JR
BROOKS, MO
COOKE, STANLEY KYLE
SEWELL, TERRI A.
HILLIARD, EARL FREDERICK JR
CHAMBERLAIN, DON
CRAWFORD, ERIC ALAN RICK
GREGORY, JAMES CHRISTOPHER
CAUSEY, CHAD
SMITH, PRINCELLA D
GRIFFIN, JOHN TIMOTHY | JOHN
ELLIOTT, JOYCE ANN
SKOCH, BERNARD KURT 'BERNIE'
WHITAKER, DAVID JEFFREY
WOMACK, STEVE
FALEOMAVAEGA, ENI

Wrangle Language Building Blocks

Transforms

Split

Extract

Filter

Derive

Header

Pivot

Aggregate

Join

Union

…

Parameter Types

Text Selection

Column Selection

Row Selection

Formula

Enumeration

Number

String

Boolean

Wrangle Language Building Blocks

Transforms	**Parameter Types**
Split	Text Selection
Extract	Column Selection
Filter	Row Selection
Derive	Formula
Header	Enumeration
Pivot	Number
Aggregate	String
Join	Boolean
Union	
…	

Wrangle Language Building Blocks

Transforms	Parameter Types	Inference Procedure
Split	Text Selection	
Extract	Column Selection	
Filter	Row Selection	
Derive	Formula	
Header	Enumeration	
Pivot	Number	
Aggregate	String	
Join	Boolean	
Union		
…		

Wrangle Language Building Blocks

Transforms	Parameter Types	Inference Procedure
Split	Text Selection	1. User Makes Selection(s)
Extract	Column Selection	
Filter	Row Selection	
Derive	Formula	
Header	Enumeration	
Pivot	Number	
Aggregate	String	
Join	Boolean	
Union		
…		

Wrangle Language Building Blocks

Transforms

Split
Extract
Filter
Derive
Header
Pivot
Aggregate
Join
Union
…

Parameter Types

Text Selection
Column Selection
Row Selection
Formula
Enumeration
Number
String
Boolean

Inference Procedure

1. User Makes Selection(s)
2. Infer Parameter Sets

Wrangle Language Building Blocks

Transforms

Split
Extract
Filter
Derive
Header
Pivot
Aggregate
Join
Union
…

Parameter Types

Text Selection
Column Selection
Row Selection
Formula
Enumeration
Number
String
Boolean

Inference Procedure

1. User Makes Selection(s)
2. Infer Parameter Sets
3. Generate Compatible Transforms

Wrangle Language Building Blocks

Transforms

Split

Extract

Filter

Derive

Header

Pivot

Aggregate

Join

Union

…

Parameter Types

Text Selection

Column Selection

Row Selection

Formula

Enumeration

Number

String

Boolean

Inference Procedure

1. User Makes Selection(s)
2. Infer Parameter Sets
3. Generate Compatible Transforms
4. Rank & Cluster Transforms

Wrangle Language Building Blocks

Transforms

Split

Extract

Filter

Derive

Header

Pivot

Aggregate

Join

Union

…

Parameter Types

Text Selection

Column Selection

Row Selection

Formula

Enumeration

Number

String

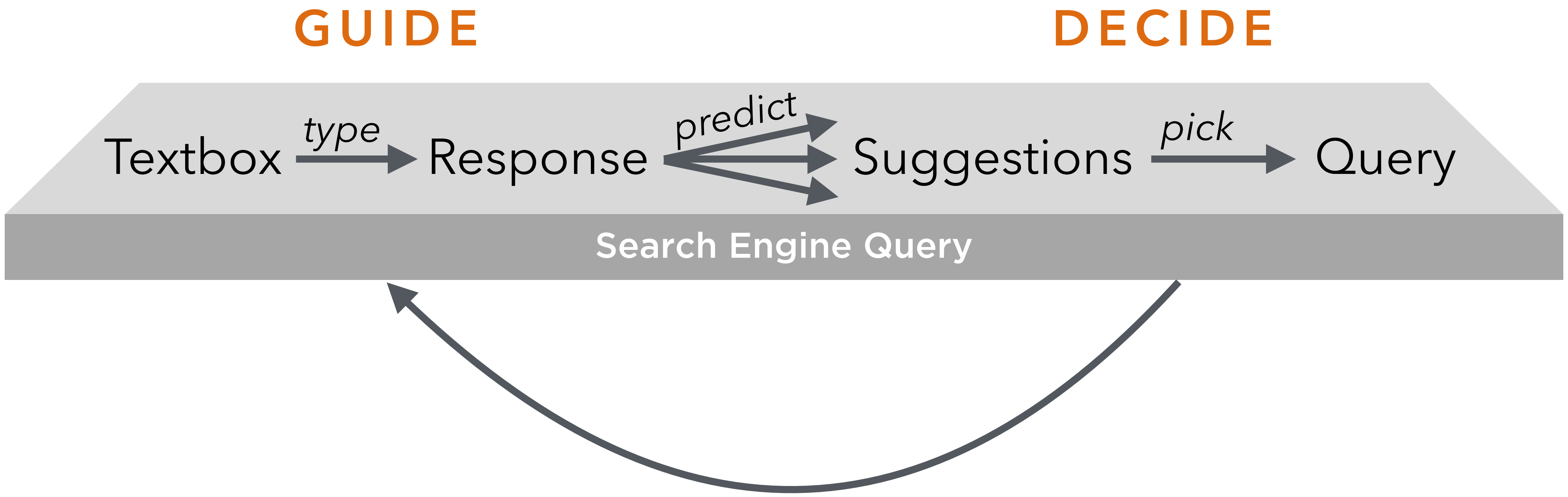
Boolean

Inference Procedure

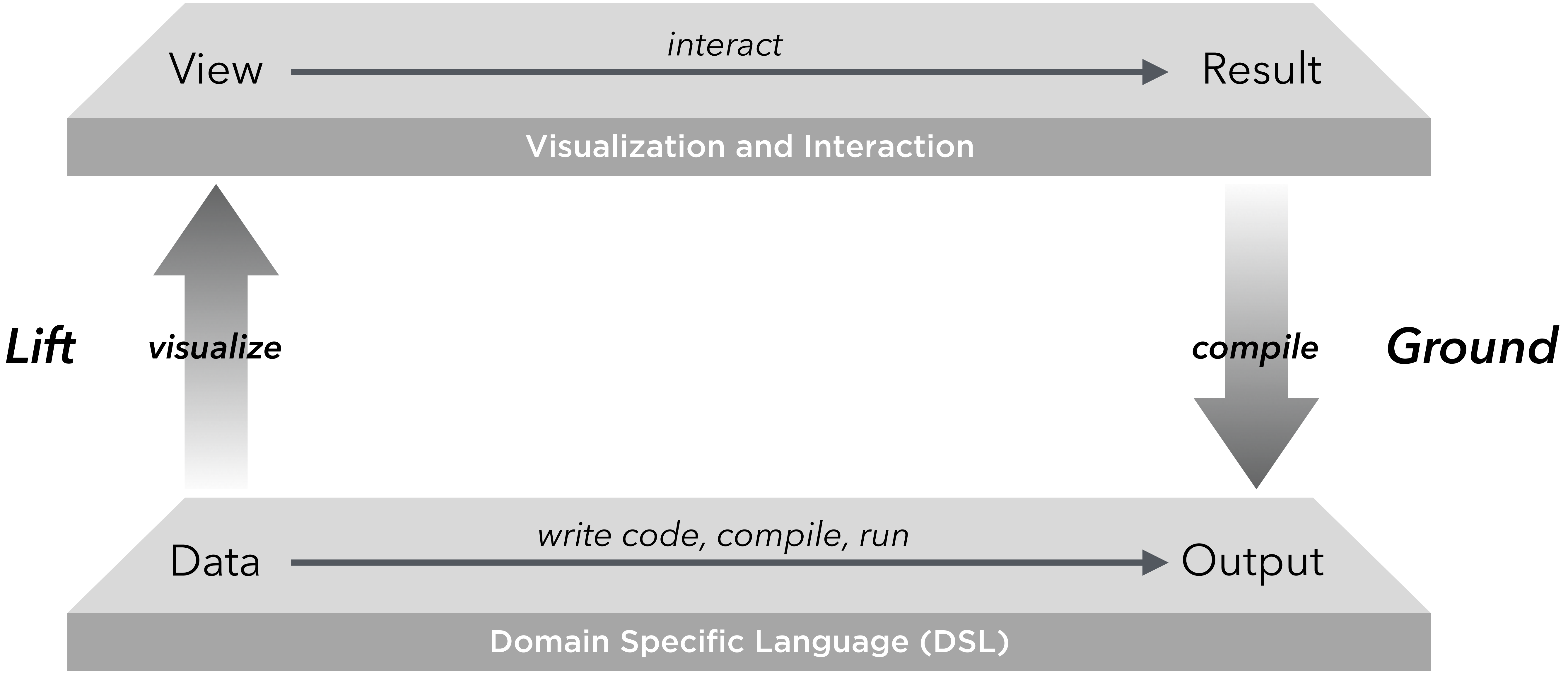
1. User Makes Selection(s)
2. Infer Parameter Sets
3. Generate Compatible Transforms
4. Rank & Cluster Transforms
5. Present Top Results

Predictive Interaction

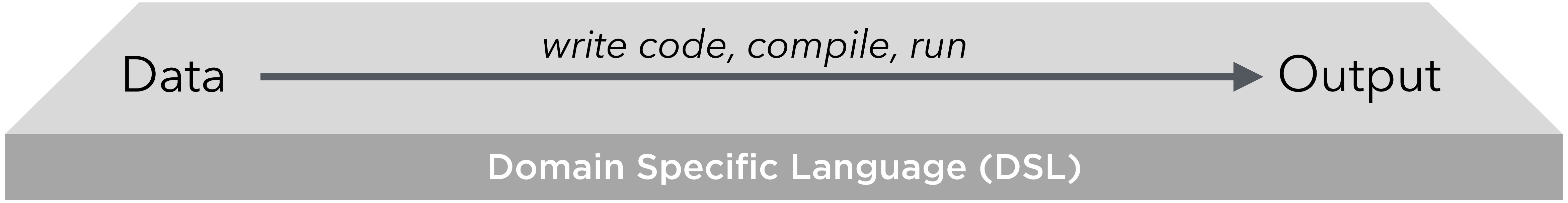
Auto-Complete



Lifting from DSL to Visual Language

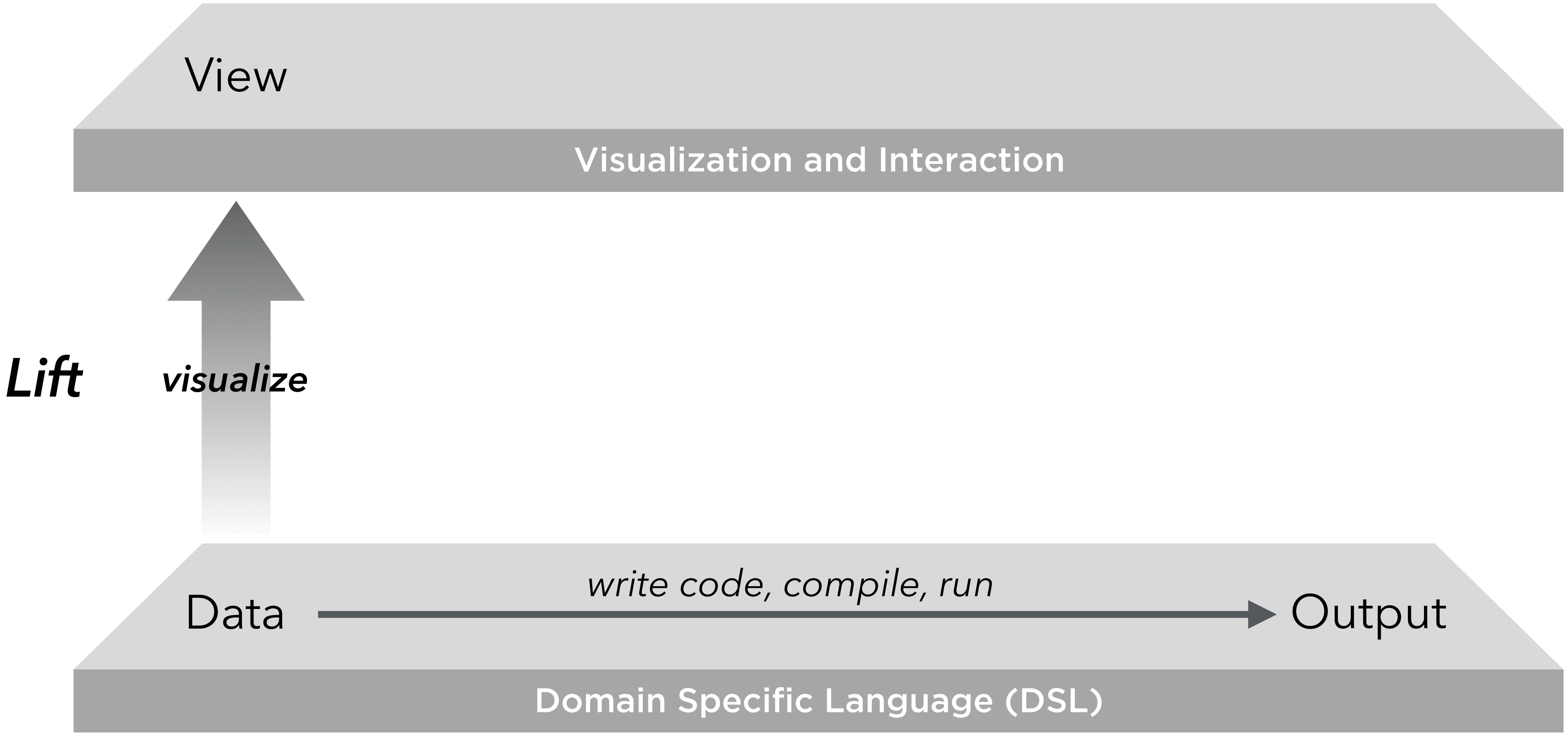


Predictive Interaction

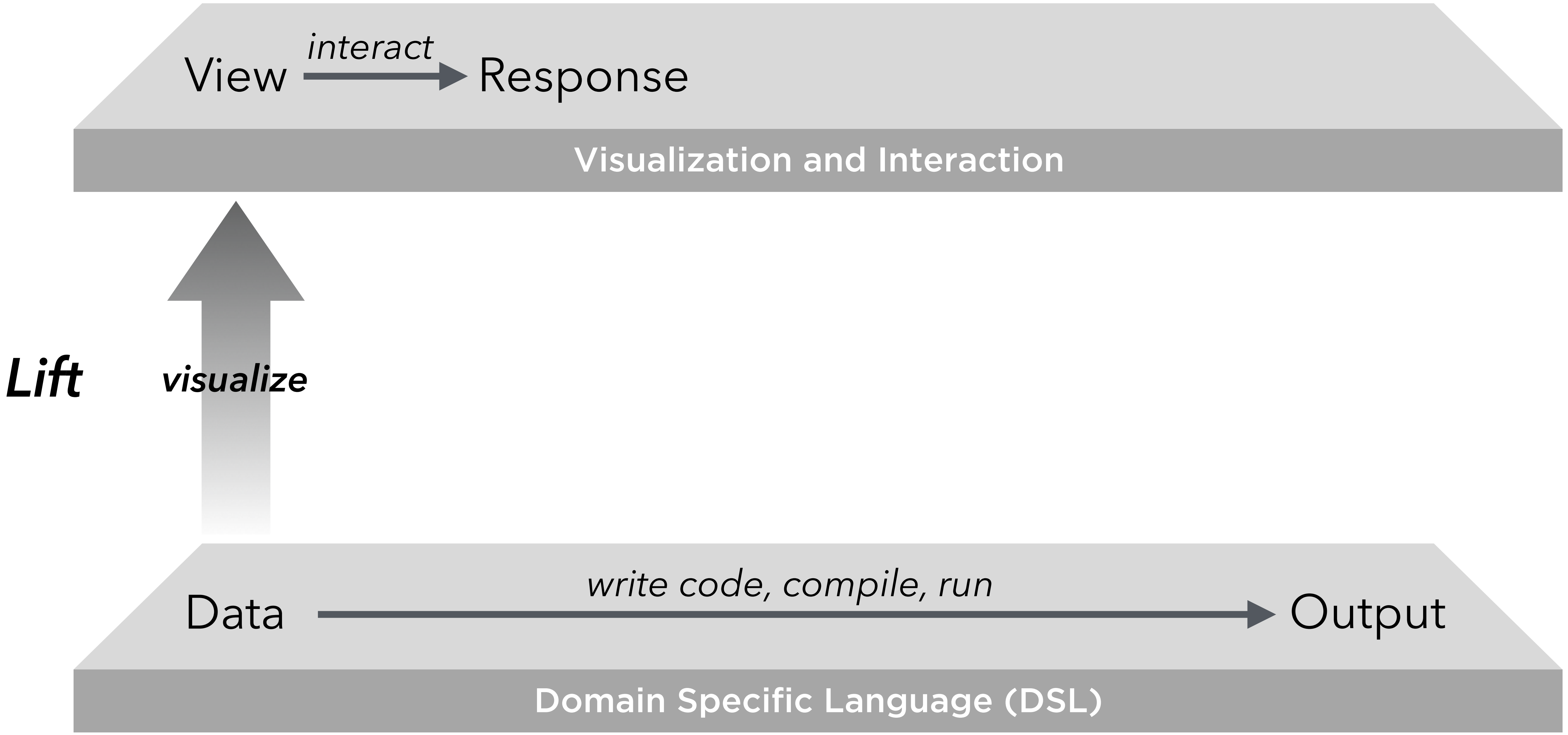


Predictive Interaction

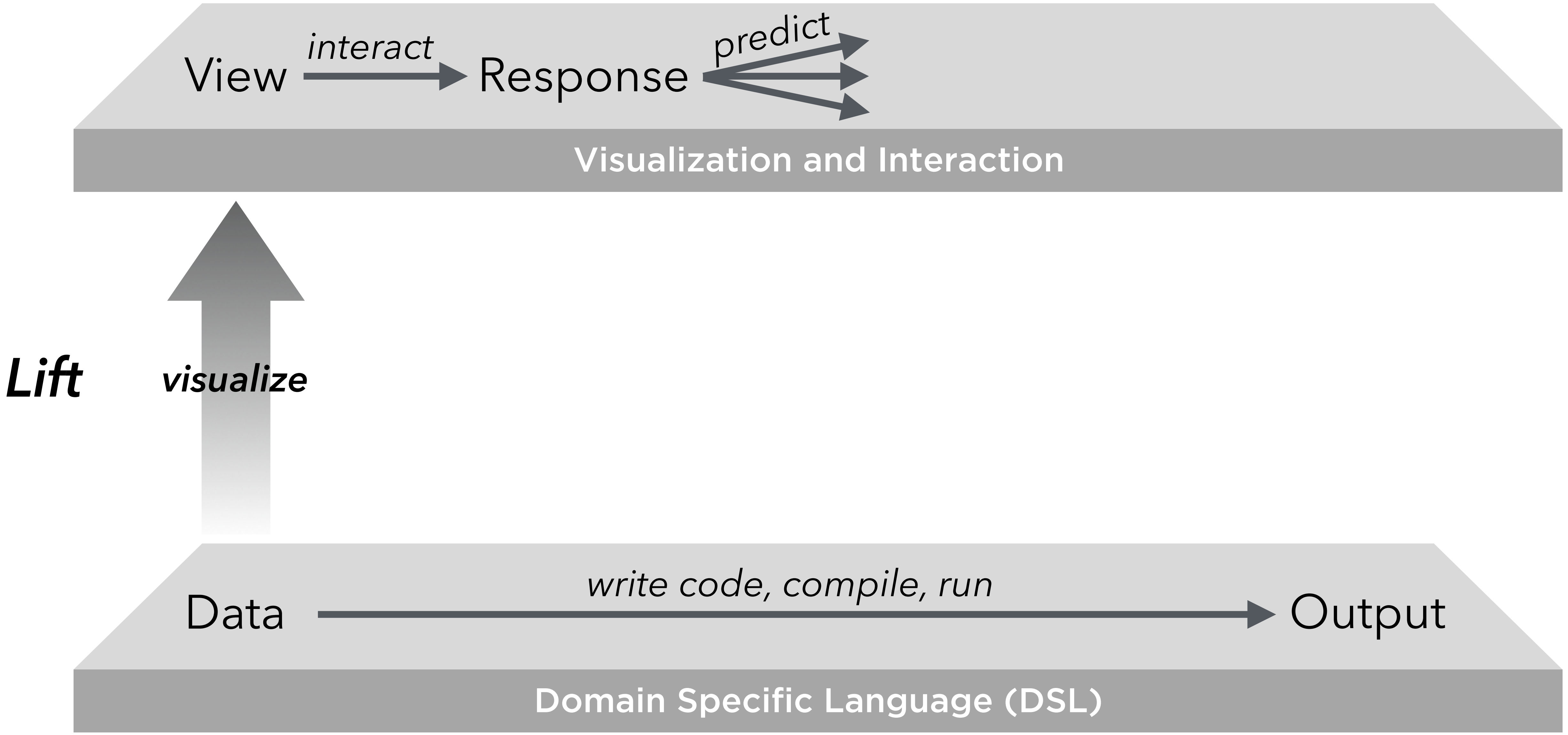
Predictive Interaction



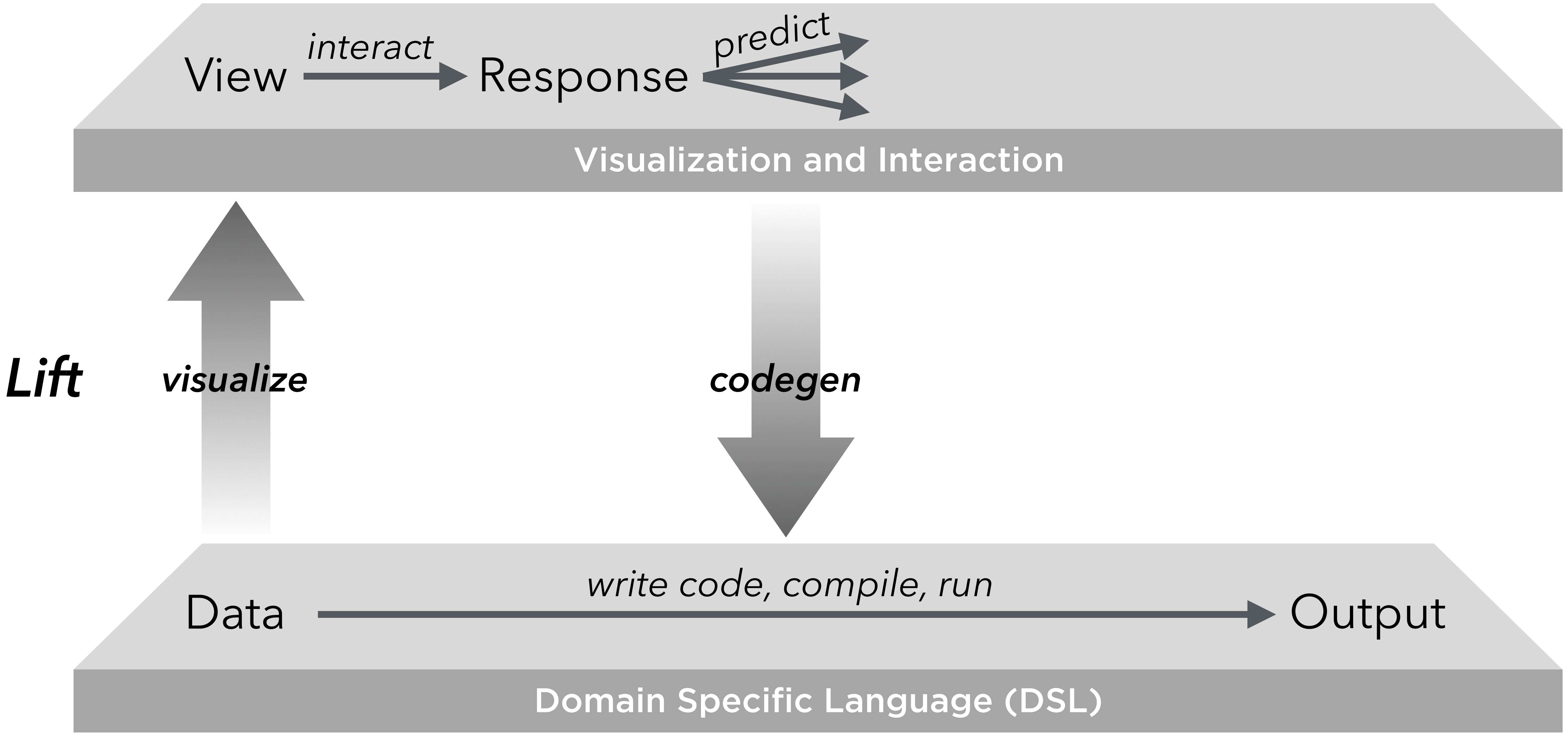
Predictive Interaction



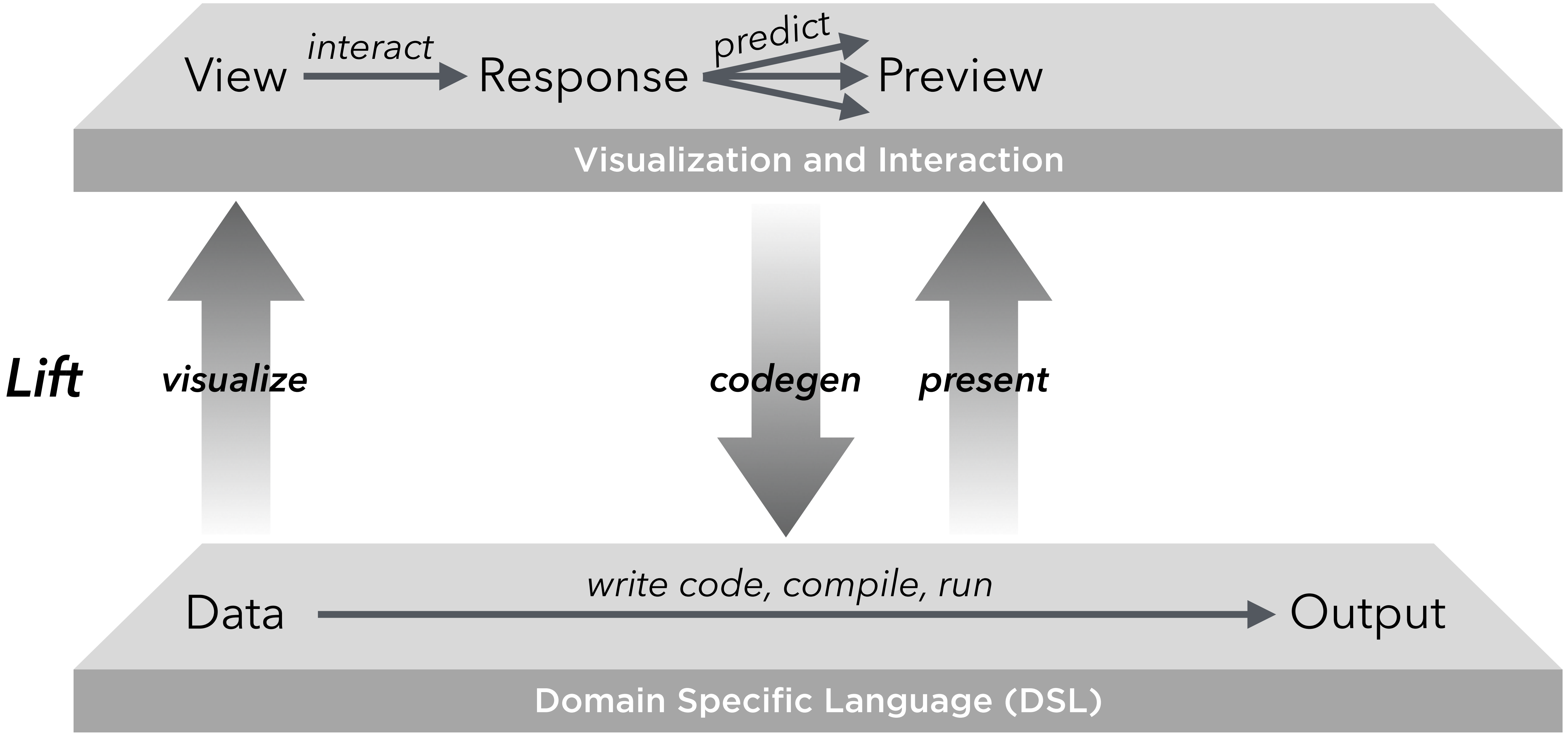
Predictive Interaction



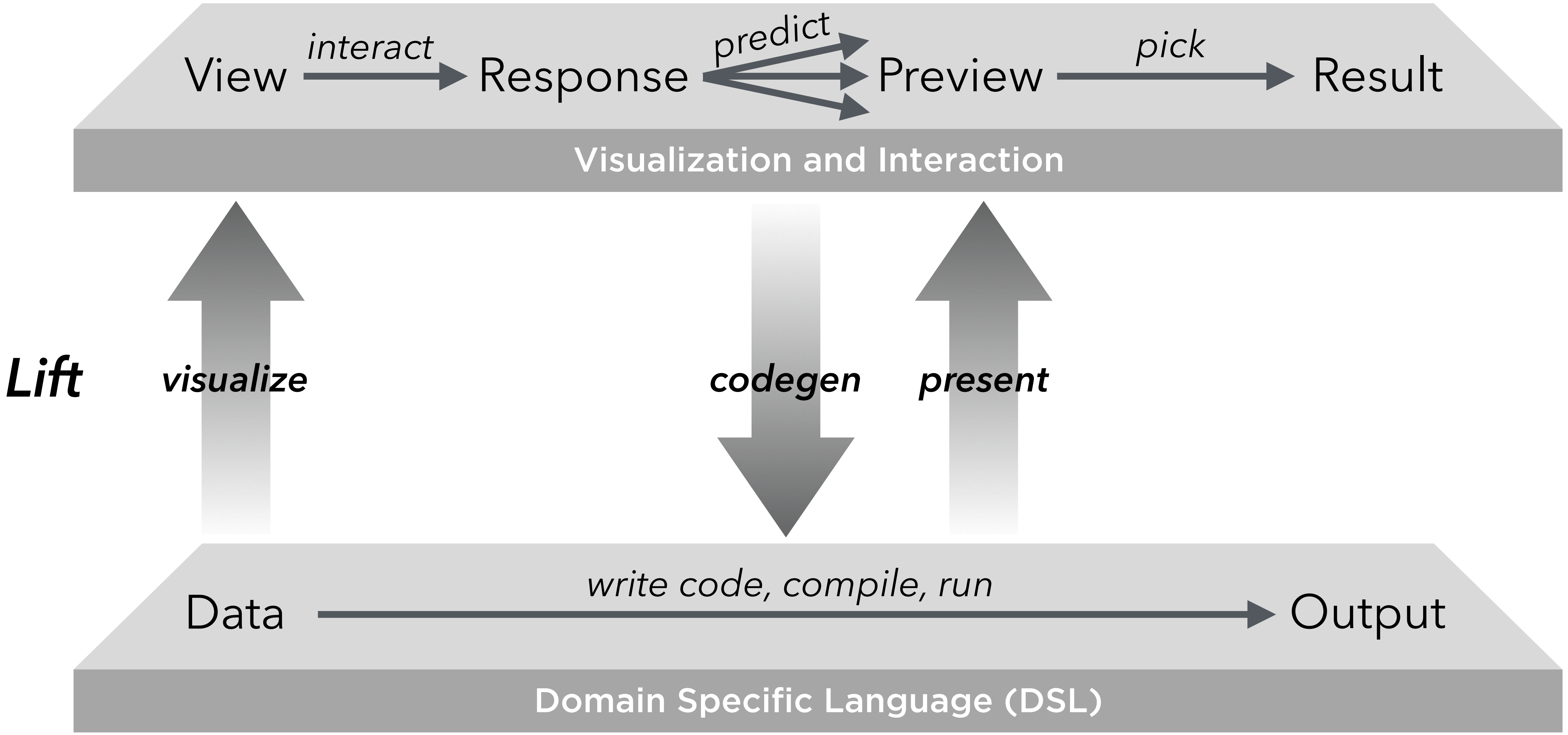
Predictive Interaction



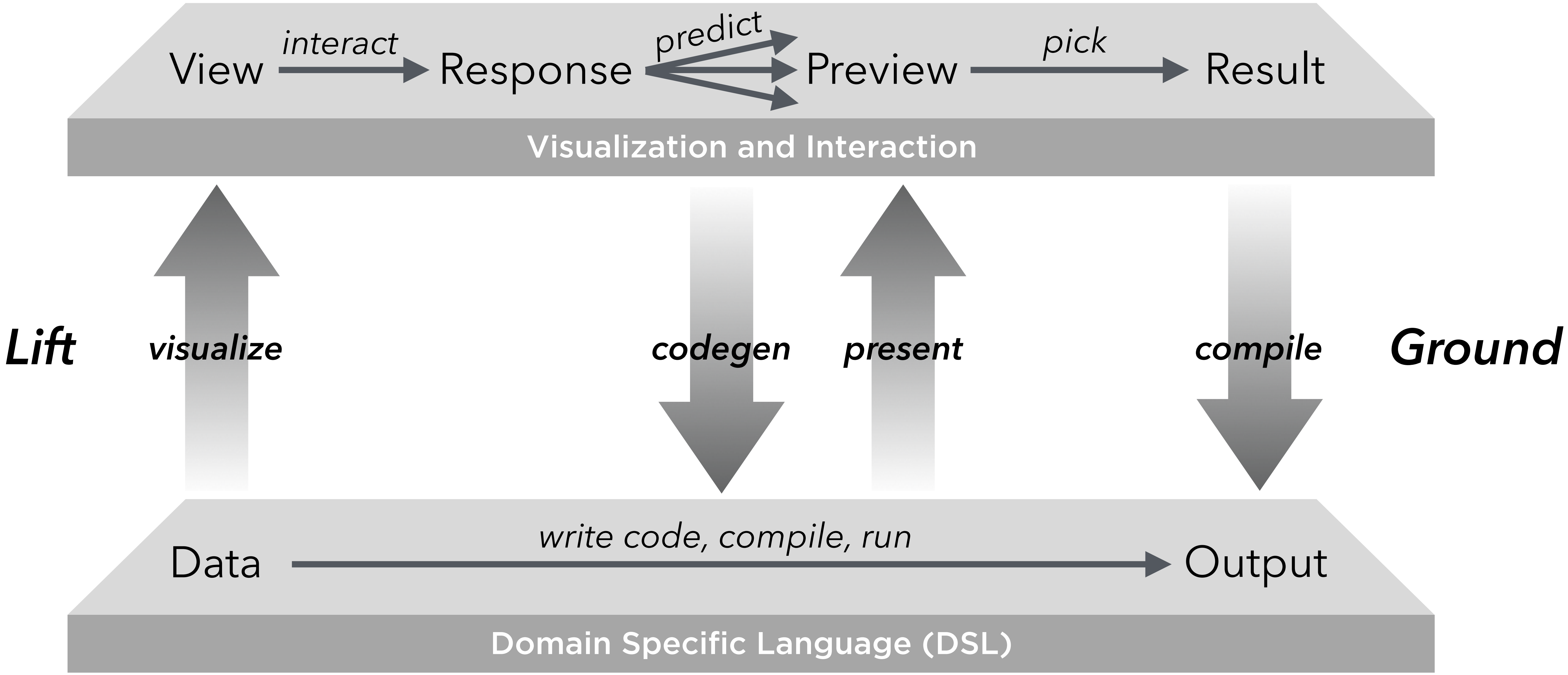
Predictive Interaction



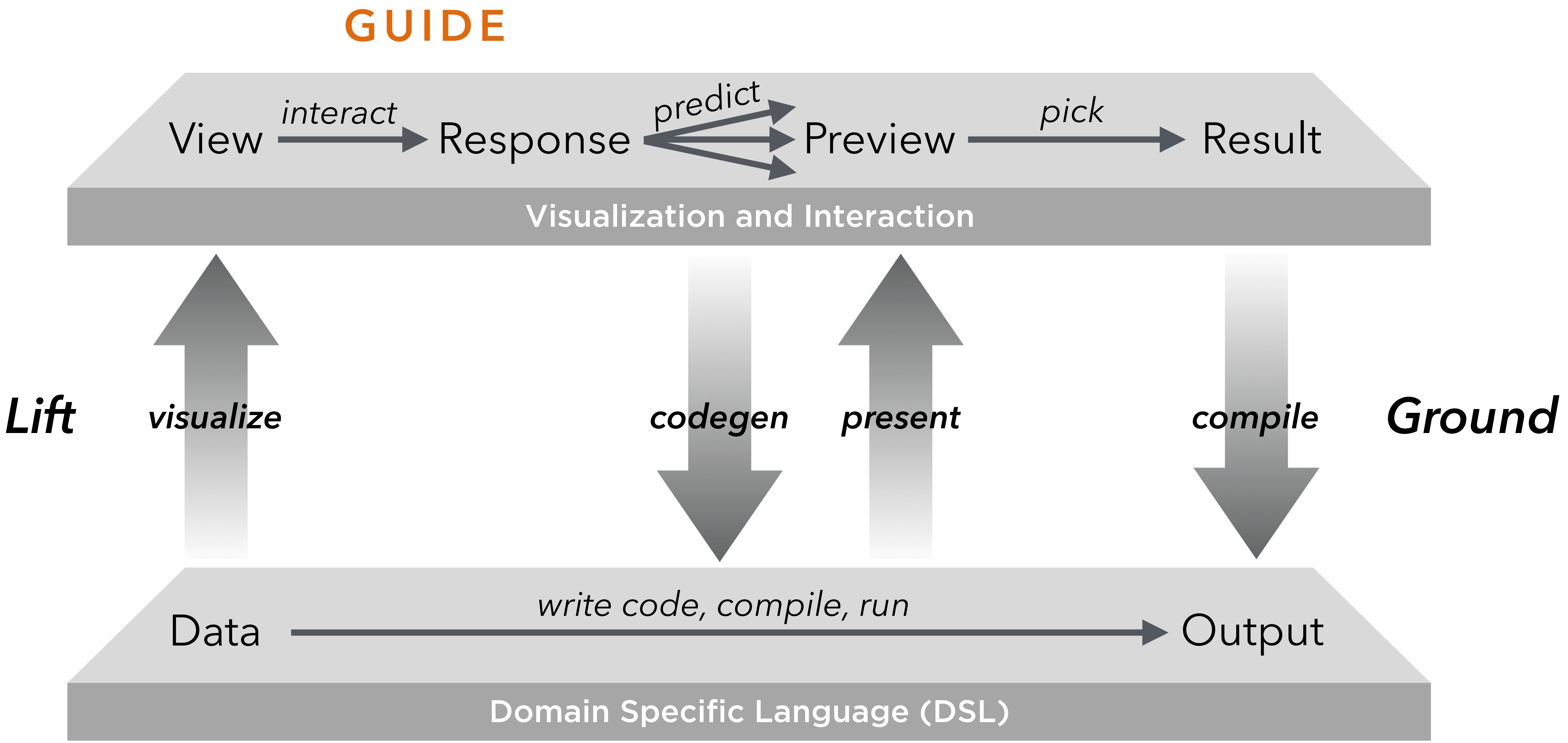
Predictive Interaction



Predictive Interaction



Predictive Interaction



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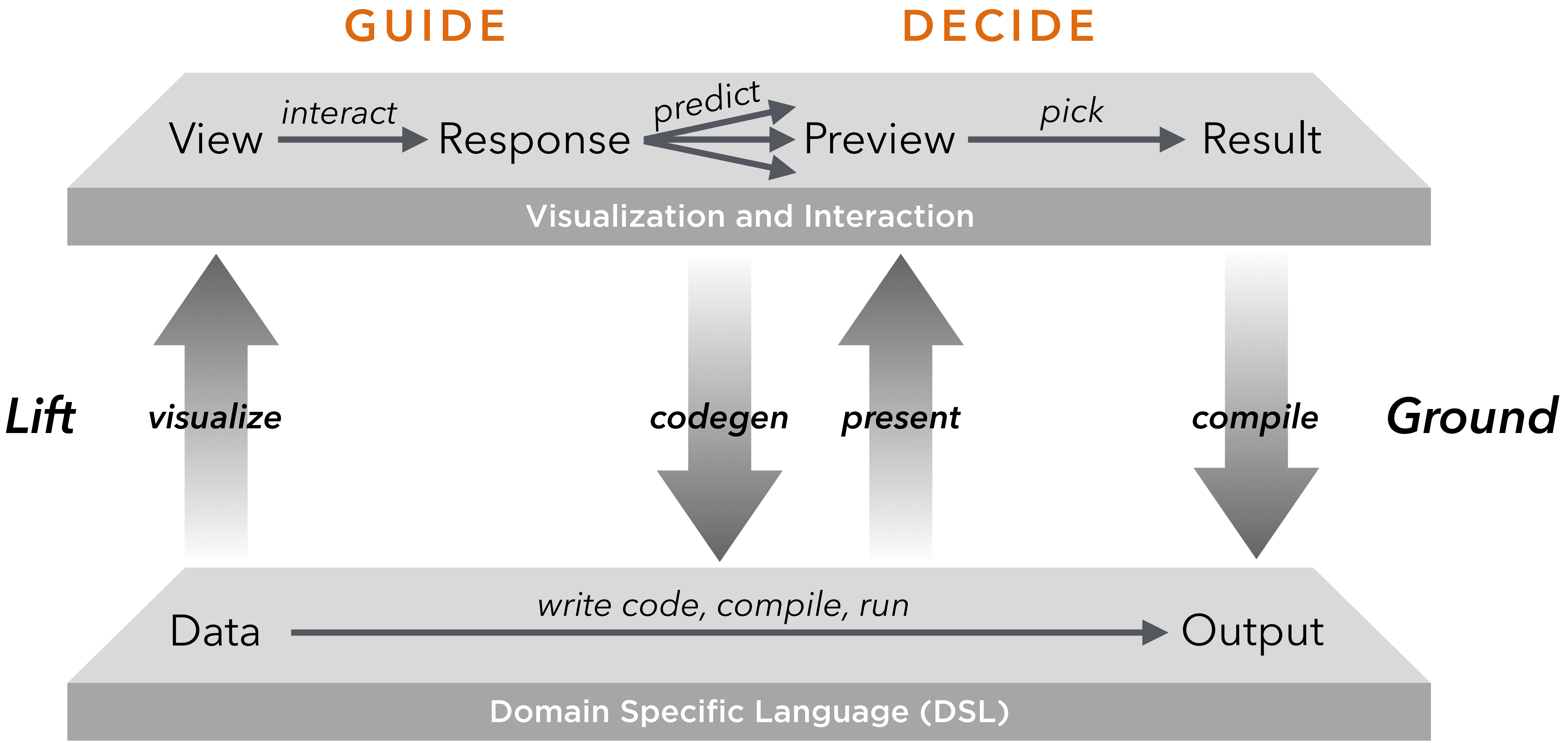

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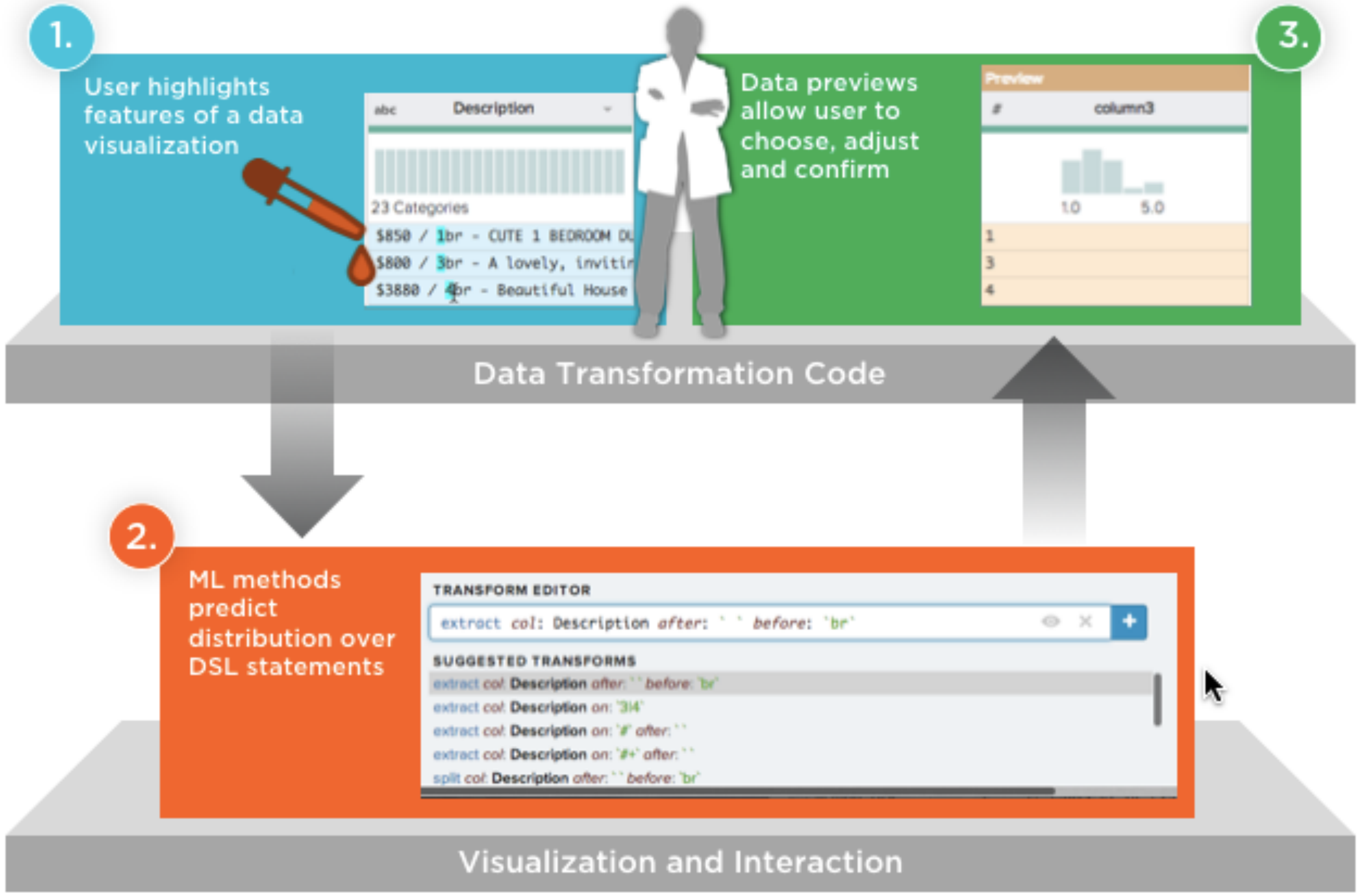
Provides means of learning from usage.

Can be re-applied to new inputs.

Cross-compile to different runtimes.



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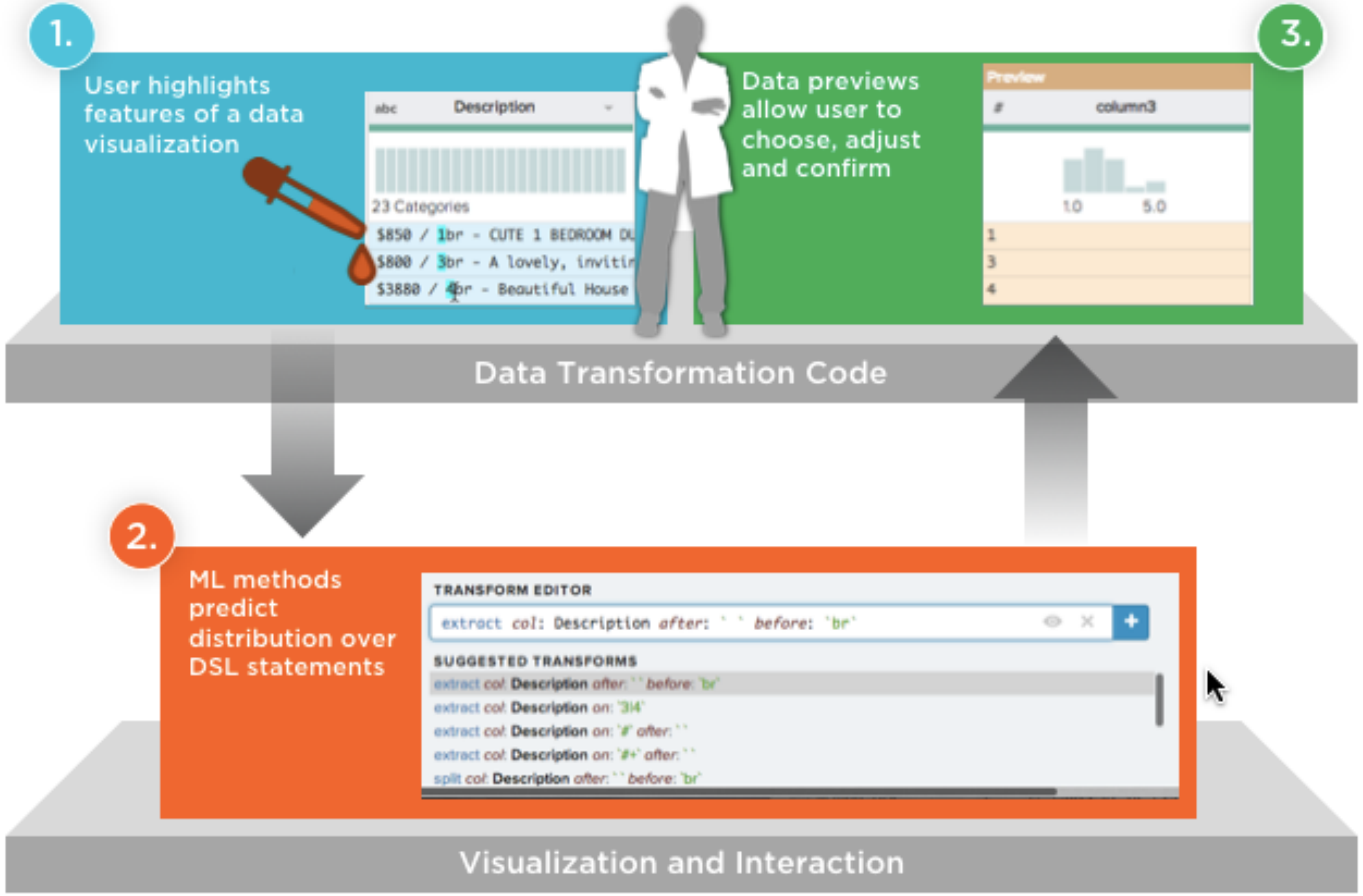

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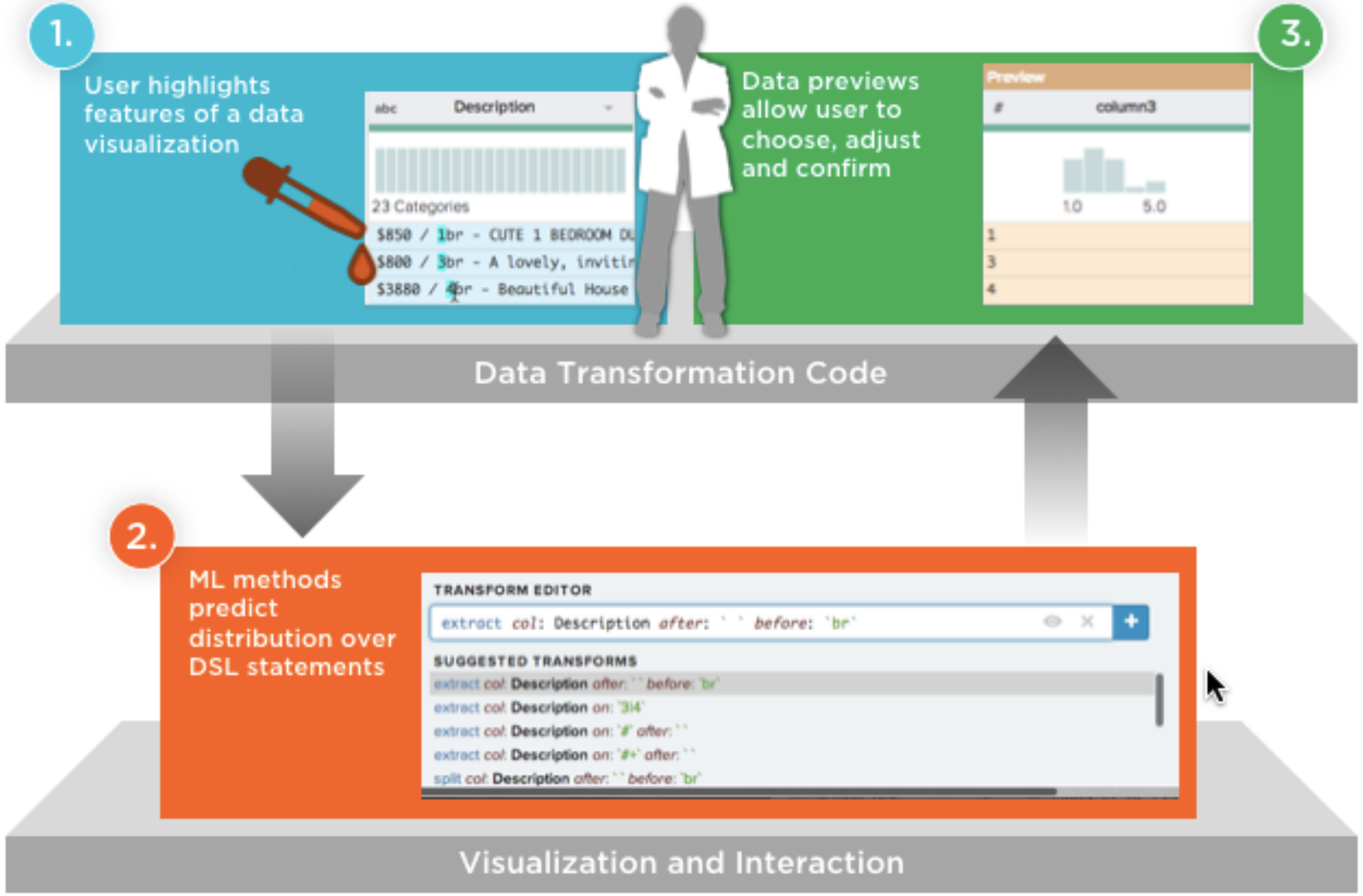

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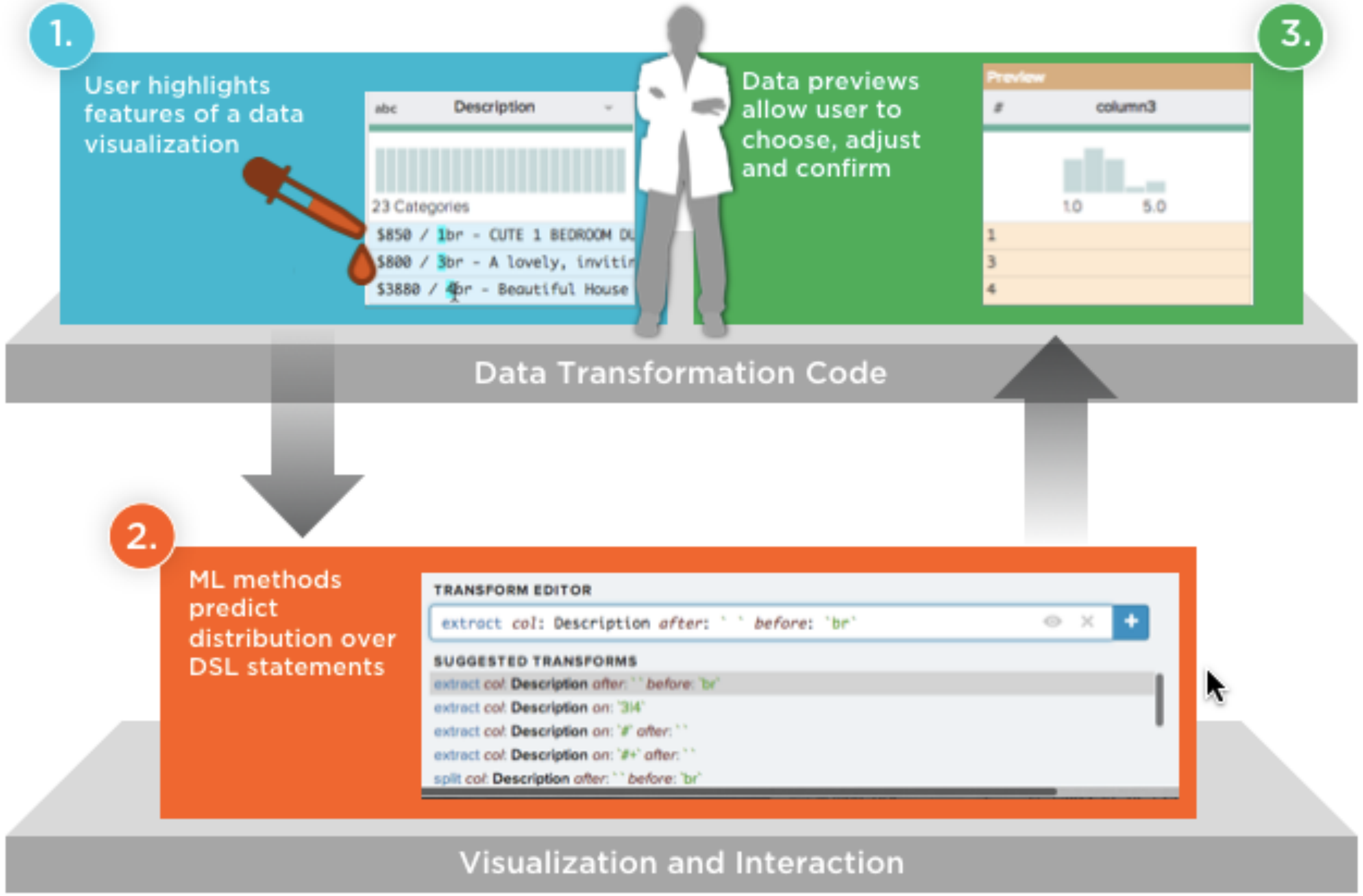

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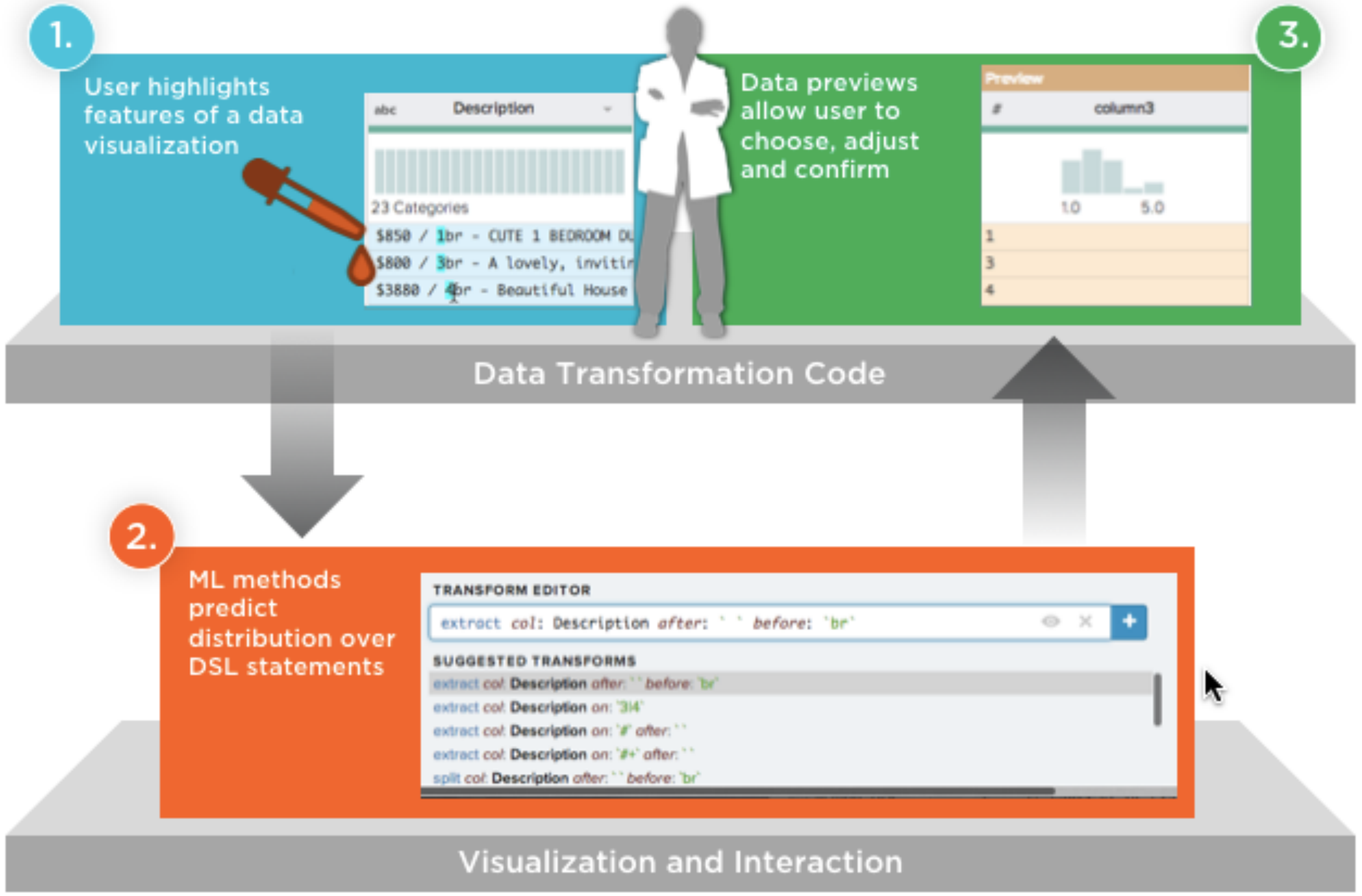
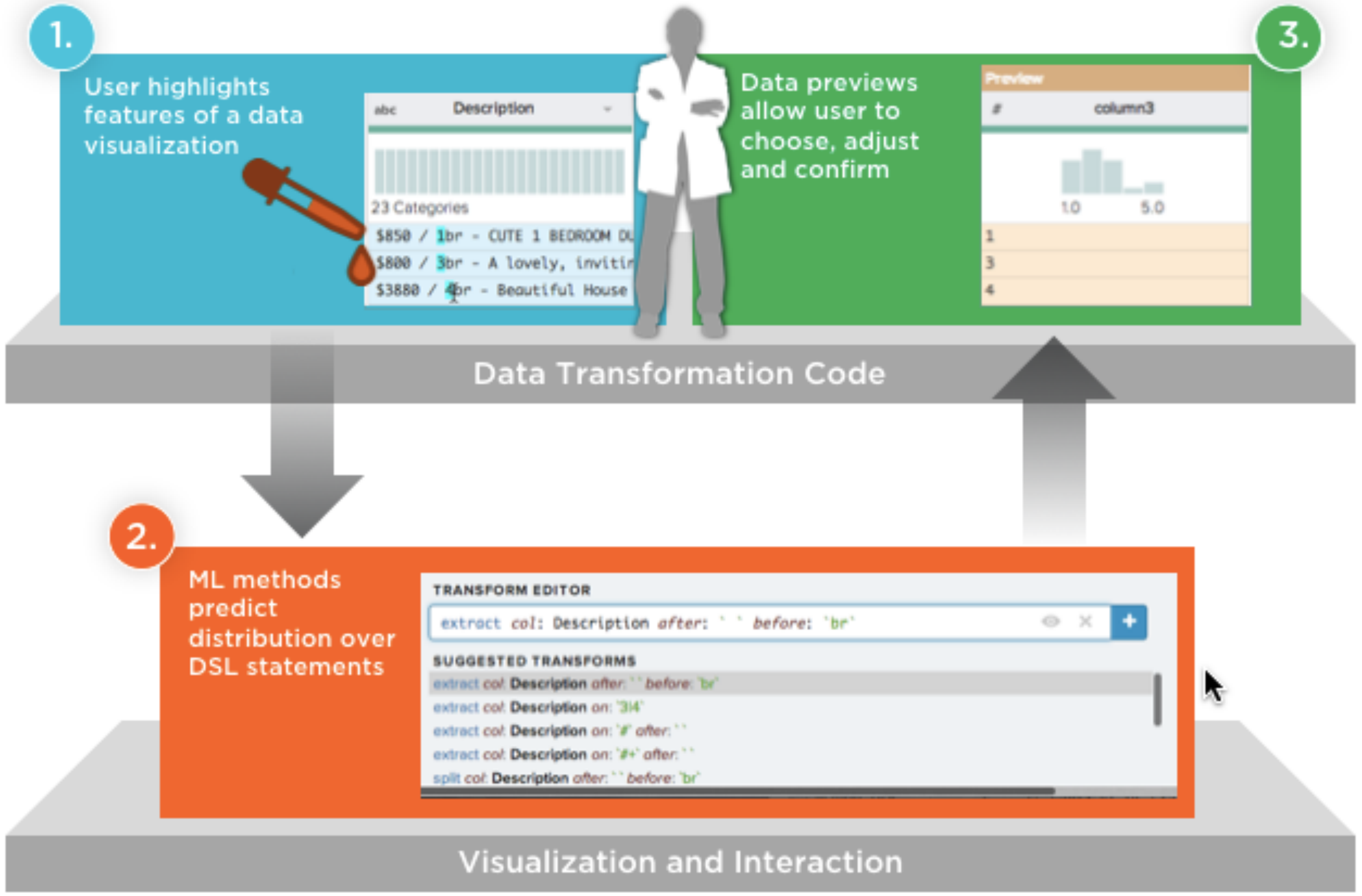


Language Design Considerations



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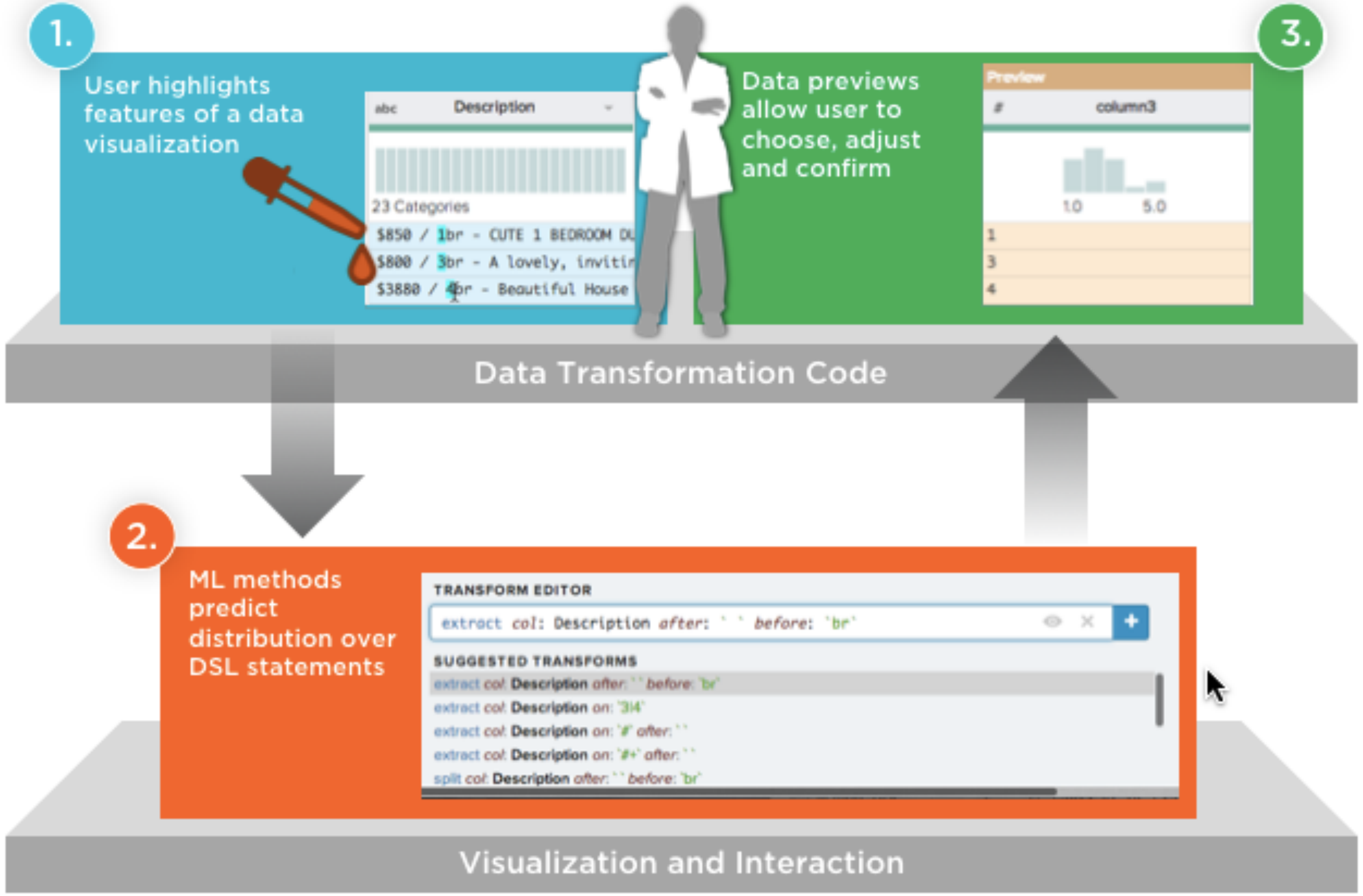

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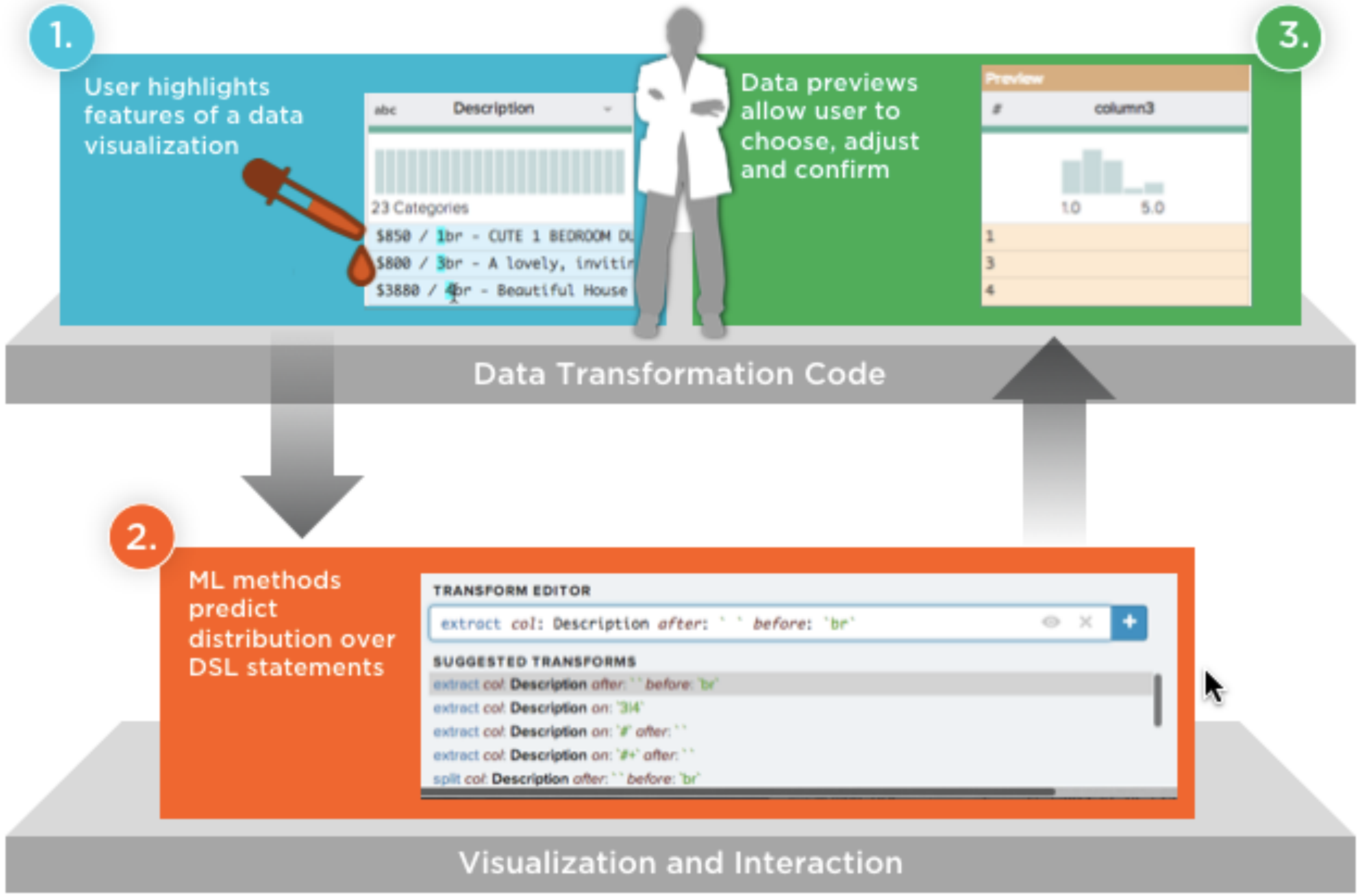

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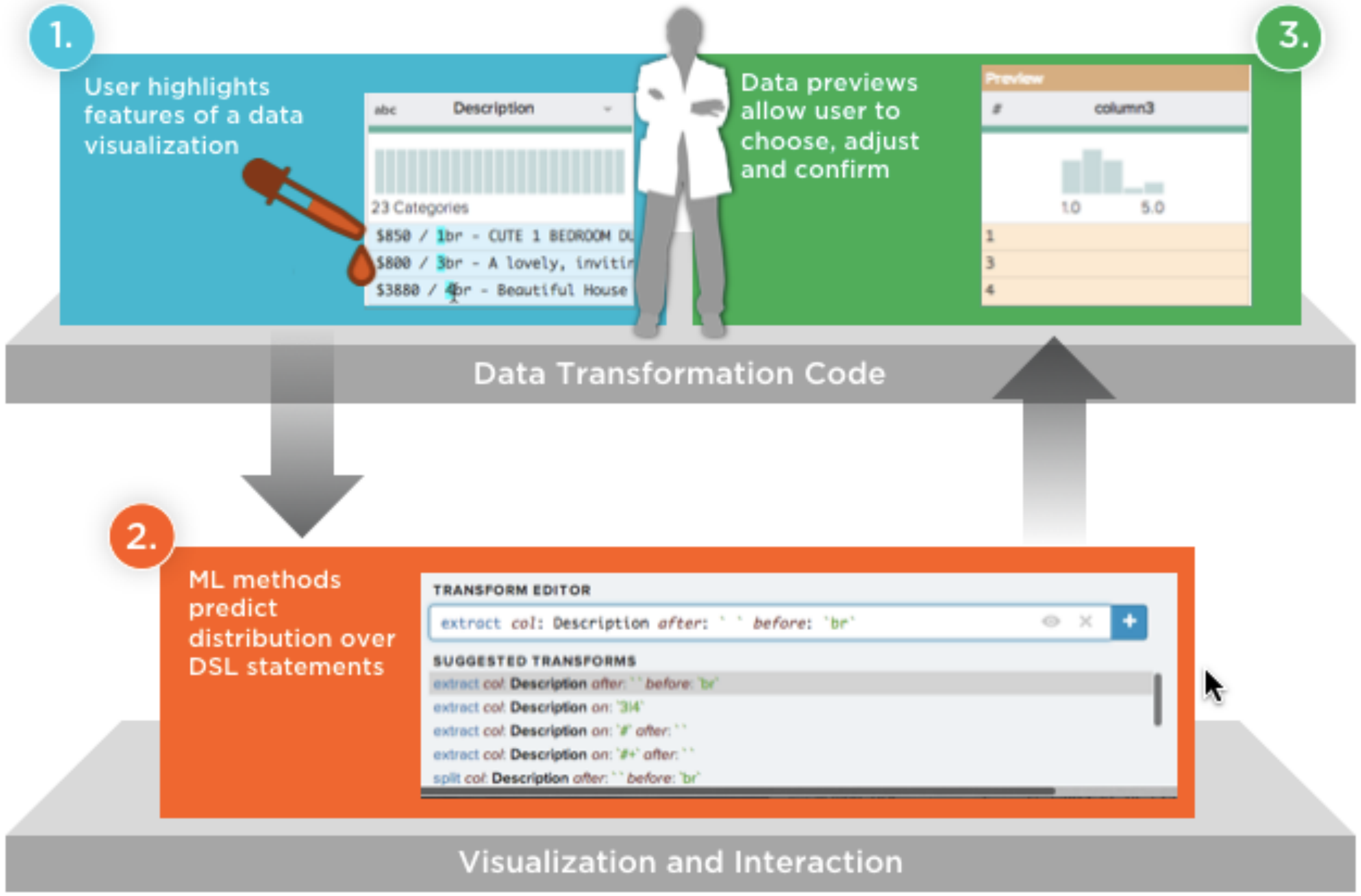

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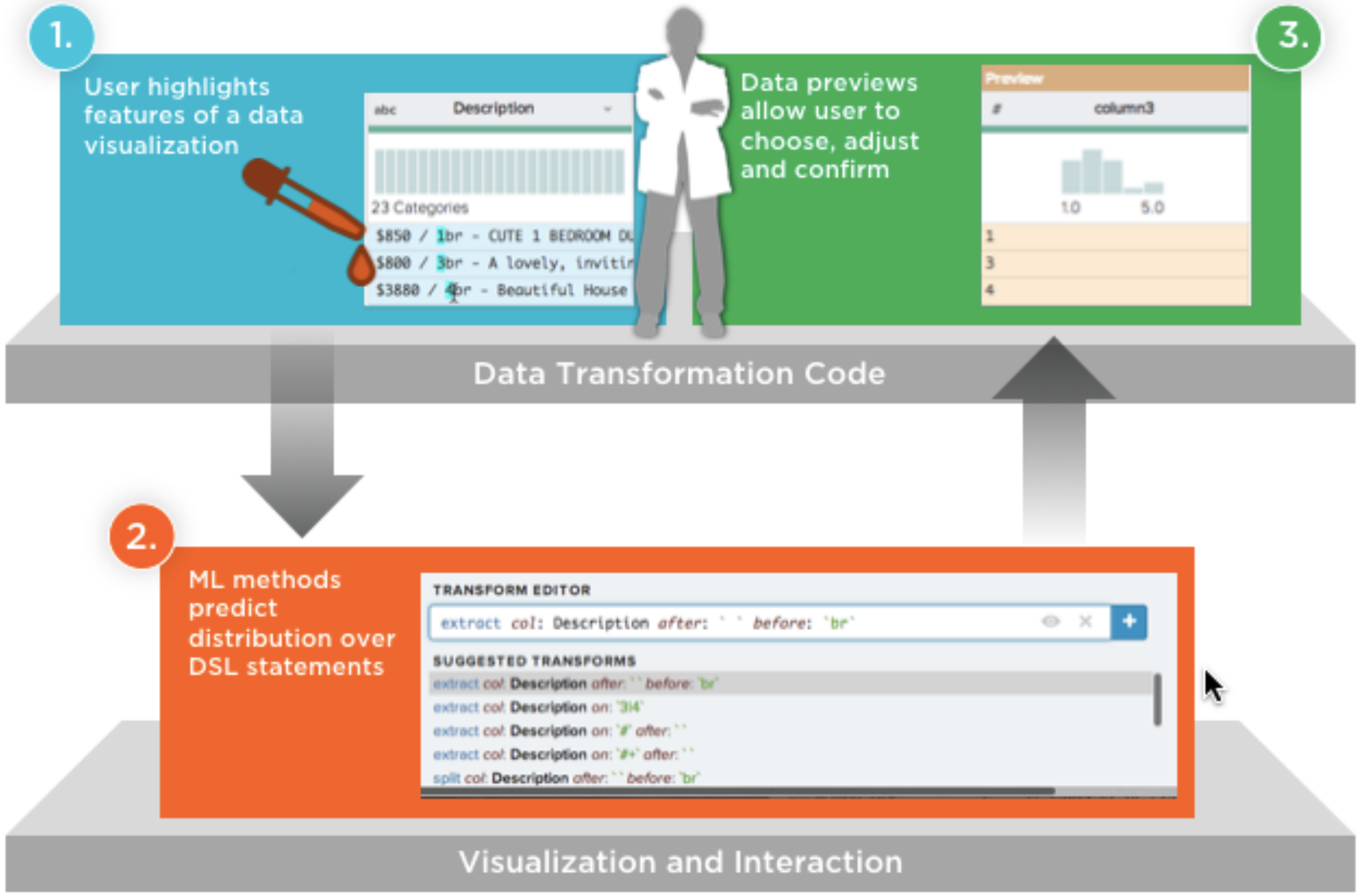
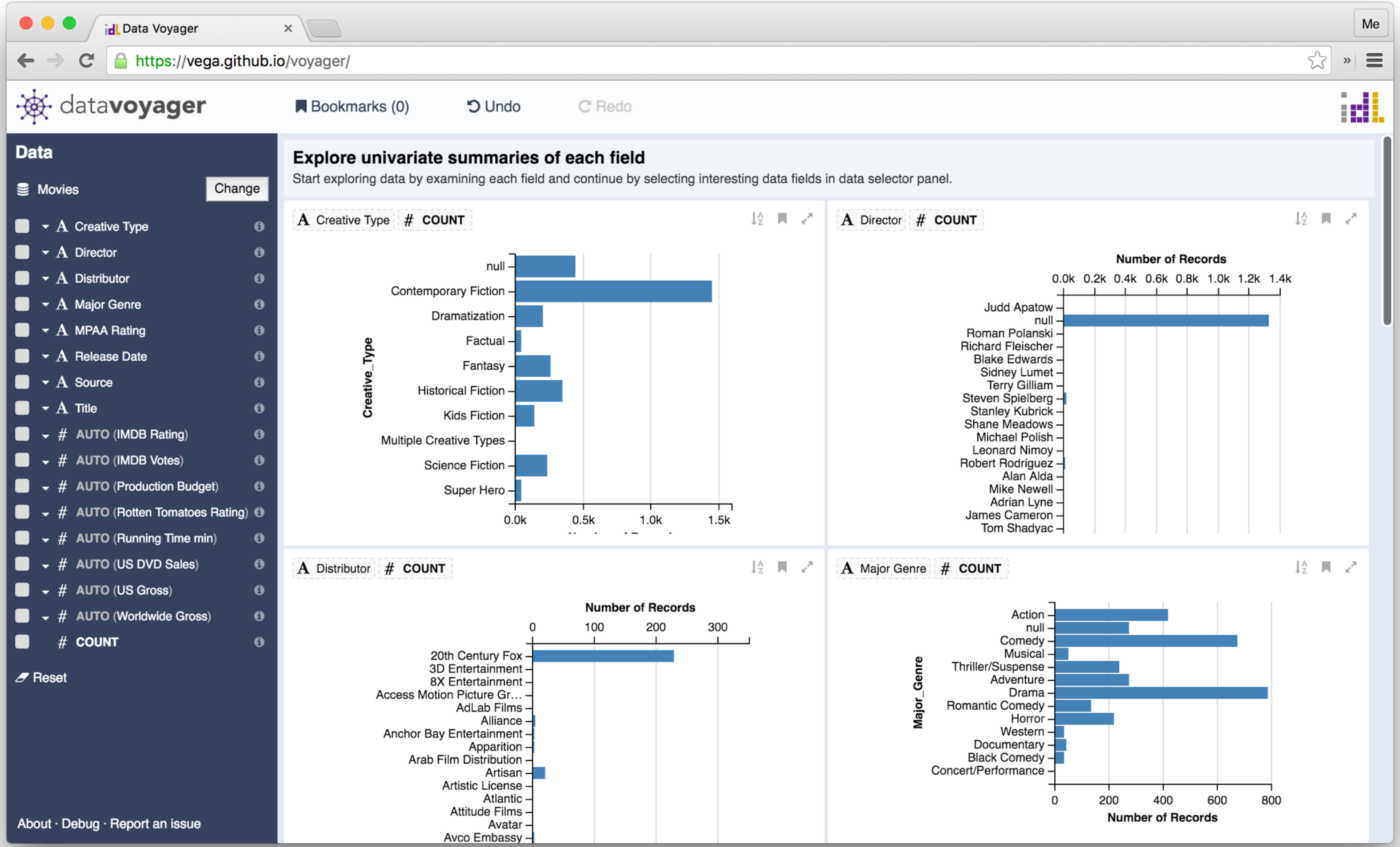
Bootstrap ranking. Can the language model provide useful suggestions without extensive training data?



Research Directions



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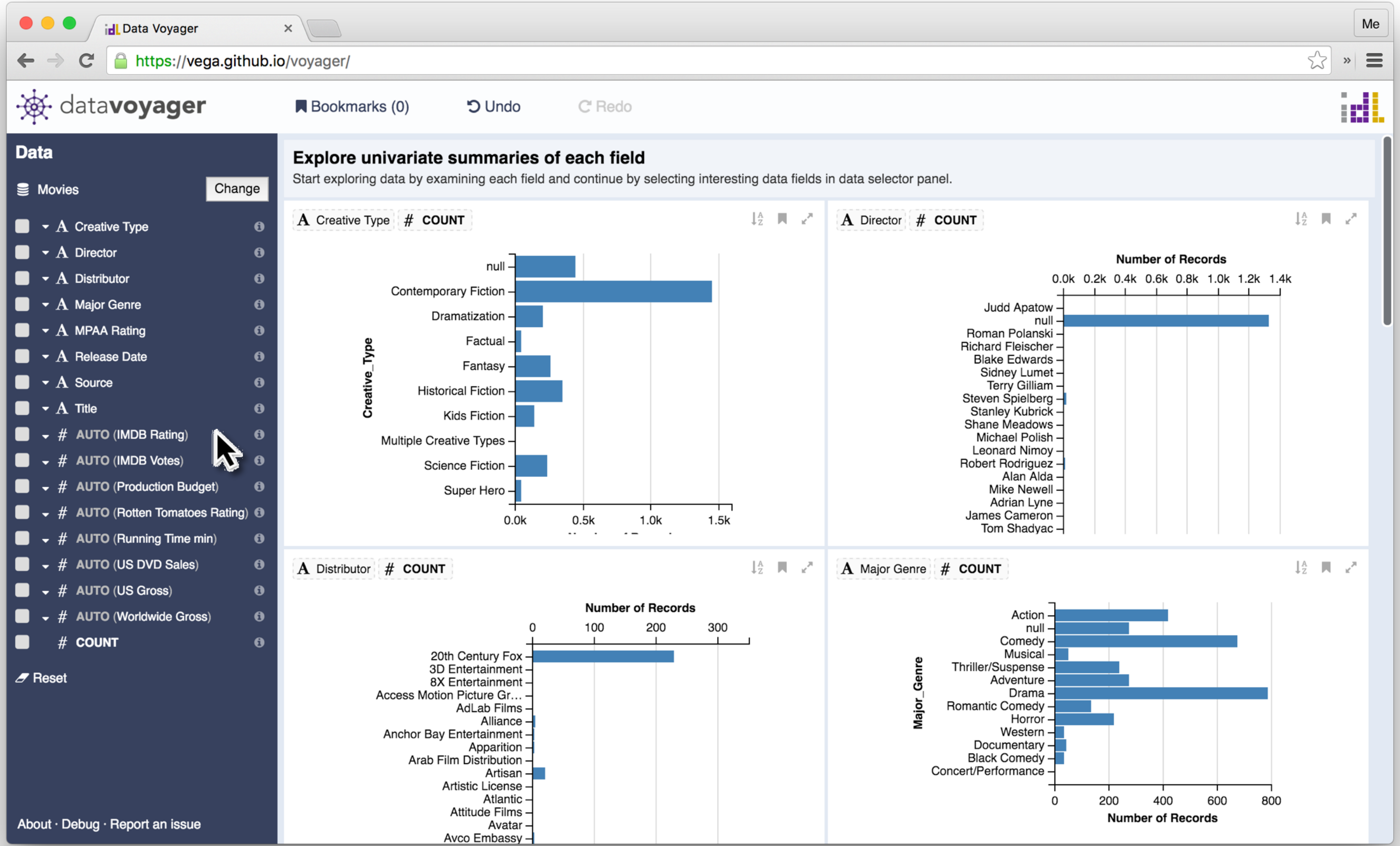

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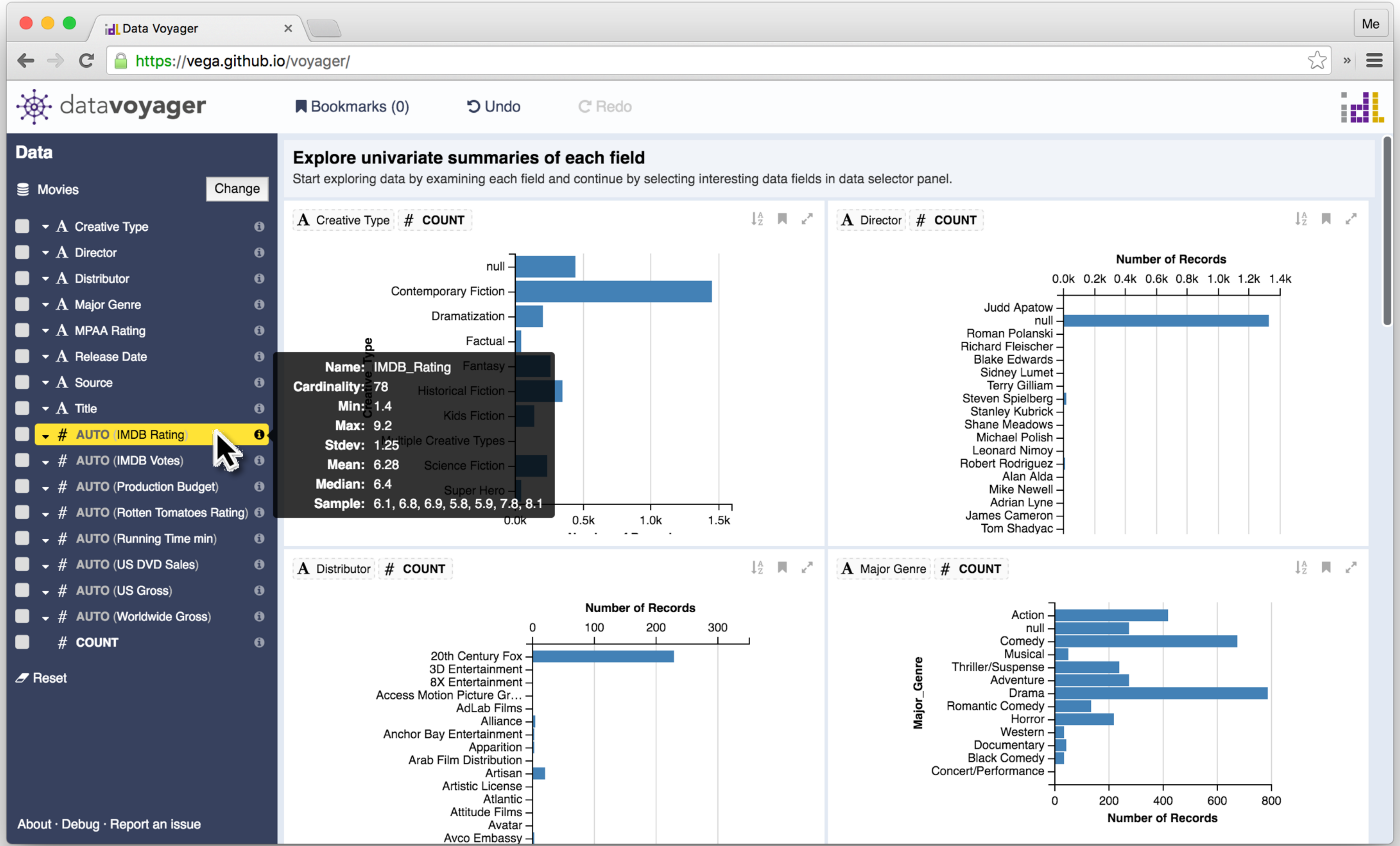

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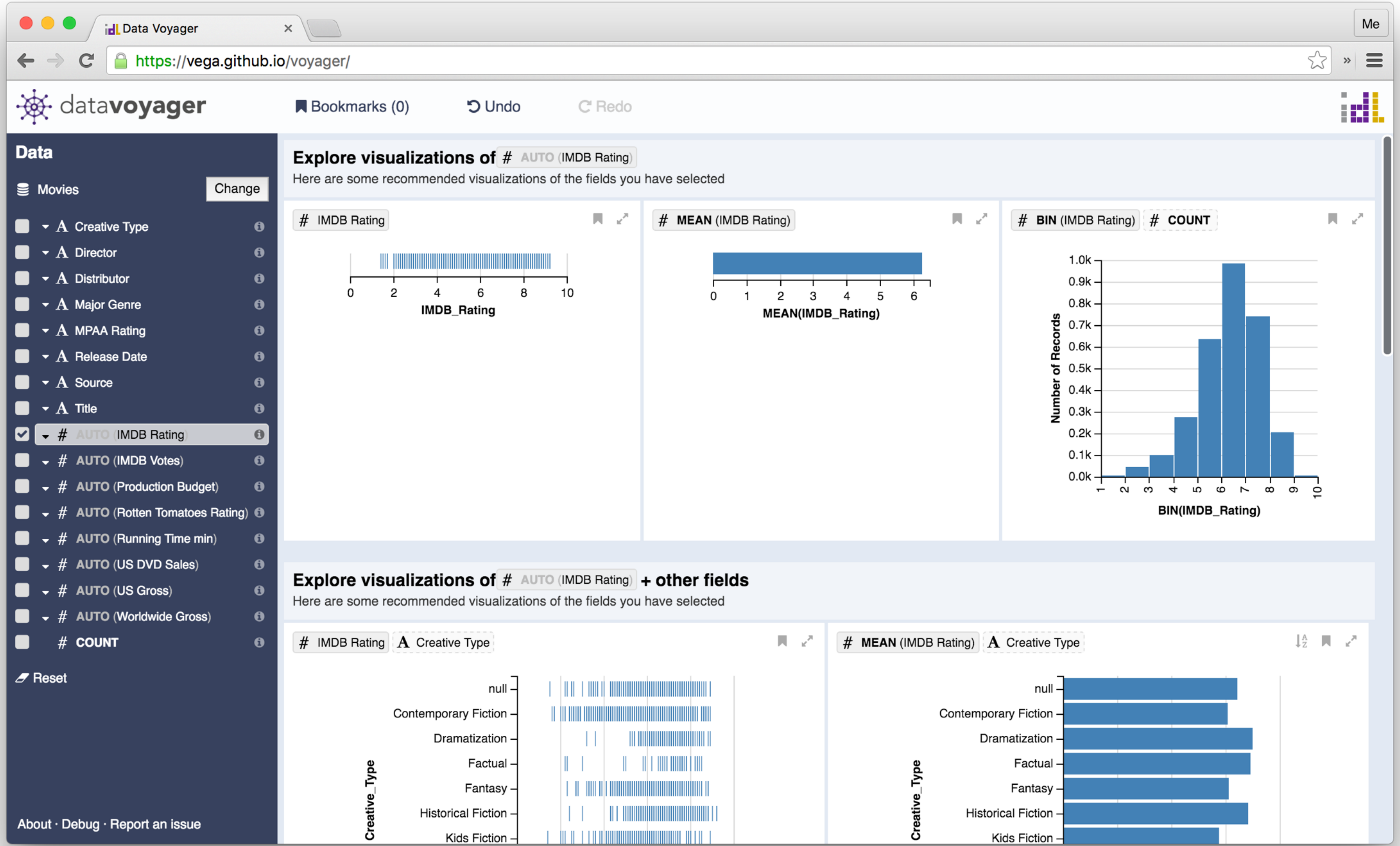

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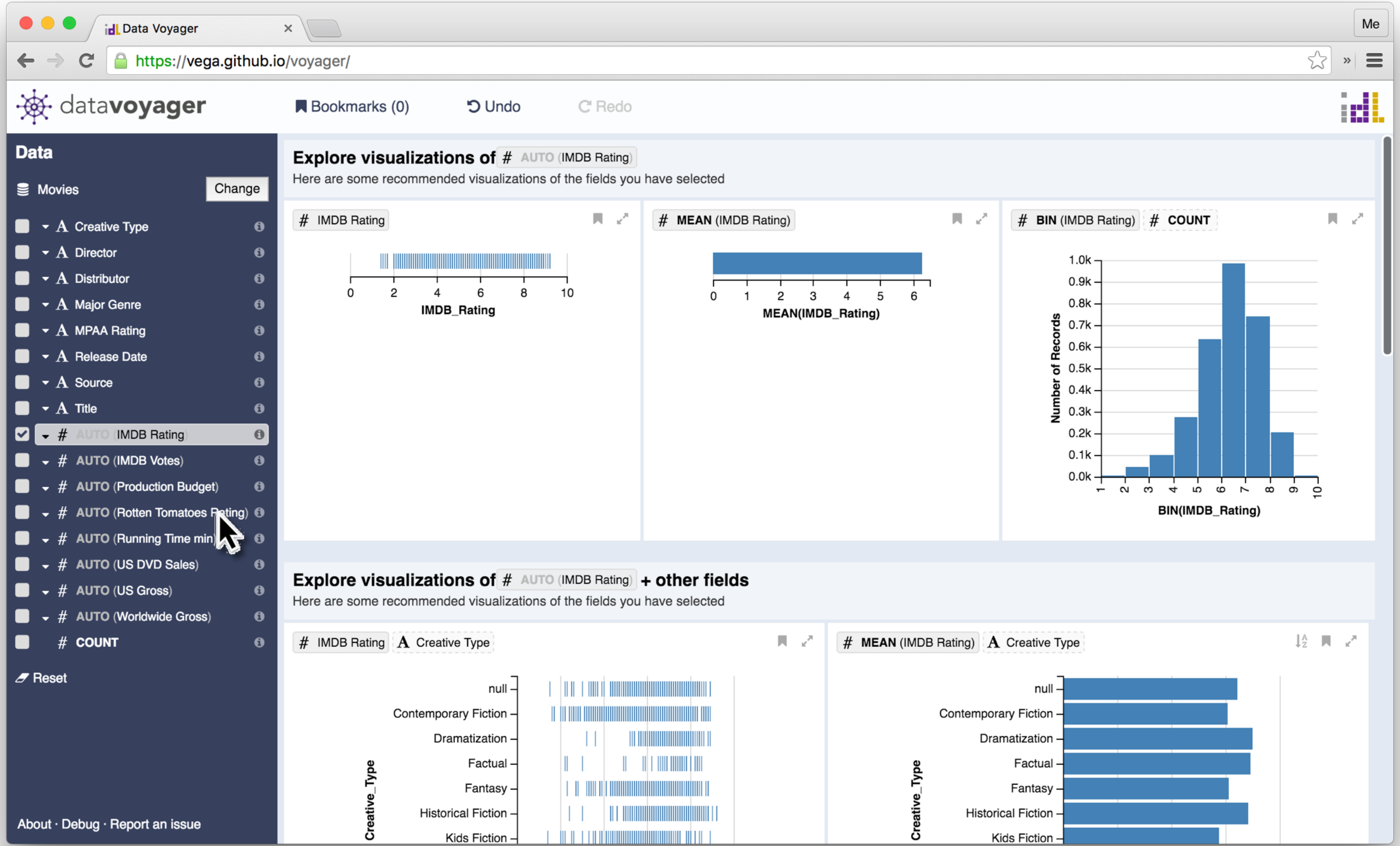

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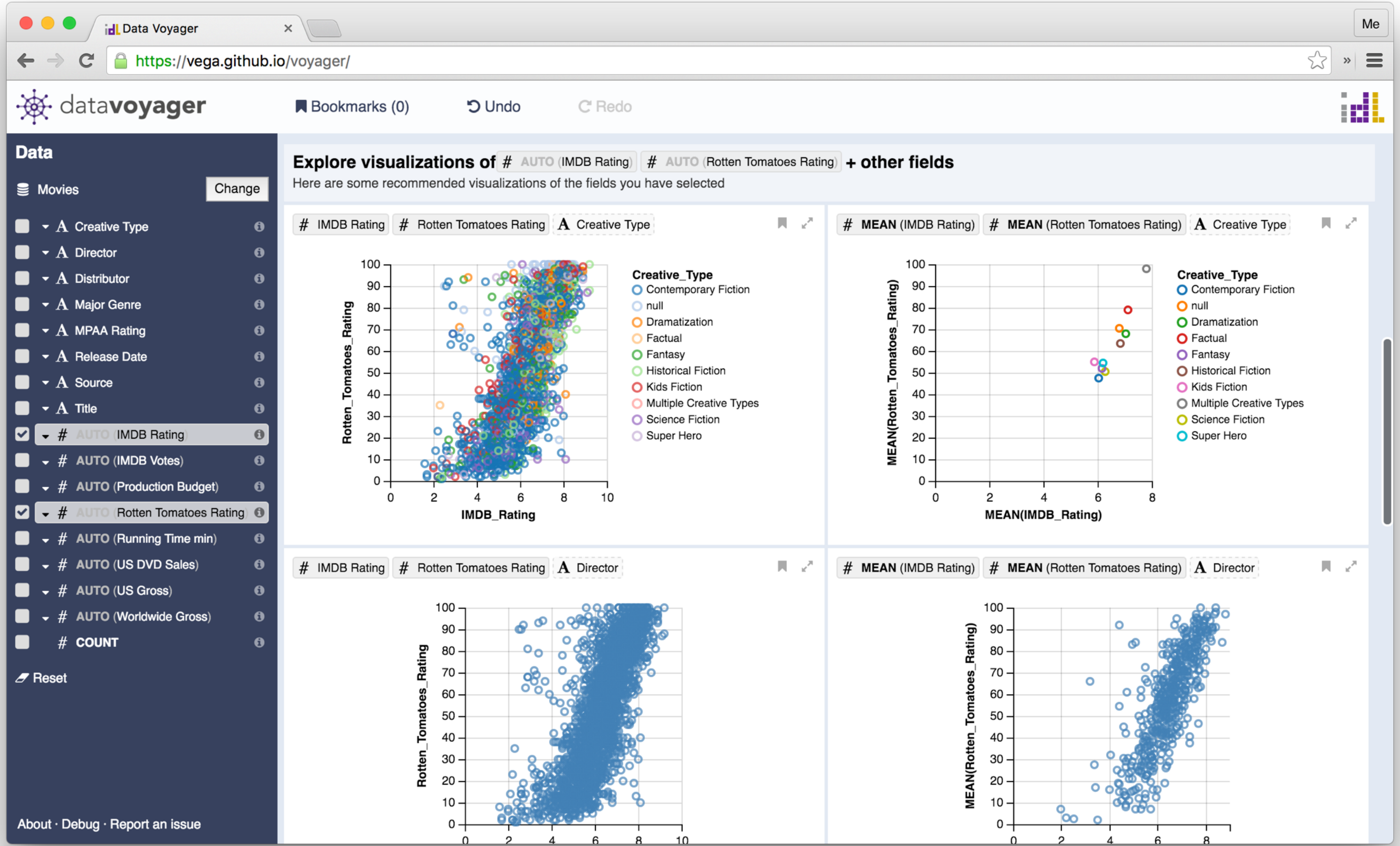

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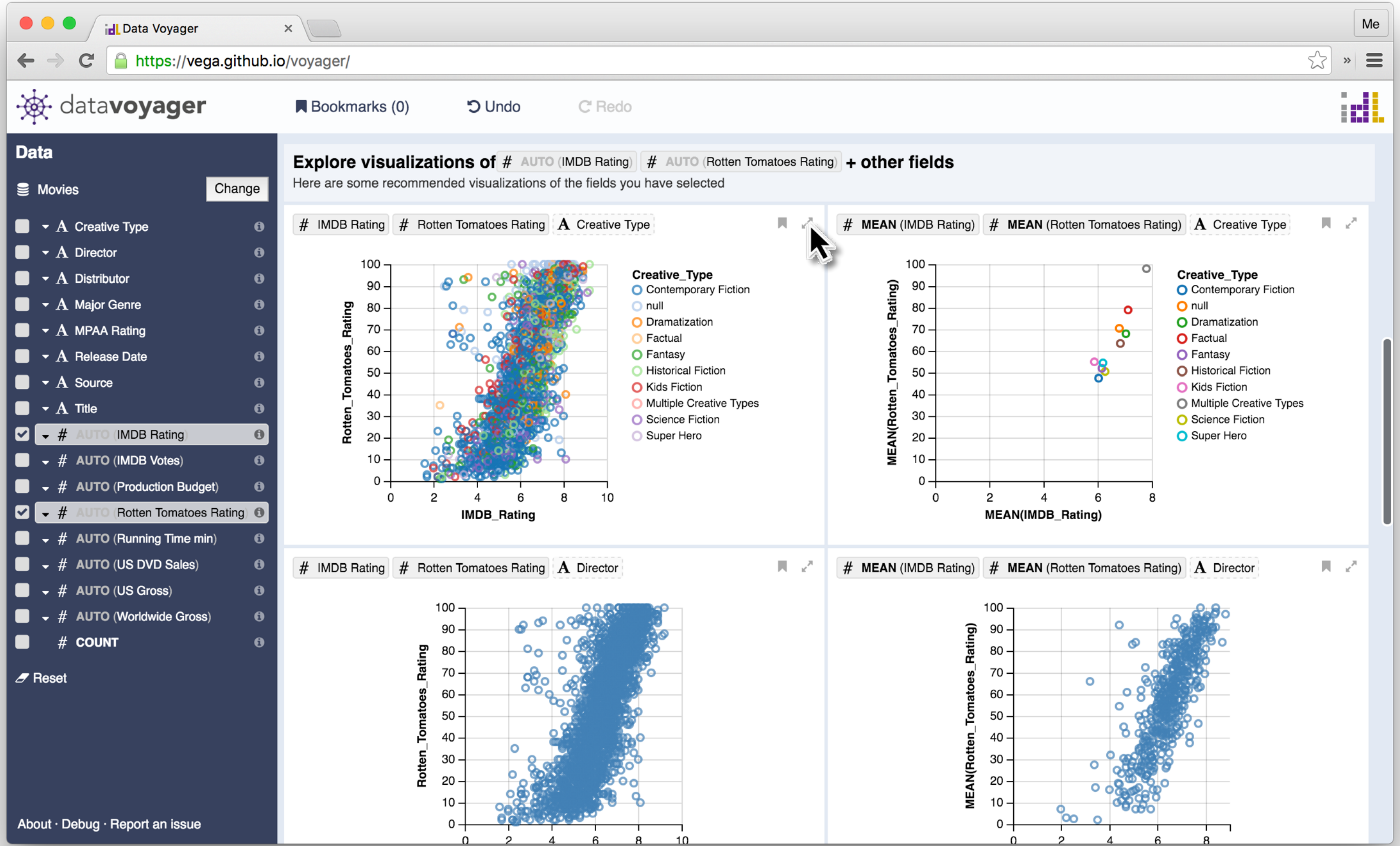

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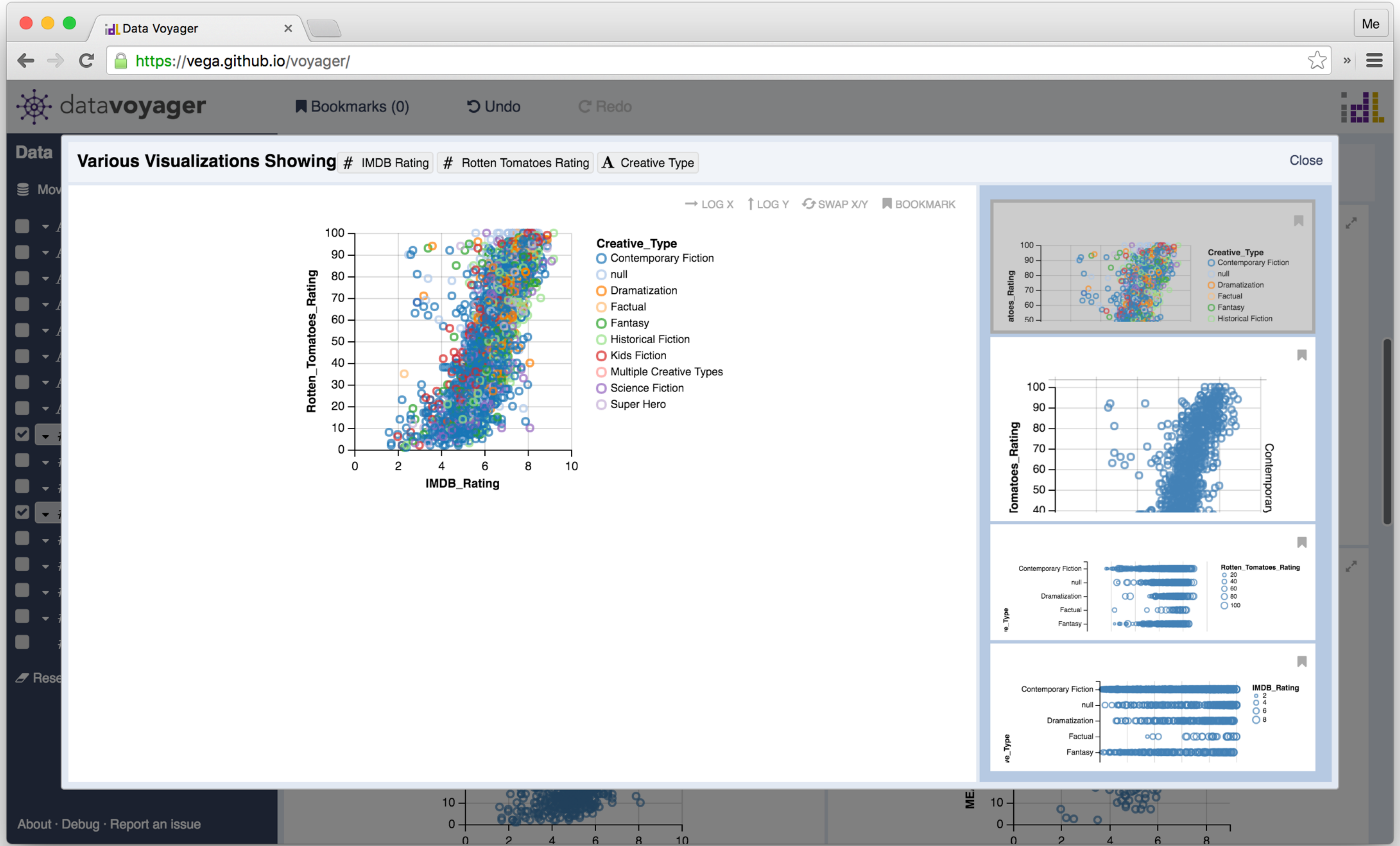

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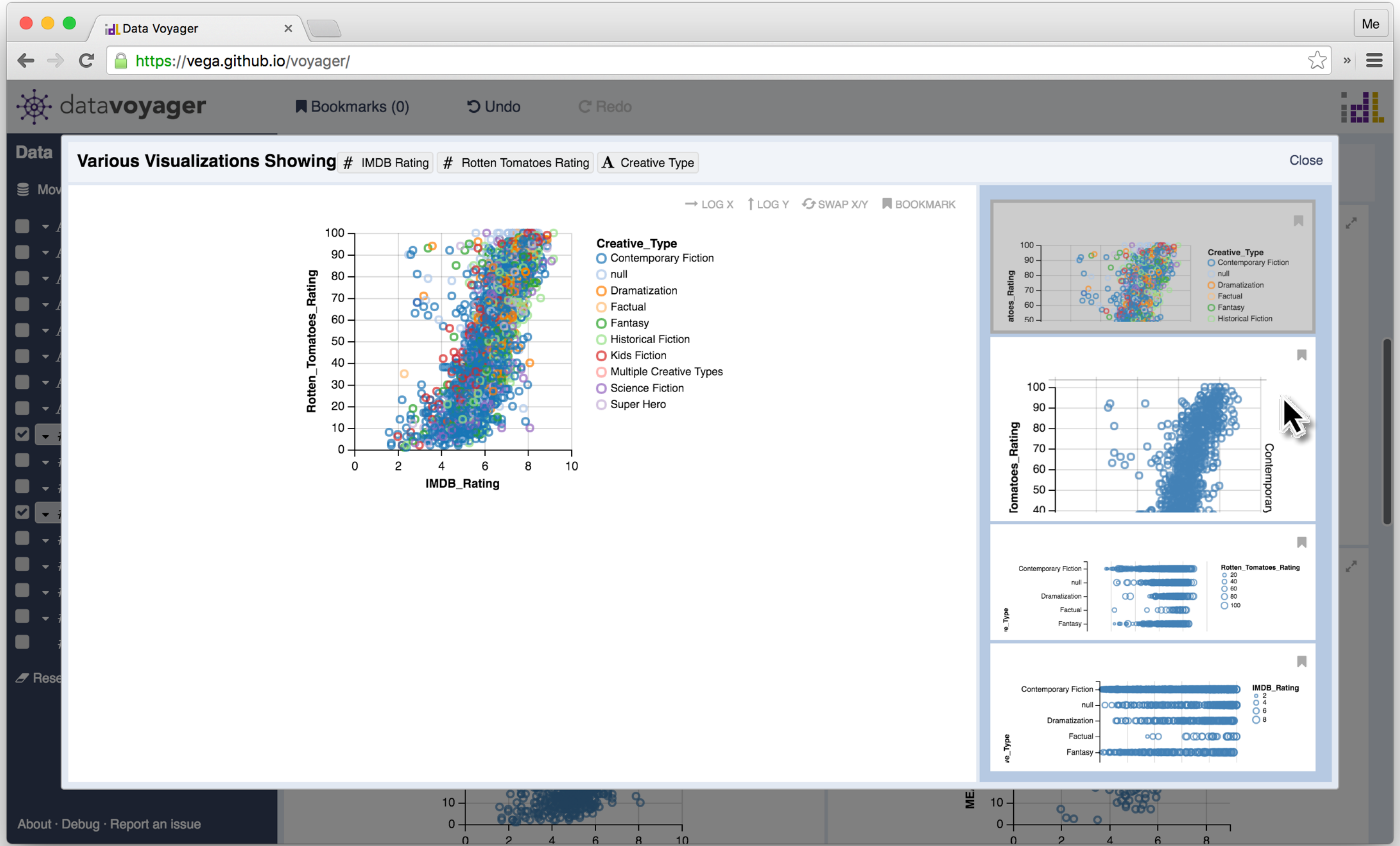

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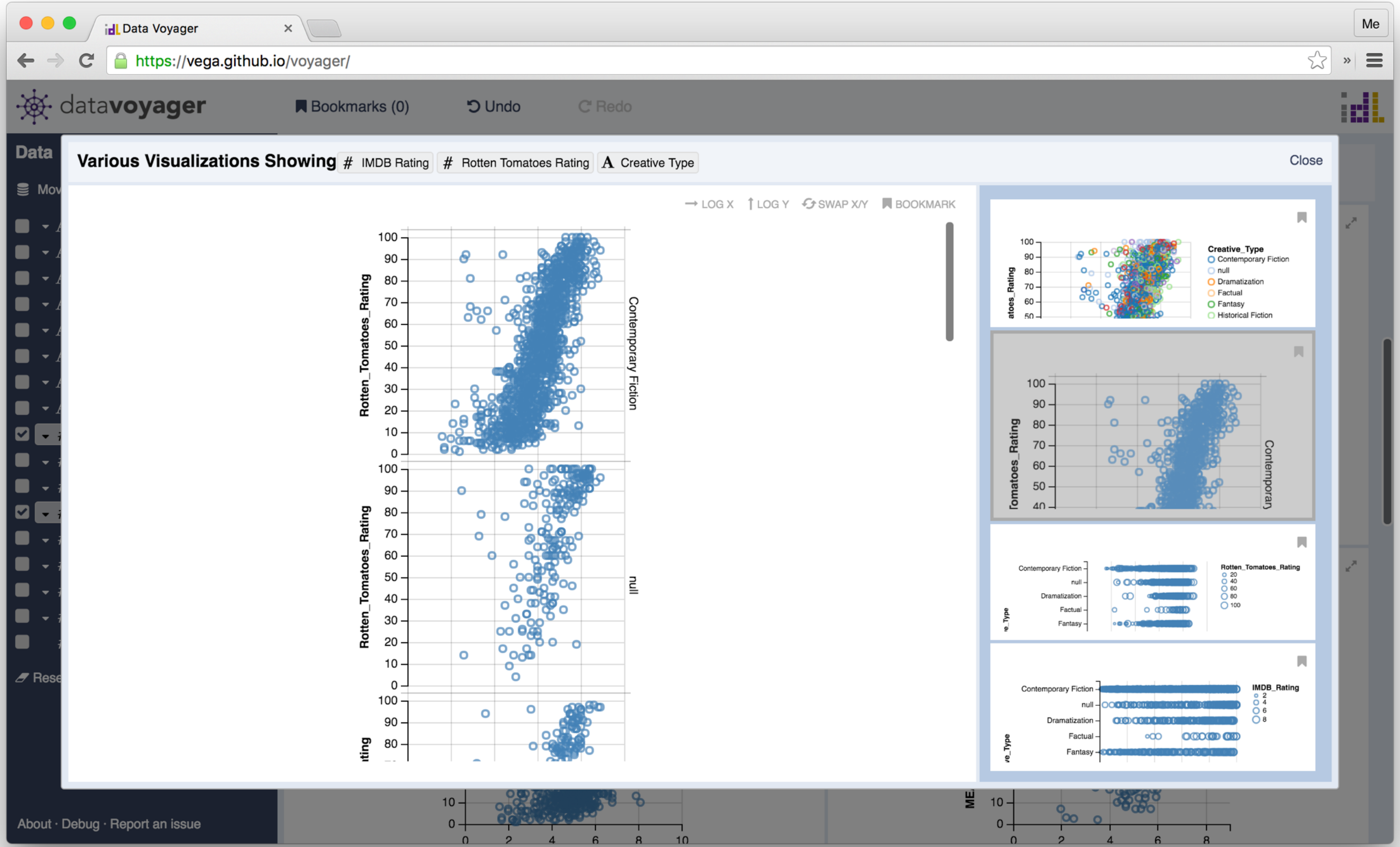

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Opportunities & Challenges

Ambiguity of Input, Ambiguity of Intent

Applicable Problem Domains & Language Designs

Mixed-Initiative Interaction

User Performance Cliffs

Error Handling & Non-Deterministic Programs

Development Costs

Research Frontiers for UI Toolkits

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Design Tools for Domain-Specific Languages

Prototype task structures. Analogous to information architecture.

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Interfaces that Learn
Provide standard set of inference procedures.
Synthesize instrumentation to enable learning over time.
Visualize and inspect domain-adapted language models.

Objectives

Accelerate successful task completion.

Scale to large data or batch repetition.

Support discovery and ambiguous intent.

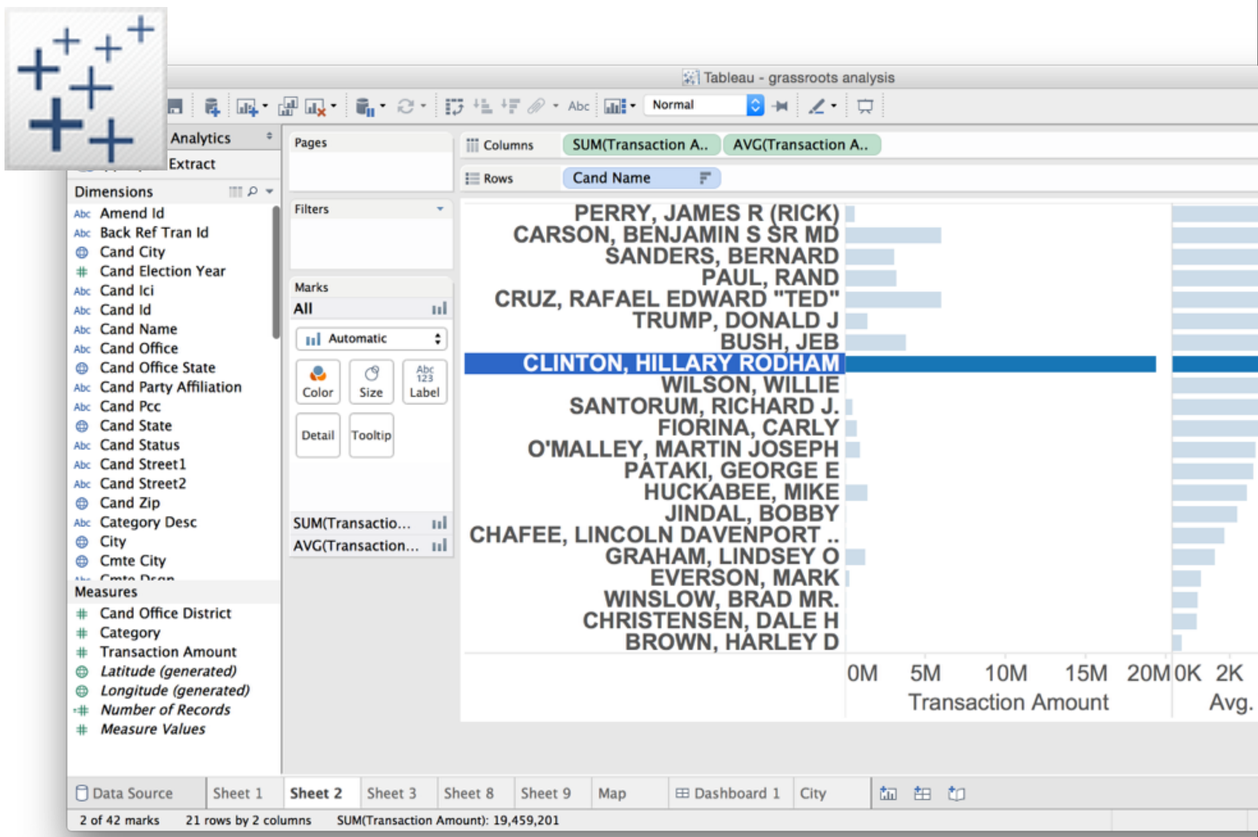
Long-term learning and improvement.

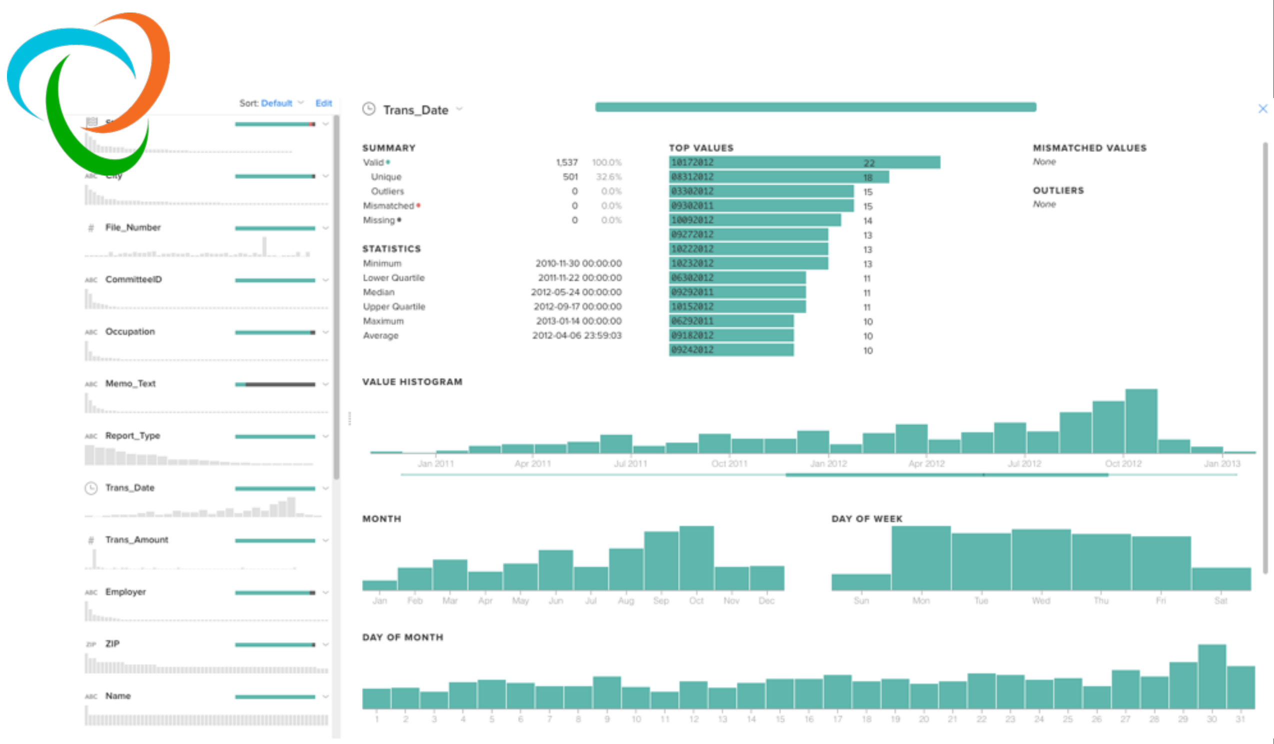
Strategy

Model user interface actions in a **domain-specific language (DSL)**. Leverage the language to

(1) predict potential actions, and

(2) decouple UI from underlying runtime.





Predictive Interaction

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