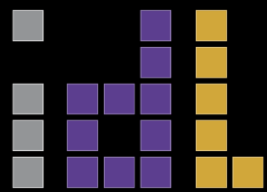


Agency + Automation

Jeffrey Heer @jeffrey_heer

U. Washington / Trifacta





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



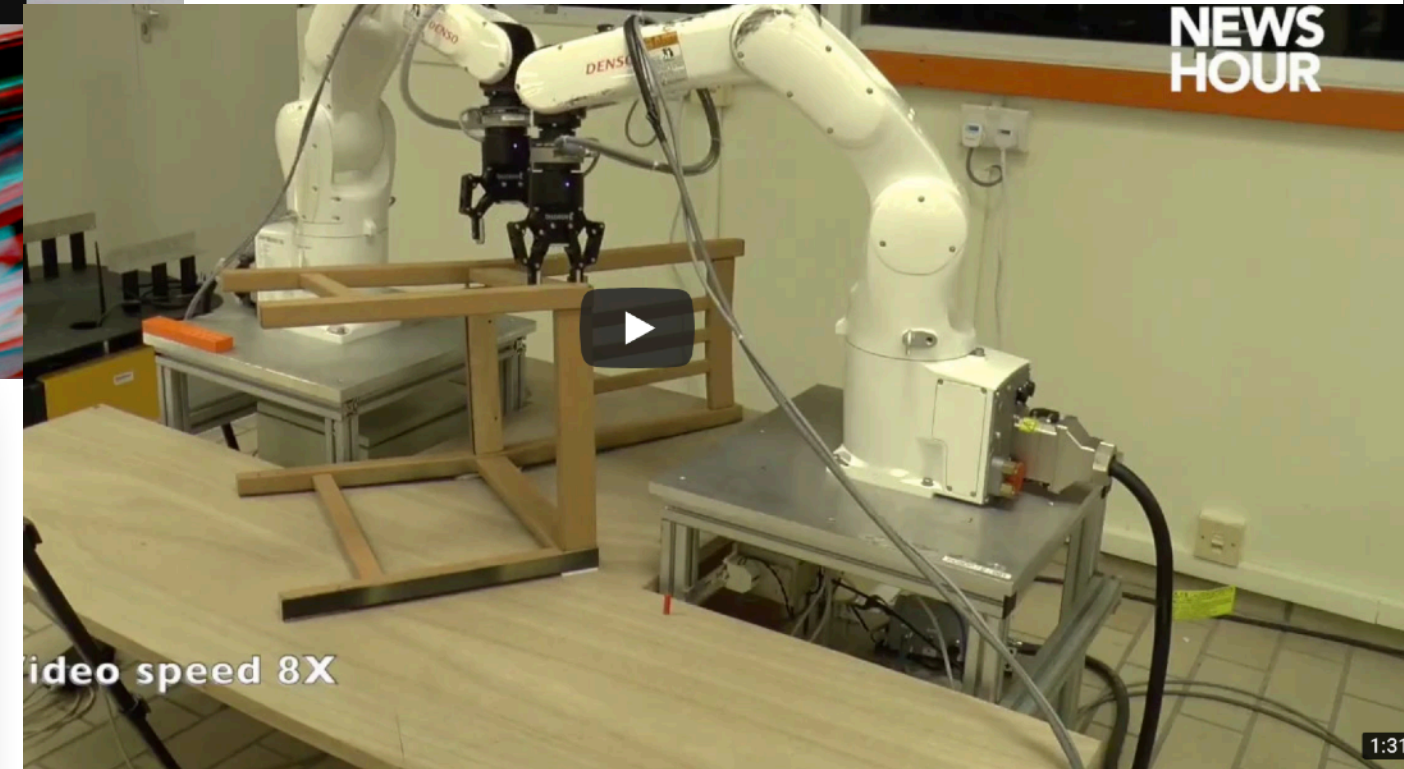
Andrew Ng ✓
@AndrewYNg

Following

Should radiologists be worried about their jobs? Breaking news: We can now diagnose pneumonia from chest X-rays better than radiologists.

stanfordmlgroup.github.io/projects/chexn...

3:20 PM - 15 Nov 2017 from Mountain View, CA

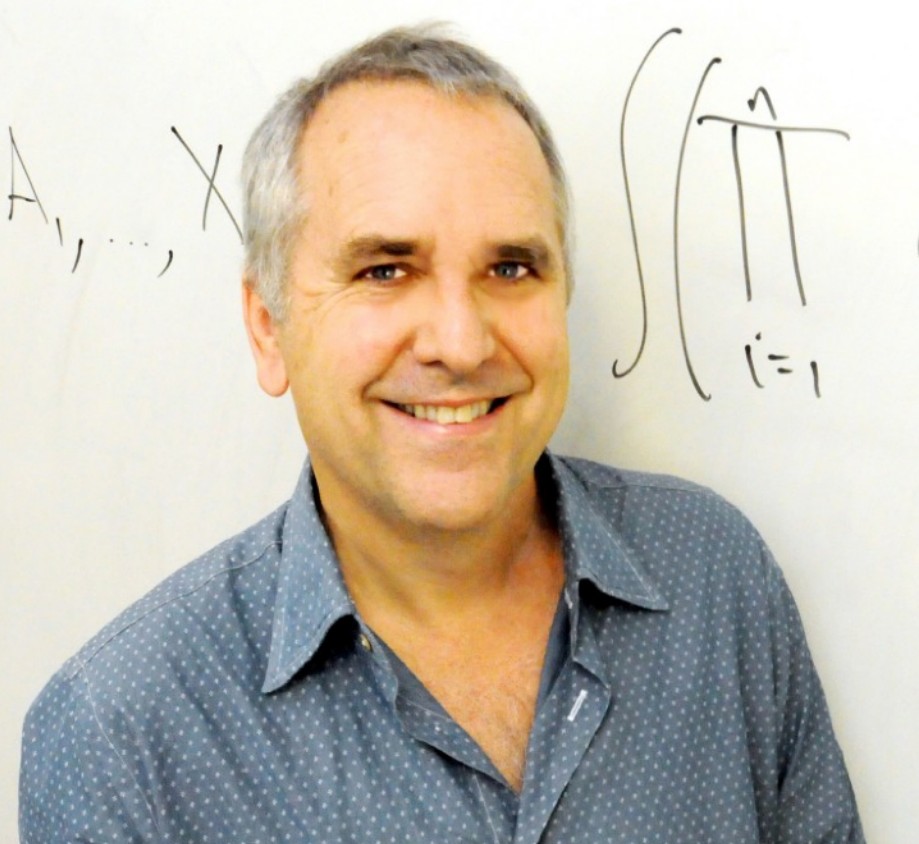


Analysis: Robots have achieved what humans never will – assembling an IKEA chair in less than 21 minutes



"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]

**While timely, these are not
new observations...**

Provide significant value-added automation.

Support uncertainty around user goals.

Allow efficient direct invocation and termination.

Employ dialog to resolve key uncertainties.

Provide mechanisms for agent-user collaboration to refine results.

Continue to learn by observing user actions.

Eric Horvitz [CHI 1999]

Principles of Mixed-Initiative User Interfaces

Eric Horvitz

Microsoft Research
Redmond, WA 98025 USA
+1 425 936 2127
horvitz@microsoft.com

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 are needed if we

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.

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.***"

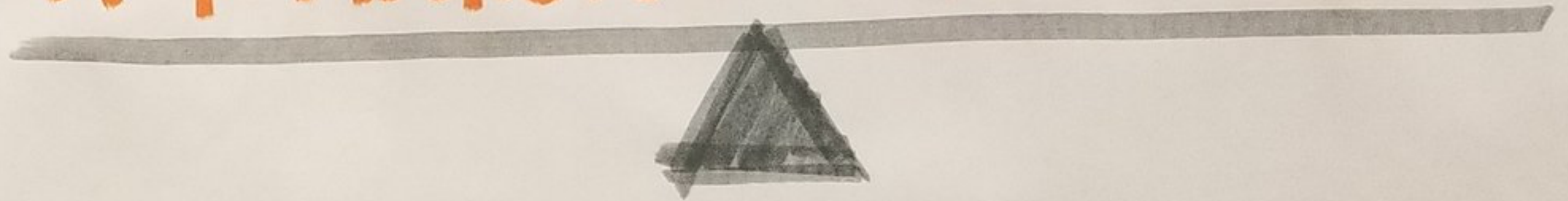
Yehoshua Bar-Hillel [Advances in Computers 1960]

DESIGN CHALLENGE:

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

AUTOMATION

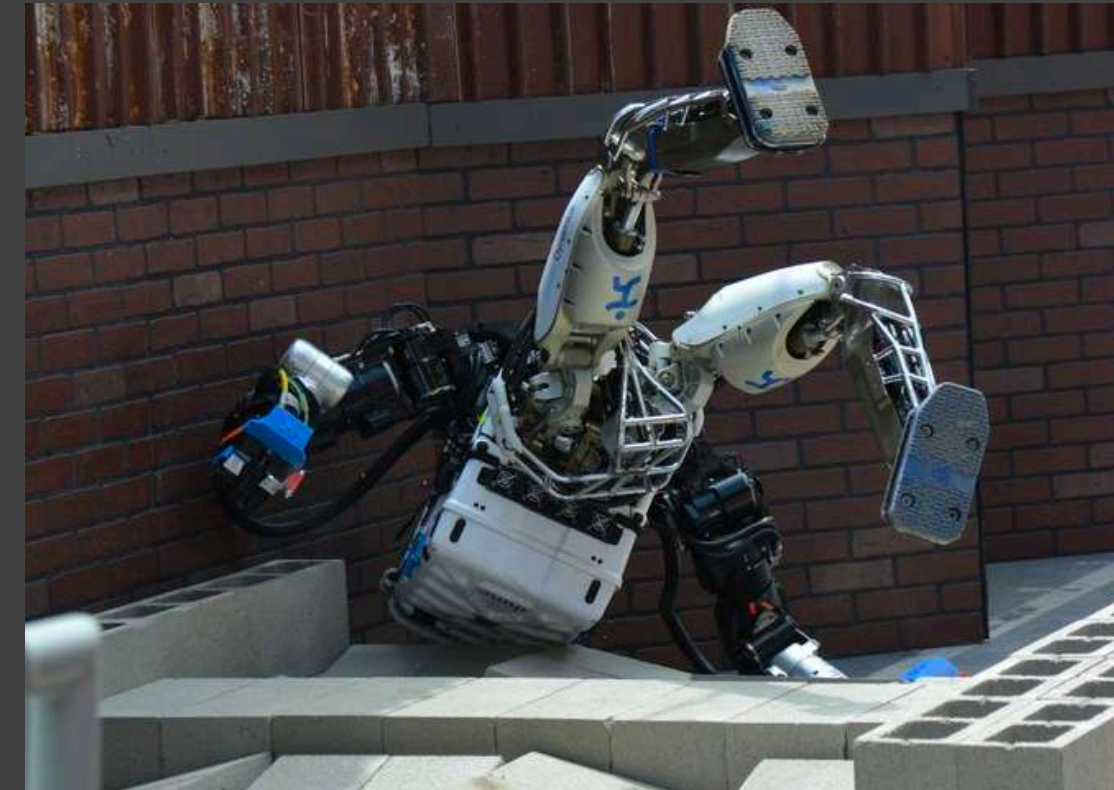
USER CONTROL



Balancing Automation and Control

Challenges of Automation:

Automated methods may be biased or inaccurate.
Consequences of poor models let loose in the world.
Loss of critical engagement & domain expertise.



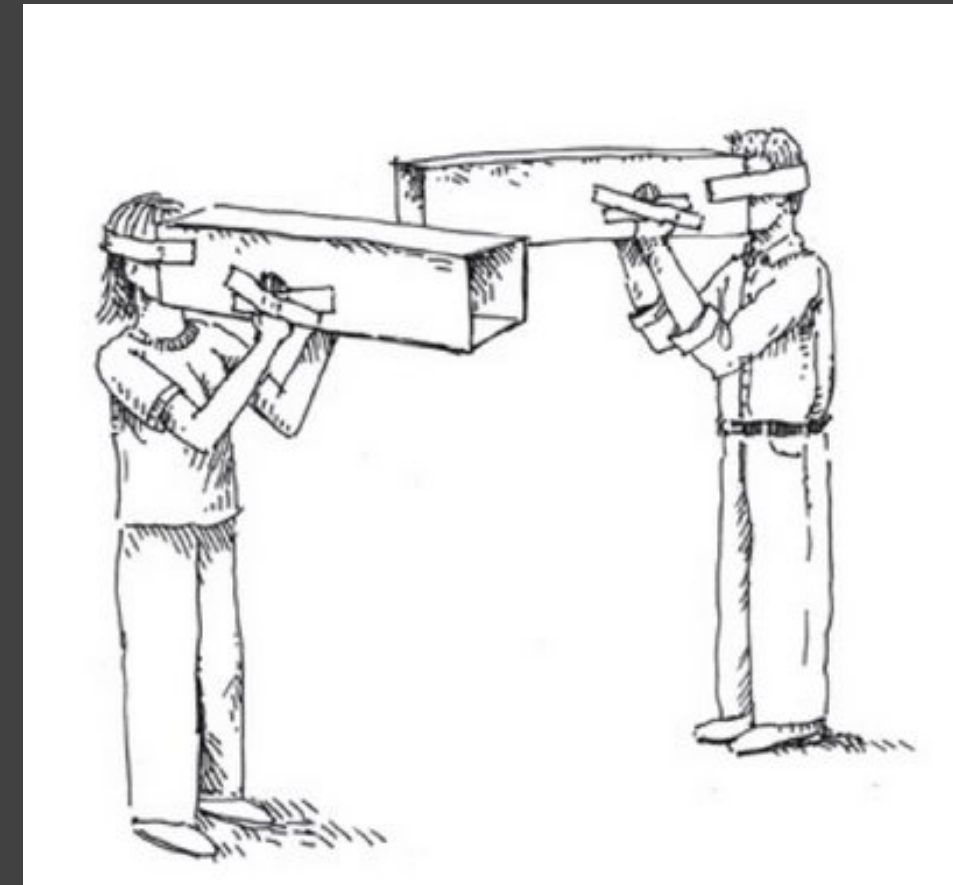
Balancing Automation and Control

Challenges of Automation:

Automated methods may be biased or inaccurate.
Consequences of poor models let loose in the world.
Loss of critical engagement & domain expertise.

Challenges of User Control:

Ambiguity of intent. Scale. Cognitive biases, mistakes.
Lack of global view -> overweight local information.



Balancing Automation and Control

Challenges of Automation:

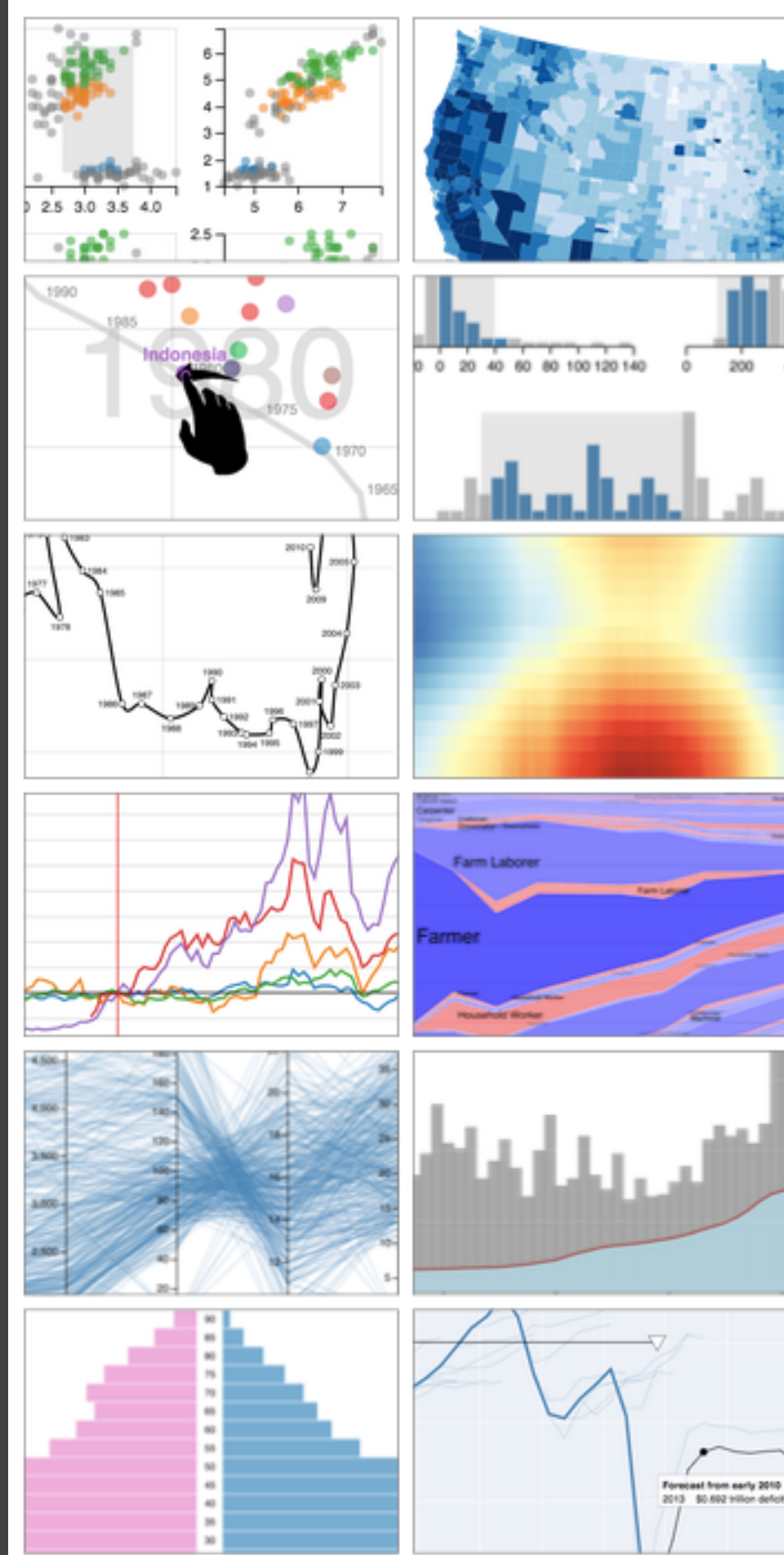
Automated methods may be biased or inaccurate.
Consequences of poor models let loose in the world.
Loss of critical engagement & domain expertise.

Challenges of User Control:

Ambiguity of intent. Scale. Cognitive biases, mistakes.
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.



EXAMPLES:

Exploratory Data Visualization

Data Cleaning & Transformation

Natural Language Translation

EXAMPLES:

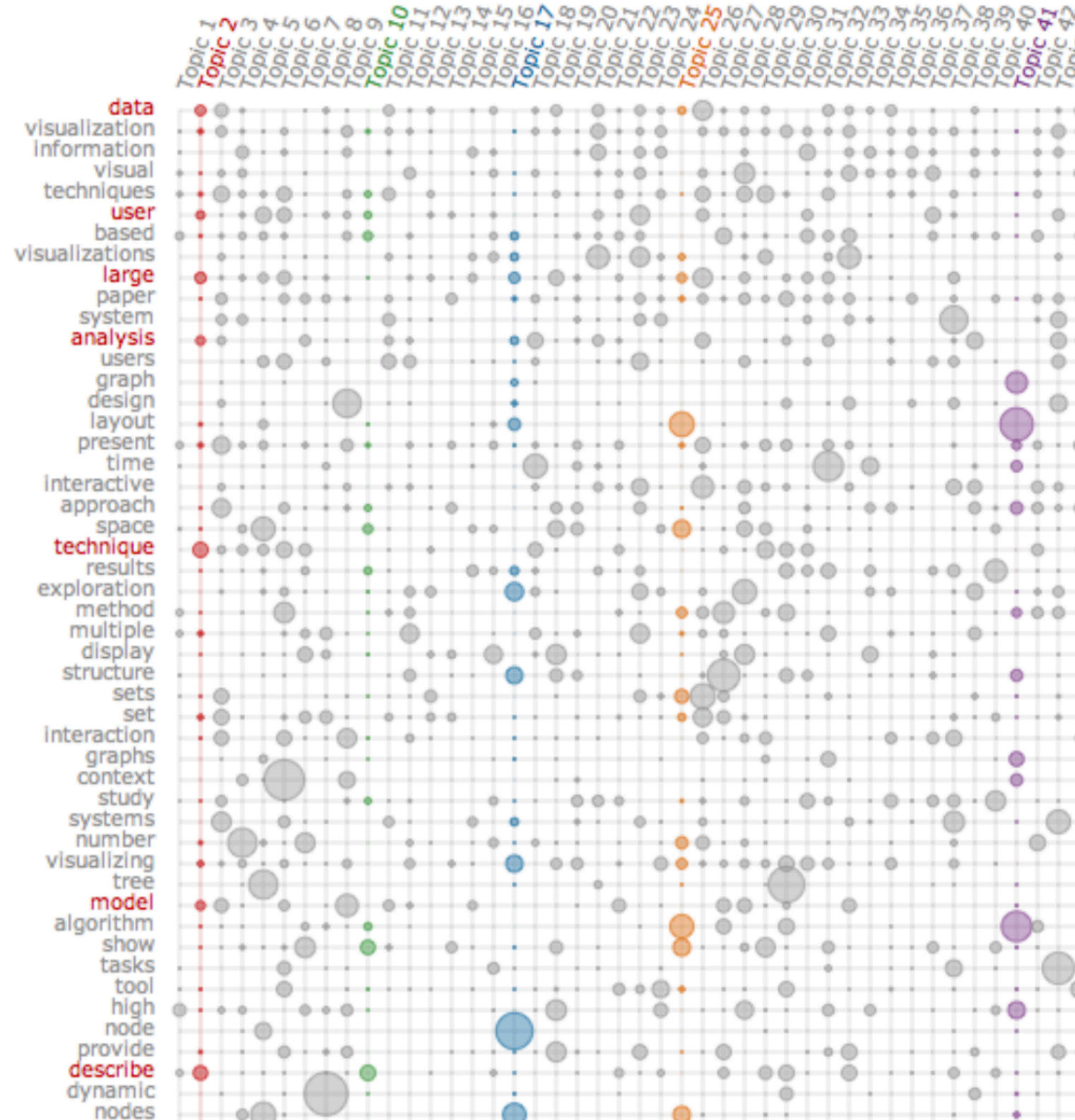
Exploratory Data Visualization

Data Cleaning & Transformation

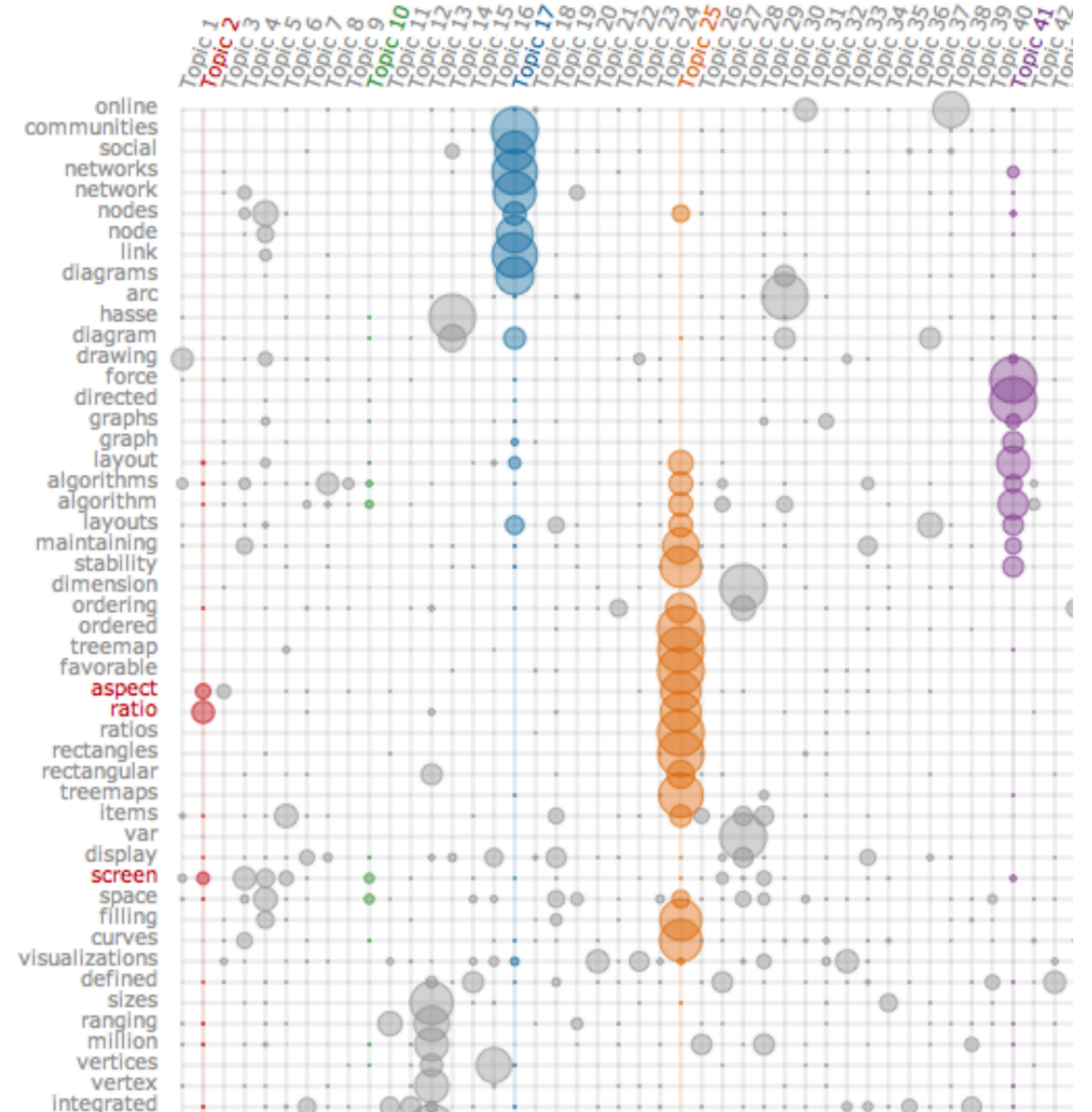
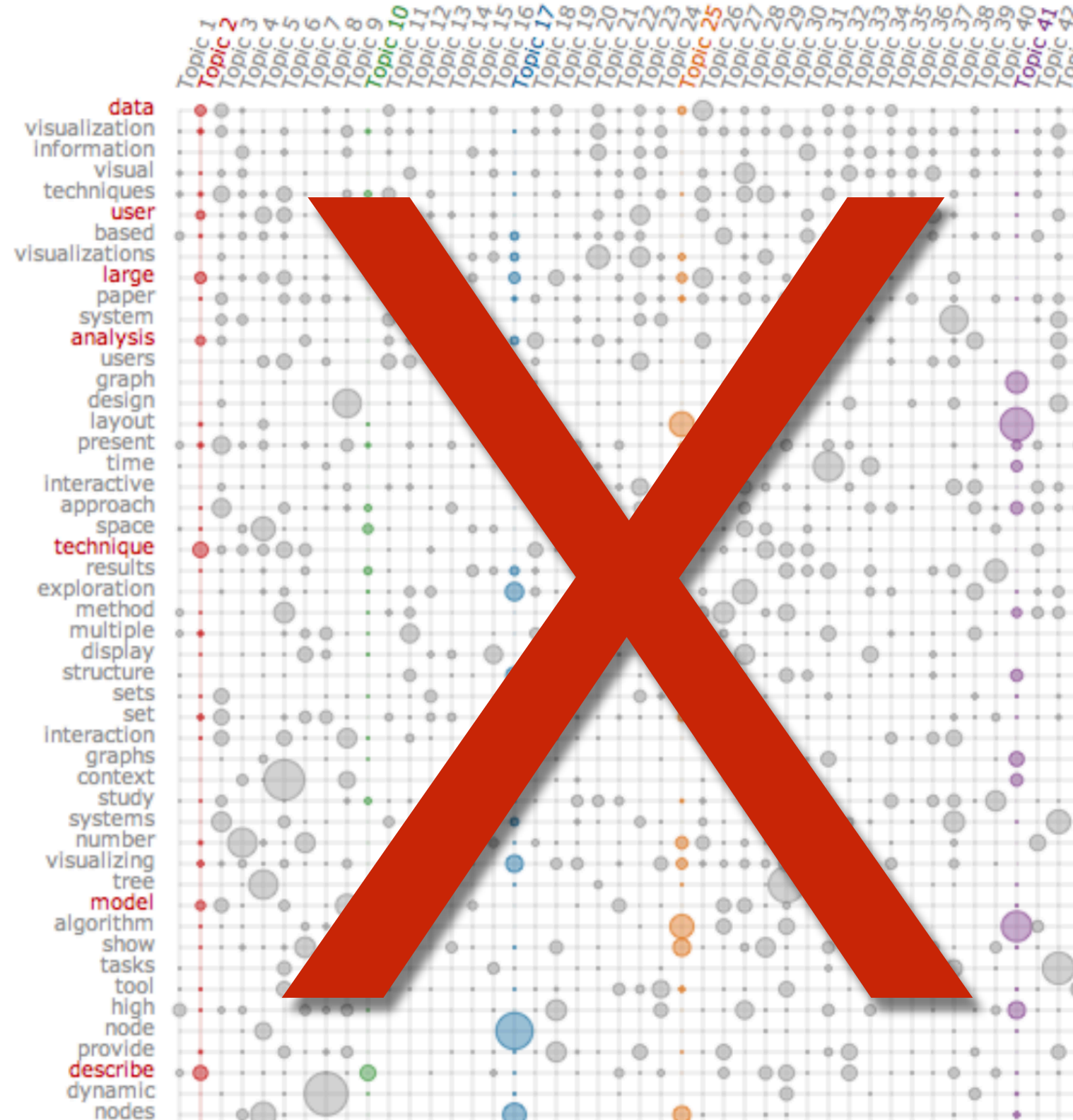
Natural Language Translation



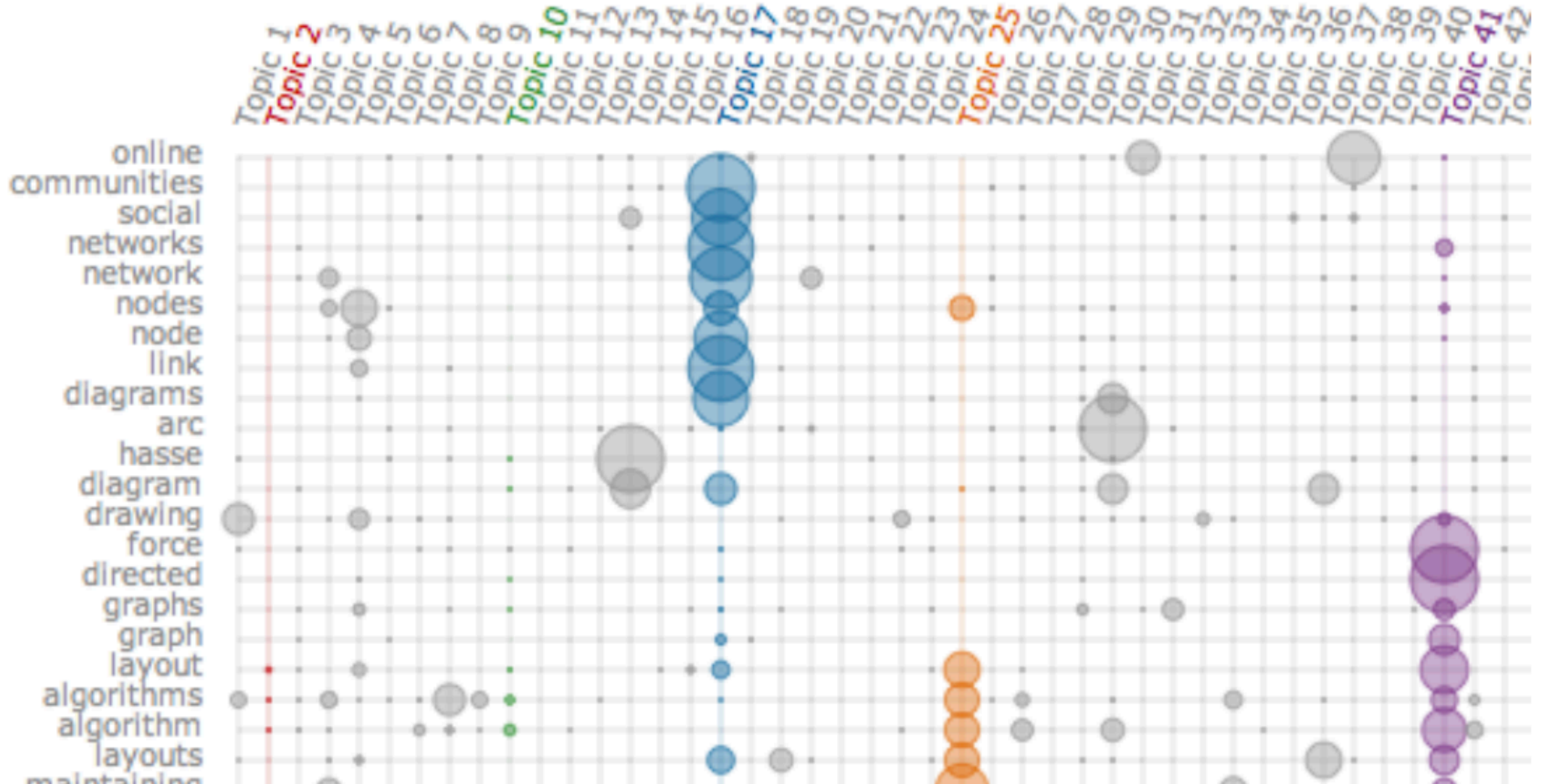
Topic Model Visualization [Chuang et al. 2012]



Topic Model Visualization [Chuang et al. 2012]



Topic Model Visualization [Chuang et al. 2012]

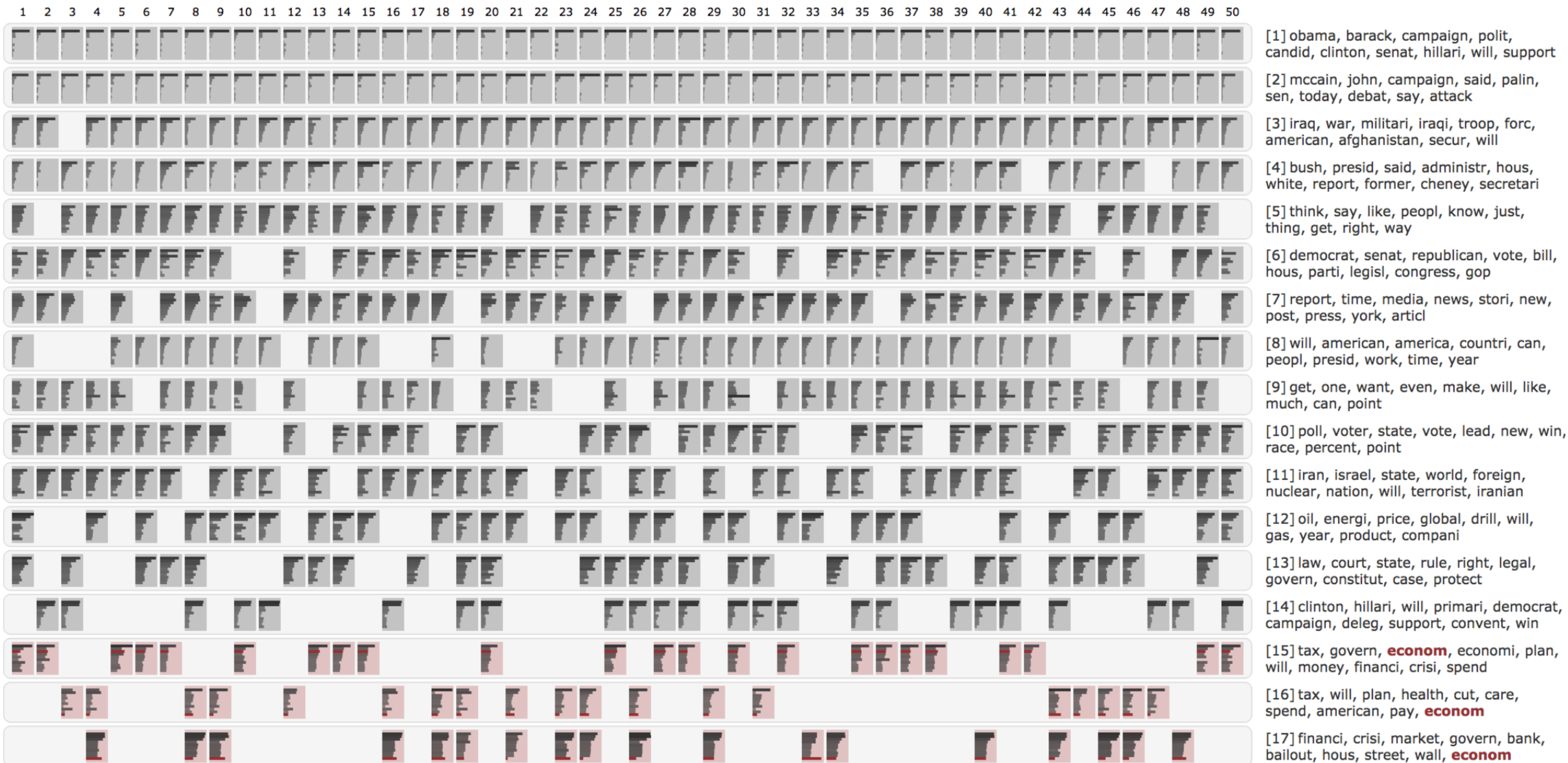


Topic Model Analysis [Chuang et al. 2015]

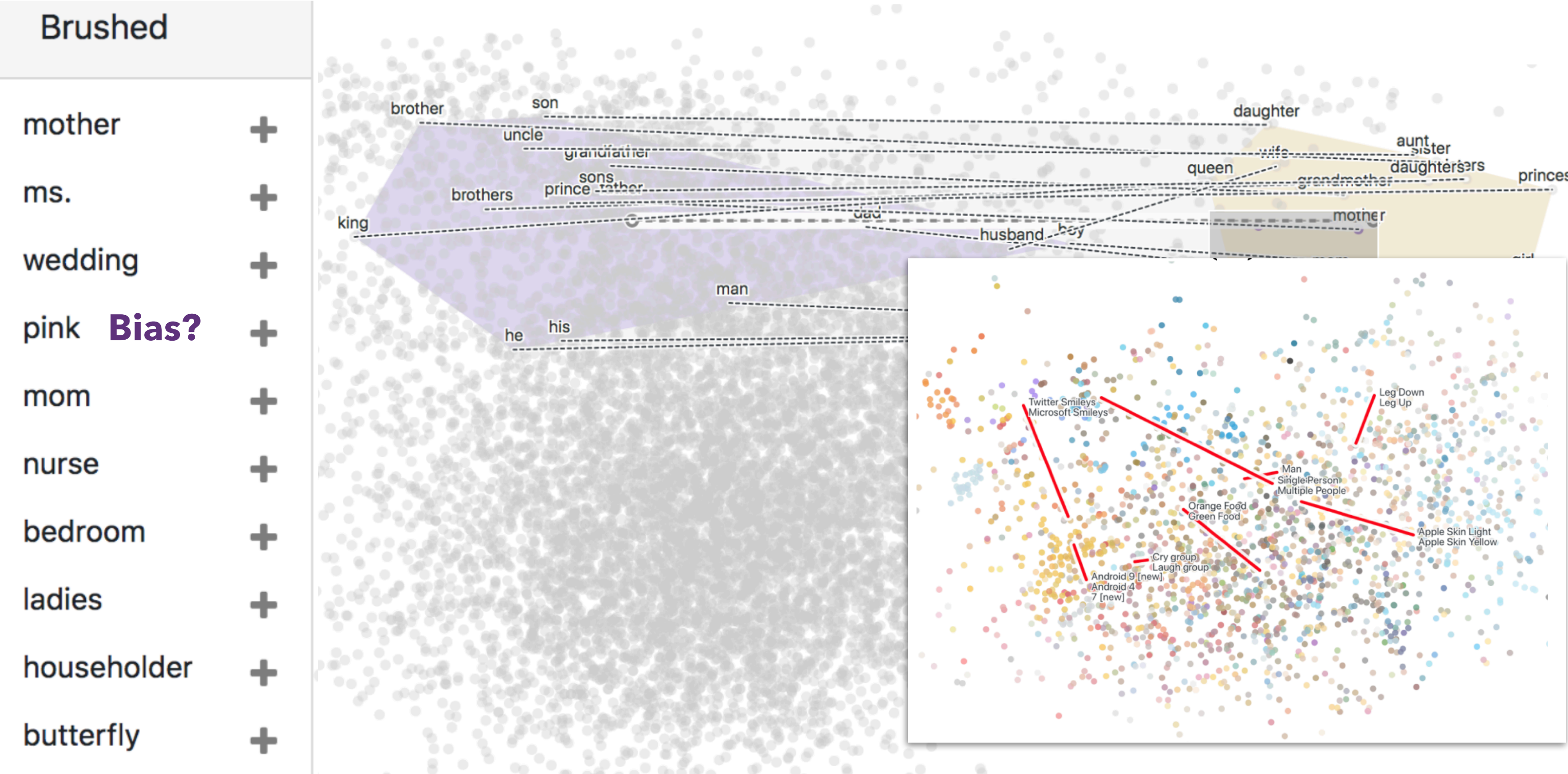
1



Topic Model Analysis [Chuang et al. 2015]

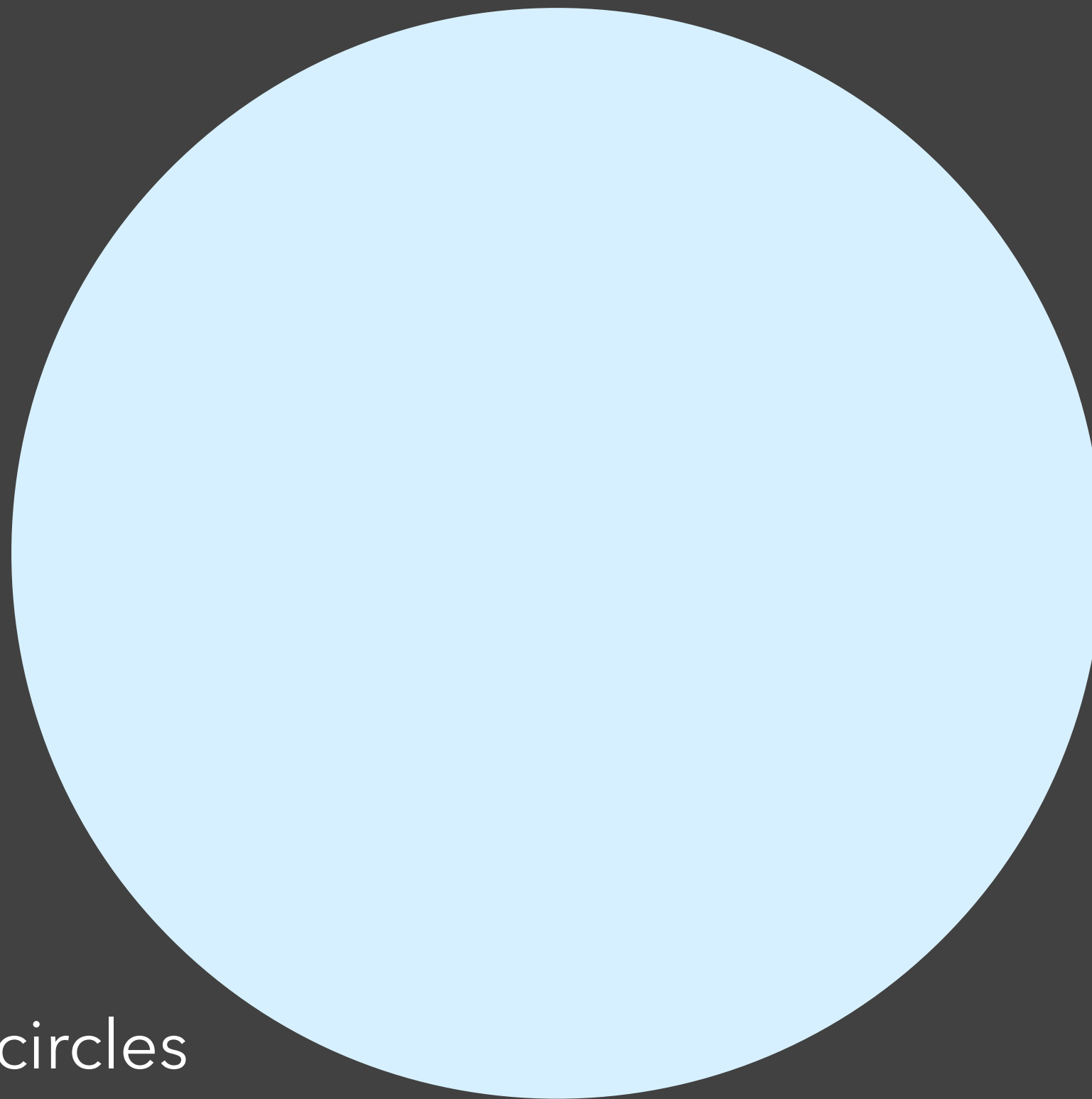
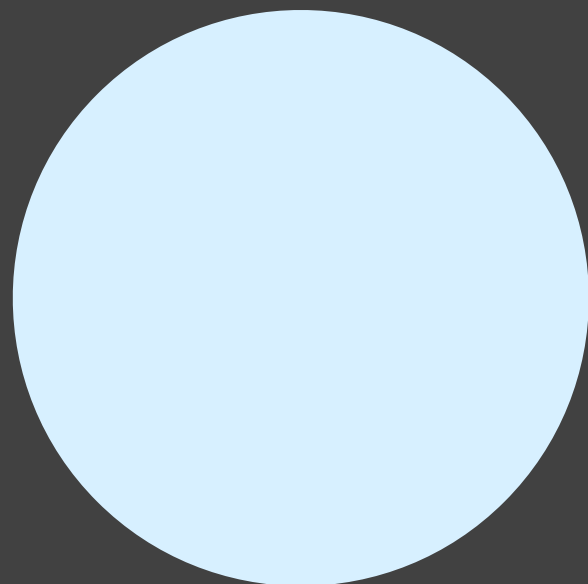


Mapping Machine-Learned Latent Spaces [Liu et al. 2019]

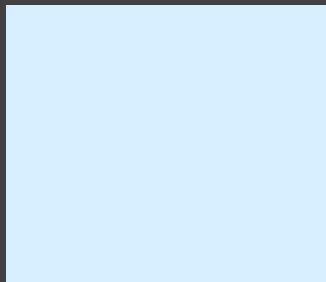


What makes a
visualization “good”?

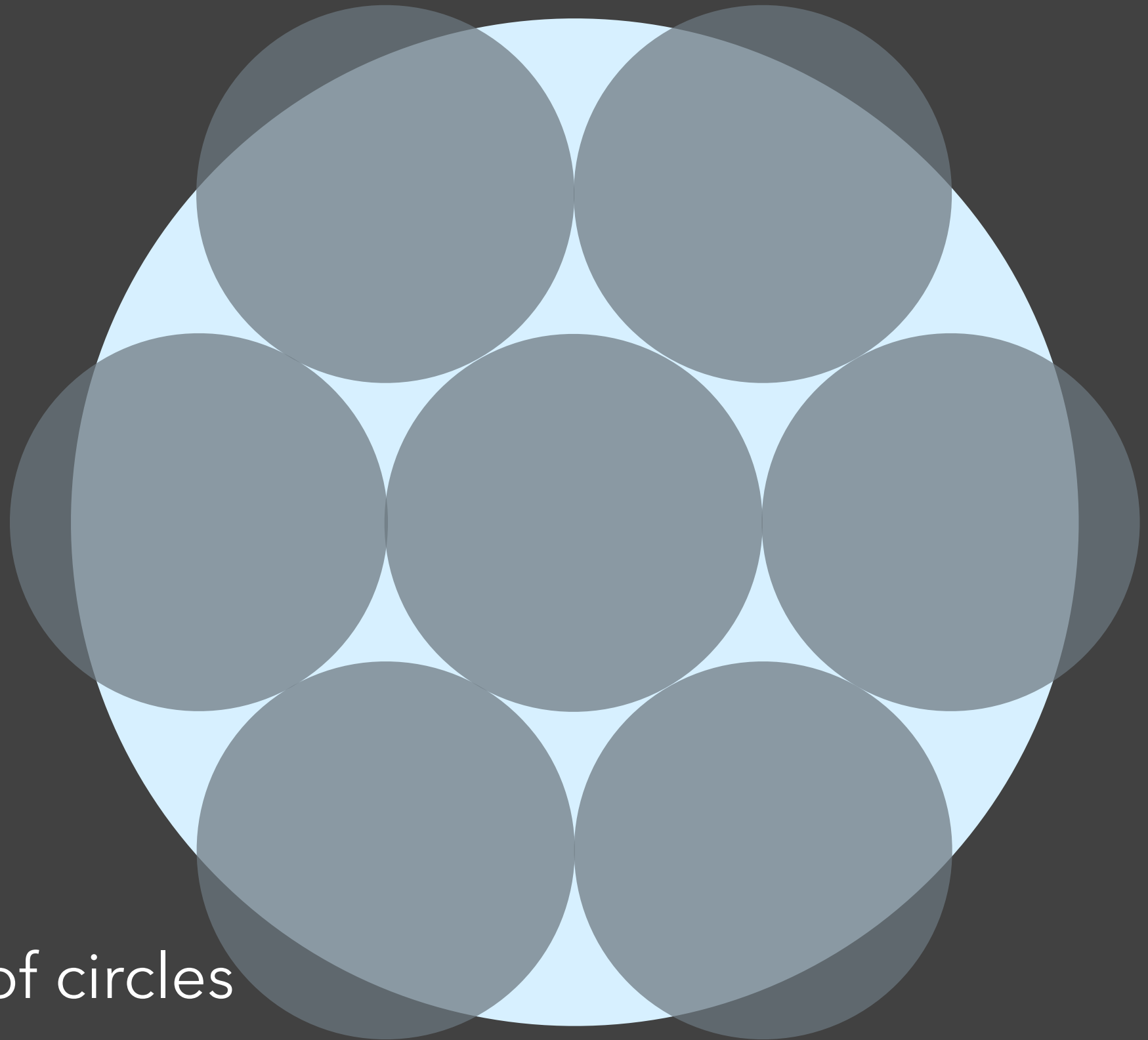
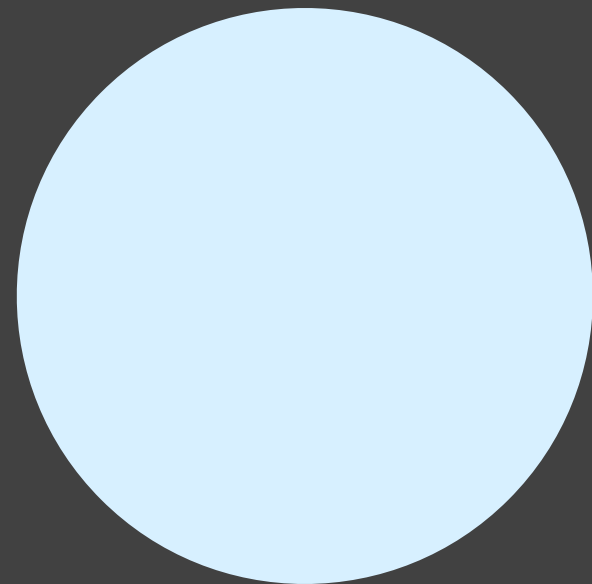
A Quick Experiment...



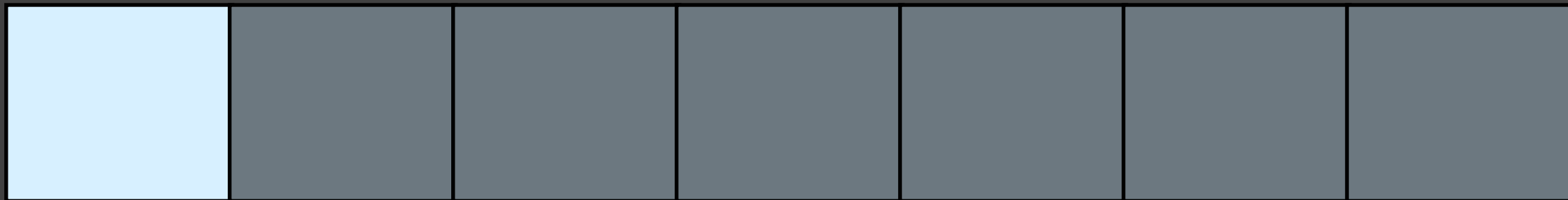
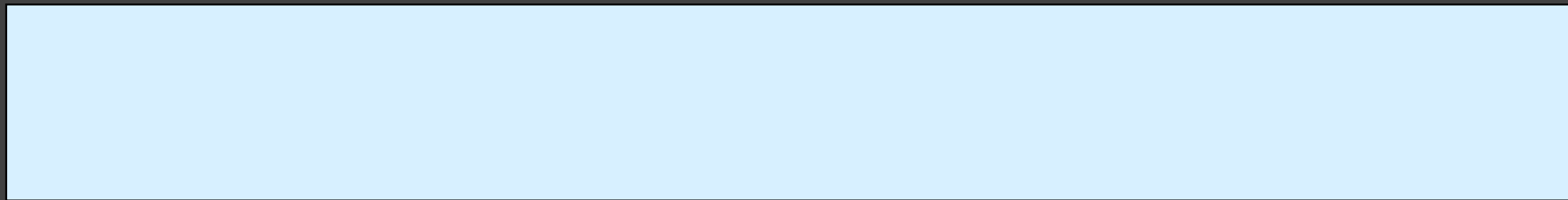
Compare **area** of circles



Compare **length** of bars

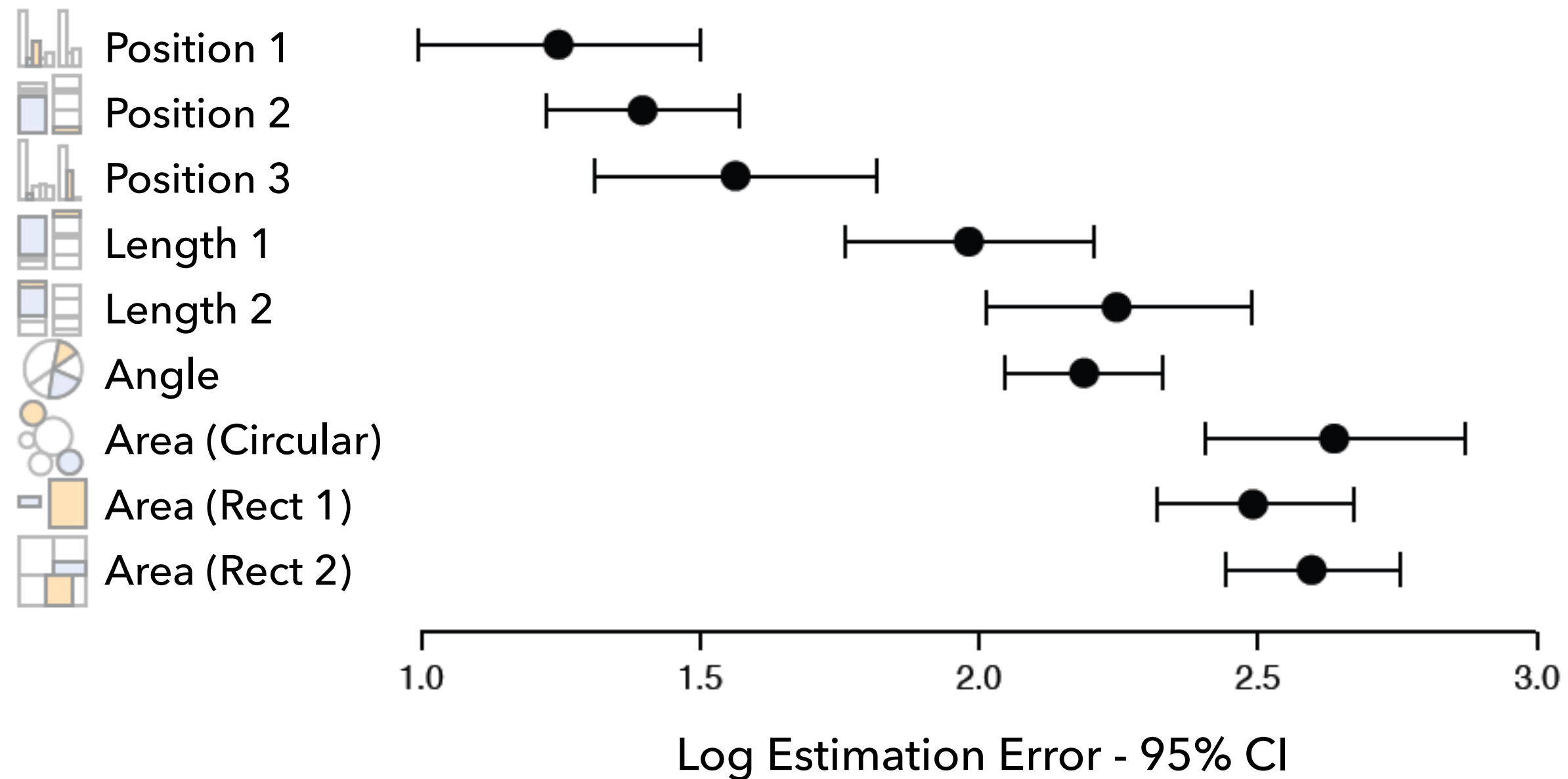


Compare **area** of circles



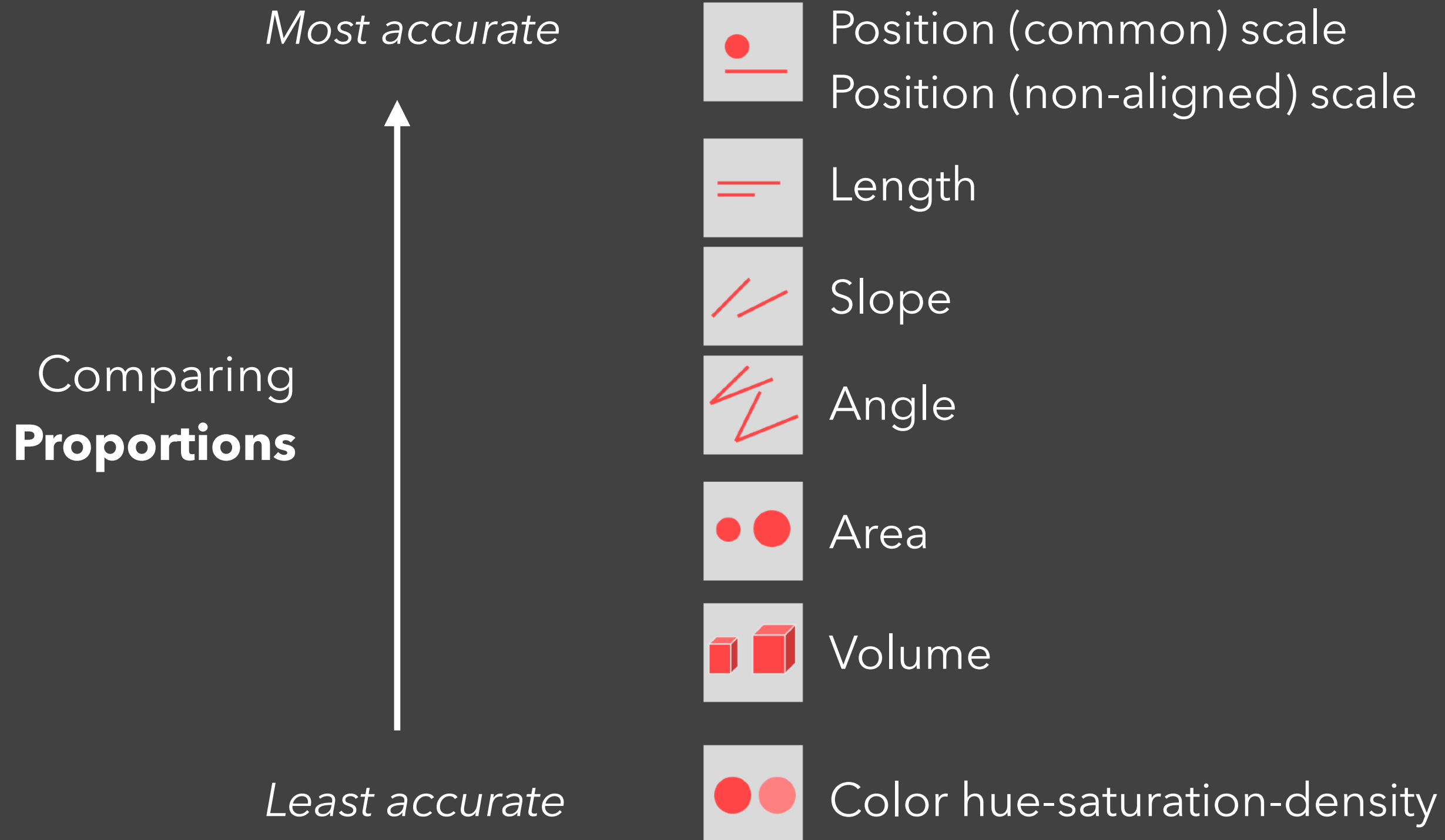
Compare **length** of bars

Accuracy of Proportion Judgments



[Cleveland & McGill 1984, Heer & Bostock 2010]

Ranking Visual Encodings



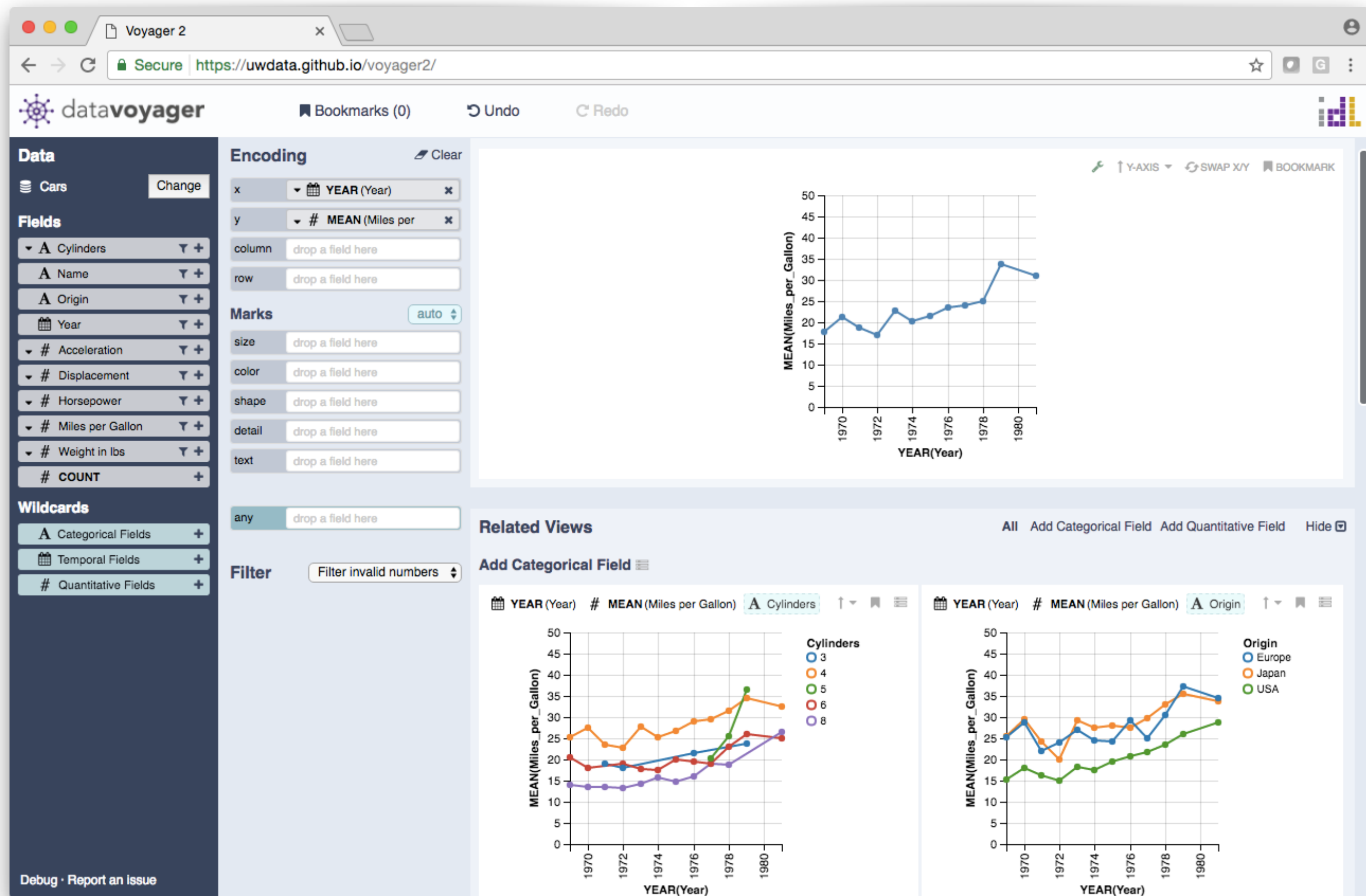
Common exploration pitfalls:

Overlook data quality issues

Fixate on specific relationships

Plus many other biases...

[Heuer 1999, Kahneman 2011, ...]



Voyager: Combine Specification and Recommendation [Wongsuphasawat 2017]

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 *optimize for related chart specifications*, seeded by the user's current focus.

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

Learn Design Trade-Offs from Experimental Data

Training Data

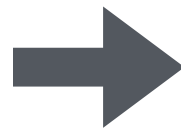
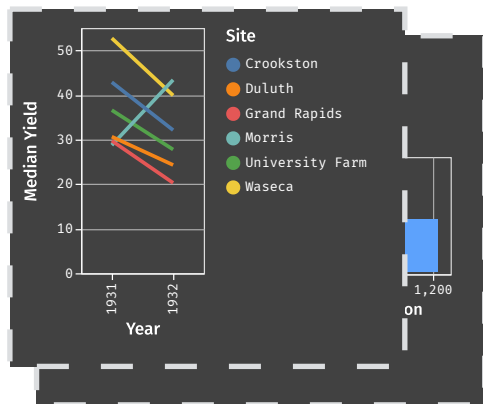
Pairs of Ranked Visualizations

Features

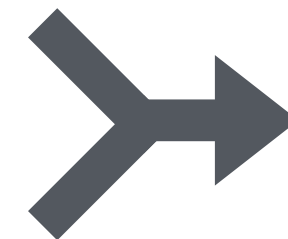
Violations of Design Constraints

Learning Algorithm

Learning to Rank with Linear SVM

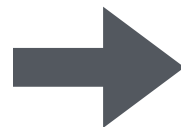
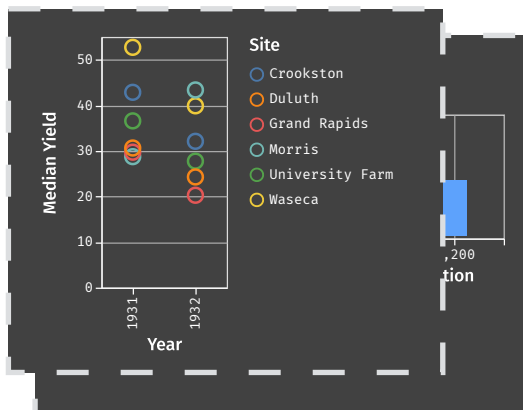


👍 Positive example
Feature Vector
 $[u_1, u_2, \dots, u_k]$



w is the weight vector
of the soft constraints

$$\arg \max_w \sum_{i \in 0 \dots k} w_i (u_i - v_i)$$



👎 Negative example
Feature Vector
 $[v_1, v_2, \dots, v_k]$

v_i : the number of
violations of constraint .

[Moritz et al. 2019]

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."

EXAMPLES:

Exploratory Data Visualization

Data Cleaning & Transformation

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.



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

Suggestions

Delete rows 8,10

Delete empty rows

Delete rows where Property_crime_rate is null

Delete rows where Year is null

ScriptExport

► Split data repeatedly on newline into rows

► Split data repeatedly on ','

rows: 408prevnext

#	Year	#	Property_crime_rate
1	Reported crime in Alabama		
2			
3	2004		4029.3
4	2005		3900
5	2006		3937
6	2007		3974.9
7	2008		4081.9
8			
9	Reported crime in Alaska		
10			
11	2004		3370.9
12	2005		3615
13	2006		3582
14	2007		3373.9

Wrangler: Interactive Visual Specification of Data Transformation Scripts

Kandel et al. [CHI 2011]

DataWrangler

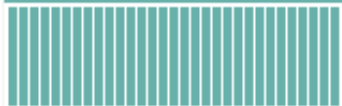
Reduces specification time, promotes the use of reusable, scalable transformations rather than idiosyncratic edits.

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

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

Wrangler: Interactive Visual Specification of Data Transformation Scripts

Kandel et al. [CHI 2011]

ABC	CAND_ID	ABC	CAND_NAME	ABC	CAND_PARTY_AFFILIATION	🕒	CAND_ELECTION_YEAR	ABC	CAND_OFFICE_STATE	ABC	CAND_OFFICE
											
	4,864 Categories		4,760 Categories		76 Categories		1986 - 2052		57 Categories		3 Categories
·	H0AK00097		COX, · JOHN · R.		REP		2014		AK		H
·	H0AL02087		ROBY, · MARTHA		REP		2016		AL		H
·	H0AL02095		JOHN, · ROBERT · E · JR		IND		2016		AL		H
·	H0AL05049		CRAMER, · ROBERT · E · "BUD" · JR		DEM		2008		AL		H
·	H0AL05163		BROOKS, · MO		REP		2016		AL		H
·	H0AL06088		COOKE, · STANLEY · KYLE		REP		2010		AL		H
·	H0AL07086		SEWELL, · TERRI · A.		DEM		2016		AL		H
·	H0AL07094		HILLIARD, · EARL · FREDERICK · JR		DEM		2010		AL		H
·	H0AL07177		CHAMBERLAIN, · DON		REP		2012		AL		H
·	H0AR01083		CRAWFORD, · ERIC · ALAN · RICK		REP		2016		AR		H
·	H0AR01091		GREGORY, · JAMES · CHRISTOPHER		DEM		2010		AR		H
·	H0AR01109		CAUSEY, · CHAD		DEM		2010		AR		H
·	H0AR01125		SMITH, · PRINCELLA · D		REP		2010		AR		H
·	H0AR02107		GRIFFIN, · JOHN · TIMOTHY		REP		2014		AR		H
·	H0AR02131		ELLIOTT, · JOYCE · ANN		DEM		2010		AR		H
·	H0AR03022		SKOCH, · BERNARD · KURT · 'BERNIE'		REP		2010		AR		H
·	H0AR03030		WHITAKER, · DAVID · JEFFREY		DEM		2010		AR		H
·	H0AR03055		WOMACK, · STEVE		REP		2016		AR		H
·	H0AS00018		FALEOMAVAEGA, · ENI		DEM		2014		AS		H
·	H0AZ01184		FLAKE, · JEFF · MR.		REP		2012		AZ		H
·	H0AZ01259		GOSAR, · PAUL · ANTHONY		REP		2016		AZ		H
·	H0AZ01283		MEHTA, · STEVE		REP		2010		AZ		H
·	H0AZ01325		TOBIN, · ANDY · HON.		REP		2014		AZ		H
·	H0AZ01333		GRESSLEY, · FORREST · DAYL		REP		2010		AZ		H
·	H0AZ03321		PARKER, · VERNON		REP		2014		AZ		H

New Step [Switch to editor](#)

Cancel

Add to Recipe

Choose a transformation

Choose transformation

Cancel Modify Add to Recipe

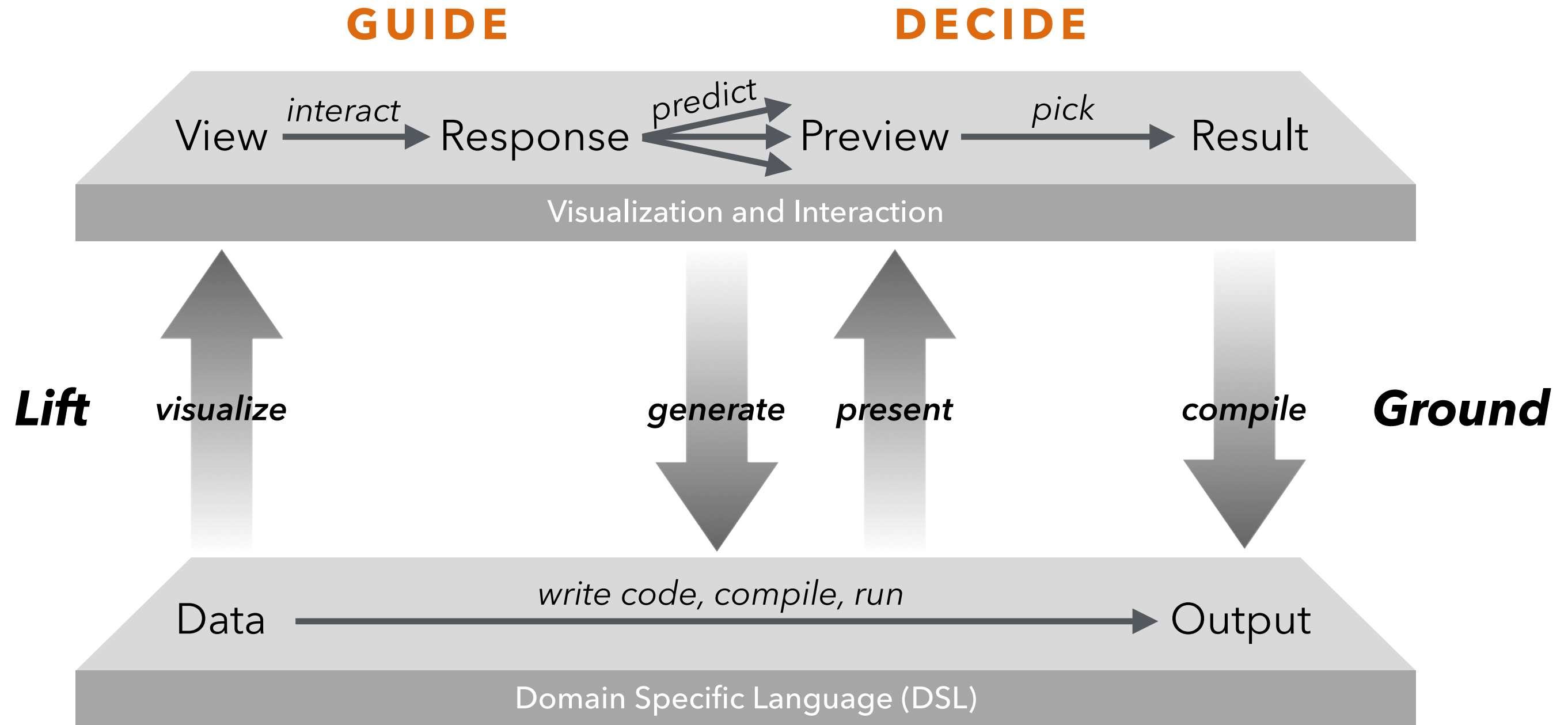
ABC	CAND_NAME	ABC	CAND_NAME1	ABC	CAND_NAME2
COX,	JOHN · R.	COX		JOHN · R.	
ROBY,	MARTHA	ROBY		MARTHA	
JOHN,	ROBERT · E · JR	JOHN		ROBERT · E · JR	
Affects 1 column, 4859 rows		Creates 2 columns			

ABC	CAND_NAME	ABC	CAND_NAME1
COX,	JOHN R.	,	
ROBY,	MARTHA	,	
JOHN,	ROBERT E JR	,	
Affects 1 column, 4859 rows		Creates 1 column	

ABC	CAND_NAME
COX, JOHN R.	
ROBY, MARTHA	
JOHN, ROBERT E JR	

Affects 1 column, 4859 rows

Predictive Interaction



EXAMPLES:

Exploratory Data Visualization

Data Cleaning & Transformation

Natural Language Translation

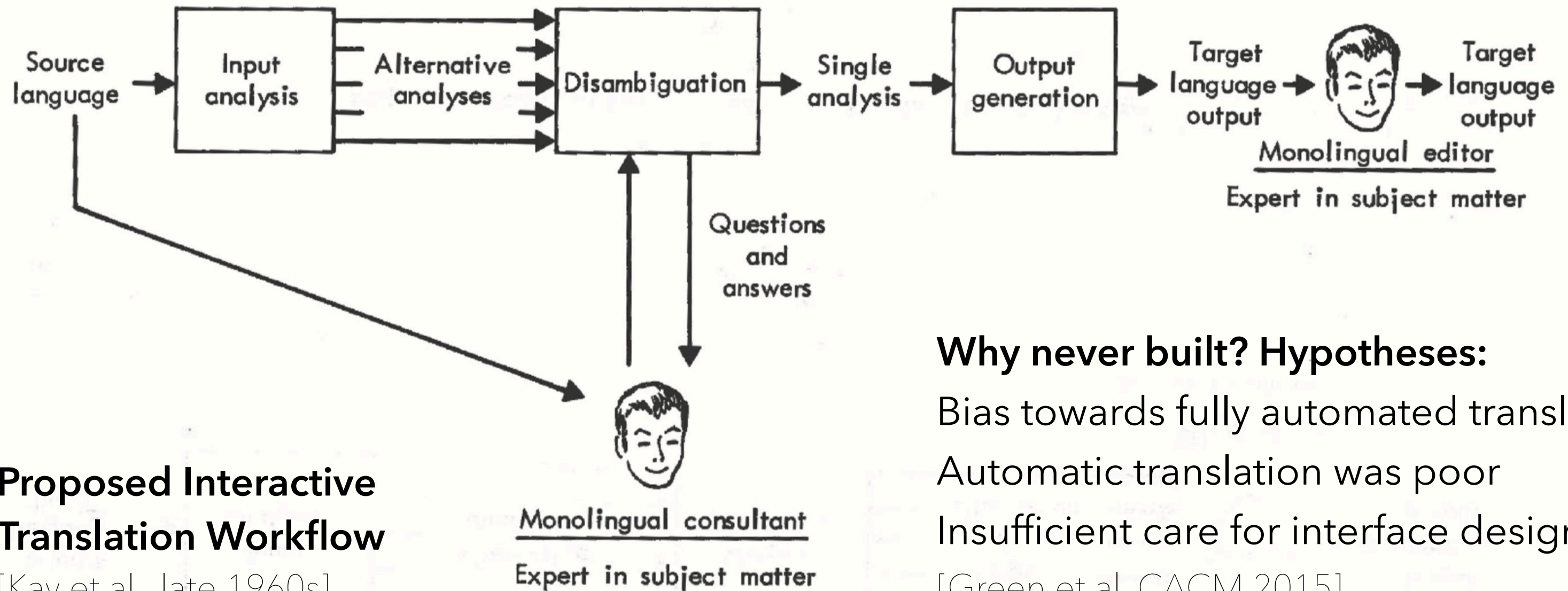
Mid-Century Prospects for Automated Language Translation

"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?



Why never built? Hypotheses:

Bias towards fully automated translation

Automatic translation was poor

Insufficient care for interface design

[Green et al. CACM 2015]

Predictive Translation Memory (PTM) [Green et al. 2014]

A À équiper le centre de formation Studeo qui est accessible aux personnes à mobilité réduite et dont nous travaillons à la réalisation dans le cadre de l'institut Jedlička, avec l'association Tap, et ça depuis six ans.

B To equip studeo training centre which is accessible to people with reduced mobility and we work to achieve in the framework of the Institute jedlička, with tap, and been there for six years.

Des enseignants se rendent régulièrement auprès des élèves de l'institut Jedličkův et leur proposent des activités qui les intéressent et les amusent.

Teachers regularly visit Jedličkův Institute students and offered them activities of interest to them and having fun.

C

Les étudiants eux-mêmes n'ont pas les moyens de se rendre à des cours, nous essayons de les aider de cette manière.

The students themselves cannot be required to attend courses, we are trying to help

E

D

Dans le cadre de l'Institut Jedlička, nous transférerons ce projet dans un nouveau

themselves cannot
themselves could not
themselves do not
themselves cannot afford

(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 [Green et al. '13, '14]

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."*

EXAMPLES:

Exploratory Data Visualization

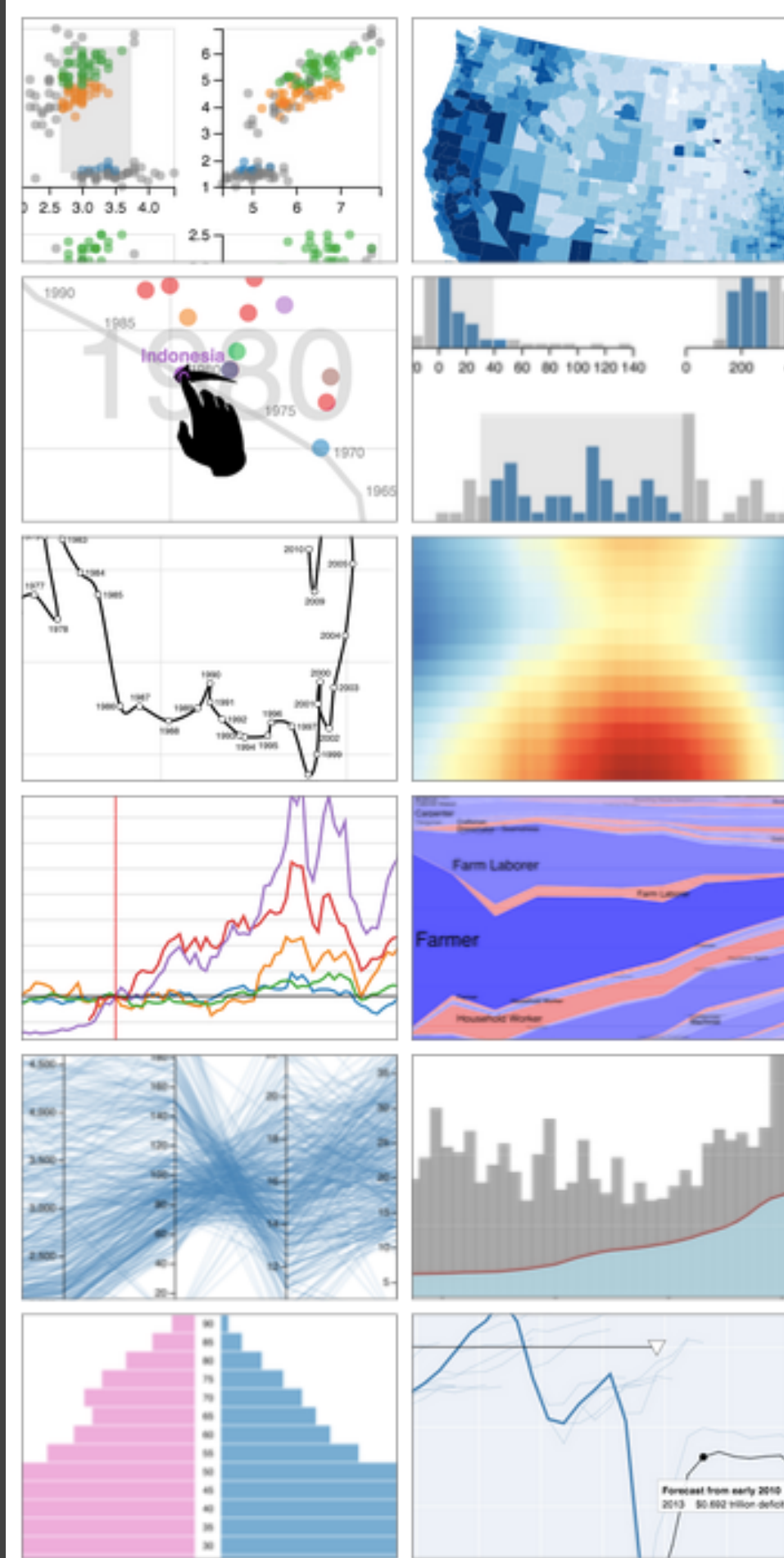
Data Cleaning & Transformation

Natural Language Translation

DESIGN CHALLENGE:

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

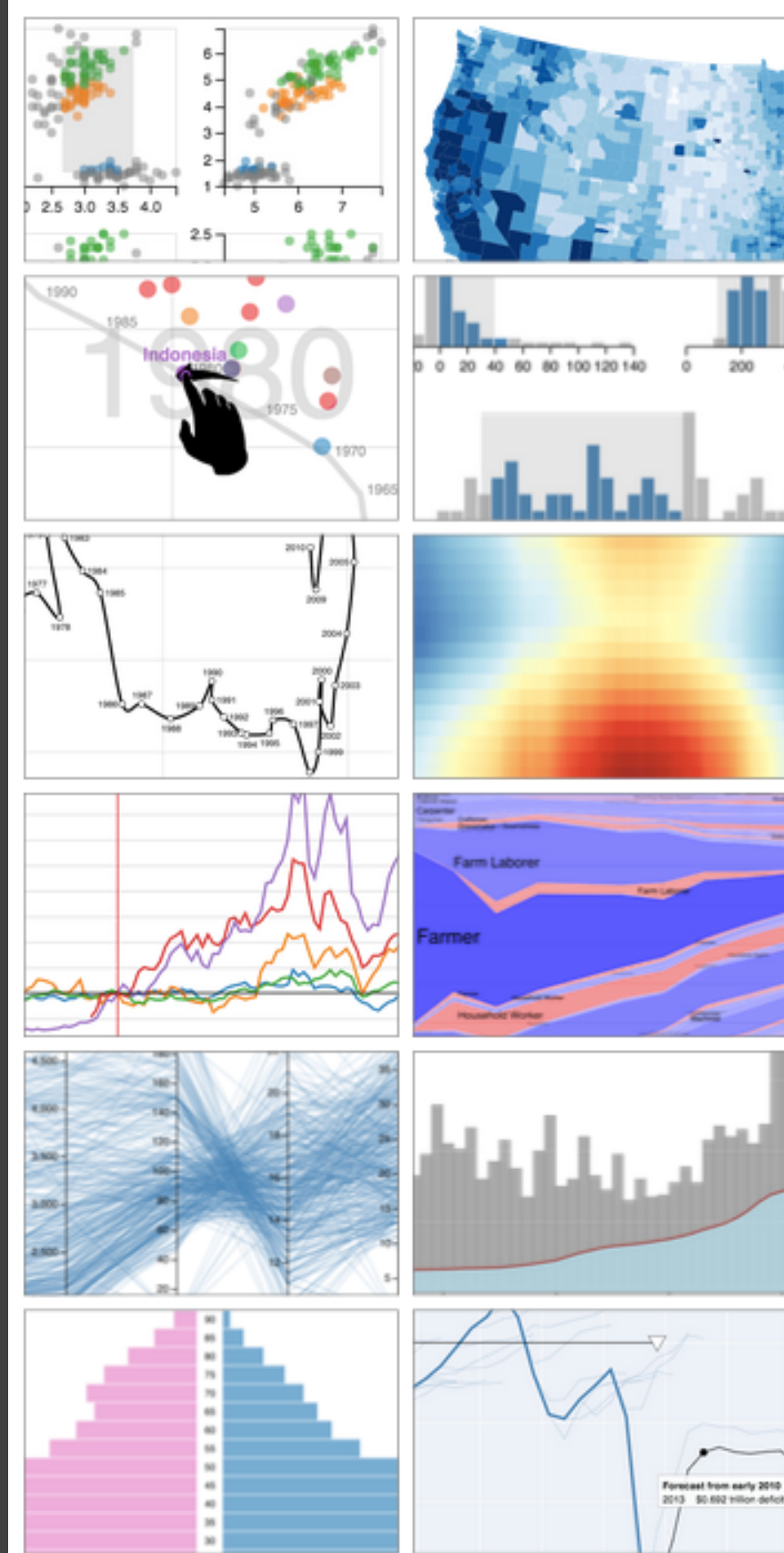
Future Challenges



Future Challenges

Design Process, Tools, & Monitoring

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



Future Challenges

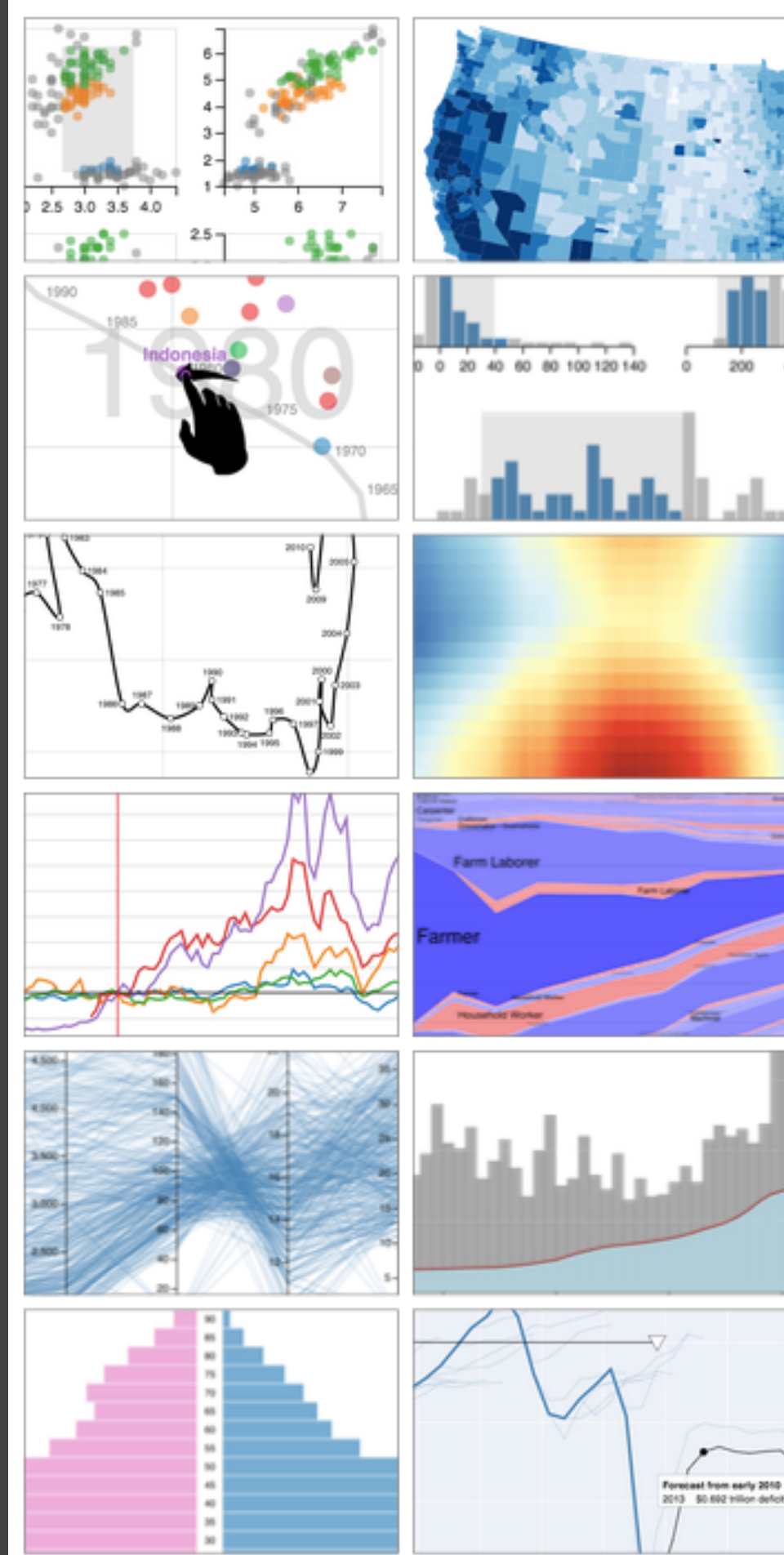
Design Process, Tools, & Monitoring

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

Mapping Machine-Learned Representations

Can ML methods suggest structural task models?

Can people help test & constrain ML models?



Predictive Interaction for Model 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...

+ starts_with(question, pattern="how many ADJ")

+ starts_with(question, pattern="ADV ADJ ADJ")

+ attr:question_type == "how many"

See more general suggestions?

Close Now

A

		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

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 ML methods suggest structural task models?

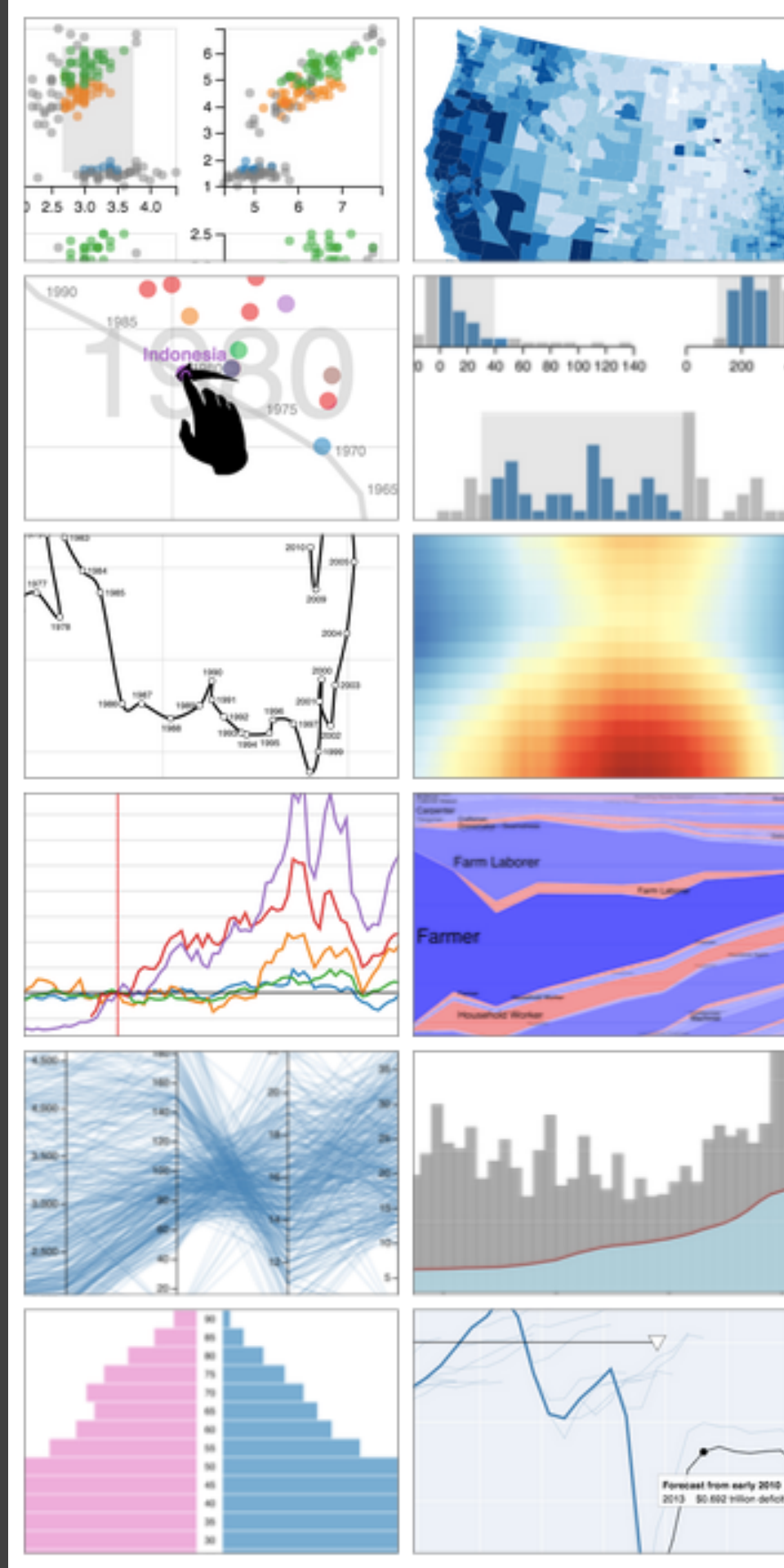
Can people help test & constrain ML models?

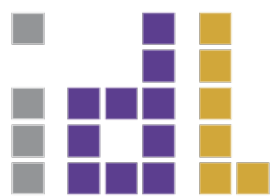
Evaluating Trade-Offs of Agency & Automation

Must go beyond result quality and productivity.

Locus of control, agency vs. passive acceptance?

Training and skill acquisition vs. de-skilled labor?





ISTC
BIG DATA



GORDON AND BETTY
MOORE
FOUNDATION

THE PAUL G. ALLEN
FAMILY FOUNDATION

Agency + Automation

Jeffrey Heer @jeffrey_heer

U. Washington / Trifacta

