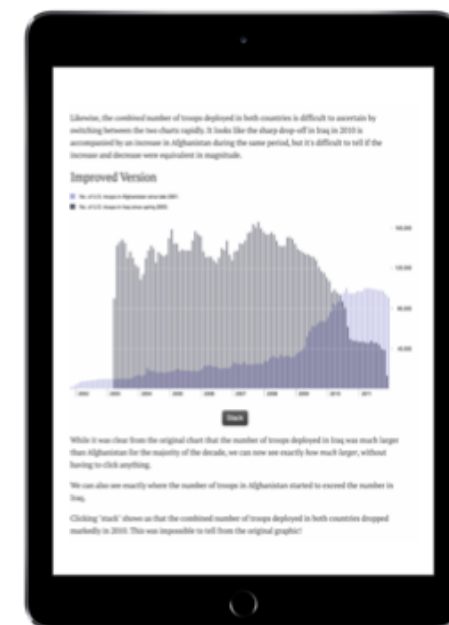
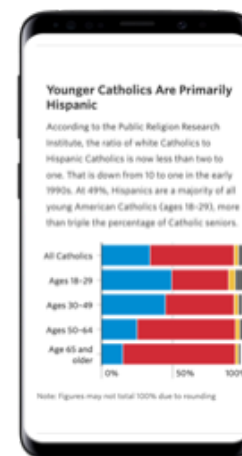


Learning to Automate Chart Layout Configurations

用机器学习自动化图表布局

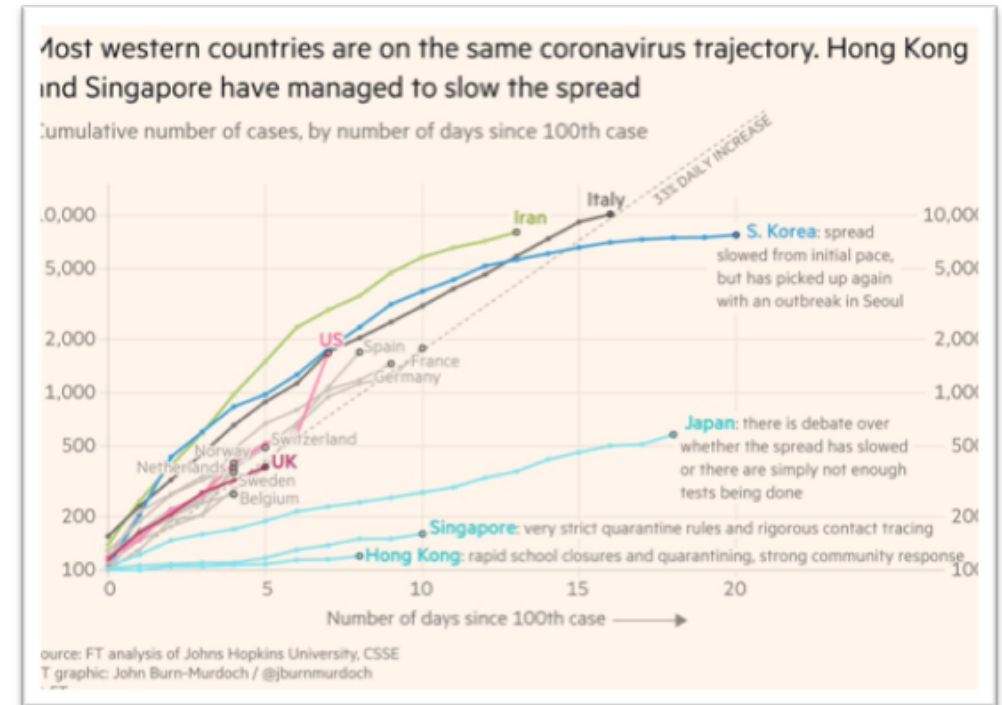
WU Aoyu

Homepage: <http://awuac.student.ust.hk>



0. Background: Chart

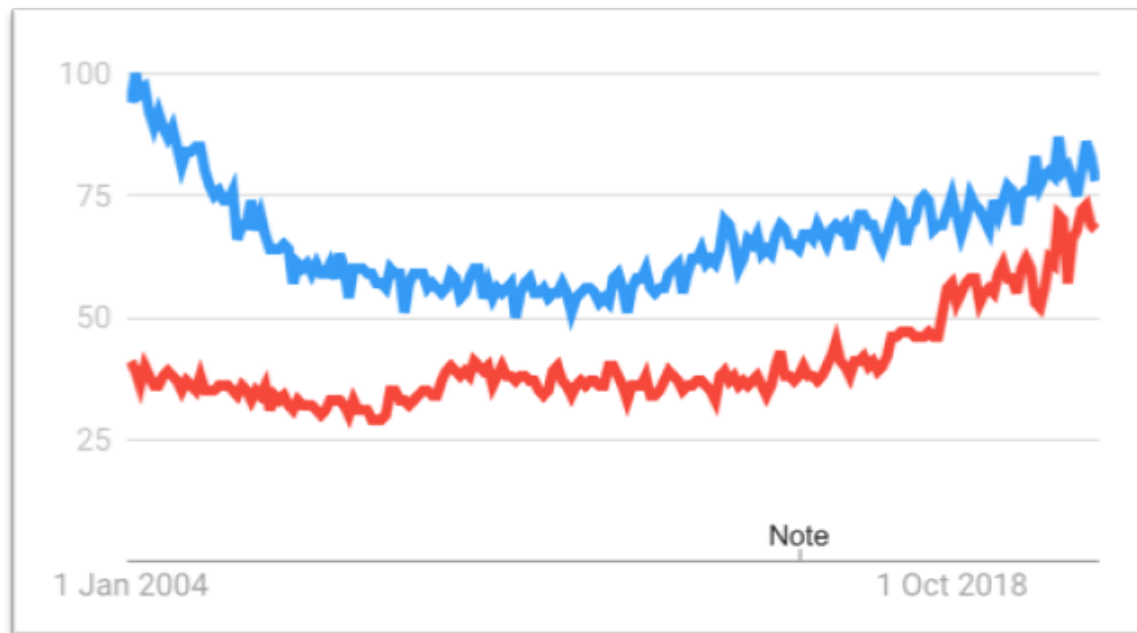
Charts are easy to read, and arguably one of the most easiest way for the masses to assess data.



By far the most visited page in NY Times

0. Background: Chart

Charts have been created and shared at an unprecedented speed.



Google Search Trend Globally: **Data** v.s. **Chart**

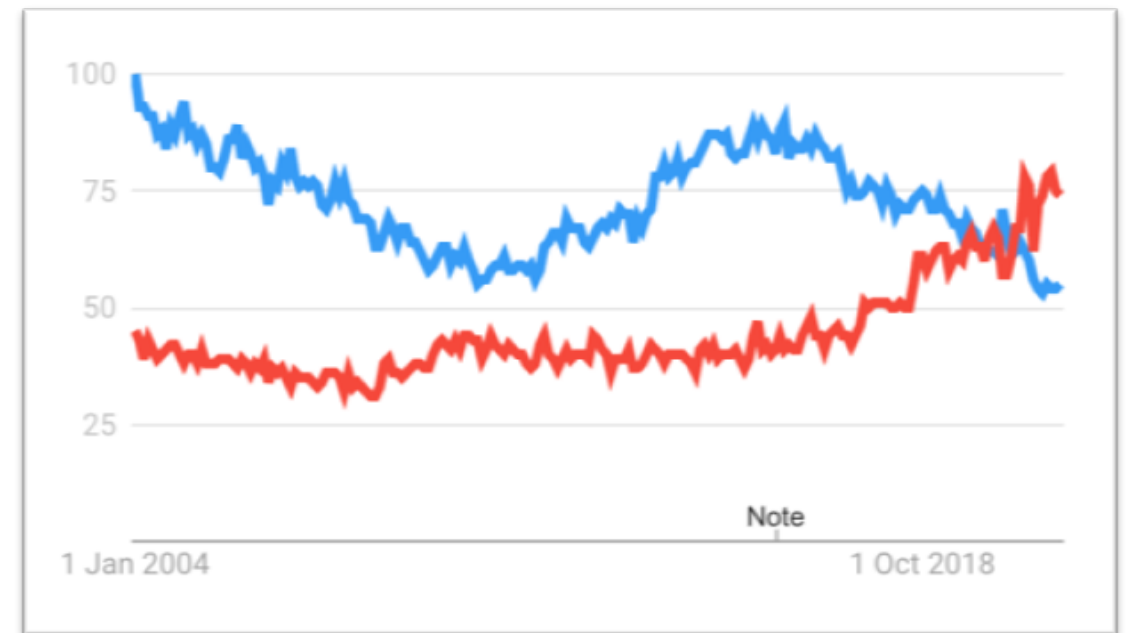
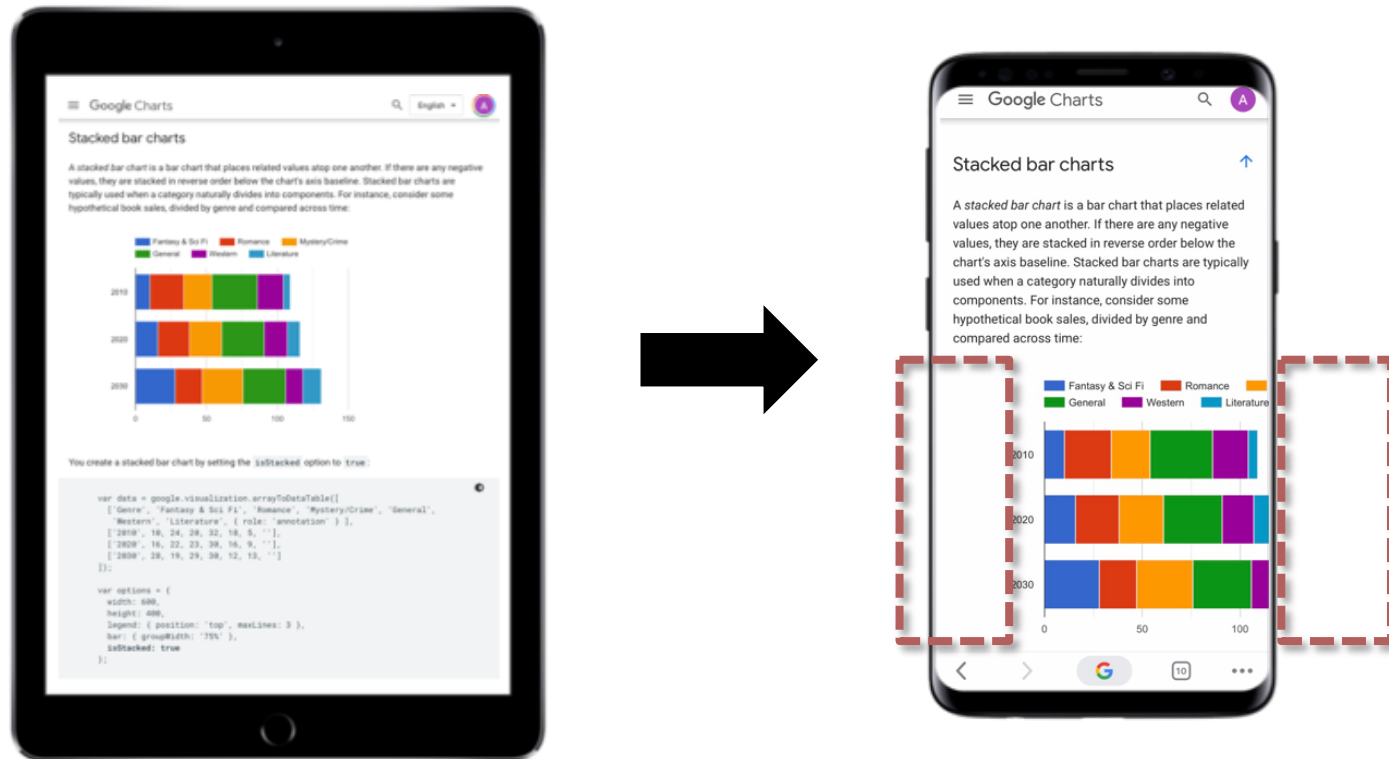


Chart has surpassed **Image** globally in Google Search Trend since Jan 2020

0. Background: Chart Layout

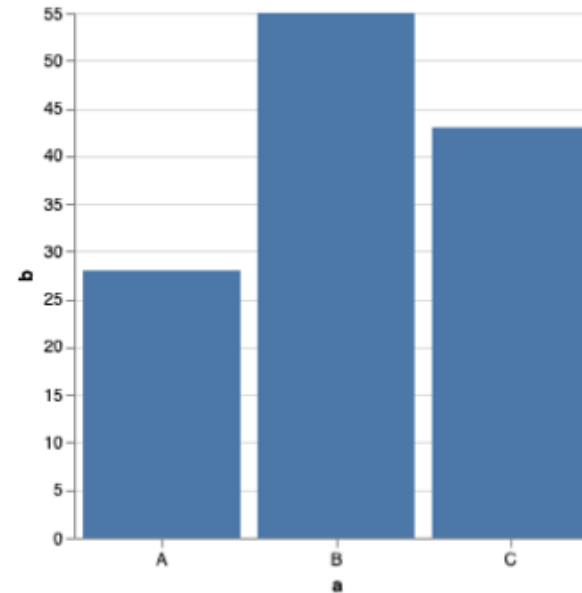
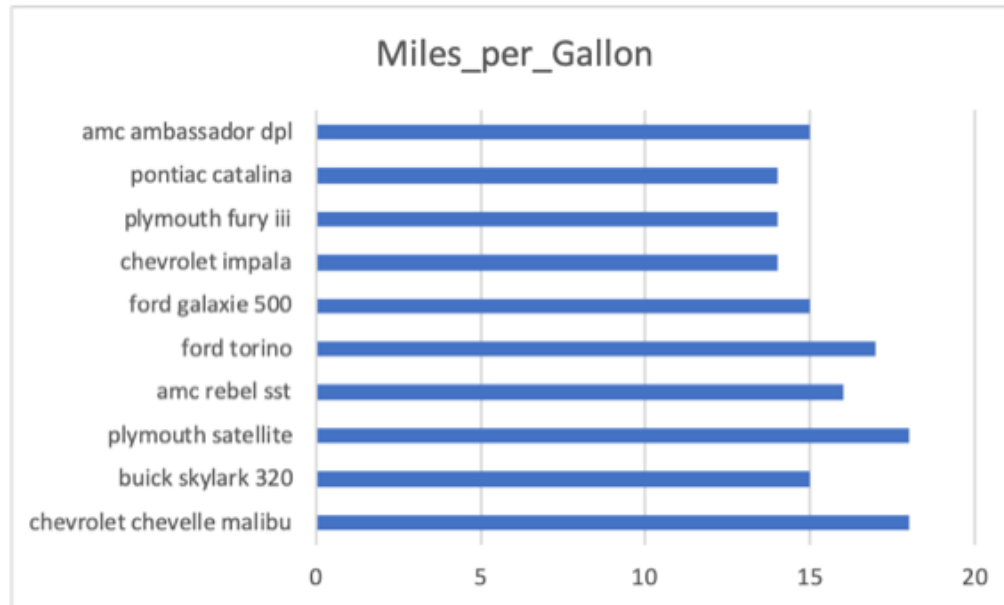
Chart layouts directly influence the readability and aesthetics.



Mobile friendliness

0. Background: Chart Layout

Chart layouts directly influence the readability and aesthetics.



Default styles in Excel (charting software) and Vega-Lite (charting library)

0. Background: Chart Layout

Manually adjusting chart layouts faces problems.



Responsive Settings



Multiple Parameters



Poor User Experience (UX)

0. Background: Chart Layout

Manually adjusting chart layouts faces problems.



Responsive Settings



Multiple Parameters

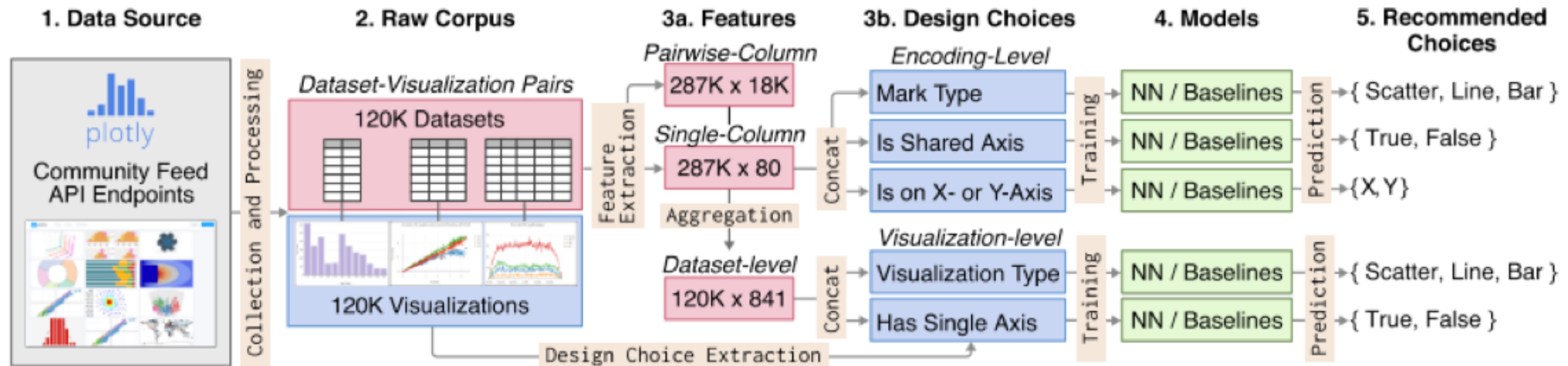


Poor User Experience (UX)

How to automatically optimize multiple parameters for chart layouts given constraints (such as screen widths)?

1. Related Work: Visualization Recommendation

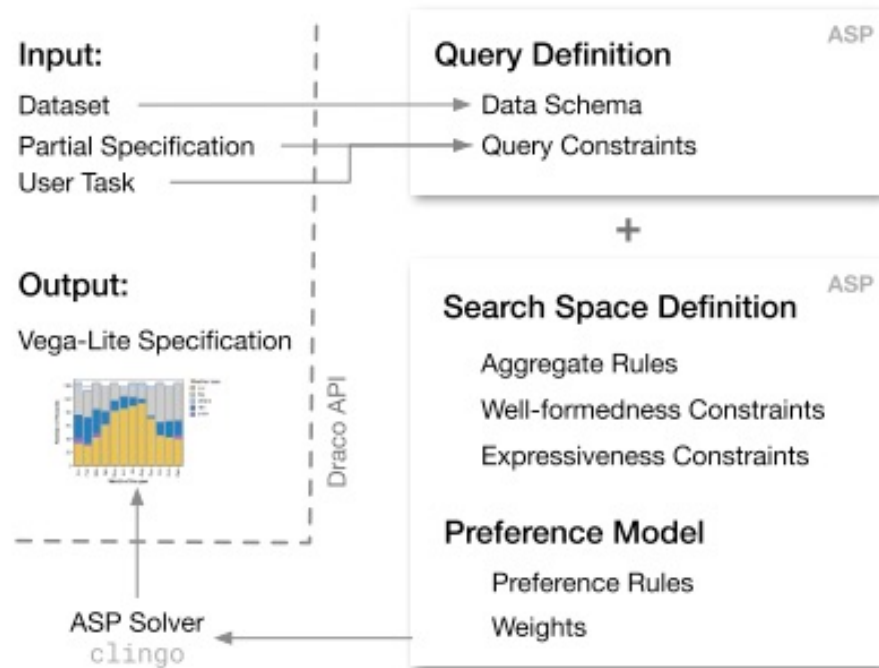
Visualization recommendation is the problem of automatically recommending visual encodings.



VizML [CHI 2019] – Machine Learning

1. Related Work: Visualization Recommendation

Most work focused on recommending data-encodings.



Draco [VIS 2018]

Incorporating decision rules from design knowledge.

Visual encoding by data type

	Quantitative	Ordinal	Nominal
Position	••	••	••
Length	==	•••	Hue (•••)
Angle	∠	Saturation (•••)	Density (•••)
Slope	///	Hue (•••)	Saturation (•••)
Area	••	Length (==)	Shape (•••)
Density	•••	Angle (∠)	Length (==)
Saturation	•••	Slope (///)	Angle (∠)
Hue	•••	Area (••)	Slope (///)
Shape	•••	Shape (•••)	Area (••)

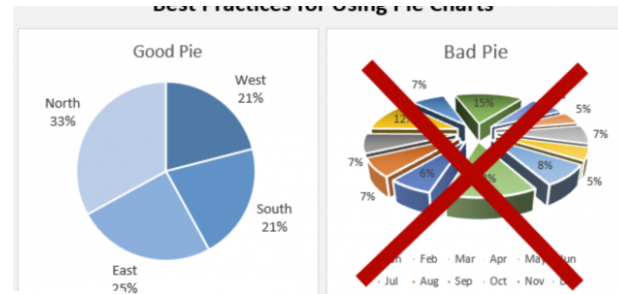
More Accurate ↑
 ↓ Less Accurate

1. Related Work: Visualization Recommendation

Less research addresses non-data-encodings (such as layouts).

Data Encodings

Rule-Based Approach



Much research about what's good/bad data encodings.

ML-based Approach

mitmedialab/viznet



VizNet is a repository providing real-world datasets that enable, among other things, (re)running empirical studies with higher ecological validity

2 Contributors 2 Issues 54 Stars 23 Forks



Much dataset

Non-data Encodings
(Layout)



Little consensus



Little dataset

2. Rule-based Approach

Problem: Automated responsive visualization

How to automatically optimize multiple parameters for chart layouts given a screen size?

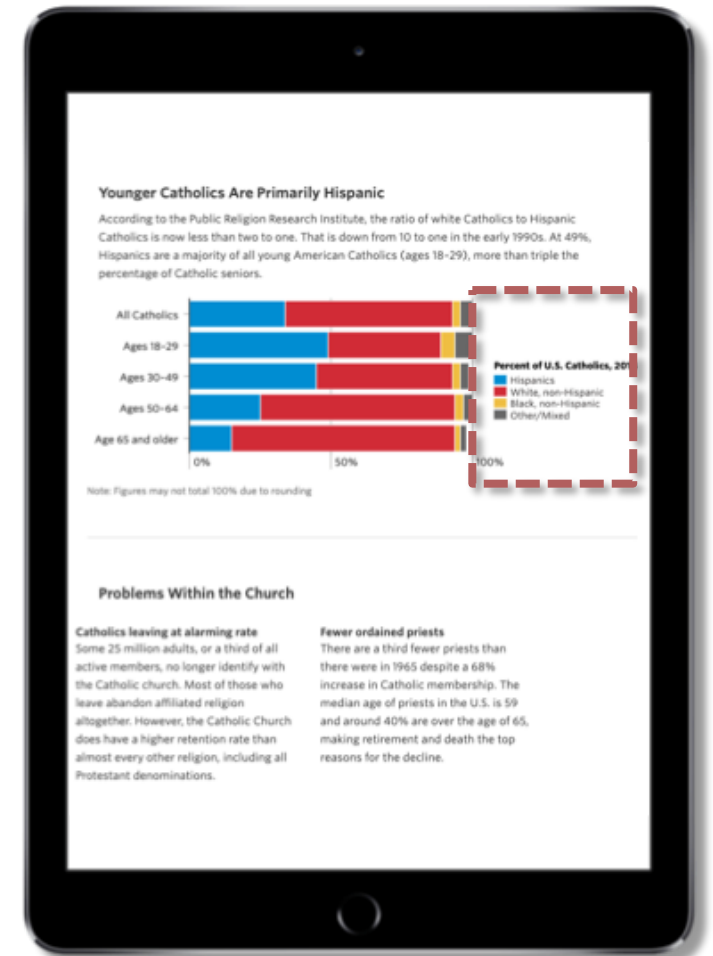
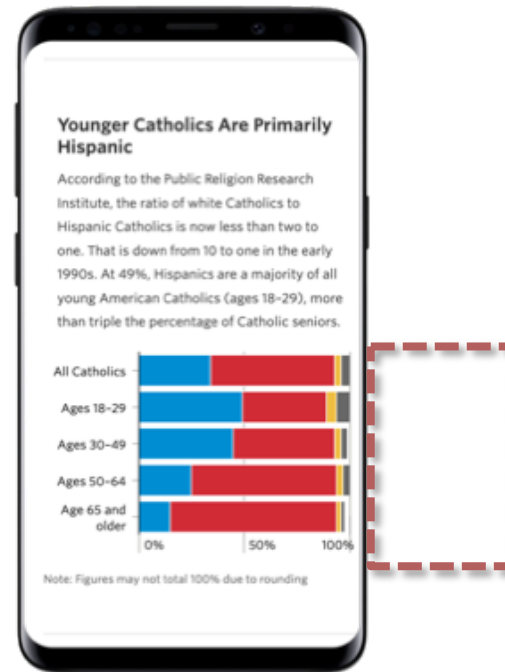
What are good/bad chart layouts?

- Mobile-friendliness issue

2. Rule-based Approach

Mobile-friendliness issue

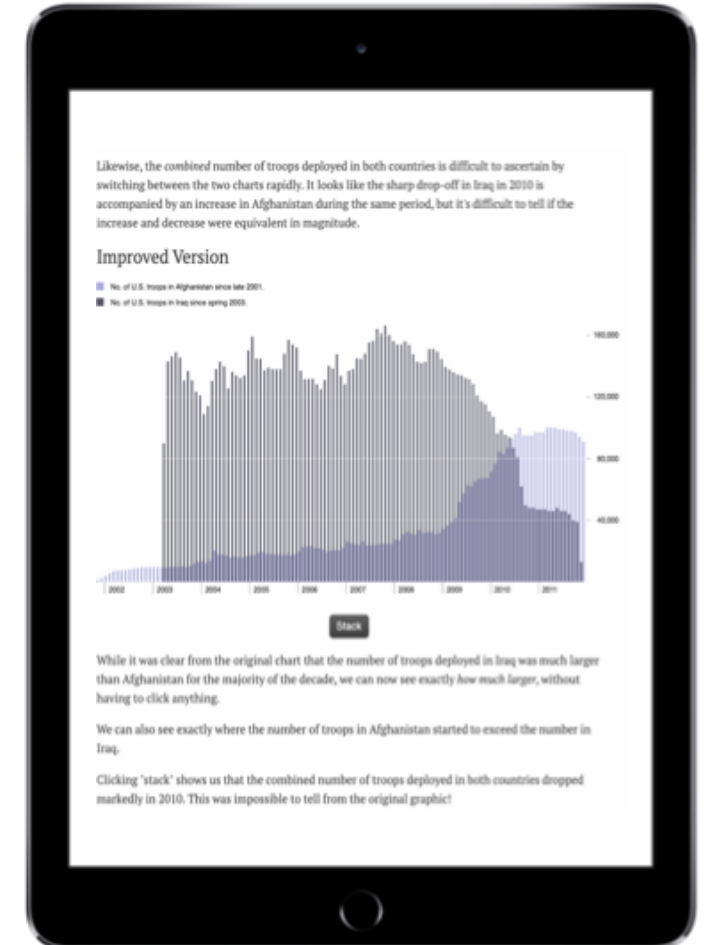
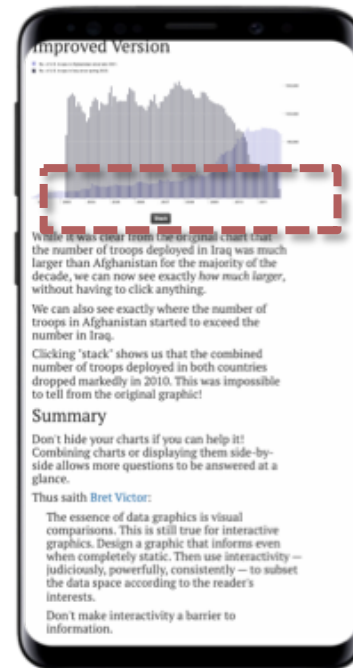
- Out-of-view-box



2. Rule-based Approach

Mobile-friendliness issue

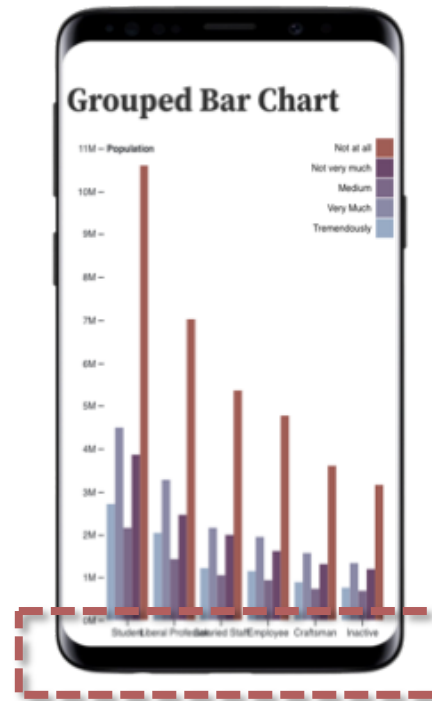
- Out-of-view-box
- Unreadable font-size



2. Rule-based Approach

Mobile-friendliness issue

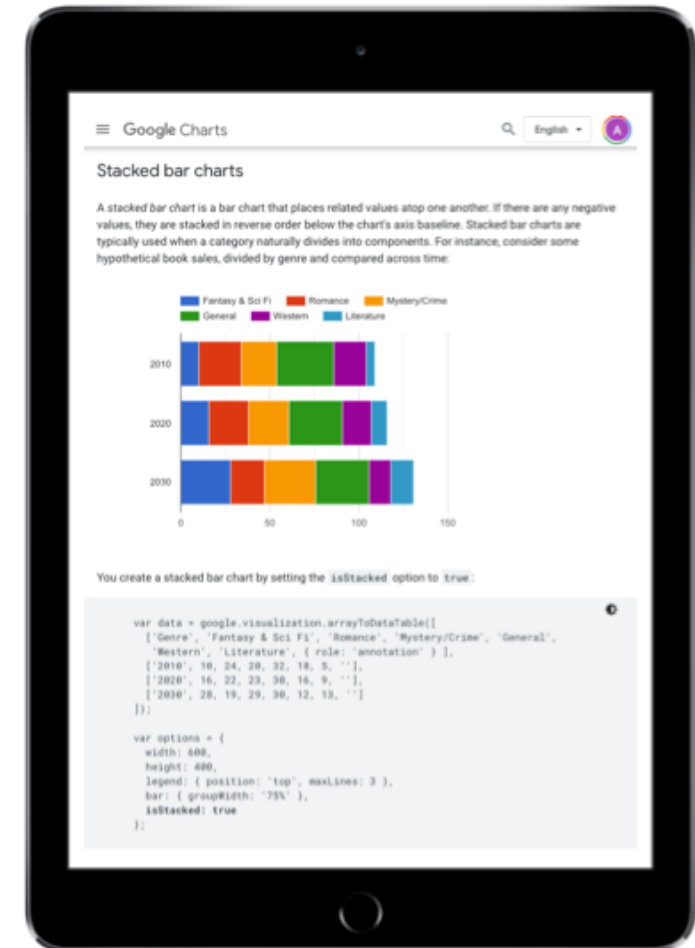
- Out-of-view-box
- Unreadable font-size
- Overlapping text



2. Rule-based Approach

Mobile-friendliness issue

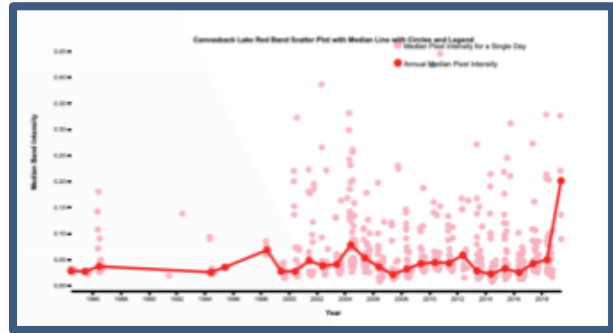
- Out-of-view-box
- Unreadable font-size
- Overlapping text
- Unwanted white space
- ...



2. Rule-based Approach

Approach: Reinforcement Learning

Environment - Chart



State(S) – Mobile-friendly Issue
Reward(R) – Change of loss (L)

Example:
S: *SmallFontSize*
L: *8px*



Action(A) – Modify the chart
Policy P(A|S)

Example:
A1: *IncreaseFontSize*
A2: *DecreaseFontSize*

2. Rule-based Approach

Approach: Reinforcement Learning

Environment - Chart



State(S) – Mobile-friendly Issue
Reward(R) – Change of loss (L)

Example:
S: SmallFontSize
L: 8px

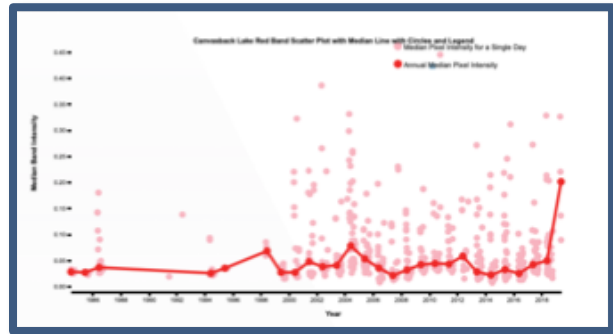
Action(A) – Modify the chart
Policy P(A|S)

Example:
A1: IncreaseFontSize
A2: DecreaseFontSize

2. Rule-based Approach

Approach: Reinforcement Learning

Environment - Chart



State(S) – Mobile-friendly Issue
Reward(R) – Change of loss (L)

Example:
S: SmallFontSize
L: 8px + 1px = 9px
R: 1px

Action(A) – Modify the chart
Policy P(A|S)

Example:
A1: IncreaseFontSize
A2: DecreaseFontSize

Increase P(A1|SmallFontSize)

2. Rule-based Approach

29 states
23 actions

The screenshot displays the MobileVisFixer application interface, which is used for tailoring web visualizations for mobile phones. The interface is divided into four main sections: Original, Deconstruction, Improved, and Control Panel.

Original iPhoneX: Shows a scatter plot with the y-axis labeled 'Gener' ranging from 0 to 2,200. Data points are labeled with numbers: 19, 17, 22, 20, 21, and 18.

Deconstruction: A list of properties for the visualization, categorized into Title, Y-Axis, X-Axis, Legend, Marks, Labels, and Annotations. For example, the Title is 'undefined', the Y-Axis is 'scaleLinear', and the Marks are 'circle'.

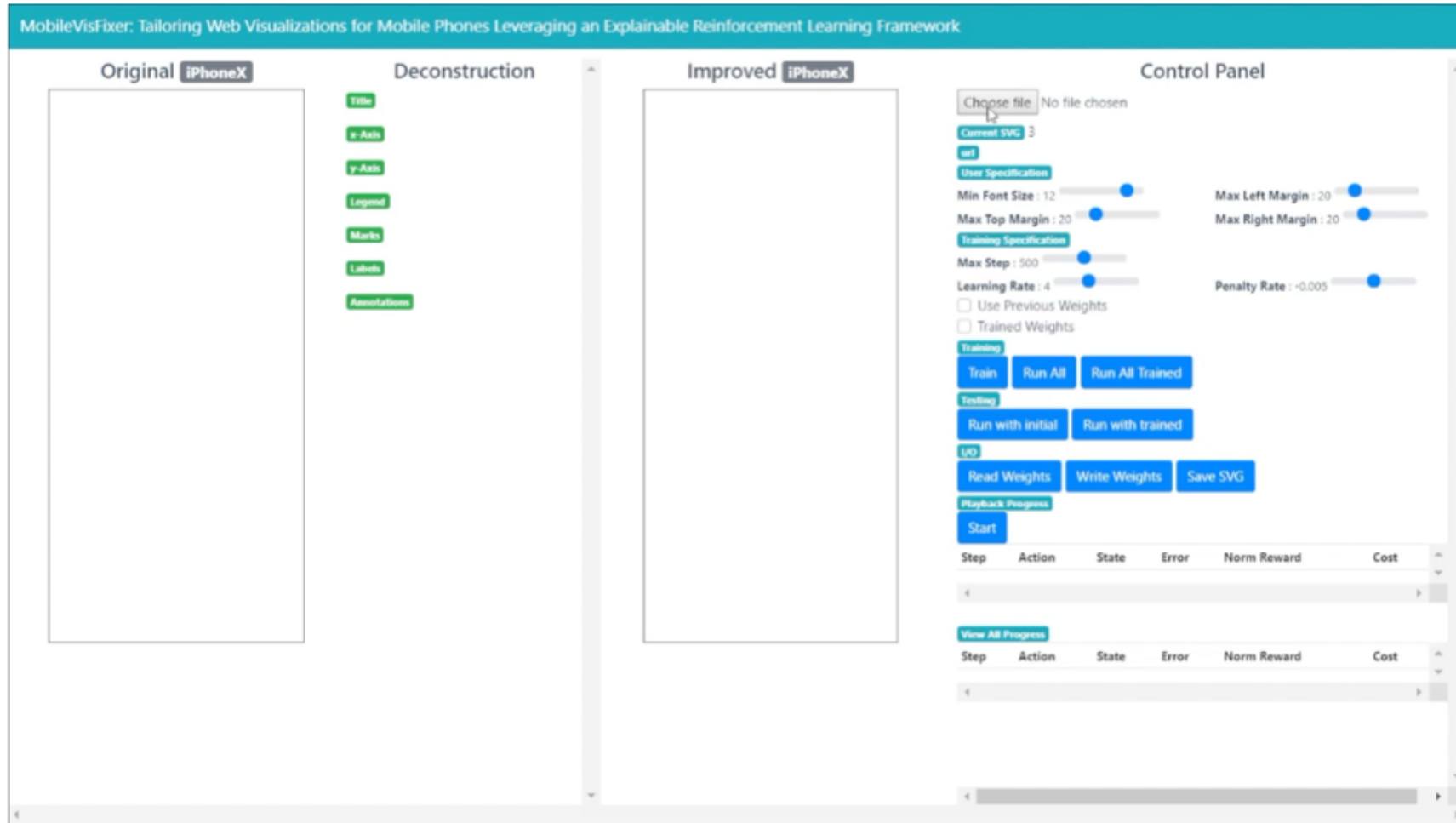
Improved iPhoneX: Shows the same scatter plot but with improved styling, including a grid and better spacing of the data points.

Control Panel: Contains various controls for the application, including a file selector (1_0_mob.svg), a 'Current SVG' field (3), and several sliders for 'User Specification' (Min Font Size: 12, Max Top Margin: 20, Max Left Margin: 20, Max Right Margin: 20, Max Step: 500, Learning Rate: 4, Penalty Rate: -0.005). There are also buttons for 'Train', 'Run All', 'Run All Trained', 'Run with initial', 'Run with trained', 'Load Weights', 'Write Weights', 'Save SVG', and 'Start'.

Playback Progress: A table showing the training progress:

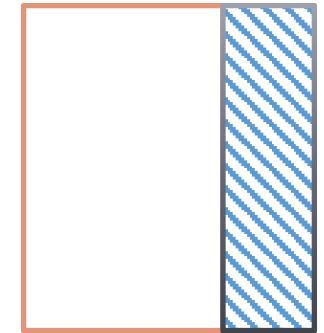
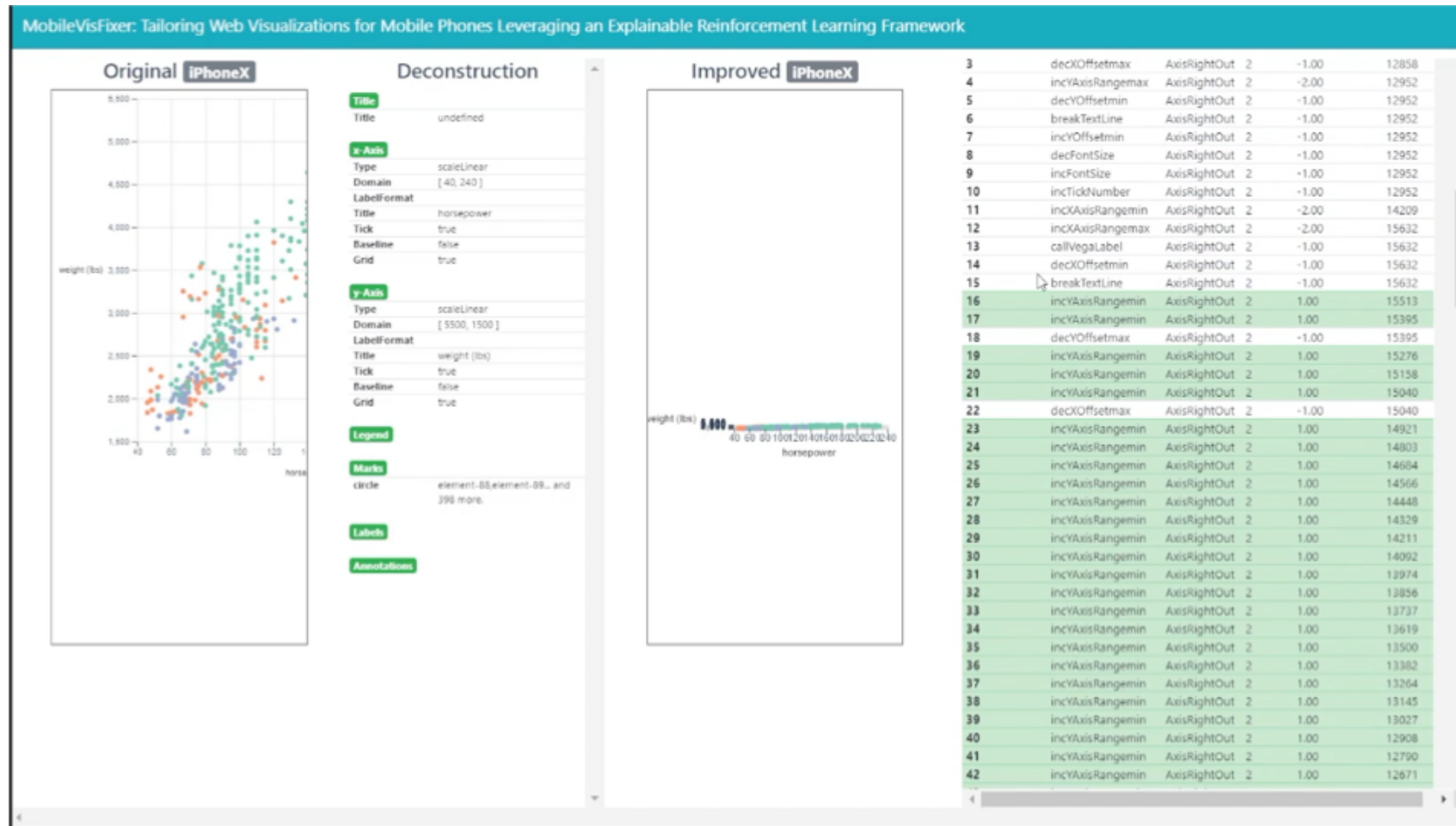
Step	Action	State	Error	Norm Reward	Cost
4	deconstructRangeMin	LeftMargin	6	Infinity	40
-1			-	-Infinity	-
0	deconstructRangeMin	TopMargin	5	0.21	18
1	deconstructRangeMin	TopMargin	5	0.21	18

2. Rule-based Approach: Limitation



When the axis exceeds the right of the view box, the agent will increase the YRangeMin.

2. Rule-based Approach: Limitation



The cost was the **area** exceeding the **view box**.



Compress height reduces this cost as well.

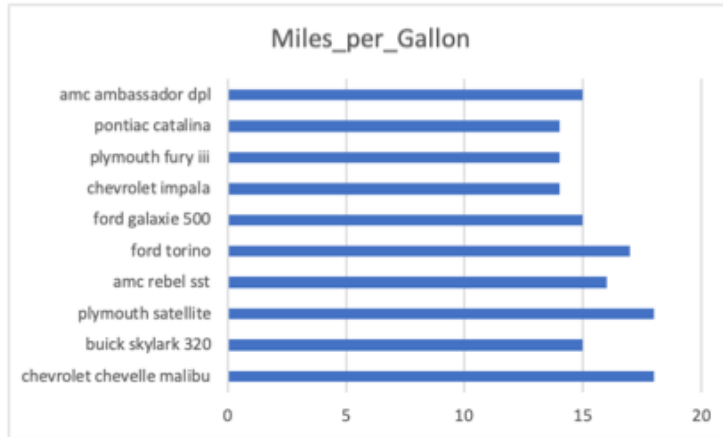
2. Rule-based Approach: Limitation

The performances highly rely on manually-crafted rules and/or cost functions.

Even seemingly reasonable cost functions might be problematic.

Can we directly learn layout qualities from human perception data?

3. Machine-Learning Based Approach



Chart



Human



Score



Difficulty in giving an accurate score
Inconsistent scoring scales among participants

3. Machine-Learning Based Approach

Comparison is an easier task than scoring a chart.

Which of the following layout do you prefer (in terms of aesthetics)?

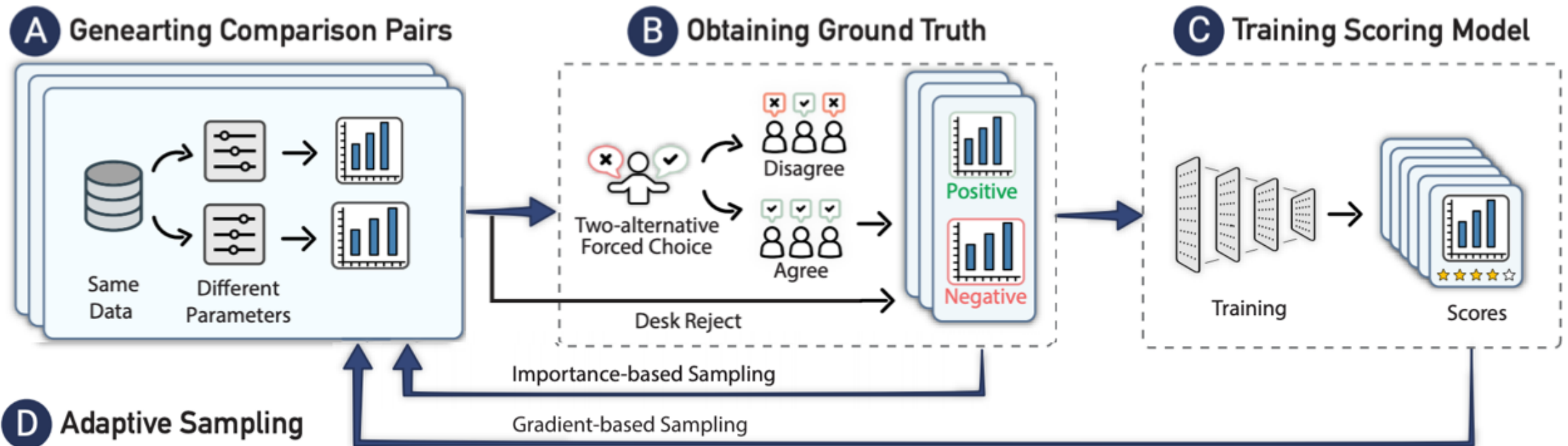
Top Bottom

Category	Top Chart Value	Bottom Chart Value
Ki	120	120
Fi	100	100
Bu	160	160
Gi	100	100
Mc	70	70
Me	40	40
Ha	110	110
Ba	140	140
Es	80	80
Ro	60	60
Fo	50	50
Hr	140	140
Br	50	50
Mo	140	140
Co	140	140
Ri	200	200
Th	80	80
Da	30	30
Bi	50	50

Two-forced Alternative Choice

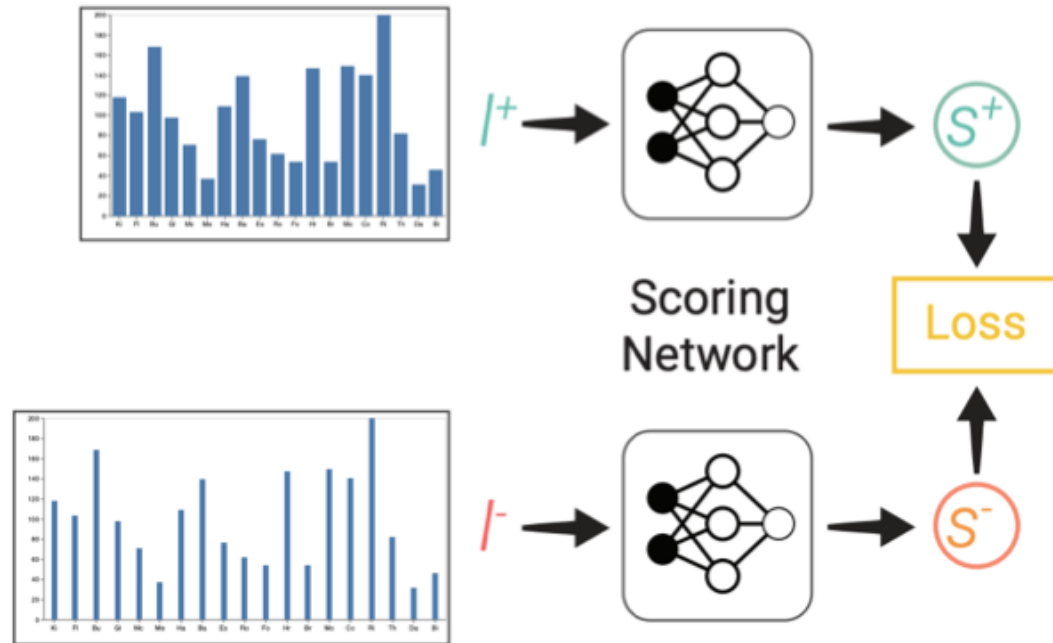
3. Machine-Learning Based Approach

Learning to automate chart configurations from crowdsourced paired comparison



3. Machine-Learning Based Approach

Deep learning on paired comparison data



To predict a higher score for the positive chart in a pair

3. Machine-Learning Based Approach: Evaluation

Two experiments:

- Exp. 1: 3 parameters in bar charts
- Exp. 2: 6 parameters in bar charts

Baseline:

- RankSVM
- Hand-crafted cost functions for layout qualities

	Ours	RankSVM	White Space	Scale	Unity	Balance	All
Exp. 1 (N = 1,177)	<u>76.60</u>	70.83	57.28	56.26	52.00	56.08	60.81
Exp. 2 (N = 1,333)	<u>78.27</u>	64.48	58.24	61.72	56.21	63.18	68.73

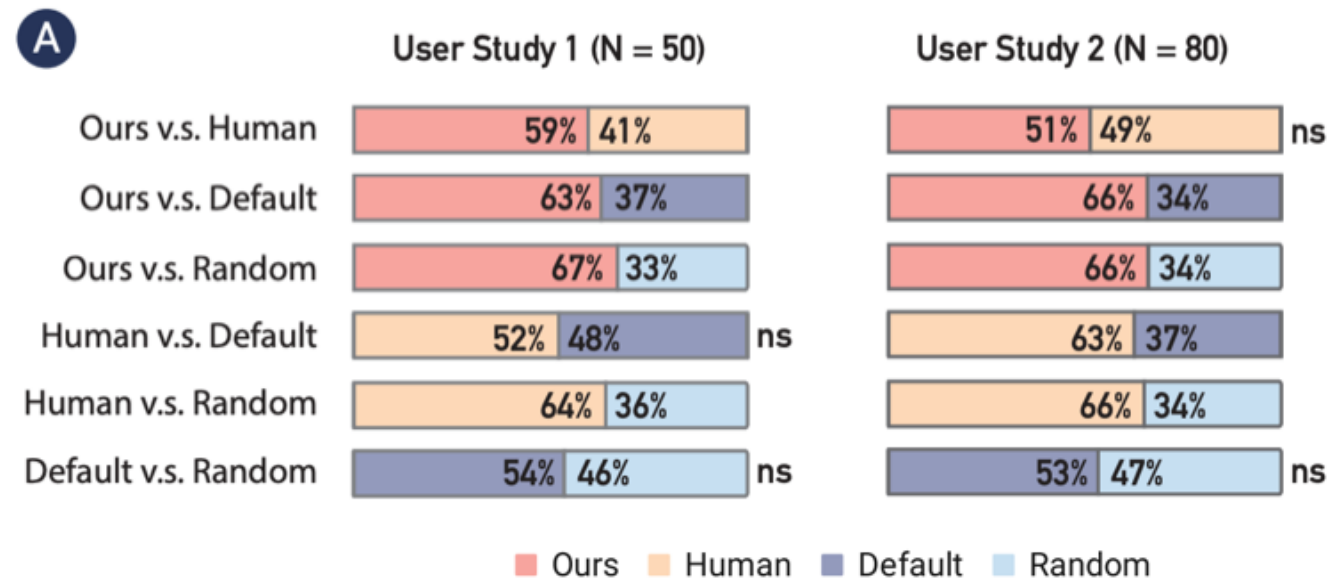
Model Performance in Accuracy

3. Machine-Learning Based Approach: Evaluation

Our method recommended better chart configurations

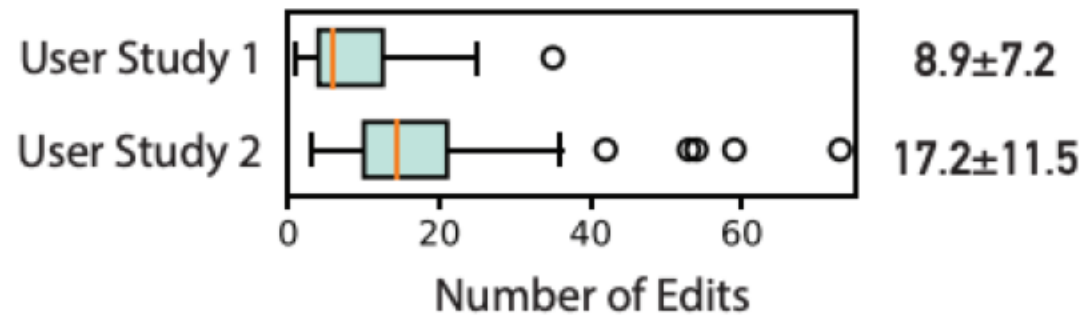
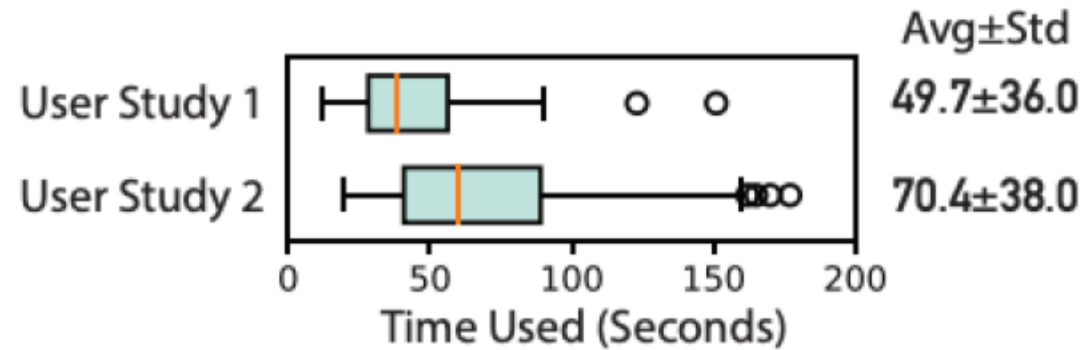
Baseline:

- Human
- Default (Excel and Vega-lite)
- Random



3. Machine-Learning Based Approach: Evaluation

Our method saved user time.



Baseline: Human

3. Machine-Learning Based Approach: Limitation

Paired comparison has exponential complexity.

6 parameters

10 possible values per parameter

= 10^6 possible combinations of parameter values

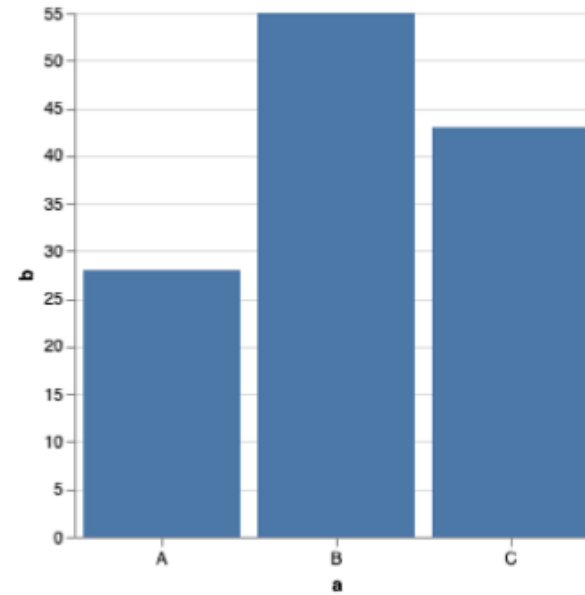
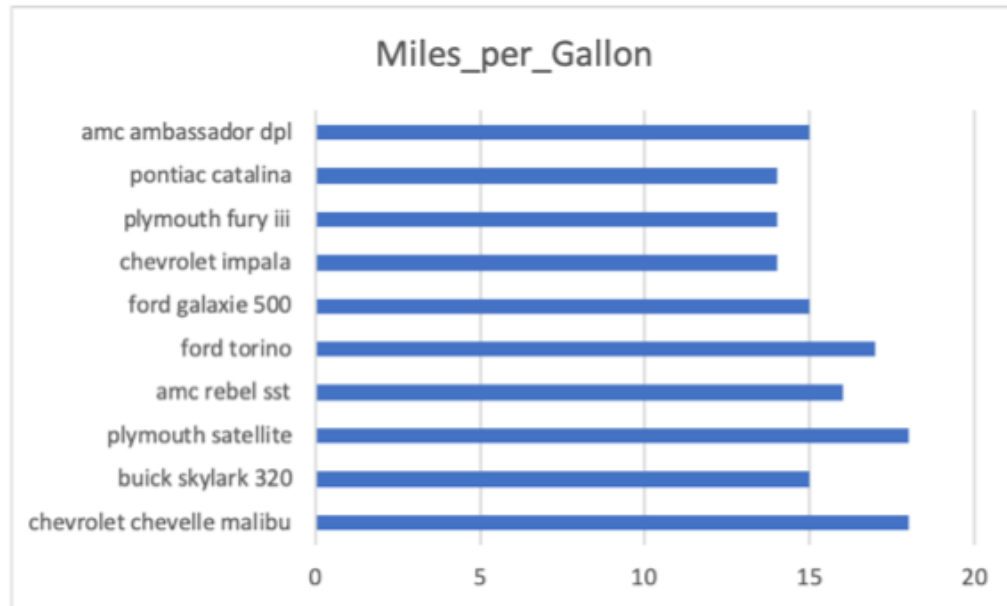
Full paired comparison requires $10^6 C 2$.



How to (adaptively) sample important pairs for comparison?

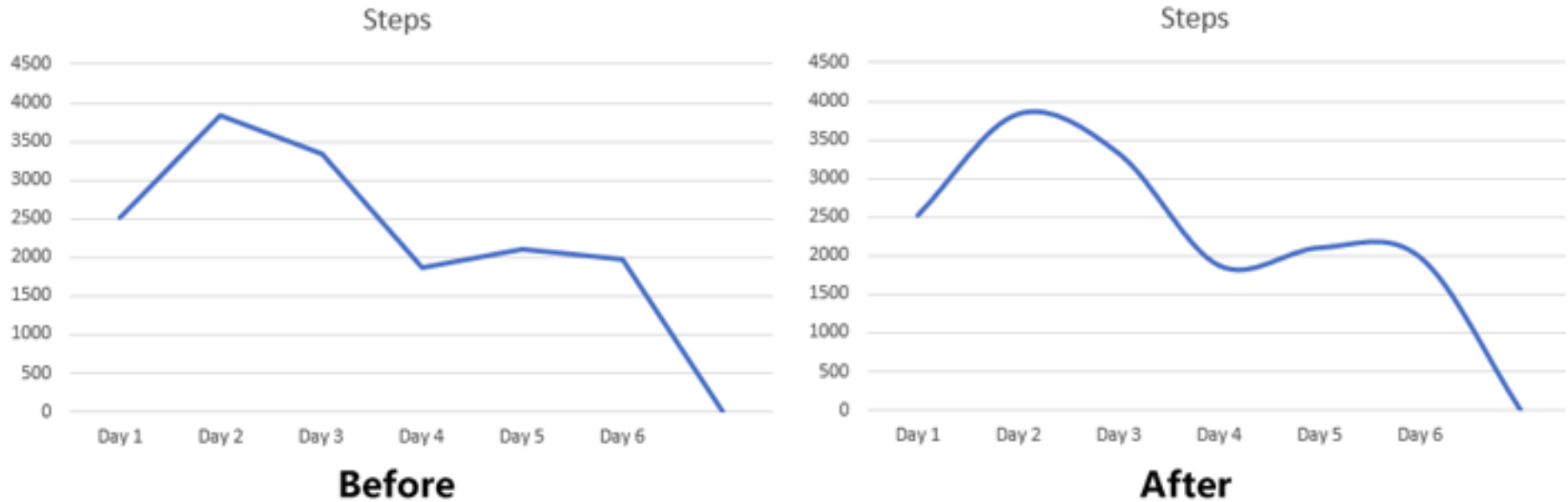
4. Discussions and Implications

- Do not trust the defaults.



4. Discussions and Implications

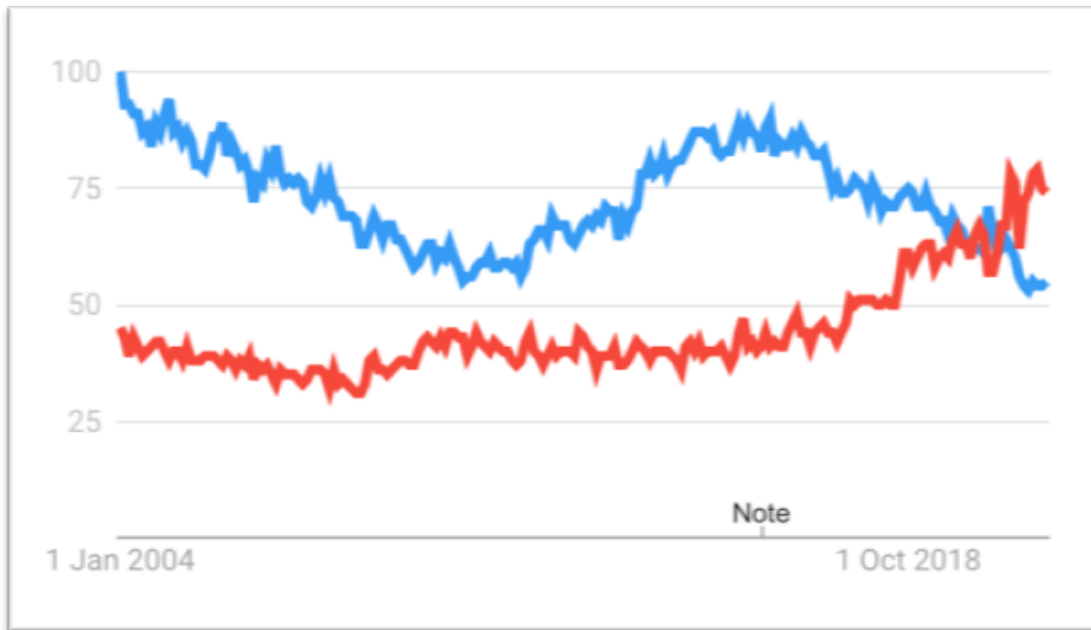
- "What is beautiful is good"?



Google's Smooth Line Chart

4. Discussions and Implications

From Data Visualization to Visualization Data



How AI could process and analyze visualizations?

- Recommendation
- Querying
- Summarizing
- ...

Chart has surpassed **Image** globally in Google Search Trend since Jan 2020

4. Discussions and Implications

What makes visualization data different?

- Visualization data is characterized as multi-modal data.

Image

Parameter

Text

Data



How to represent and fuse different modals?



How to translate from one modal to another?



How to align one modal with another?

4. Discussions and Implications

What makes visualization data different?

- Visualization data is characterized as multi-modal data.
- Visualization data is unnatural artefacts purposefully constructed with domain knowledge, which is difficult to learn.



How to develop ML models that are more tailored to visualization data?



How to combine ML approaches with domain knowledge?

4. Discussions and Implications

What makes visualization data different?

- Visualization data is characterized as multi-modal data.
- Visualization data is unnatural artefacts purposefully constructed with domain knowledge, which is difficult to learn.
- Visualization data is more susceptible to detailed local information.

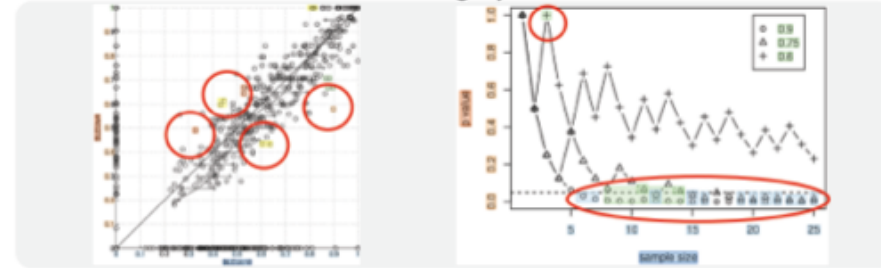


How to develop ML models with high accuracy and granularity?

(a) Merged Labels due to Tight Spacing



(b) Text Characters as Plotting Symbols



4. Discussions and Implications

What makes visualization data different?

- Visualization data is characterized as multi-modal data.
- Visualization data is unnatural artefacts purposefully constructed with domain knowledge, which is difficult to learn.
- Visualization data is more susceptible to detailed local information.
- The encoded data brings up several data-specific challenges such as mathematical reasoning.



How to learn mathematical reasoning?

5. Take-home Messages

- Chart layouts influence user experiences (UX) such as readability and aesthetics.
- It is helpful to automate parameter configurations via ML, saving user time and improving results.
- Visualization is becoming a new type of data that warrants deep research.

