VizCommender

Computing Text-Based Similarity in Visualization Repositories for Content-Based Recommendations

Michael Oppermann, Robert Kincaid, and Tamara Munzner

Conference Talk, IEEE VIS 2020

michaeloppermann.com/work/viz-commender

THE UNIVERSITY OF BRITISH COLUMBIA

tableau

Large-scale visualization repositories

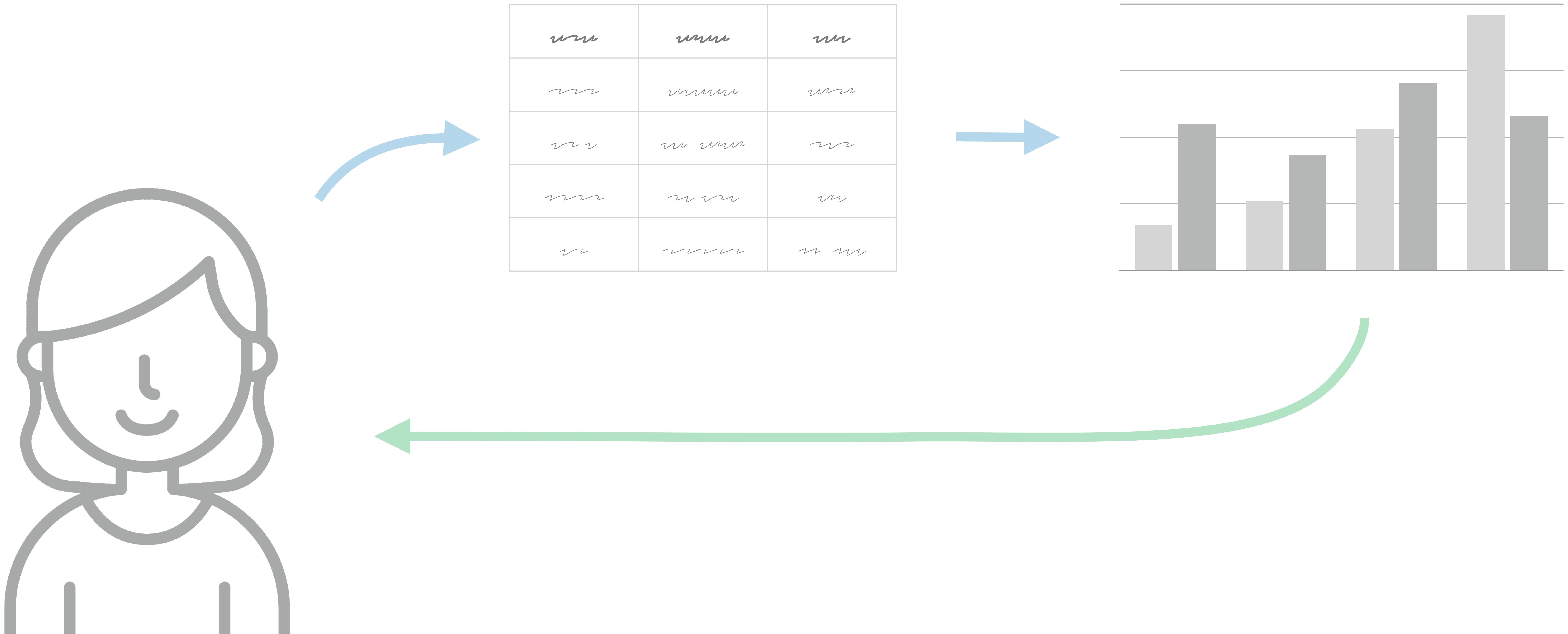
Users have difficulty discovering relevant content.

Users often start from scratch instead of reusing content.

Recommendation systems are increasingly used to assist users by surfacing relevant content.

Visual encoding recommendation

Tableau ShowMe, Voyager, Draco, Data2Vis, …



~~Visual encoding~~ recommendation

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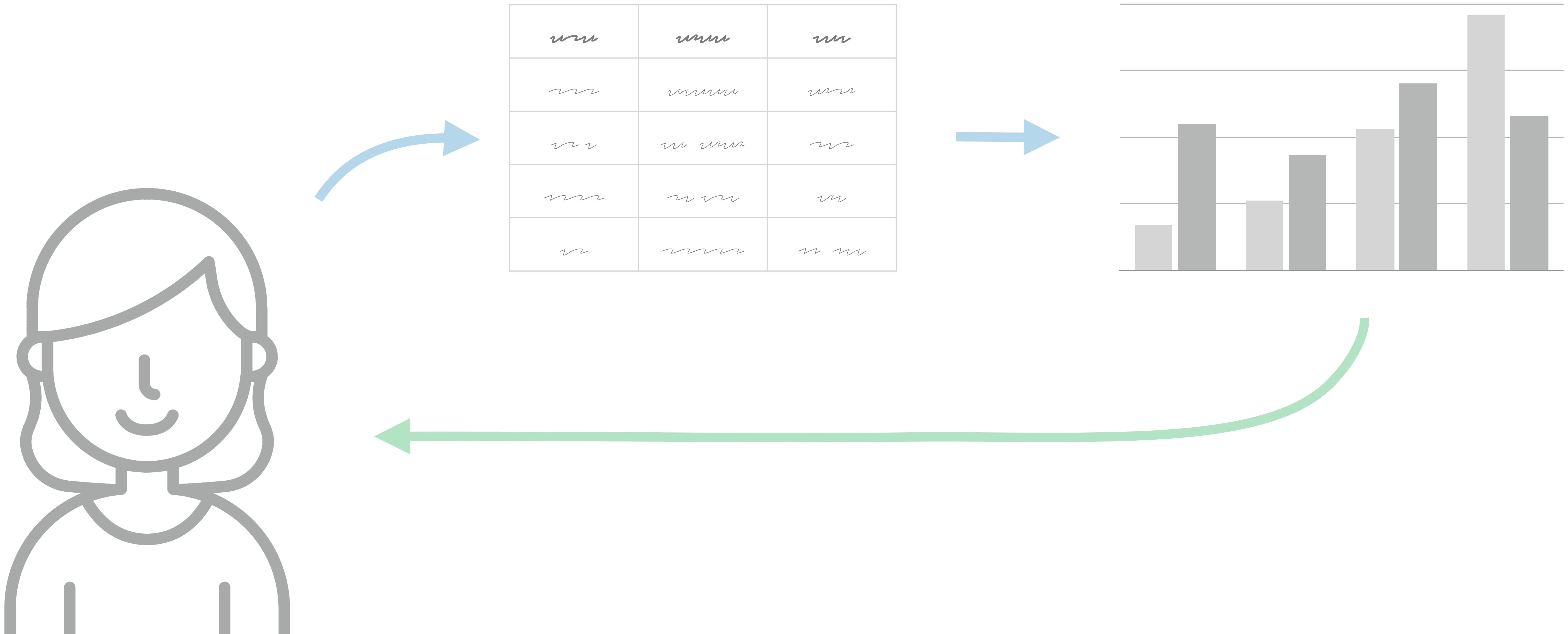
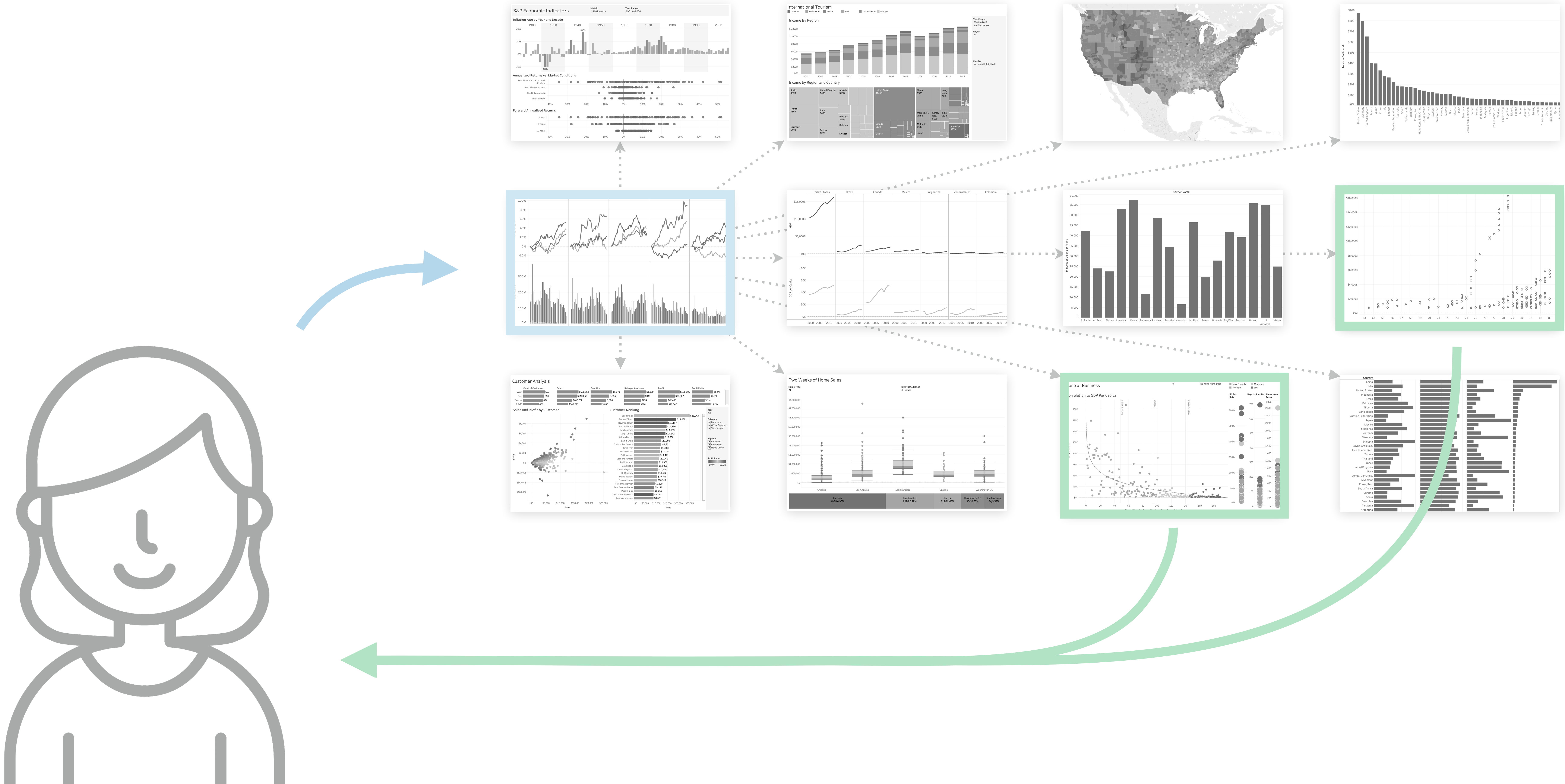


Visualization workbook recommendations based on content features



Recommendation Systems

Content-based filtering

Collaborative filtering

Recommendation Systems

Content-based filtering

- Focus of our work
- Finding relevant items based on their actual content
- Less diverse but more accurate recommendations
- Allows identification of *near-duplicate* items

Collaborative filtering

Recommendation Systems

Content-based filtering

Collaborative filtering

- Recommendations based on user interactions
- Requires no domain knowledge, allows fast computation, serendipitous recommendations
- *Cold start* problem for new items or new users

Recommendation Systems

Content-based filtering

Collaborative filtering

Hybrid system

Recommendation Systems

Content-based filtering

Collaborative filtering

Hybrid system

Which content features are most informative for comparisons?

What techniques can we use for comparing and ranking viz specifications?

Text-based similarity measure

- Content-based recommendations
- Facilitate information seeking

Overview

Close collaboration with the *Recommender Systems Group* at Tableau

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VizCommender

- Extract content from viz specifications
- Analysis & feature engineering
- Proof-of-concept interface

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User study: Crowdsourced human text similarity judgements

Comparative model analysis

VizCommender prototype

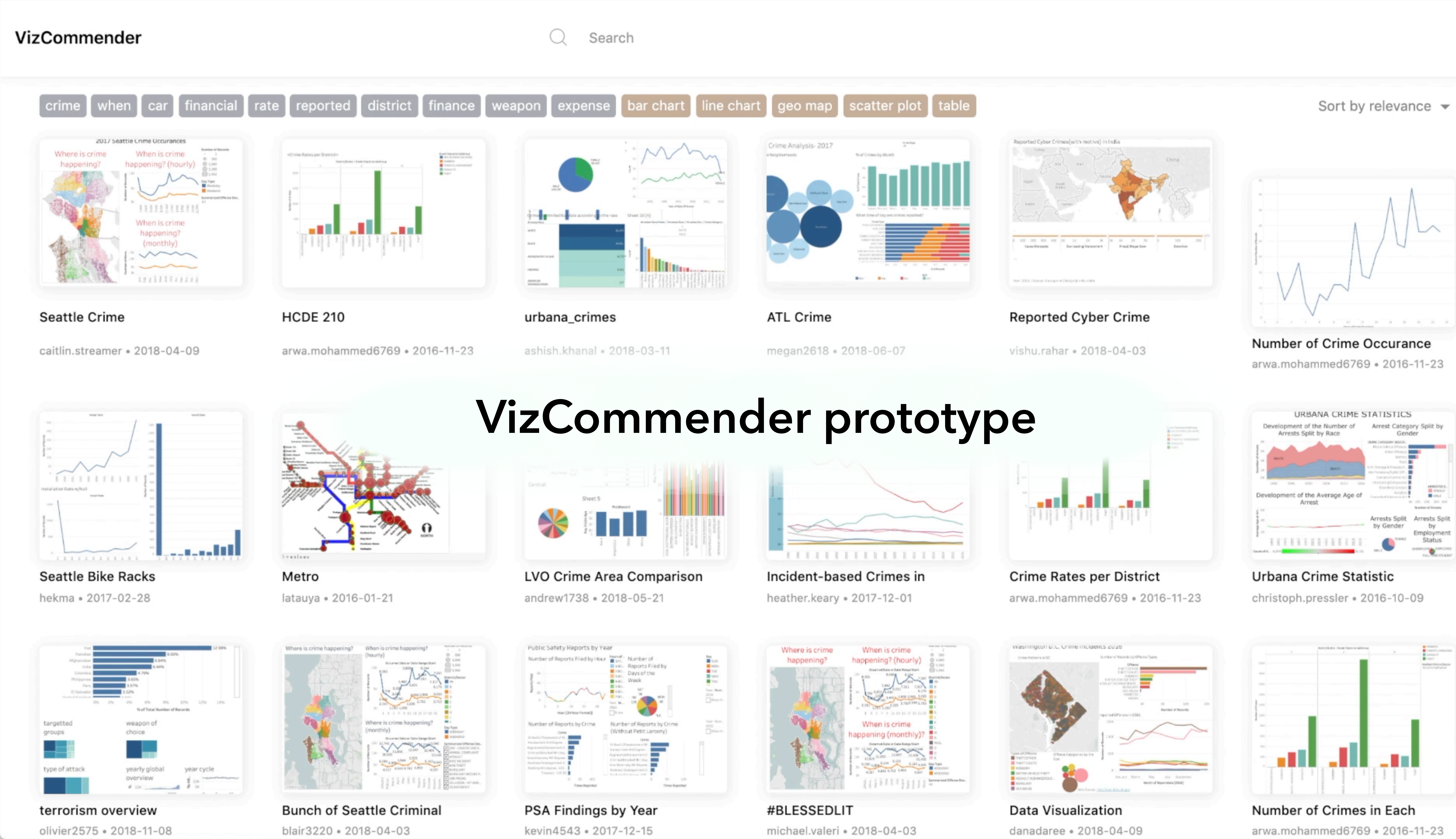
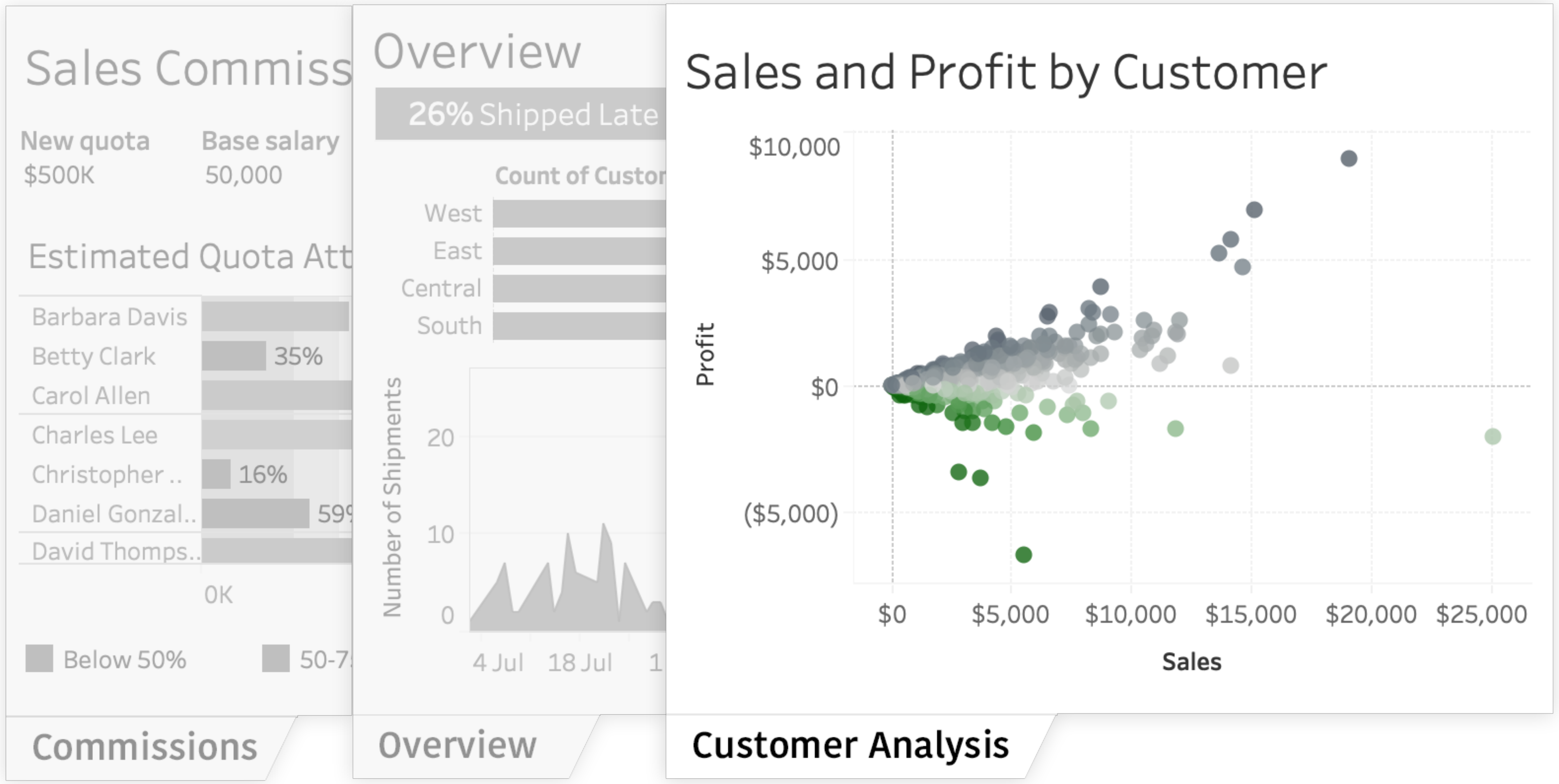
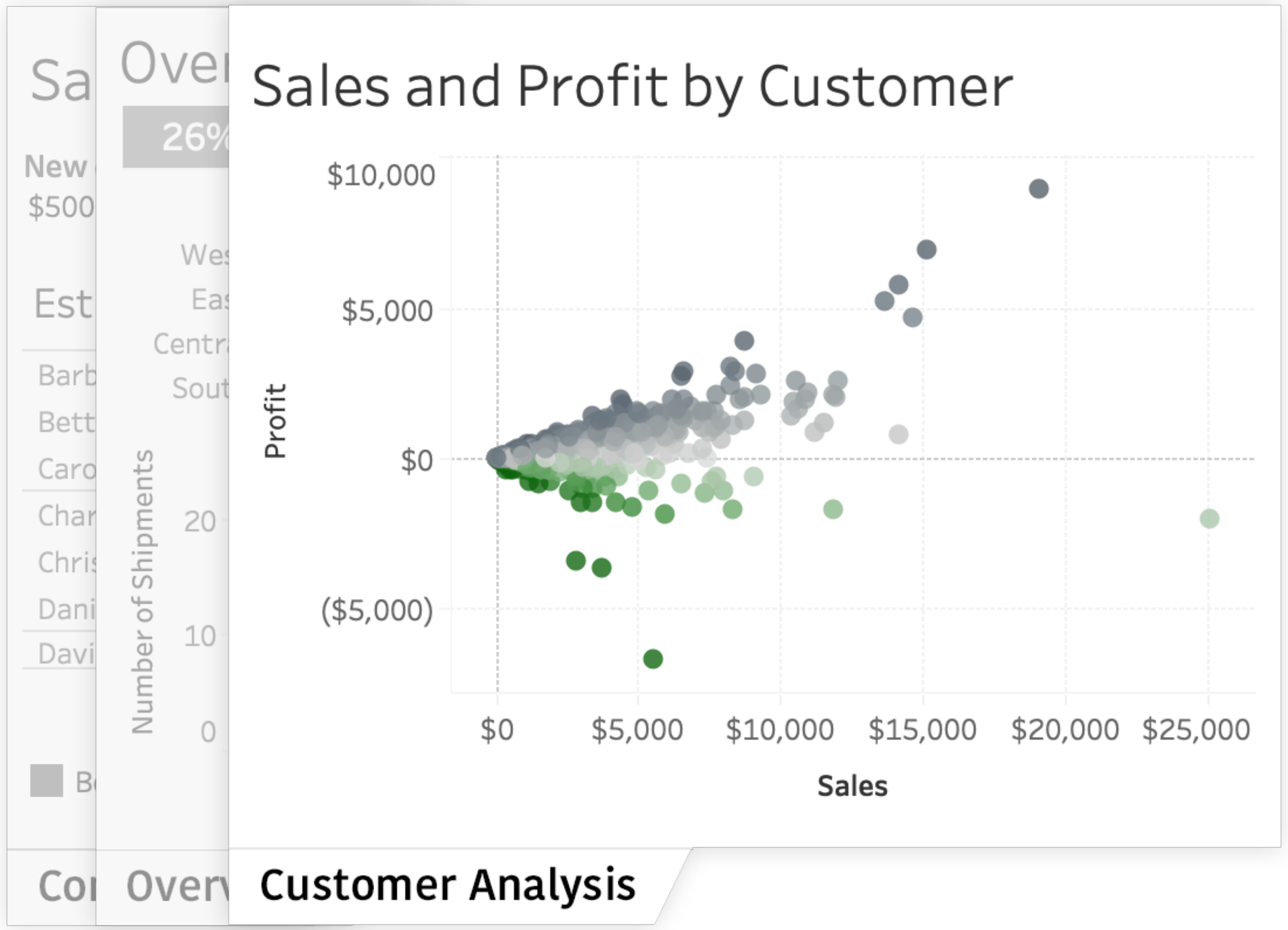


Tableau Visualization Workbook



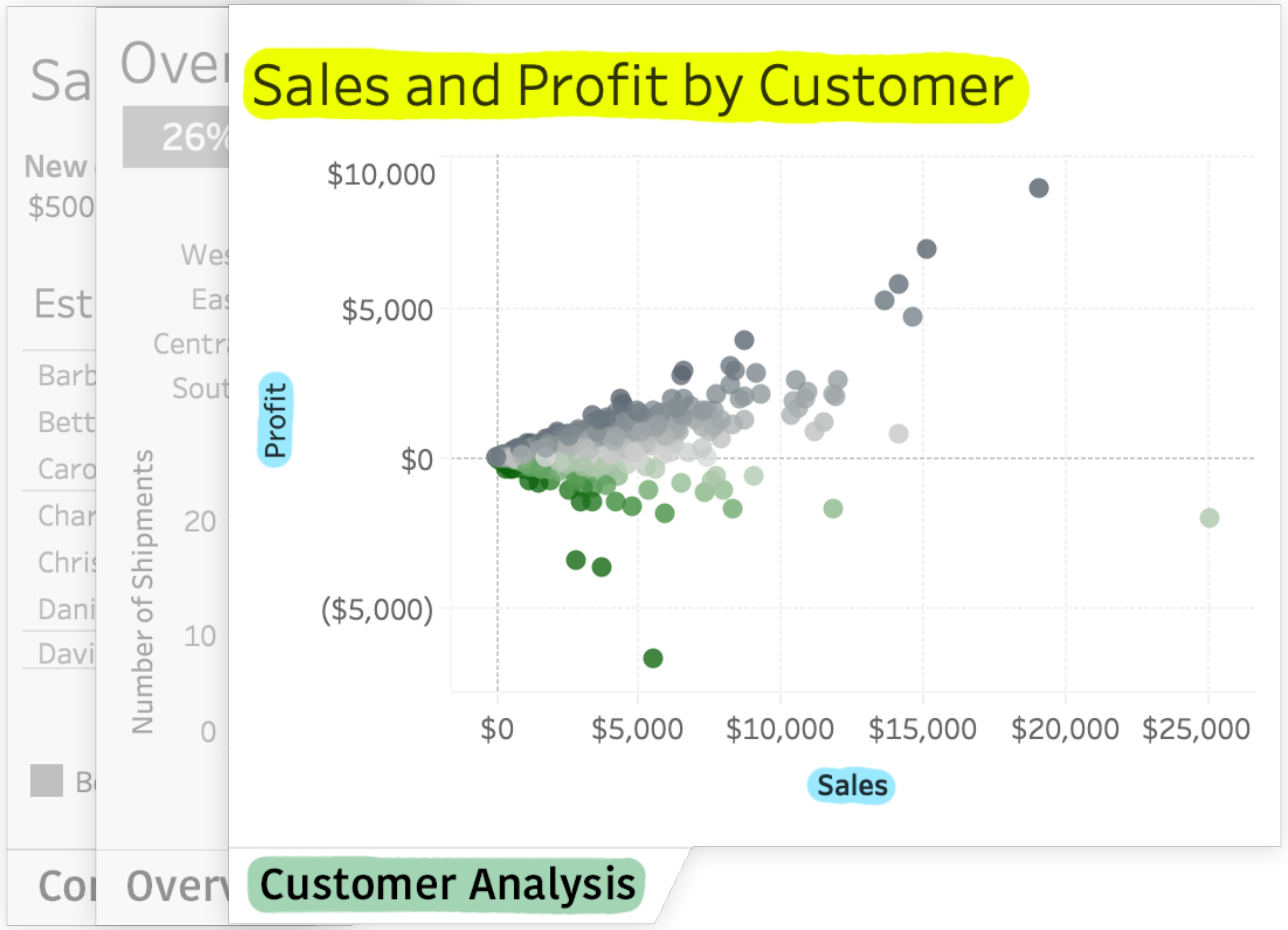
Workbook



Visualization Specification

```
<worksheet name="Customer Analysis">
    <layout-options>
        <title>
            <formatted-text>
                <run>Sales and Profit by Customer</run>
            </formatted-text>
        </title>
    </layout-options>
    <table>
        <rows>...[sum:Profit:qk]</rows>
        <cols>...[sum:Sales:qk]</cols>
    </table>
    ...
</worksheet>
```

Workbook



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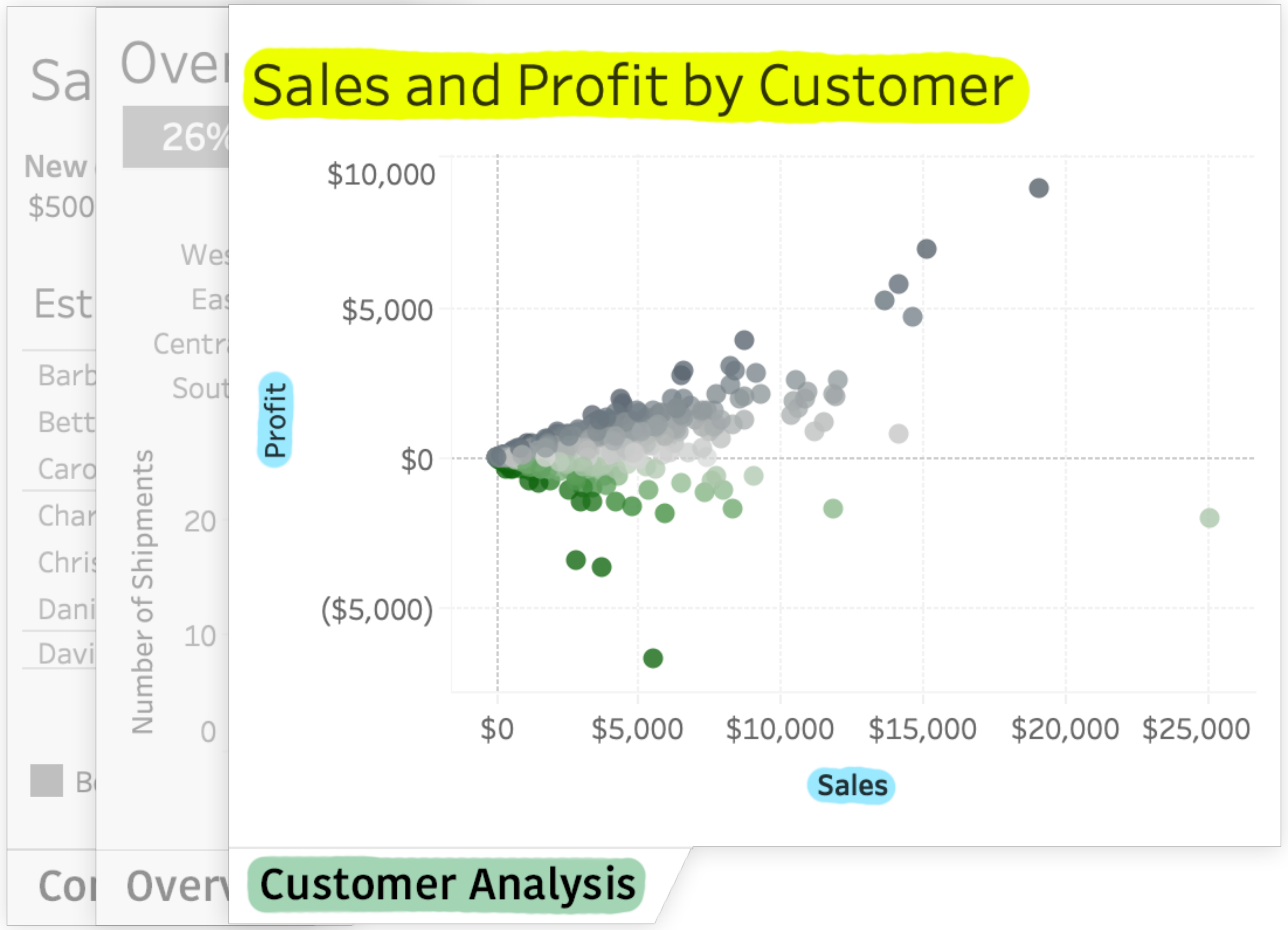

City	Customer Name	Sales	Discount	. . .

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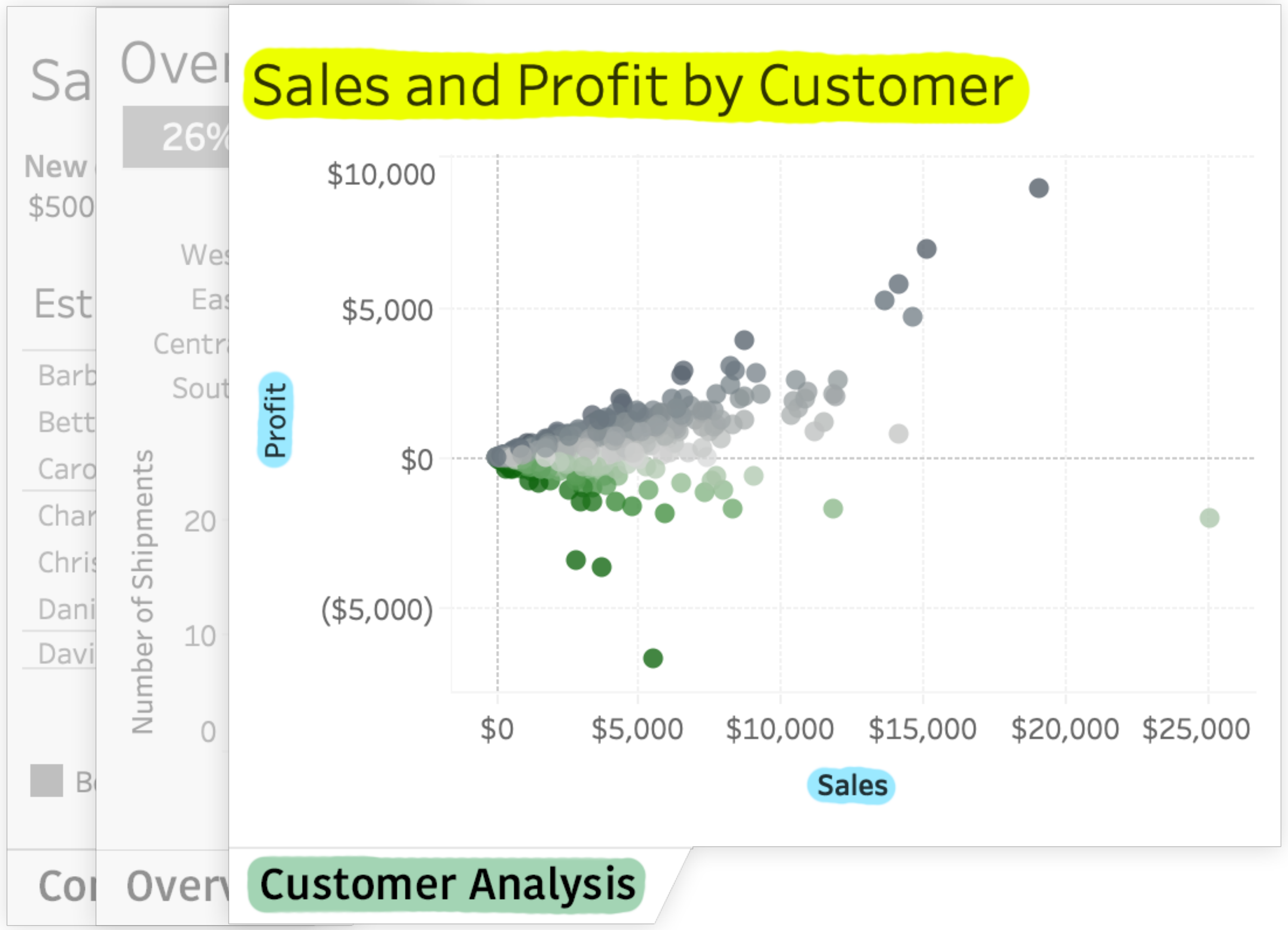

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    </table>
    ...
</worksheet>
```

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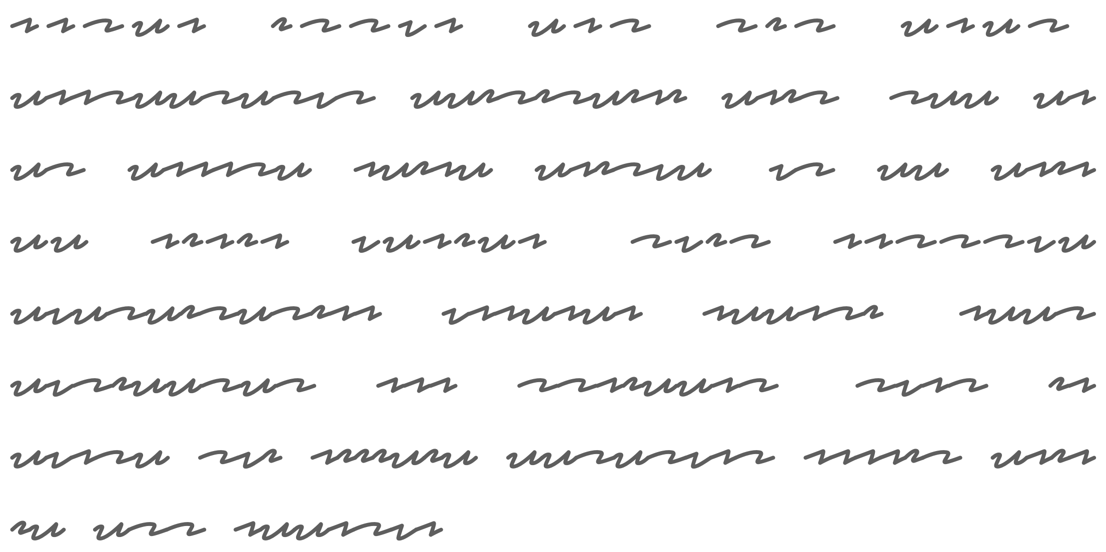
            ...
        </metadata-record>
        <metadata-record class="column">
            <remote-name>Customer Name</remote-name>
            ...
            <remote-name>Sales</remote-name>
```

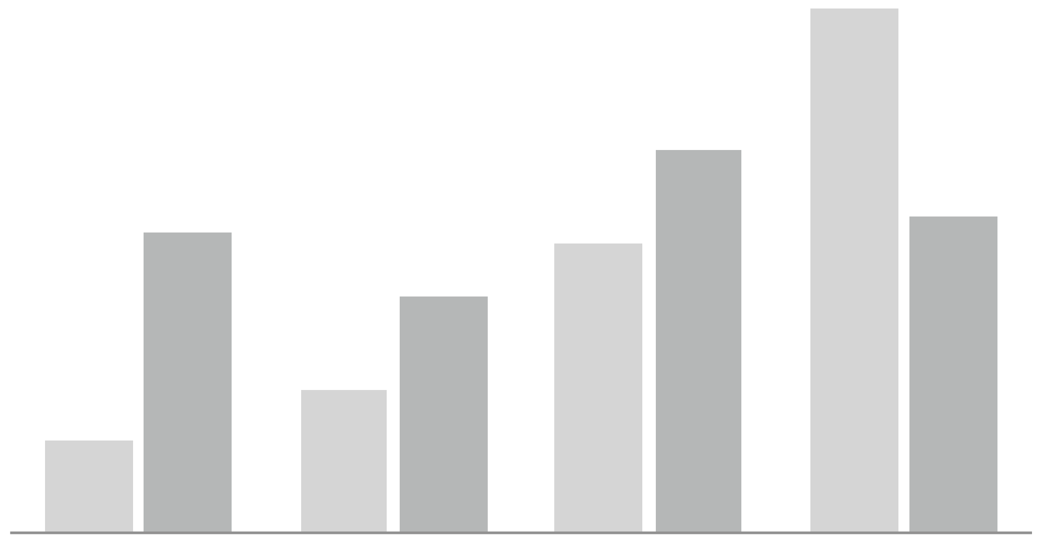
Initial Experiments

Extracted text

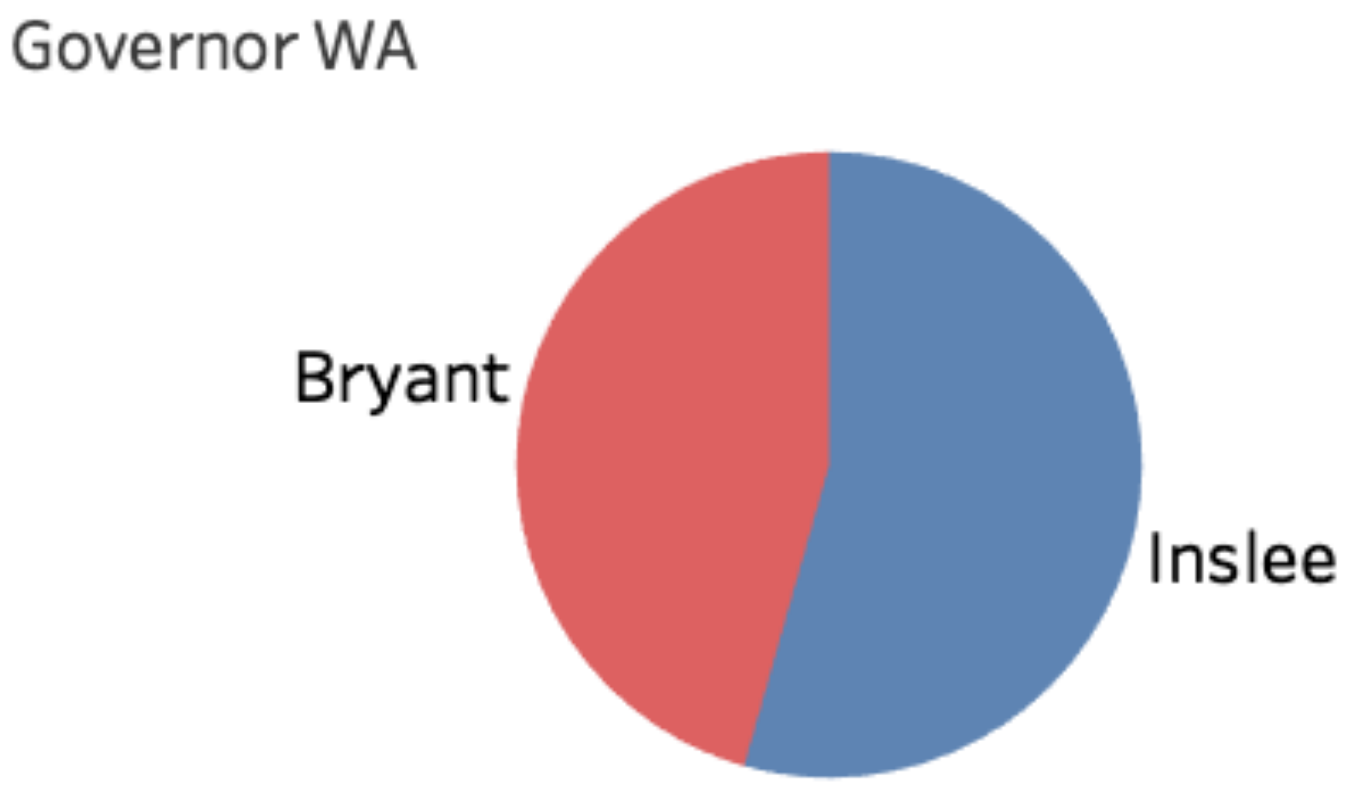


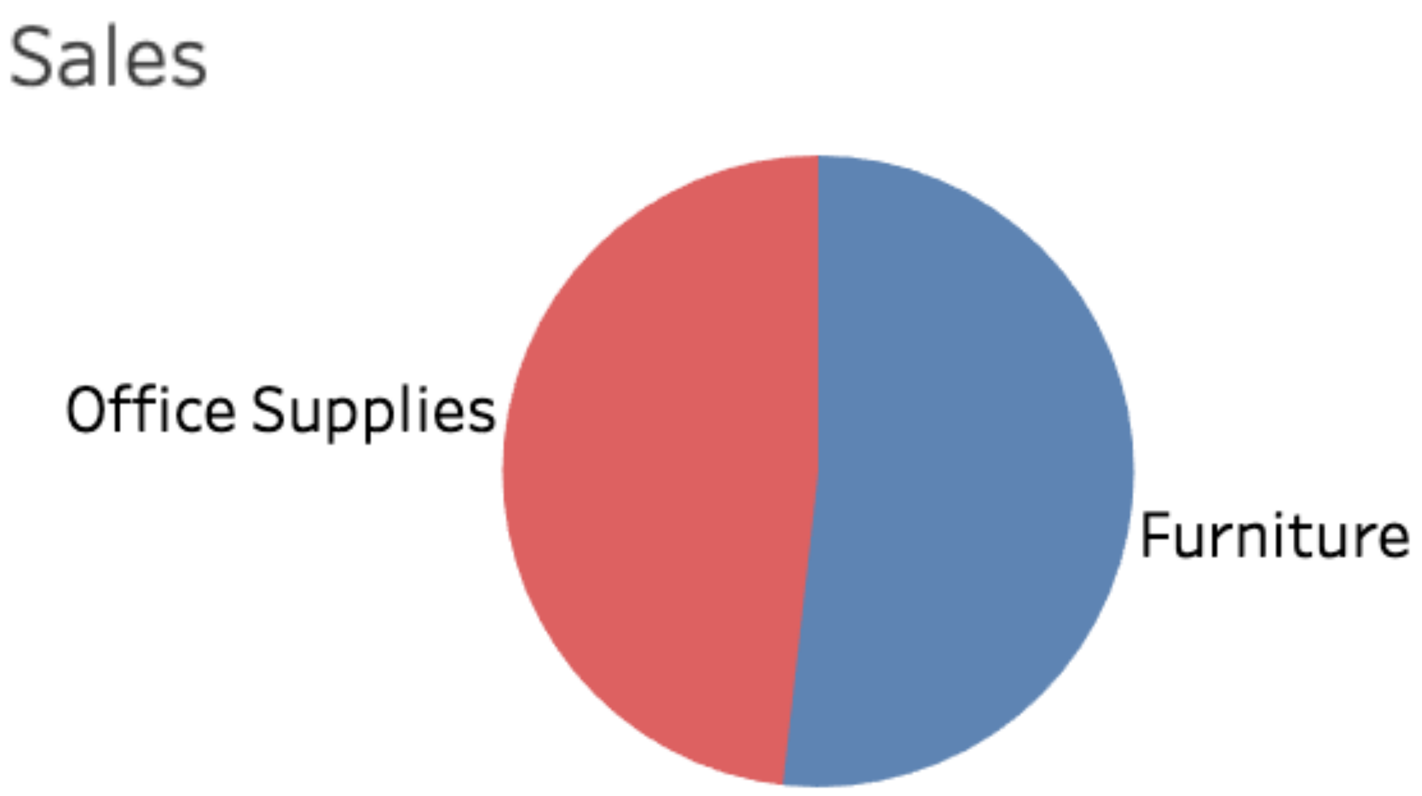
+

Visual encodings



Different data, same encoding





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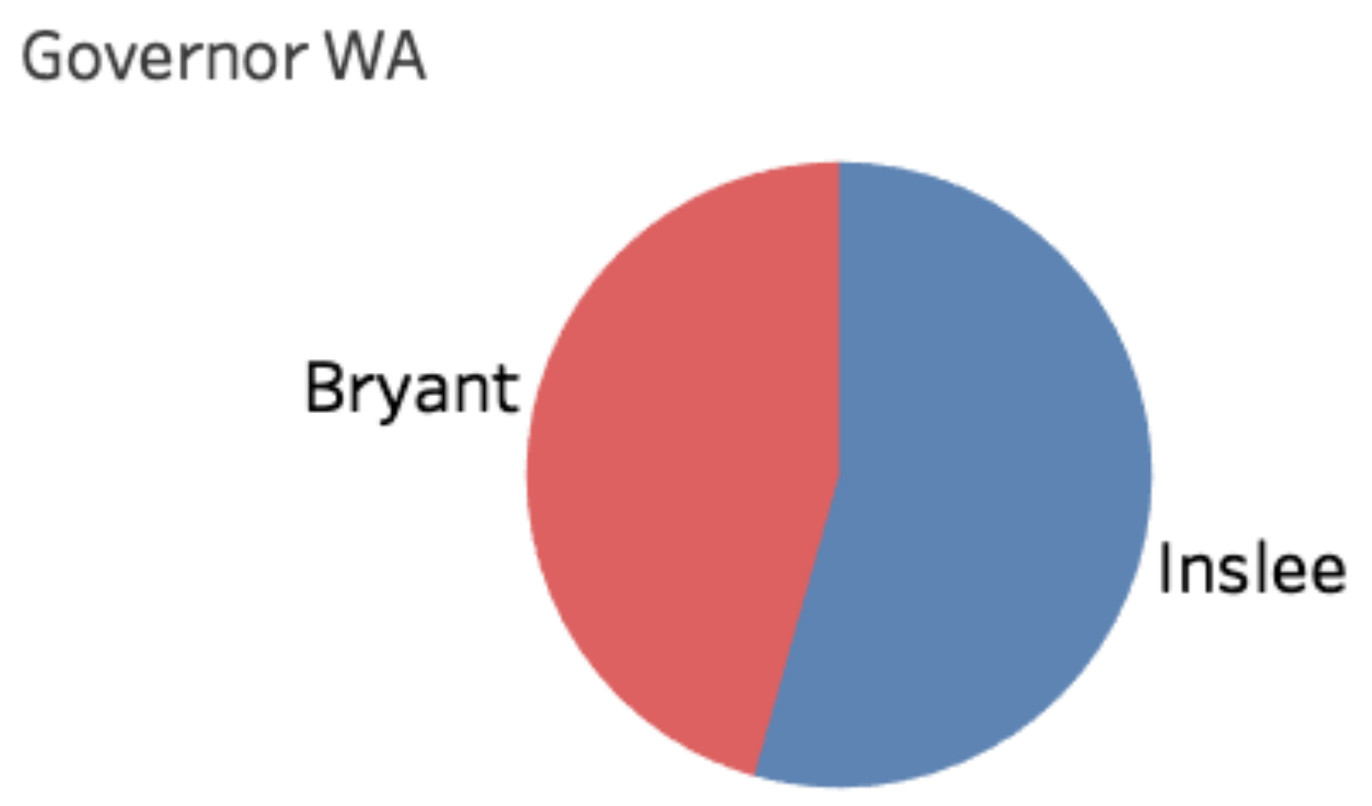
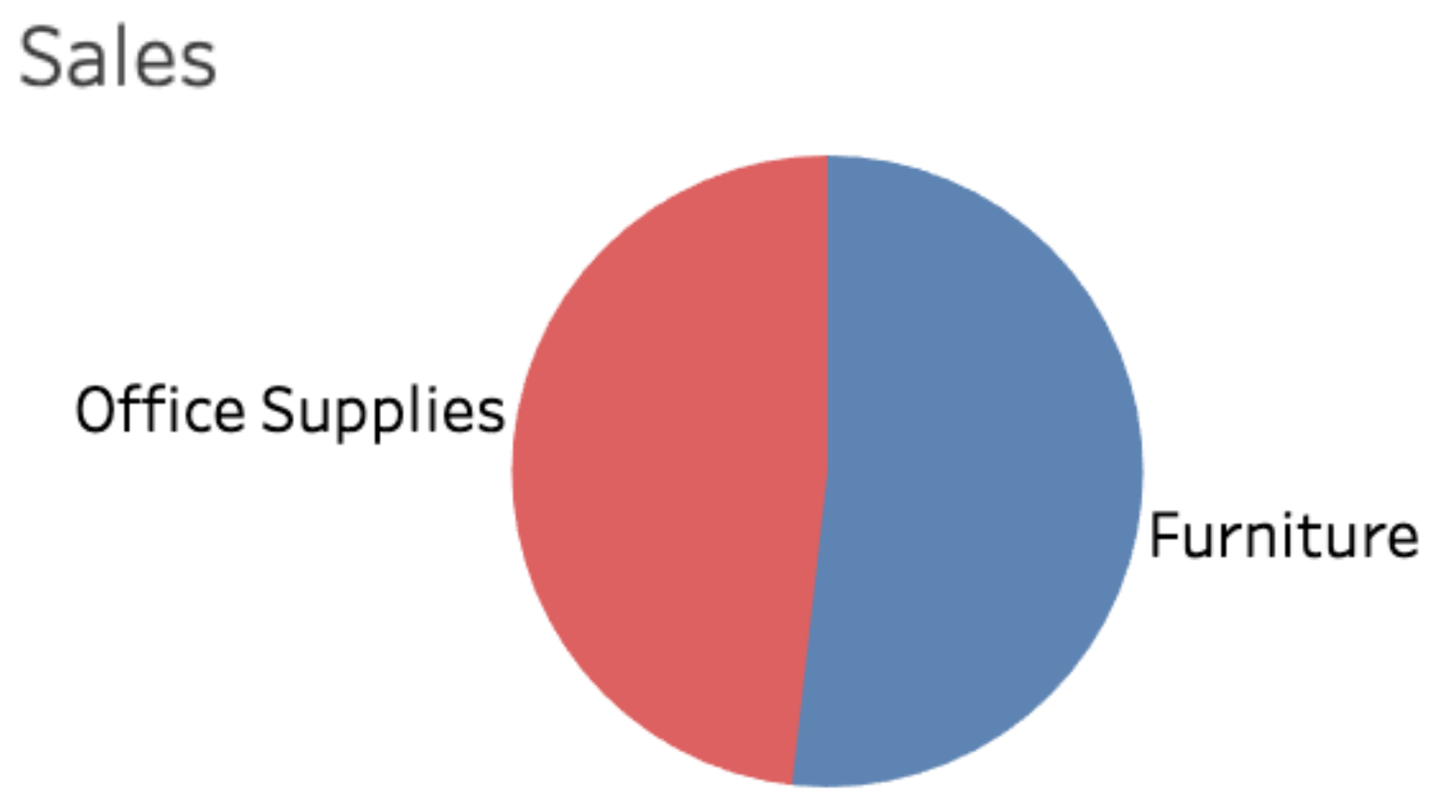
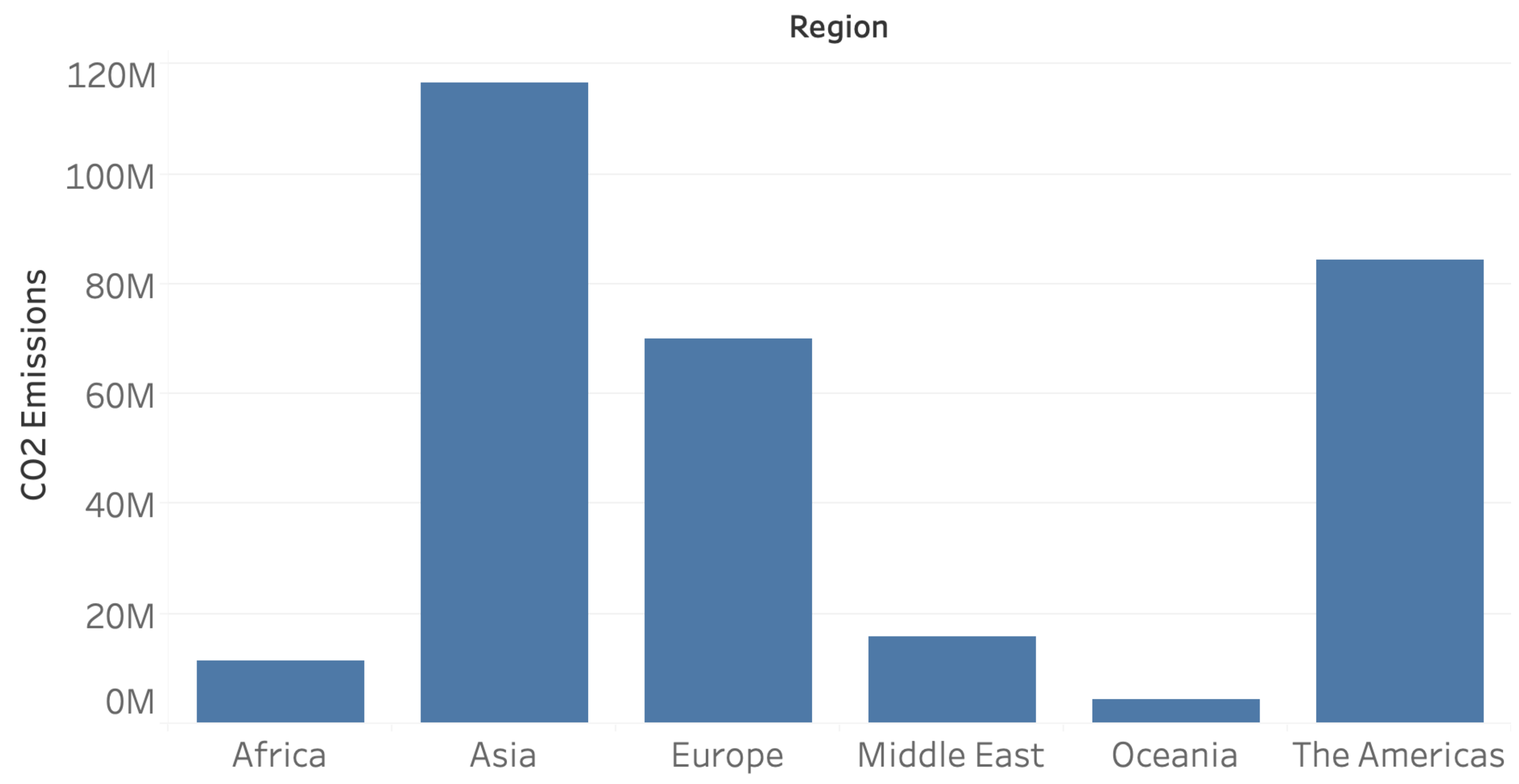
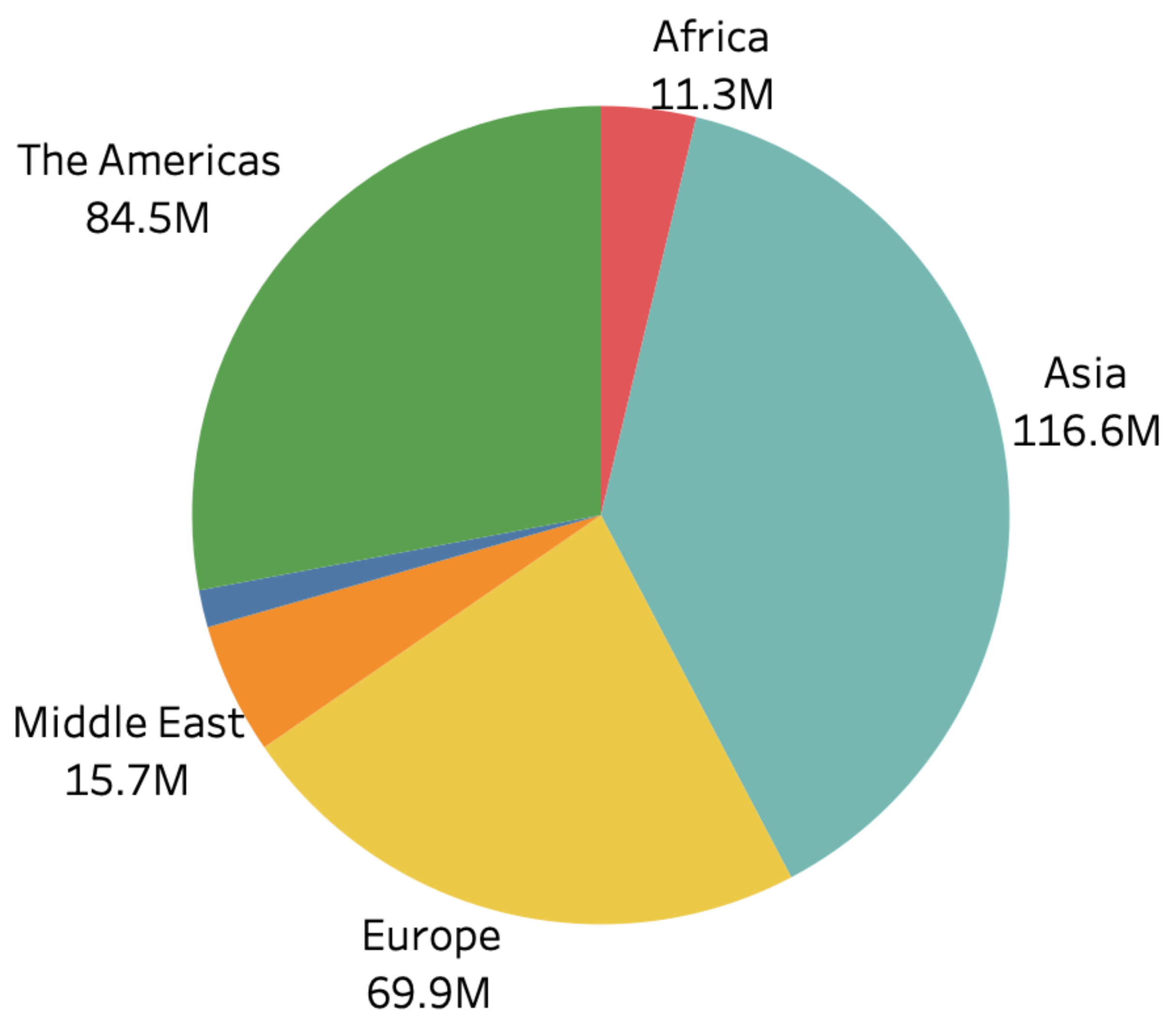




Same data, different visual encodings





Features: Leaving Out Visual Encodings

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For design inspiration and learning

- Need visual style

Features: Leaving Out Visual Encodings

For design inspiration and learning

- Need visual style

Our primary task: Information seeking

- Core enterprise task
- Subject matter of a workbook
- **Do not need** visual style (marks, colors, layout properties, …)

Data Challenges

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Very limited text

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Additional challenges:

- Multi-sheet workbooks and nested visualizations

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- Multiple versions

Data Challenges

Very limited text

Additional challenges:

- Multi-sheet workbooks and nested visualizations
- Incomplete workbooks
- Multiple versions
- Out-of-vocabulary words

Extracted text

customer analysis sales profit discount commission segment ratio ranking count ship performance target furniture office home supplies city drilldown late early product category forecast order quantity target ...

Extracted text

```
customer analysis sales profit discount
commission segment ratio ranking count ship
performance target furniture office home
supplies city drilldown late early product
category forecast order quantity target ...
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Transform?

Numeric document representation

0.37546	0.13540	0.01713	0.04225	0.01993	...

Extracted text

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Transform?

Numeric document representation

0.37546	0.13540	0.01713	0.04225	0.01993	...

Comparisons?

Extracted text

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Transform?

Recommendations

Numeric document representation

0.37546	0.13540	0.01713	0.04225	0.01993	...

Comparisons?

NLP Models

- **TF-IDF** & cosine similarity
- **Latent semantic indexing (LSI)** & cosine similarity
- **Latent dirichlet allocation (LDA)** & Jensen-Shannon divergence
- **Word embeddings (Doc2Vec, GloVe)** & cosine similarity

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User study: Crowdsourced human text similarity judgements

Comparative model analysis

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Crowdsourced human similarity judgements

2-Alternative Forced Choice Experiment

135 Triplets

Reference

Alternative 1

Alternative 2

2-Alternative Forced Choice Experiment

135 Triplets

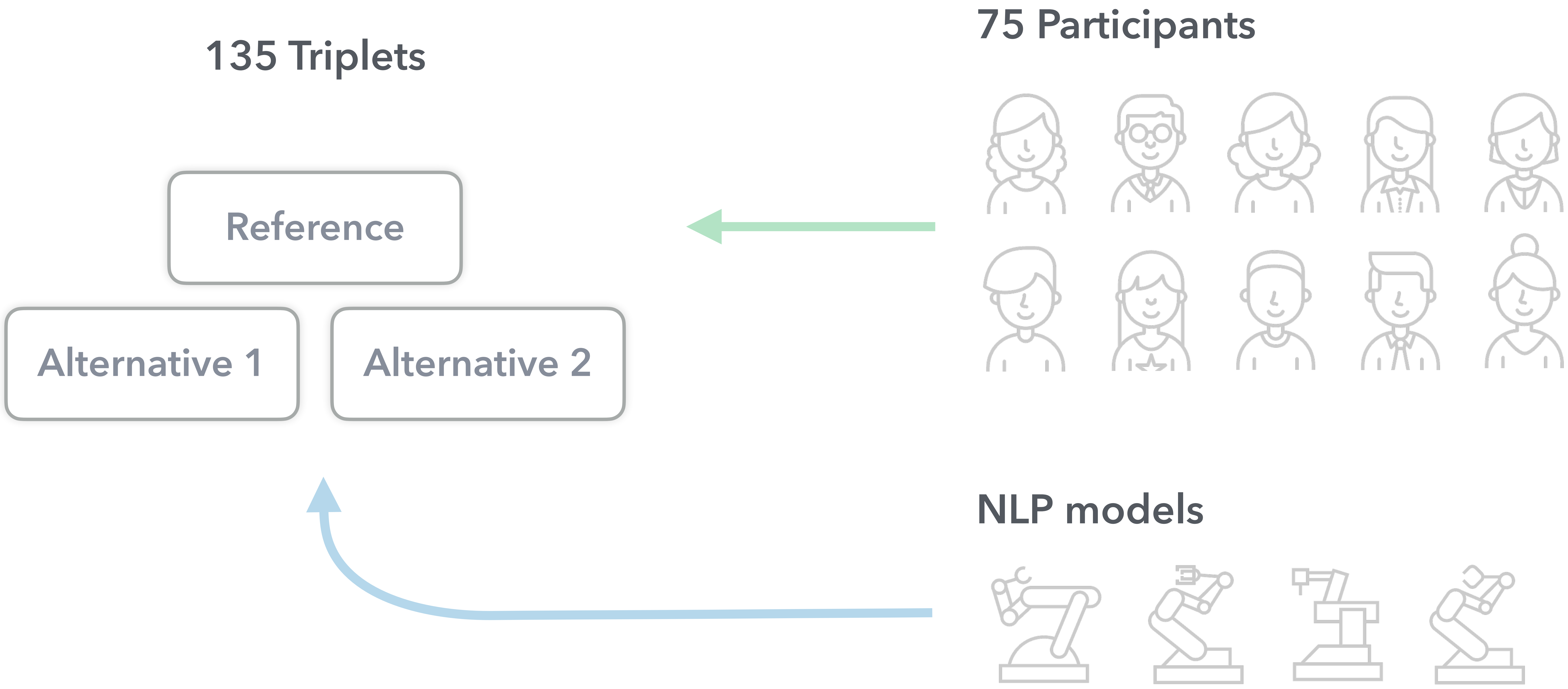
Reference

Alternative 1

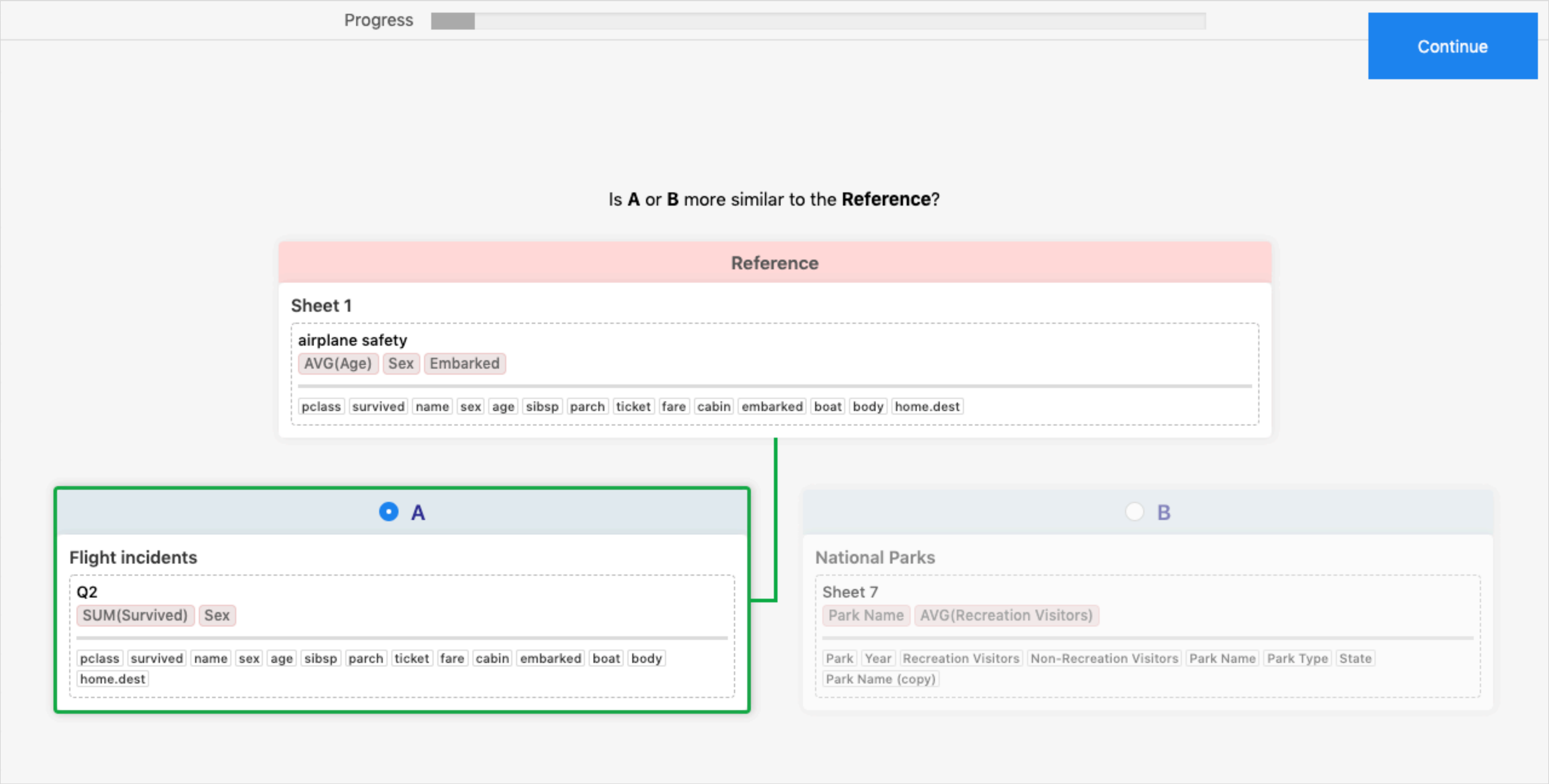
Alternative 2

75 Participants

2-Alternative Forced Choice Experiment



Experimental Stimulus



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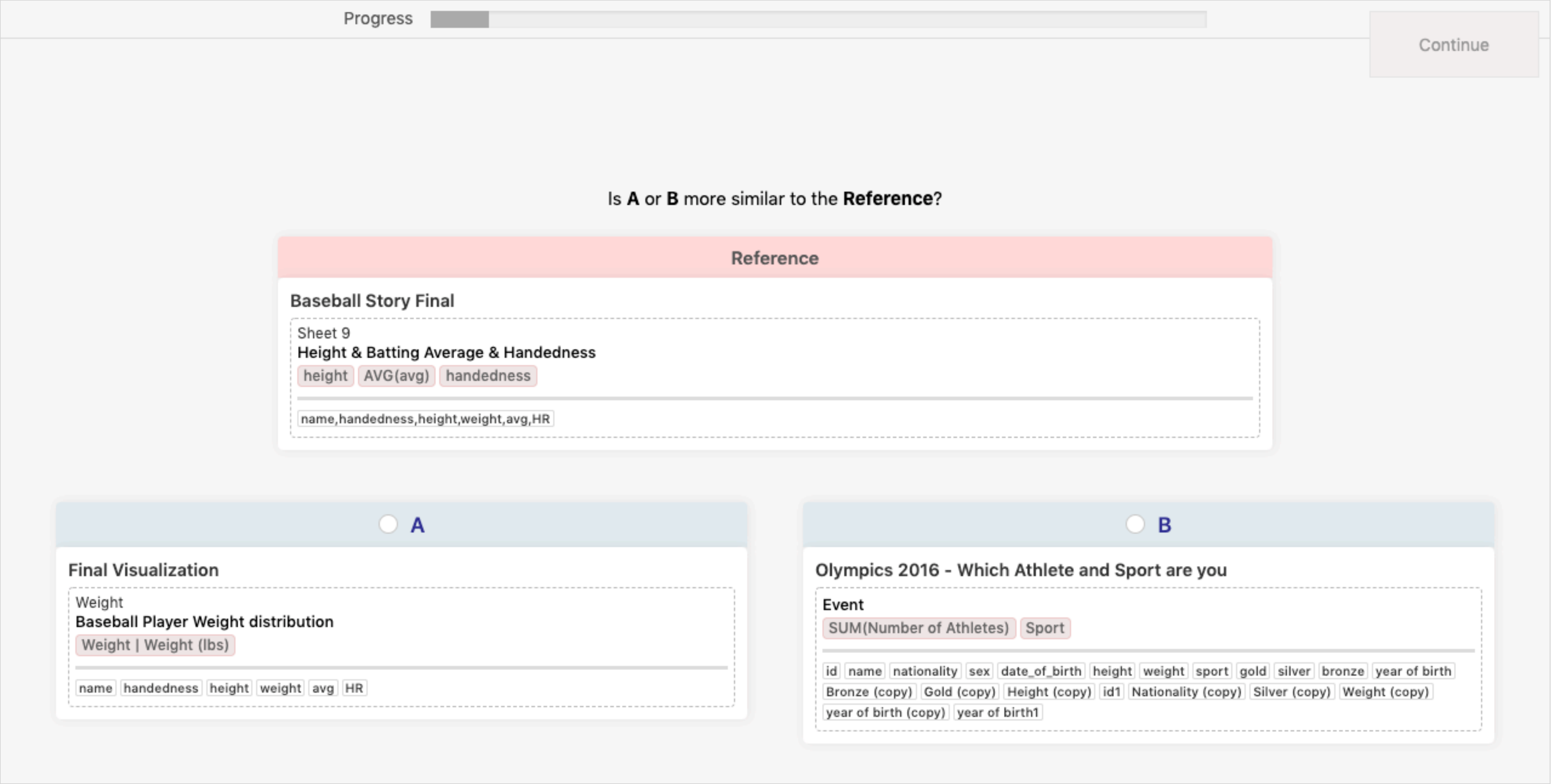

Agreement Scores

	LDA	TF-IDF	GloVe	Doc2Vec	LSI
TF-IDF	.978				
GloVe	.978	1			
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LSI	.935	.956	.956	.848	
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- Very good alignment between human similarity judgements and off-the-shelf model predictions
- LDA performed slightly better

News article

Gov. Gavin Newsom declared a state of emergency Tuesday in response to wildfires in California, as the state gave evacuation orders and battled the effects of a sweltering heat wave, rolling blackouts and the coronavirus pandemic.

By early Wednesday morning, the state fire authorities had ordered residents to evacuate in parts of Santa Cruz, San Mateo, Napa and Sonoma Counties, in Northern California, where thunderstorms brought lightning strikes this week.

The largest fire in the region, called the SCU Lightning Complex, had spread to 35,000 acres in several counties east of San Jose and was 4 percent contained. Another fire, called the LNU Lightning Complex fire, was quickly growing north of the Bay Area, with 32,000 acres burned by about 9:30 Tuesday night.

That fire forced evacuations in parts of Napa and Sonoma, with the authorities warning of an "immediate threat to life" in some places. Local news outlets showed structures consumed by flames in Vacaville, about 35 miles southwest of Sacramento, and fire overtaking a camera meant to help spot wildfires on Mount Vaca. Photos and videos on social media showed flames lapping at the road and, in the hours before dawn, some images showed a glowing red sky, as the fire lit up dense smoke.

To the south, residents in Oakland and San Francisco could smell smoke as they woke up on Wednesday morning. The authorities around Northern California warned of poor air quality in addition to the rising heat …

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Extracted text from viz workbook

customer analysis sales profit discount commission segment ratio ranking count ship performance target furniture office home supplies city drilldown late early product category forecast order quantity ...

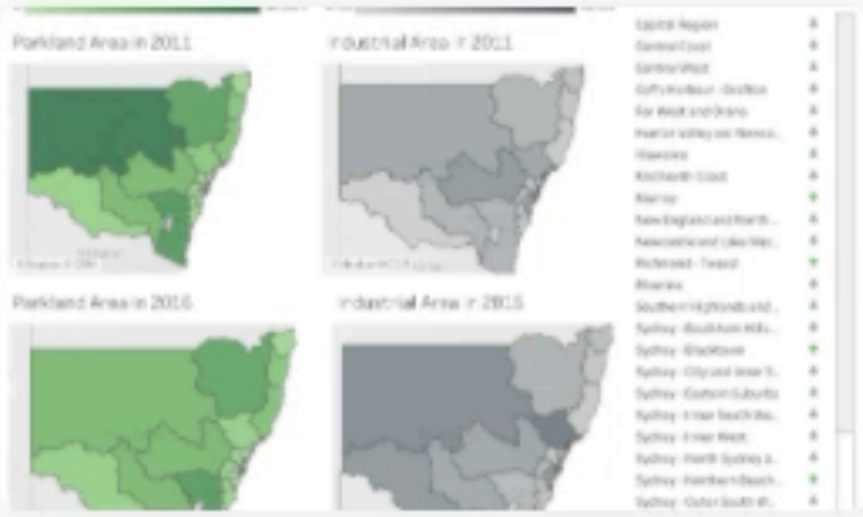
Proof-of-concept implementation

VizCommender

Search

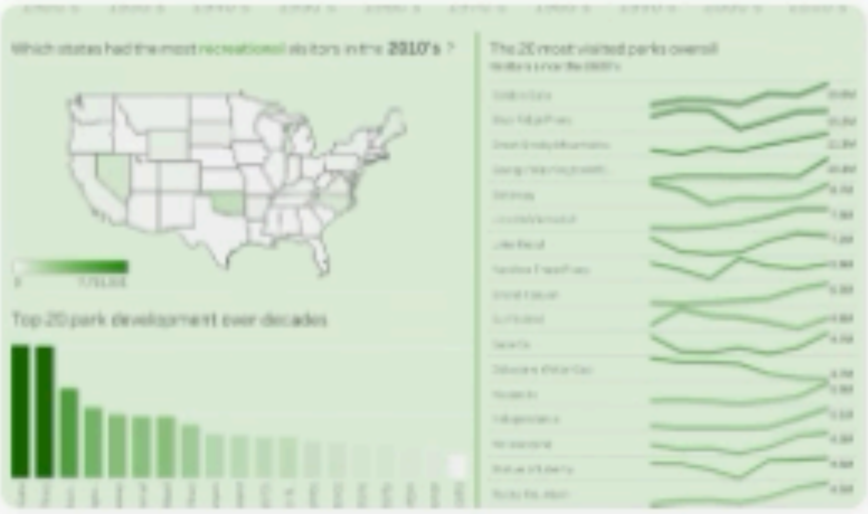
park national visit fewer visitor makeover montime country zip com bar chart area chart line chart bubble chart table

Sort by relevance



landuserv3
bing4493 • 2017-05-08

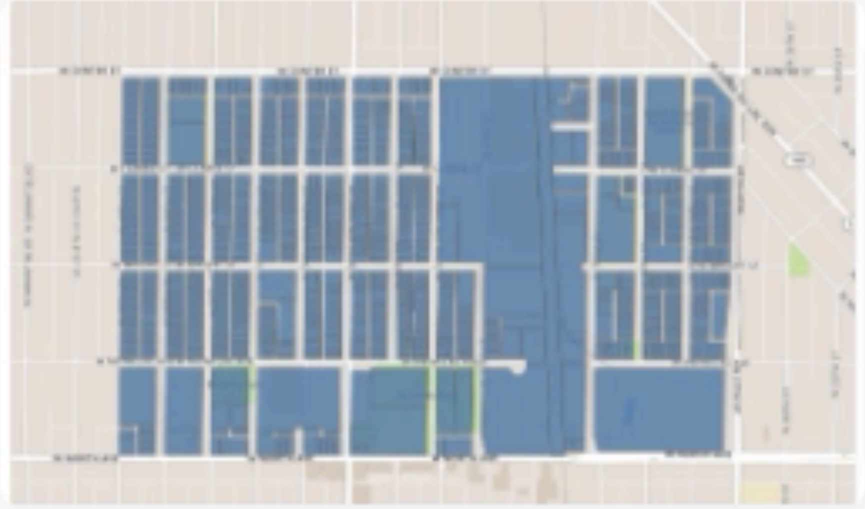
Makeover Monday Week 23 -
mak.gill • 2017-06-05



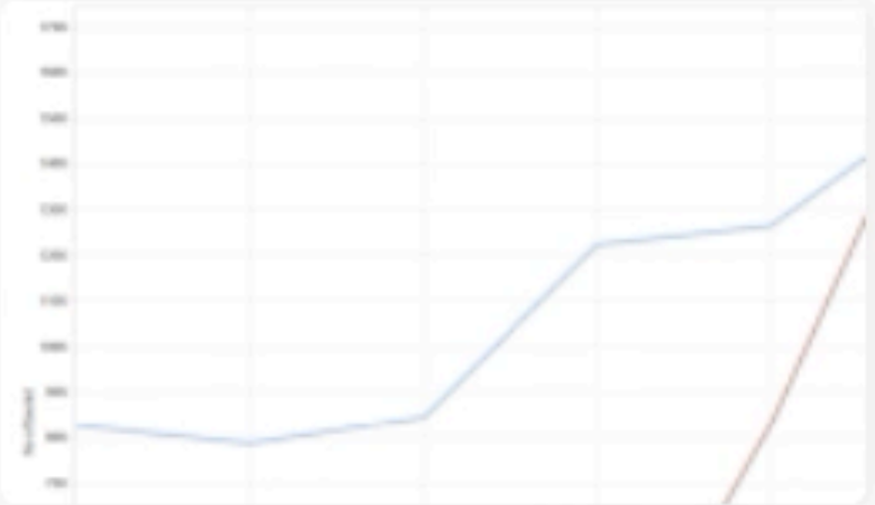
Makeover Monday Week 23
frans.rasmussen7740 • 2017-06-08

ASBURY Dashboard
brian.jones3491 • 2018-02-09

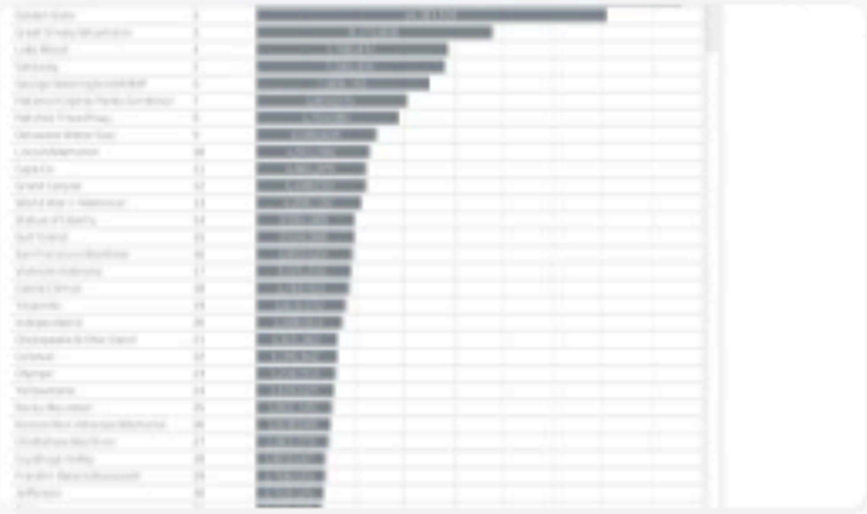
Makeover Monday Week 23
esben.michelsen • 2017-06-05



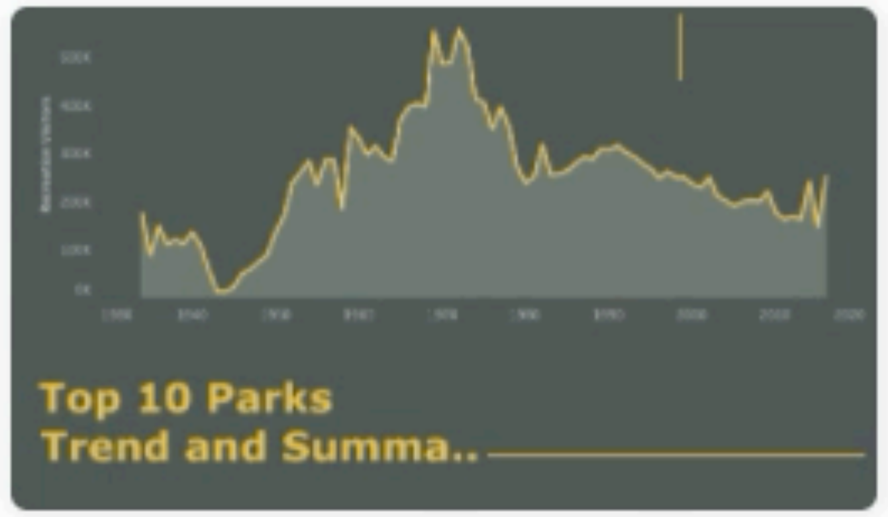
Metcalfe Park
safe.sound.mke • 2017-12-15



Grant's Nepalese Tourism
hollidaygg • 2015-03-08

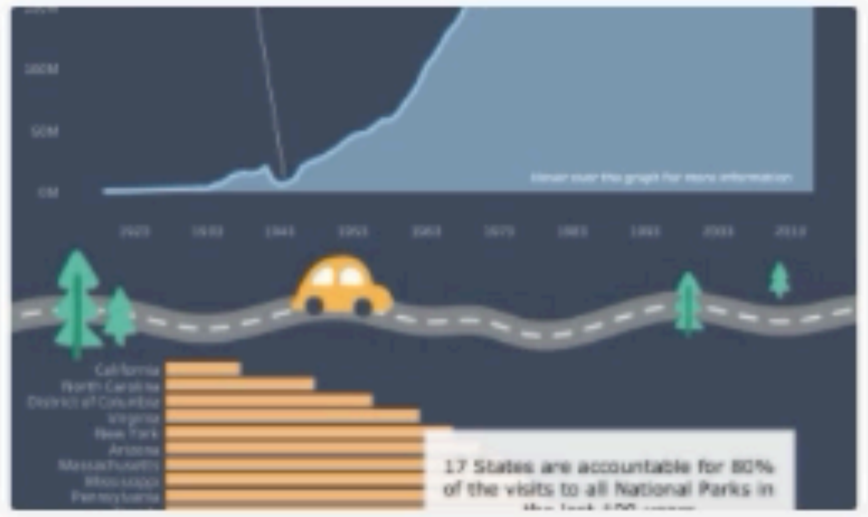


Makeover Monday week 23
priyesh.singh • 2017-06-05



National Parks
poojagandhi • 2017-06-05

Top National Parks in Ame
sarah.bartlett • 2017-06-05



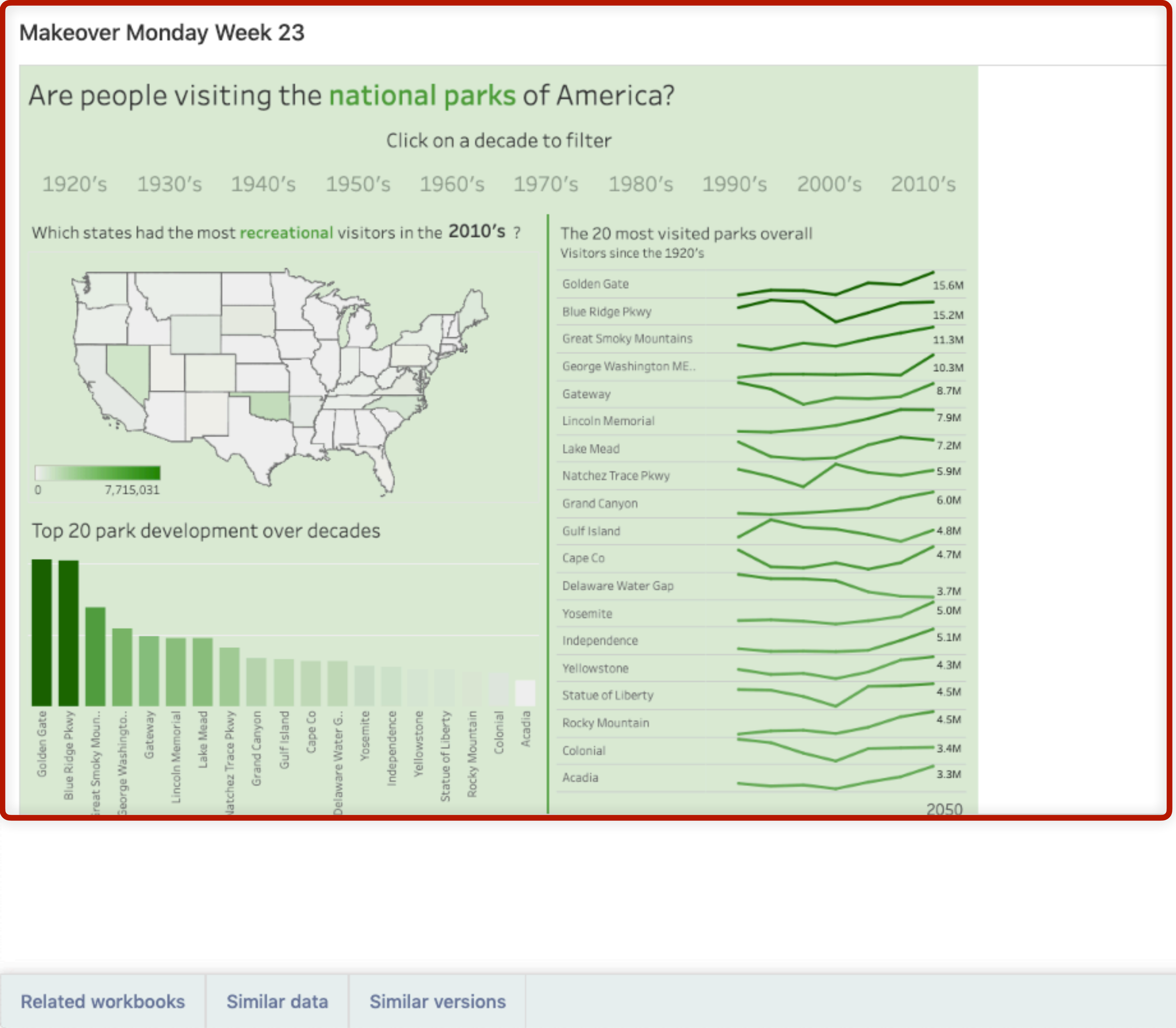
The National Parks Have N
pablolgomez • 2017-06-05

MakeOver Monday TOTC 2017
nick.bignell • 2017-06-05

Grant's Nepalese Tourism3
hollidaygg • 2015-03-08

MM Live
nai.louza • 2017-06-05

Windermere
lester.nare • 2018-06-08



Interactive workbook

Recommendation panel

Similarity facets for different user tasks

- Related workbooks
- Similar data
- Similar versions

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Similarity facets for different user tasks

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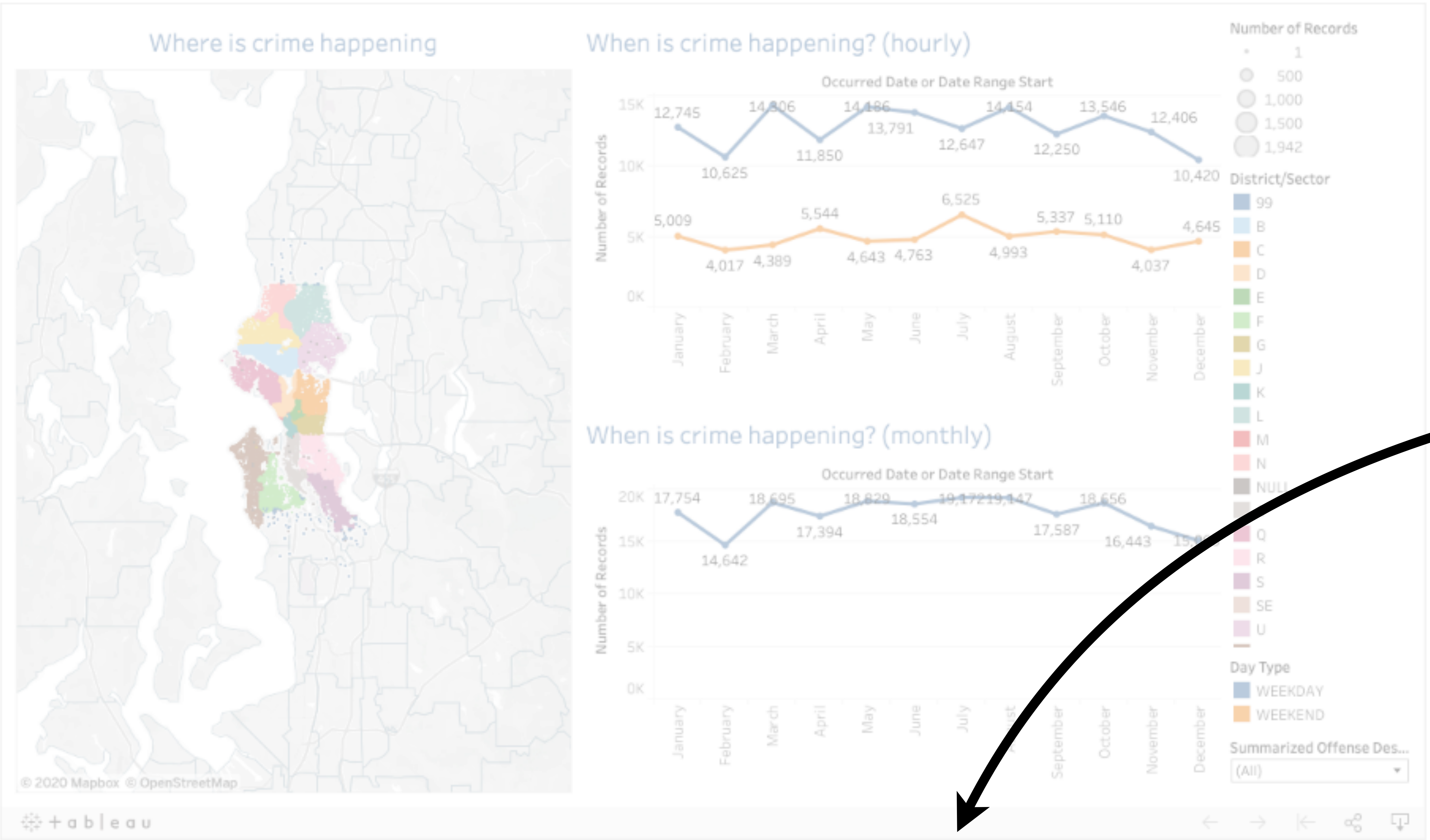
Seattle crime



Similarity facets for different user tasks

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Seattle Crime
caitlin.streamer

Seattle Crime Dashboard
kelsey.hofmann

Crime in Seattle
danya.setiawan

Related workbooks | Similar data | Similar versions

Generalizable to other viz specifications

Generalizable to other viz specifications

tableau
Power BI
Looker
Google Data Studio
plotly
Qlik
SISENSE
...

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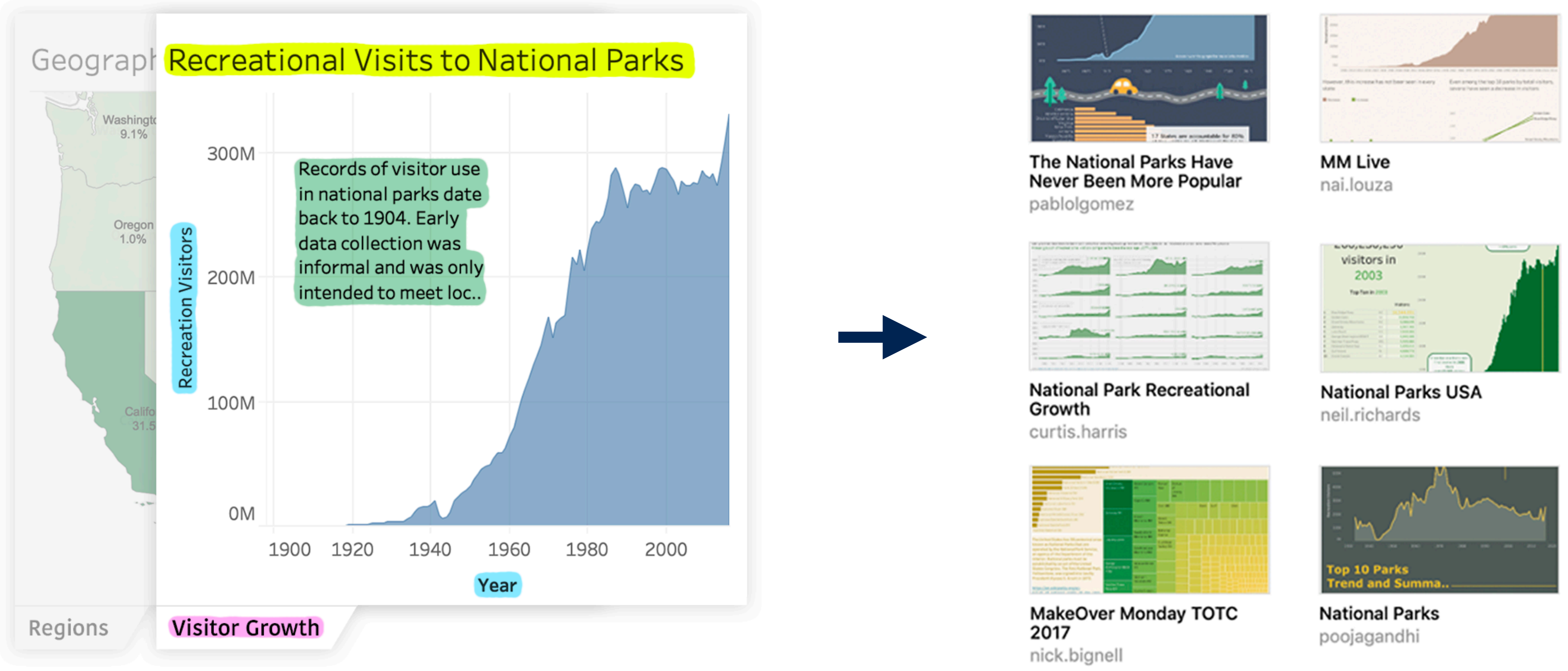
michaeloppermann.com/work/viz-commender



Contributions

- Challenges for content-based visualization recommendations
- Design and implementation of a proof-of-concept pipeline
- Analysis of applicable NLP techniques and a user study assessing the alignment with human judgements of similarity

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Interactive Visual Analysis Tool

Participants   Triplets   Models

Participants (75)

Filter triplets | Disagree with majority | Temporal alignment

ID	TIMING	TOTAL RT	AVG. RT	MEDIAN RT	MIN. RT	MAX. RT	POS A	POS B	INTRA-RATER AGREEMENT	INTER-RATER AGREEMENT	EXPERT AGREEMENT	DIFFICULTY	BOTH RELEVANT	NONE RELEVANT	DEMOGRAPHICS
187		17min (19)	22s	16s	4s	2min	21	26	100%	96%	97.87%	3/5	2/5	2/5	54, female, Training
184		12min (15)	16s	13s	7s	37s	21	26	100%	91%	93.62%	2/5	2/5	2/5	57, female, Training
183		10min (10)	12s	7s	2s	2min	22	25	50%	85%	82.98%	4/5	4/5	2/5	30, male, College, no degree
182		17min (21)	22s	18s	8s	60s	27	20	100%	91%	89.36%	3/5	4/5	2/5	34, female, Bachelor's degree
181		5min (6)	6s	5s	3s	32s	24	23	100%	83%	85.11%	2/5	4/5	3/5	40, male, Bachelor's degree
180		7min (10)	9s	7s	3s	34s	21	26	100%	98%	95.74%	1/5	3/5	1/5	26, female, Bachelor's degree
179		7min (11)	9s	8s	4s	24s	22	25	50%	87%	85.11%	5/5	3/5	3/5	53, male, Bachelor's degree
176		6min (8)	8s	7s	3s	25s	24	23	50%	91%	89.36%	2/5	2/5	1/5	31, male, College, no degree
175		7min (9)	10s	6s	3s	32s	26	21	100%	98%	95.74%	2/5	3/5	2/5	32, female, Bachelor's degree
174		10min (13)	13s	10s	5s	37s	25	22	100%	96%	93.62%	1/5	2/5	1/5	35, female, Bachelor's degree
173		11min (13)	15s	12s	4s	55s	20	27	100%	98%	95.74%	5/5	2/5	1/5	28, male, College, no degree
172		8min (10)	11s	8s	3s	1min	17	30	50%	87%	85.11%	2/5	5/5	1/5	30, male, College, no degree
171		6min (7)	8s	7s	3s	29s	27	20	100%	98%	95.74%	2/5	1/5	2/5	23, female, Bachelor's degree
170		9min (11)	11s	9s	3s	31s	24	23	100%	91%	89.36%	3/5	4/5	2/5	55, female, Bachelor's degree
169		7min (9)	10s	9s	4s	20s	22	25	100%	94%	91.49%	2/5	2/5	2/5	47, female, Bachelor's degree
168		14min (16)	18s	7s	3s	3min	27	20	100%	74%	76.6%	4/5	2/5	5/5	39, male, Bachelor's degree
167		13min (17)	16s	14s	4s	1min	22	25	100%	87%	89.36%	2/5	3/5	2/5	40, female, Bachelor's degree
166		20min (28)	26s	12s	4s	3min	23	24	100%	81%	78.72%	2/5	3/5	2/5	40, male, Associate degree
165		14min (17)	18s	7s	3s	4min	22	25	100%	91%	89.36%	2/5	2/5	2/5	30, female, Bachelor's degree
164		4min (7)	5s	5s	2s	10s	25	22	100%	89%	91.49%	1/5	2/5	2/5	36, male, Bachelor's degree
163		14min (15)	18s	15s	4s	44s	22	25	50%	91%	89.36%	4/5	2/5	3/5	36, male, College, no degree
161		7min (9)	9s	8s	4s	20s	28	19	50%	98%	97.87%	3/5	2/5	2/5	37, male, Bachelor's degree
160		30min (32)	38s	35s	13s	1min	29	18	50%	91%	89.36%	5/5	5/5	2/5	69, female, College, no degree
159		8min (9)	10s	7s	3s	37s	24	23	0%	87%	85.11%	2/5	2/5	1/5	33, female, Bachelor's degree
158		7min (9)	9s	8s	4s	27s	24	23	100%	85%	87.23%	1/5	2/5	2/5	40, female, High school
157		18min (20)	23s	17s	6s	2min	23	24	100%	94%	95.74%	3/5	2/5	3/5	39, female, Bachelor's degree
155		10min	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	41, male, College, no

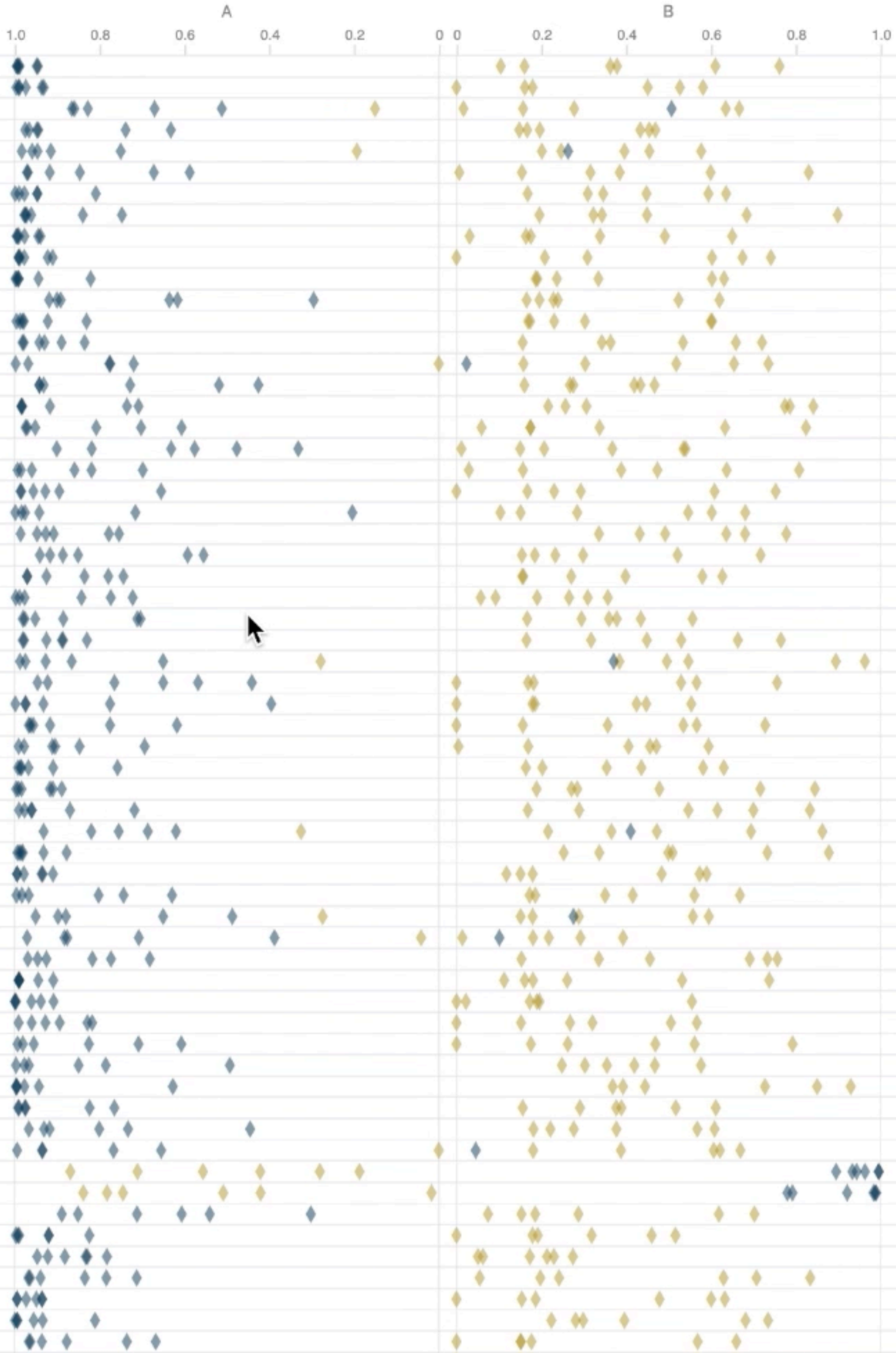
Participants Triplets Models

Triplets

☑ tfidf ☑ lda_150 ☑ lsi_150 ☑ glove_pre ☑ glove_tf ☑ d2v_new

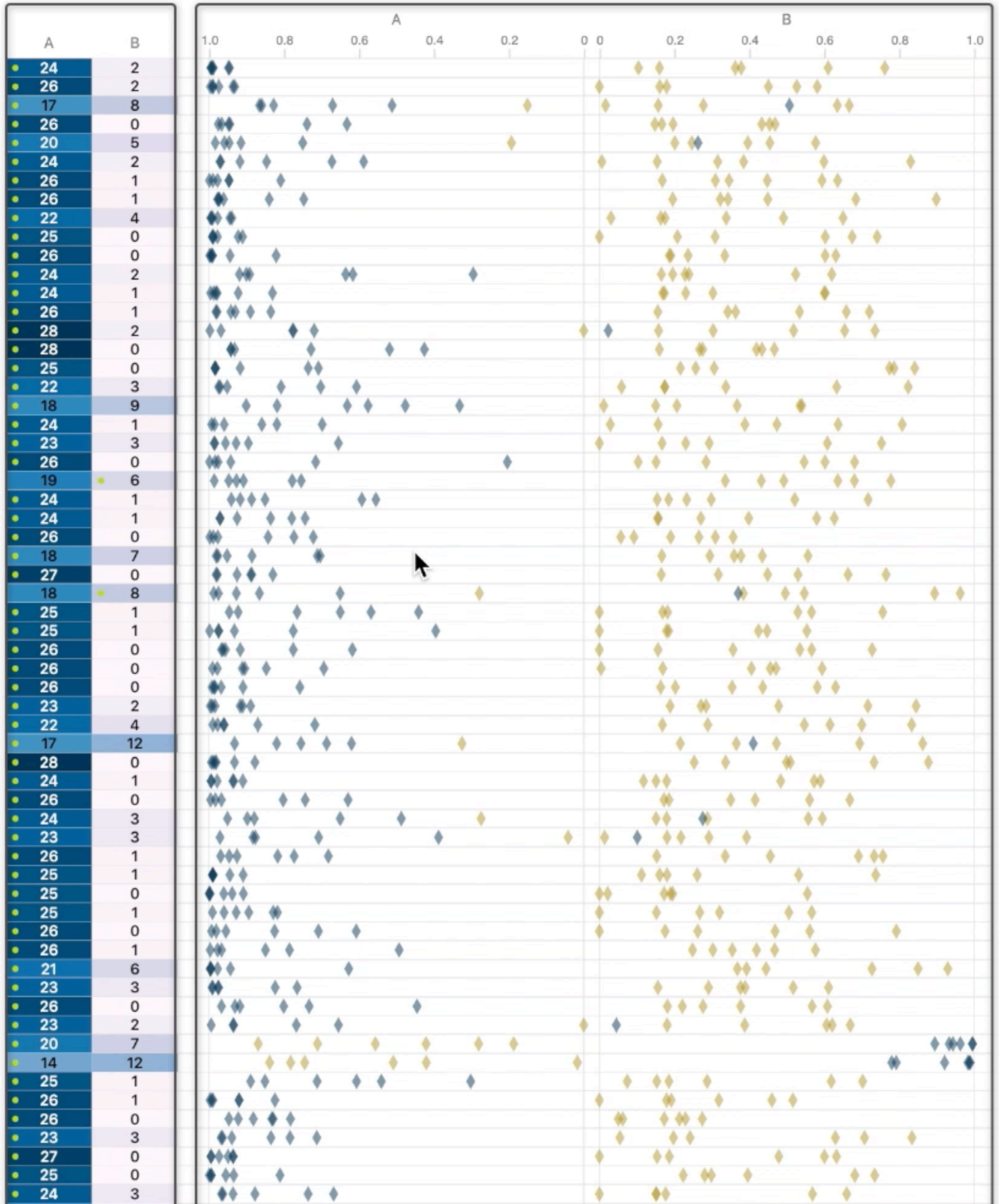
Filter triplets Settings

Mean RT	Median RT	A	B
17s	15s	24	2
18s	13s	26	2
16s	9s	17	8
15s	11s	26	0
15s	14s	20	5
14s	9s	24	2
21s	12s	26	1
18s	8s	26	1
29s	16s	22	4
11s	10s	25	0
11s	6s	26	0
23s	11s	24	2
13s	8s	24	1
13s	10s	26	1
18s	10s	28	2
12s	10s	28	0
11s	6s	25	0
28s	13s	22	3
16s	12s	18	9
16s	14s	24	1
9s	8s	23	3
12s	8s	26	0
18s	12s	19	6
17s	11s	24	1
42s	12s	24	1
29s	11s	26	0
27s	15s	18	7
8s	6s	27	0
13s	12s	18	8
12s	11s	25	1
15s	8s	25	1
14s	7s	26	0
7s	6s	26	0
12s	9s	26	0
17s	14s	23	2
23s	18s	22	4
29s	26s	17	12
15s	12s	28	0
17s	13s	24	1
9s	7s	26	0
21s	14s	24	3
16s	13s	23	3
16s	13s	26	1
14s	7s	25	1
11s	6s	25	0
19s	8s	25	1
21s	15s	26	0
17s	9s	26	1
18s	16s	21	6
26s	14s	23	3
18s	10s	26	0
21s	12s	23	2
9s	6s	20	7
19s	13s	14	12
20s	14s	25	1
38s	19s	26	1
13s	11s	26	0
20s	13s	23	3
8s	7s	27	0
19s	13s	25	0
42s	14s	24	3



Human Judgements

Model Predictions



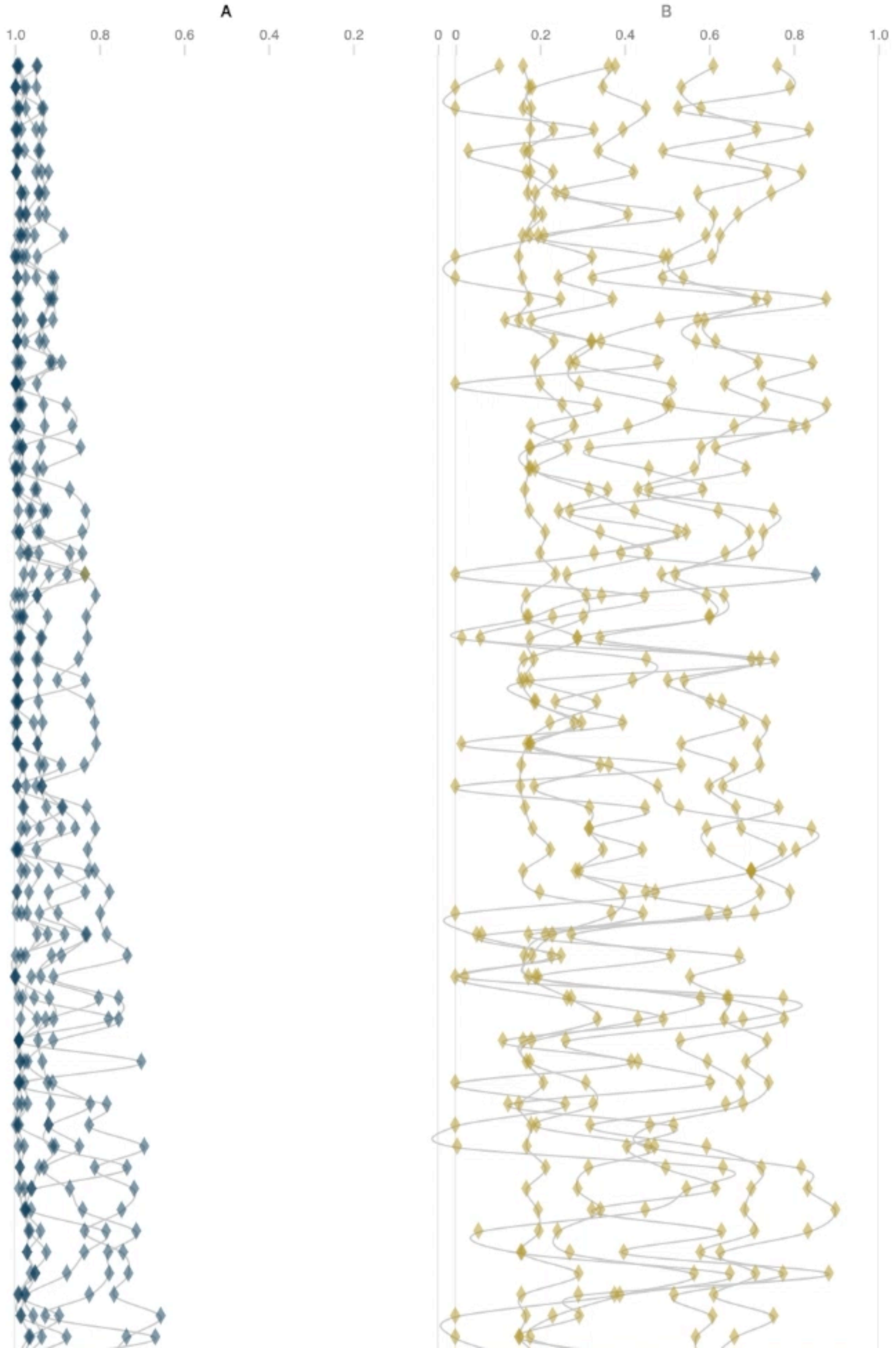
Participants
Triplets
Models
Triplets
tfidf
lda_150
lsi_150
glove_pre
glove_tf
d2v_new
Filter triplets
Settings
Mean RT
Median RT
A
B
Reference
1990-2015 Australian Social and Housing Trends.
Sheet 3
Average Residential House Price in the Greater Sydney Region, 1990-2015.
SUM(Price) | Average House Price (Sydney) AUD$
Year (Sheet12) | Year
SUM(Women Median Marriage Age)
SUM(% of 20-24 Population in Tertiary Education.)
Year
% of 20-24 Population in Tertiary Education.
Men Median Marriage Age
Women Median Marriage Age
Price
% Change
$ Change
Sum of annual income
Year1
Year2
Year3
Rising House Prices, incomparable to inflated Salary 1990-2015
Sheet 1
Percentage of 20-24 year old population enrolled in tertiary education, 1990-2015.
SUM(% of 20-24 Population in Tertiary Education.) | % (as a decimal)
Year
Year
% of 20-24 Population in Tertiary Education.
Men Median Marriage Age
Women Median Marriage Age
Price
% Change
$ Change
Sum of annual income
Year1
Year2
Year3
Sothebystest2.1.1.1
Incline Village1
AVG(Average Days on Market)
Area
YEAR(Date)
Date
Area
Type
City
Zip code
State
Median Sales Price
Average List Price
Average Sold Price
Average Days on Market
Highest Sold Price
Lowest Sold Price
Properties Sold
% Sold Price to Average List Price
Total Dollar Volume Sold

Participants Triplets Models

Triplets

tfidf lda_150 lsi_150 glove_pre glove_tf d2v_new Filter triplets Settings

Mean RT	Median RT	A	B
17s	15s	24	2
16s	11s	25	0
18s	13s	26	2
18s	16s	22	3
29s	16s	22	4
15s	8s	25	1
24s	12s	27	0
9s	6s	26	0
26s	15s	23	2
16s	11s	23	2
13s	10s	23	3
19s	15s	16	10
17s	13s	24	1
14s	10s	26	1
17s	14s	23	2
14s	10s	25	1
15s	12s	28	0
17s	11s	24	1
14s	10s	22	4
17s	12s	25	0
19s	8s	26	0
21s	16s	23	2
17s	16s	22	5
23s	16s	24	3
16s	11s	23	2
21s	12s	26	1
13s	8s	24	1
12s	8s	26	0
34s	14s	15	12
17s	15s	24	2
11s	6s	26	0
19s	13s	25	0
18s	16s	27	1
13s	10s	26	1
8s	7s	27	0
8s	6s	27	0
12s	12s	25	1
20s	12s	24	1
11s	9s	26	1
25s	18s	23	4
13s	11s	24	2
13s	11s	26	0
16s	15s	18	10
11s	6s	25	0
20s	17s	25	1
18s	12s	19	6
14s	7s	25	1
10s	9s	26	0
11s	10s	25	0
14s	7s	25	1
38s	19s	26	1
7s	6s	26	0
56s	13s	27	2
23s	18s	22	4
18s	8s	26	1
20s	13s	23	3
42s	12s	24	1
18s	13s	23	2
26s	14s	23	3
9s	8s	23	3
42s	14s	24	3



Participants Triplets Models

Triplets

tfidf lda_150 lsi_150 glove_pre glove_tf d2v_new Filter triplets Settings

Mean RT	Median RT	A	B
17s	15s	24	2
16s	11s	25	0
18s	13s	26	2
18s	16s	22	3
29s	16s	22	4
15s	8s	25	1
24s	12s	27	0
9s	6s	26	0
26s	15s	23	2
16s	11s	23	2
13s	10s	23	3
19s	15s	16	10
17s	13s	24	1
14s	10s	26	1
17s	14s	23	2
14s	10s	25	1
15s	12s	28	0
17s	11s	24	1
14s	10s	22	4
17s	12s	25	0
19s	8s	26	0
21s	16s	23	2
17s	16s	22	5
23s	16s	24	3
16s	11s	23	2
21s	12s	26	1
13s	8s	24	1
12s	8s	26	0
34s	14s	15	12
17s	15s	24	2
11s	6s	26	0
19s	13s	25	0
18s	16s	27	1
13s	10s	26	1
8s	7s	27	0
8s	6s	27	0
12s	12s	25	1
20s	12s	24	1
11s	9s	26	1
25s	18s	23	4
13s	11s	24	2
13s	11s	26	0
16s	15s	18	10
11s	6s	25	0
20s	17s	25	1
18s	12s	19	6
14s	7s	25	1
10s	9s	26	0
11s	10s	25	0
14s	7s	25	1
38s	19s	26	1
7s	6s	26	0
56s	13s	27	2
23s	18s	22	4
18s	8s	26	1
20s	13s	23	3
42s	12s	24	1
18s	13s	23	2
26s	14s	23	3
9s	8s	23	3
42s	14s	24	3