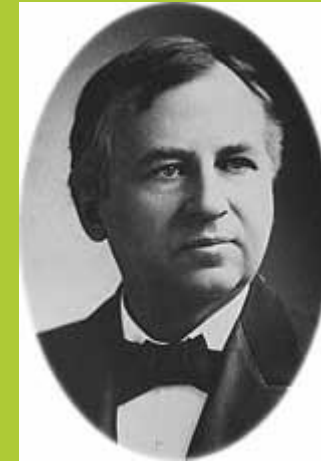


# Attribution – the \$X million question





**I know half the money I spend on advertising is wasted, but I can never find out which half.**



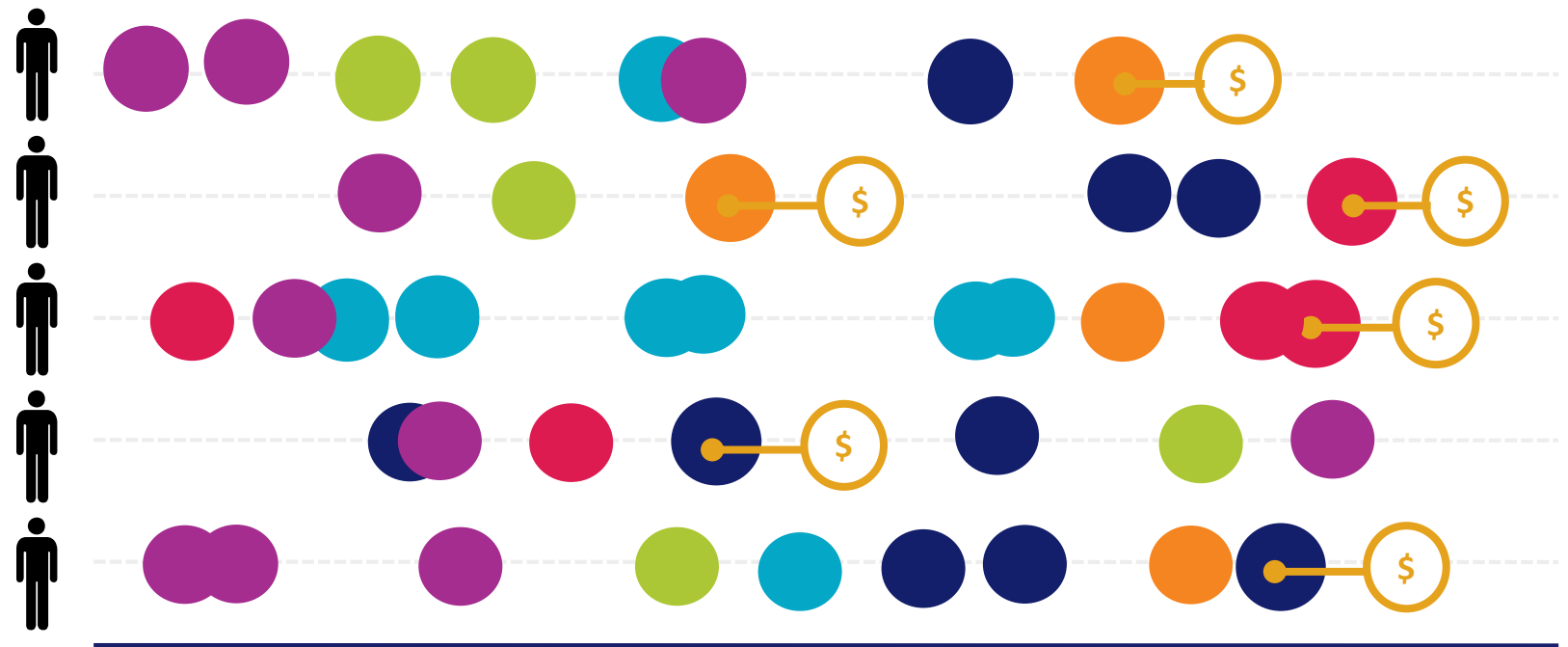
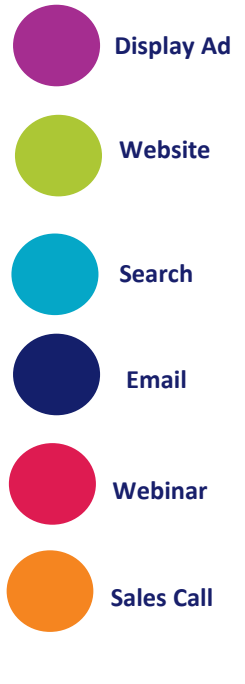
# Attribution - the \$X million question

**The “Last Touch” Standard**

- Last Ad Clicked
- Last interaction

**The Reality**

Campaigns reach customers multiple times, across multiple channels, over extended periods of time

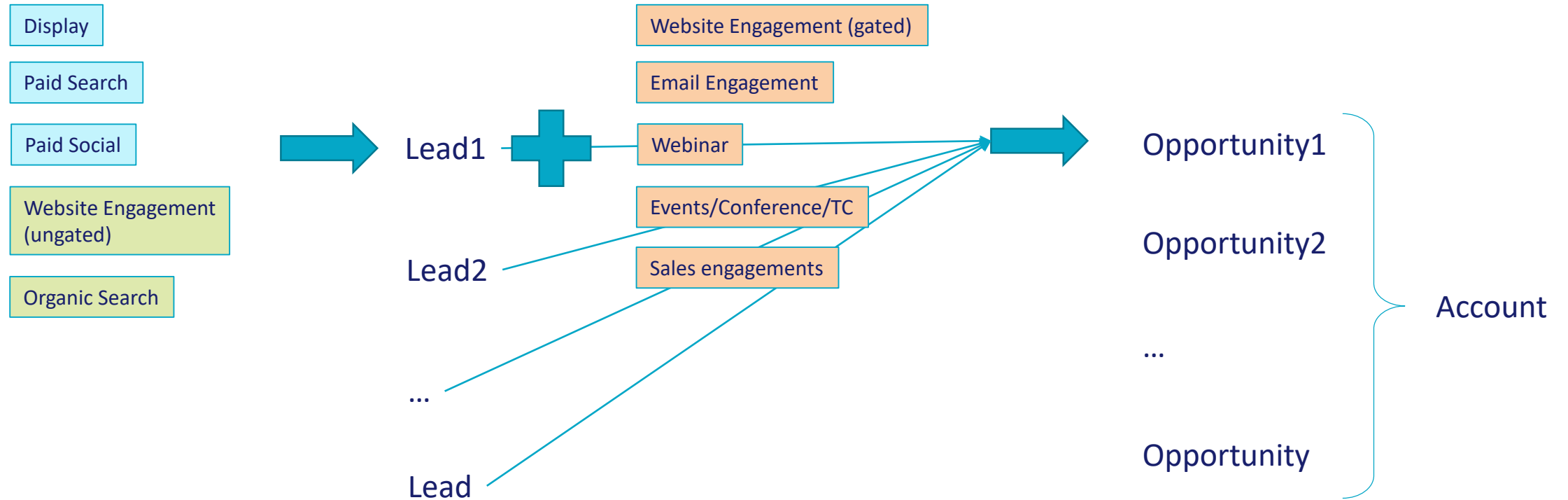


# Two broad classes of models

	<b>Multi-Touch Attribution (MTA)</b>	<b>Media Mix Modeling (MMM)</b>
<b>Data:</b>	Atomic, user-level data	Aggregated, granular data
<b>Modeling approach:</b>	Logistic regression/hazard models, Markov model, game theoretic	Regression-based approach
<b>Data grain:</b>	Requires consistent, x-device identity (different vendors may use different IDs)	Can include non-addressable media like TV, Radio, Print, etc. and in-store sales
<b>Result grain:</b>	Enables effectiveness estimates at a more granular level	Holistic estimate across all channels
<b>Purpose:</b>	Determines credit allocation and therefore CPA	Calculates allocation and the marginal effect, the value of an incremental \$1 to a given channel or subchannel
<b>Forecast:</b>	User-level predictive model can be used for RTB and site personalization	Predictive model can be used to estimate future sales totals

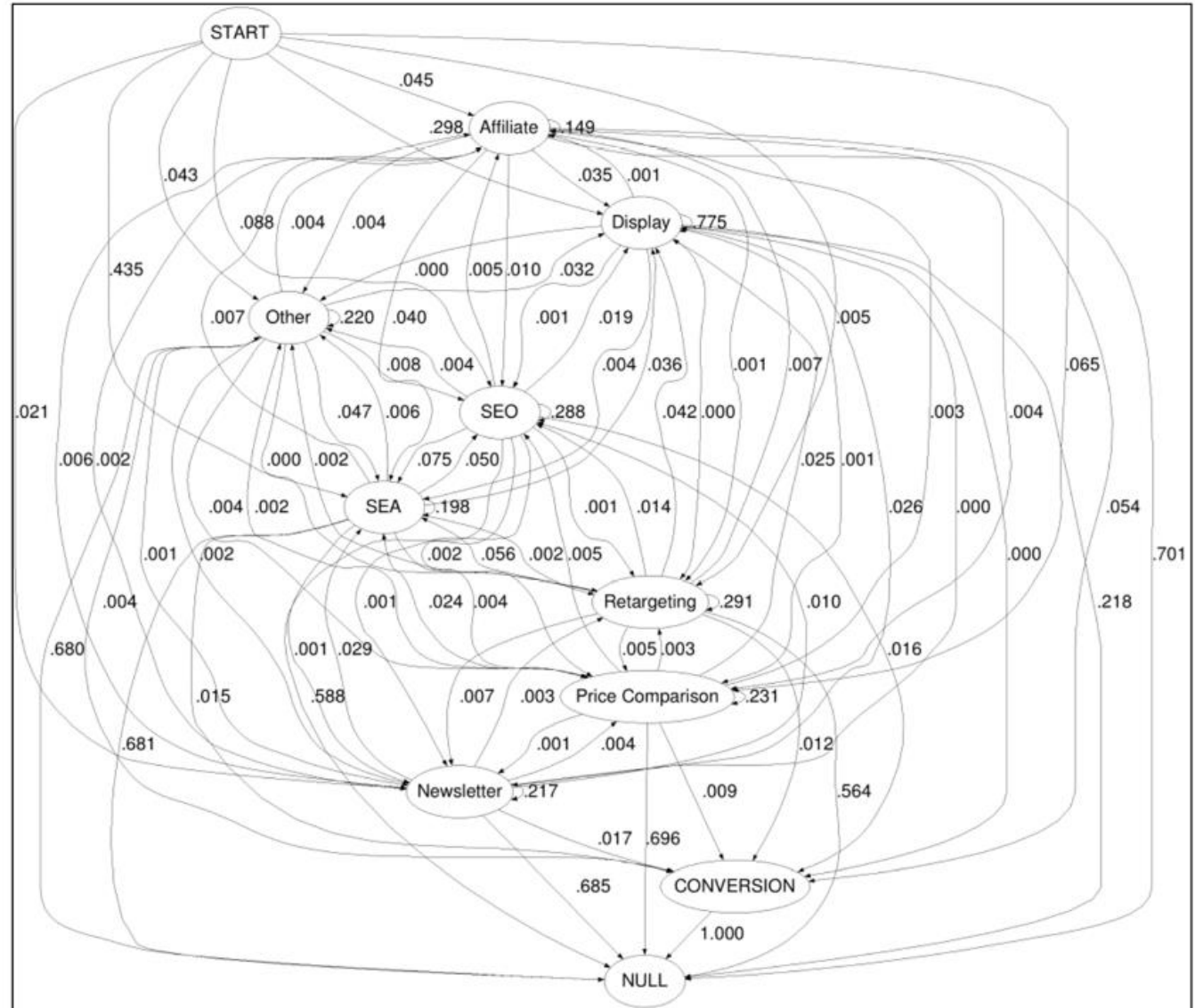
# Channels that influence lead and revenue conversions

- Attribution of leads vs. attribution of revenue



# Markov Chain Methodology

- Markov Chain Models estimate of transition between states.
- In Attribution, states are advertising from channels and two end states:
  - A conversion
  - A non-conversion (NULL) state
- Does well on principal goals
  - Objectivity
  - Predictive Accuracy
  - Interpretability
  - Versatility
  - Efficiency
- Best practice is to include at least one lag.



Anderl, et al, "Mapping the Customer Journey"

# Markov Chain Model Input and Output

Input

Output



ga_client_id	ga_timestamp	touch_num	touchpoint	custom_channel	custom_source	campaign	first_touch_fractional_value	last_touch_fractional_value	linear_touch_fractional_value	markov_model_fractional_value
1000003111	2018-04-13 06:07:04 UTC	6	last touch	Paid Search - Brand	Google	Campaign name A	0	1	0.17	0.13
1000003111	2018-03-25 06:02:11 UTC	5		Paid Search - Brand	Google	Campaign name A	0	0	0.17	0.13
1000003111	2018-03-25 05:05:57 UTC	4		Paid Search - Brand	Google	Campaign name A	0	0	0.17	0.13
1000003111	2018-03-24 07:02:11 UTC	3		Paid Search - Brand	Google	Campaign name A	0	0	0.17	0.13
1000003111	2018-03-24 06:55:56 UTC	2		Paid Search - Brand	Google	Campaign name A	0	0	0.17	0.13
1000003111	2018-03-24 06:53:25 UTC	1	first touch	Organic Search	Google	(not set)	1	0	0.17	0.35
1000126400	2018-05-14 14:02:12 UTC	7	last touch	Display	Google	Campaign name B	0	1	0.14	0.08
1000126400	2018-03-29 19:16:31 UTC	6		Display	Google	Campaign name B	0	0	0.14	0.08
1000126400	2018-03-16 18:26:25 UTC	5		Display	Google	Campaign name B	0	0	0.14	0.08
1000126400	2018-03-15 02:02:10 UTC	4		Paid Search - Brand	Google	Campaign name C	0	0	0.14	0.13
1000126400	2018-03-15 00:58:37 UTC	3		Paid Search - Brand	Google	Campaign name C	0	0	0.14	0.13
1000126400	2018-03-15 00:57:51 UTC	2		Organic Search	Google	(not set)	0	0	0.14	0.36
1000126400	2018-03-15 00:56:38 UTC	1	first touch	Paid Search - Brand	Google	Campaign name C	1	0	0.14	0.13
1000126954	2018-01-16 08:28:19 UTC	1	first touch	Paid Search - Non Brand	Google	Campaign name D	1	0	1.00	1.00
1000145451	2018-05-01 14:05:26 UTC	4	last touch	Display	Google	Campaign name E	0	1	0.25	0.25
1000145451	2018-03-02 13:00:16 UTC	3		Display	Google	Campaign name E	0	0	0.25	0.25
1000145451	2018-03-01 18:02:10 UTC	2		Display	Google	Campaign name E	0	0	0.25	0.25
1000145451	2018-03-01 17:04:17 UTC	1	first touch	Display	Google	Campaign name E	1	0	0.25	0.25
1000189009	2018-05-11 17:02:12 UTC	6	last touch	Organic Search	Google	(not set)	0	1	0.17	0.18
1000189009	2018-05-11 15:02:11 UTC	5		Organic Search	Google	(not set)	0	0	0.17	0.18
1000189009	2018-05-10 19:45:42 UTC	4		Organic Search	Google	(not set)	0	0	0.17	0.18
1000189009	2018-05-10 17:41:23 UTC	3		Organic Search	Google	(not set)	0	0	0.17	0.18
1000189009	2018-03-03 14:32:19 UTC	2		Direct	Direct	(not set)	0	0	0.17	0.13
1000189009	2018-03-03 01:44:44 UTC	1	first touch	Direct	Direct	(not set)	1	0	0.17	0.13
1000201235	2018-03-28 23:07:35 UTC	1	first touch	Paid Search - Brand	Google	Campaign name F	1	0	1.00	1.00
1000375842	2018-01-25 09:06:39 UTC	2	last touch	Organic Search	Bing	(not set)	0	1	0.50	0.50
1000375842	2018-01-09 05:50:54 UTC	1	first touch	Organic Search	Bing	(not set)	1	0	0.50	0.50
1000384716	2018-02-28 13:04:29 UTC	5	last touch	Organic Search	Google	(not set)	0	1	0.20	0.21
1000384716	2018-02-18 13:00:17 UTC	4		Organic Search	Google	(not set)	0	0	0.20	0.21
1000384716	2018-02-16 14:02:11 UTC	3		Organic Search	Google	(not set)	0	0	0.20	0.21
1000384716	2018-02-16 13:18:25 UTC	2		Organic Search	Google	(not set)	0	0	0.20	0.21
1000384716	2018-01-17 13:47:08 UTC	1	first touch	Direct	Direct	(not set)	1	0	0.20	0.15
1000402403	2018-04-04 19:02:18 UTC	3	last touch	Paid Search - Brand	Google	Campaign name G	0	1	0.33	0.33
1000402403	2018-04-04 16:02:11 UTC	2		Paid Search - Brand	Google	Campaign name G	0	0	0.33	0.33
1000402403	2018-03-29 21:19:14 UTC	1	first touch	Paid Search - Brand	Google	Campaign name G	1	0	0.33	0.33

Note: Data is illustrative only. It resembles actual data but has been modified for confidentiality.

# How much lead credit re-attributed?

Attribution Model - Total Fractional Credit  
By Channel and Journey Length

Journey Length  
2 376

Custom Channel	First Touch Fractional Val..	Last Touch Fractional Valu..	Linear Touch Fractional Va..	Markov Model Fractional ..
Direct	30%	17%	22%	23%
Display	7%	6%	7%	6%
Eloqua	5%	11%	9%	6%
Organic Search	28%	36%	33%	38%
Organic Social	1%	1%	1%	0%
Paid Search - Brand	10%	8%	9%	8%
Paid Search - Non Brand	8%	7%	7%	7%
Paid Social	5%	4%	5%	4%
Product	0%	1%	1%	0%
Referral	6%	8%	8%	7%

Attribution Model - Total Fractional Credit  
By Channel and Journey Length

Journey Length  
3 376

Custom Channel	First Touch Fractional Val..	Last Touch Fractional Valu..	Linear Touch Fractional Va..	Markov Model Fractional ..
Direct	30%	15%	20%	22%
Display	6%	6%	6%	6%
Eloqua	4%	12%	9%	6%
Organic Search	29%	37%	34%	41%
Organic Social	1%	1%	1%	0%
Paid Search - Brand	10%	8%	9%	8%
Paid Search - Non Brand	8%	6%	7%	6%
Paid Social	5%	5%	5%	5%
Product	0%	1%	1%	0%
Referral	6%	9%	8%	7%

Note: Data is illustrative only. It resembles actual data but has been modified for confidentiality.



# Media Mix Modeling

- MMM grew out of econometric methods.

- Classical regression technique:

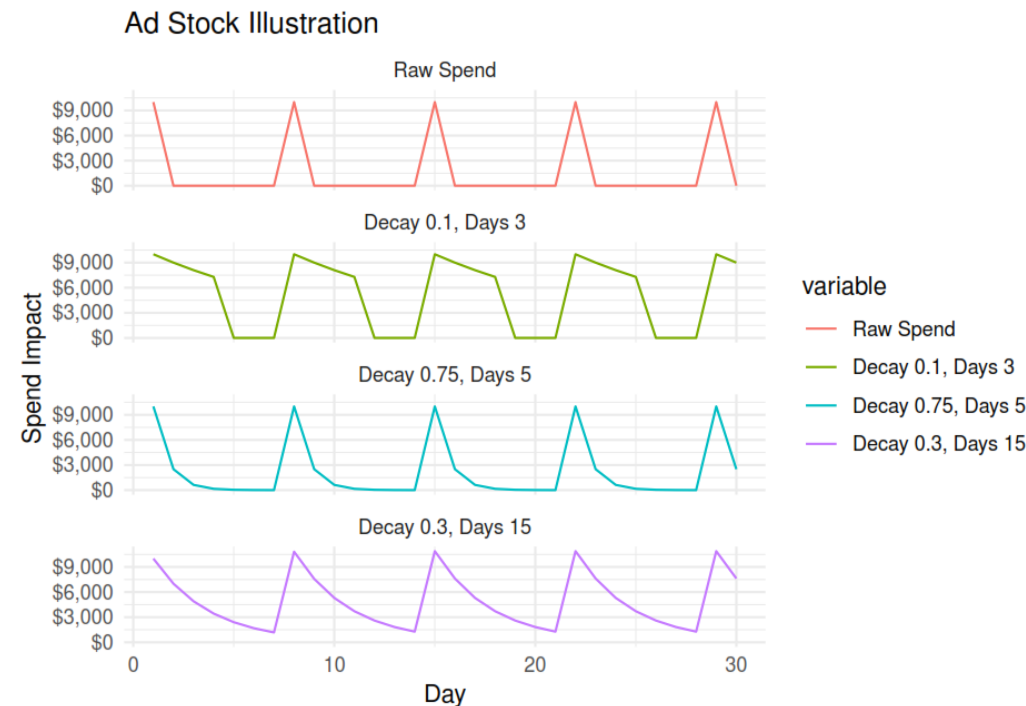
$$\text{conv}_t = \beta_0 + \beta_m \cdot \text{month}_t + \beta_{dow} \cdot \text{weekday}_t + \beta_d \cdot \text{display}_t + \beta_v \cdot \text{video}_t + \beta_s \cdot \text{search}_t + \beta_{soc} \cdot \text{social}_t + \beta_{org} \cdot \text{organic}_t + \epsilon_t$$

- In reality, models include additional complexities:

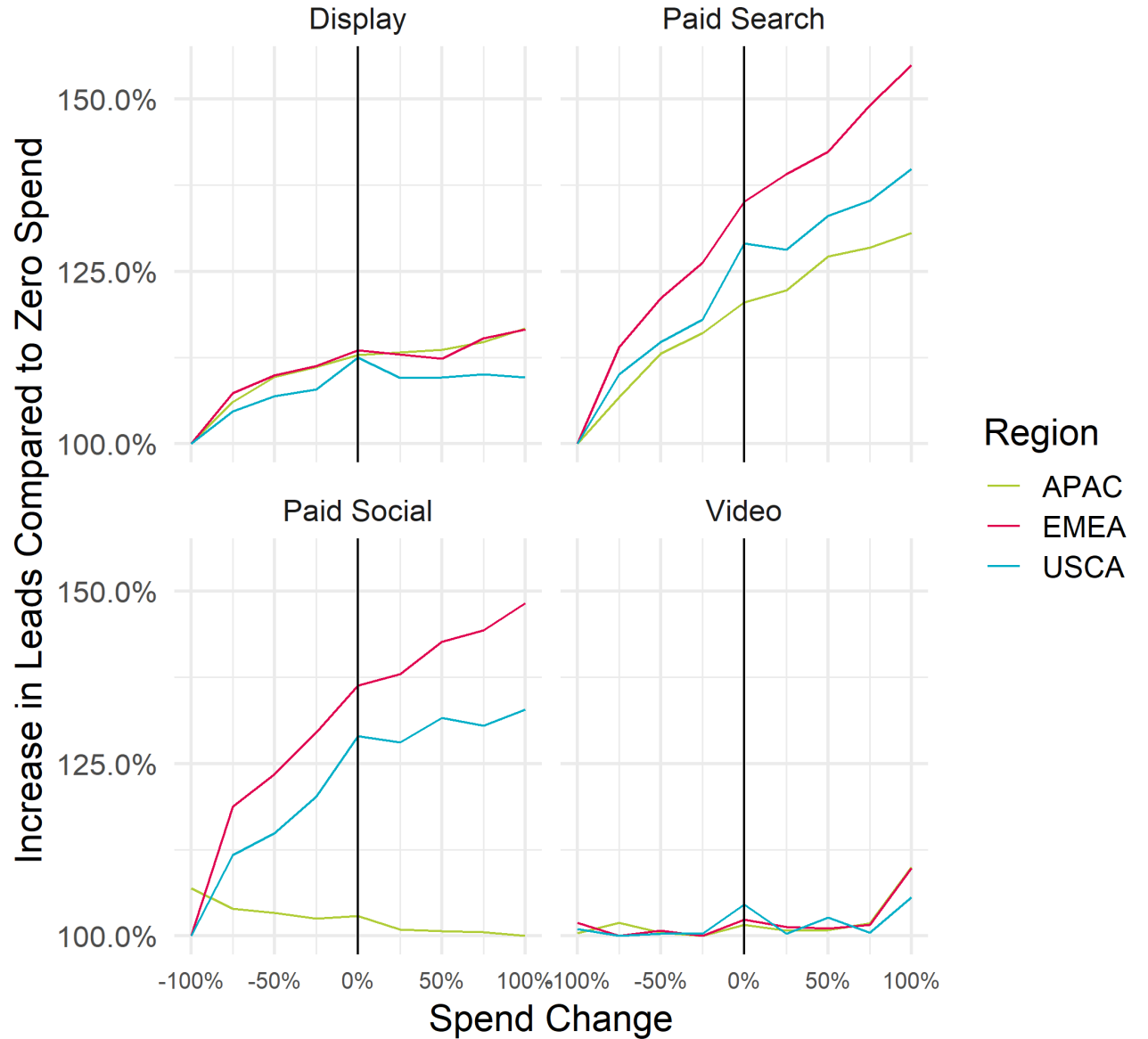
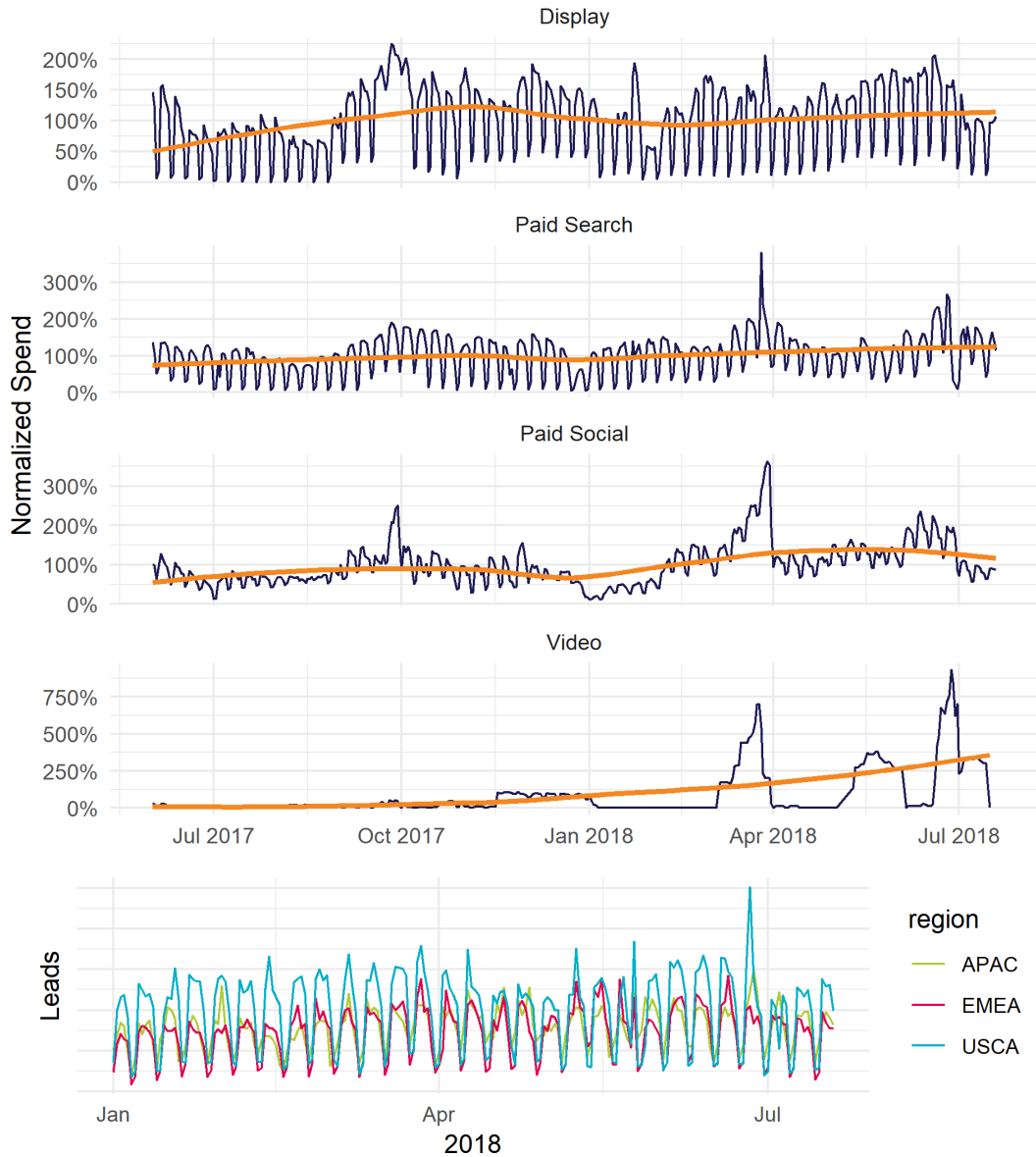
- Transformations for diminishing returns
- Incorporation of Ad Stock variables
- Interactions

- Regression context allows inference while “holding all else equal”.

- Model complexity demands visual results for practitioners—no one wants a table of coefficients.



# MMM Input and Output



Note: Data is illustrative only. It resembles actual data but has been modified for confidentiality.

Tableau - demo file with MMM simulation v6\_oct 19 - Tableau license expires in 13 days

File Data Server Window Help

Sheet1!\_20181017\_USCA\_sim\_results (20181017\_U...

Connections: 20181017\_USCA\_sim\_results (Microsoft Excel)

Sheets: Sheet1, Sheet1\_20181017\_USCA\_sim\_results, New Union

Connection: Live (selected), Extract

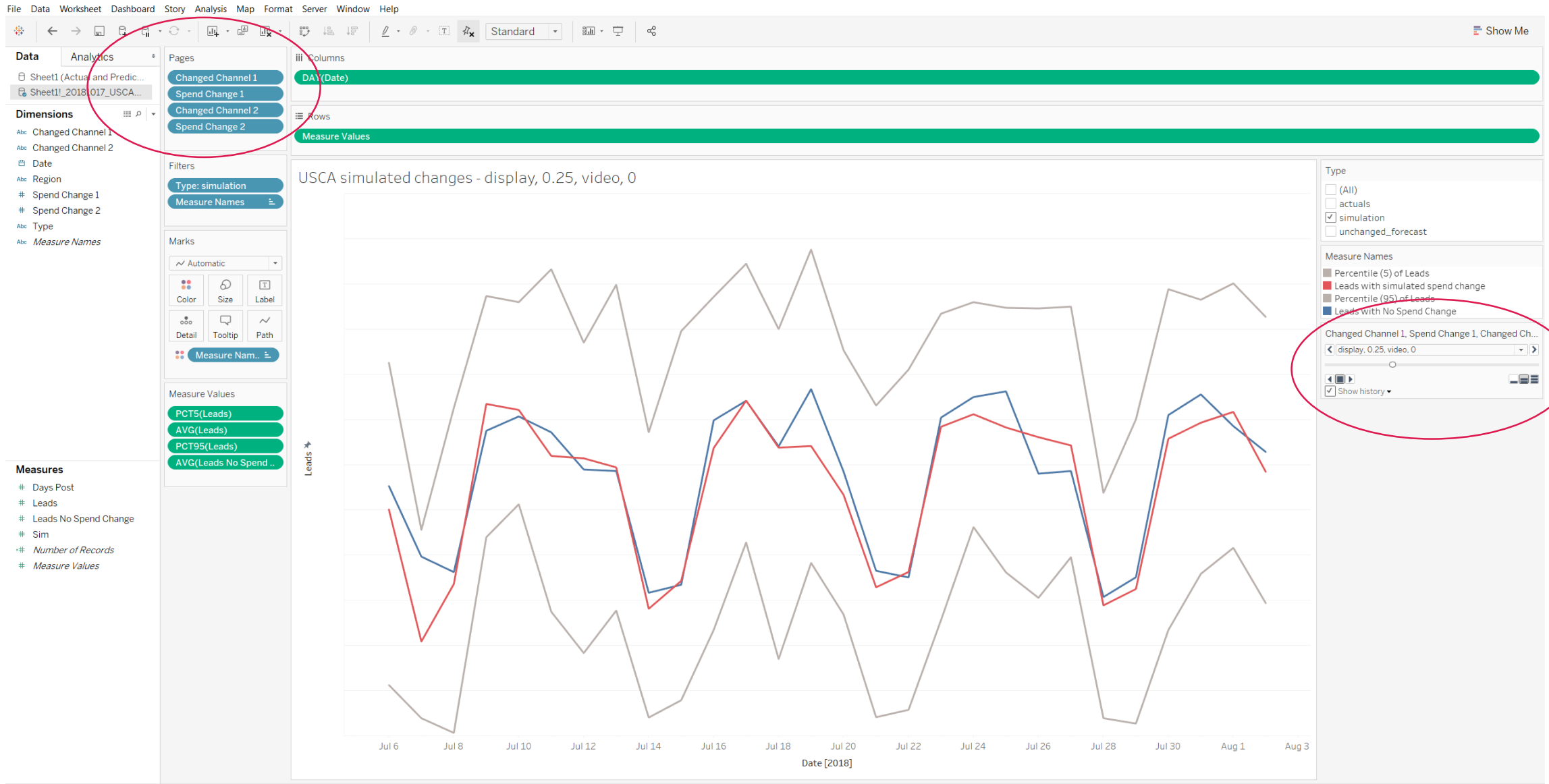
Filters: 0 | Add

Sort fields: Data source order | Show hidden fields

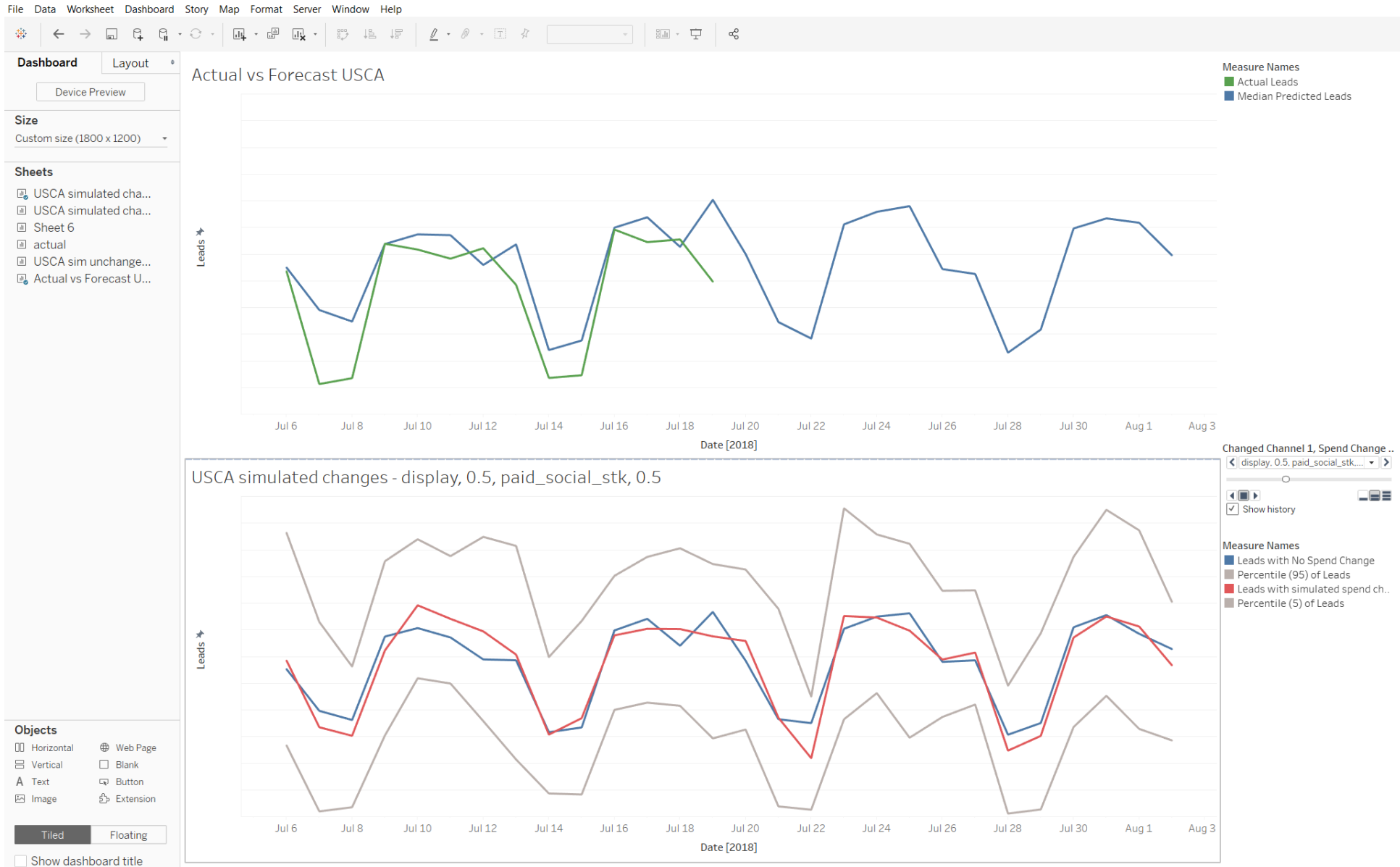
Field Name	Table	Remote Field Name
⊕ Spend Change 1	Sheet1!20181017!USCA!simresults	spend_change_1
⊕ Changed Channel 1	Sheet1!20181017!USCA!simresults	changed_channel_1
⊕ Spend Change 2	Sheet1!20181017!USCA!simresults	spend_change_2
⊕ Changed Channel 2	Sheet1!20181017!USCA!simresults	changed_channel_2
⊕ Sim	Sheet1!20181017!USCA!simresults	sim
⊕ Days Post	Sheet1!20181017!USCA!simresults	days_post
⊕ Type	Sheet1!20181017!USCA!simresults	type
⊕ Leads	Sheet1!20181017!USCA!simresults	leads
⊕ Date	Sheet1!20181017!USCA!simresults	date
⊕ Region	Sheet1!20181017!USCA!simresults	region
⊕ Leads No Spend Change	Sheet1!20181017!USCA!simresults	leads_no_spend_change

© Data Source | USCA simulated changes | USCA simulated changes - pres... | Dashboard | Sheet 6 | actual | USCA sim unchanged forecast | Actual vs Forecast USCA | Chen Zhao

Note: Data is illustrative only. It resembles actual data but has been modified for confidentiality.



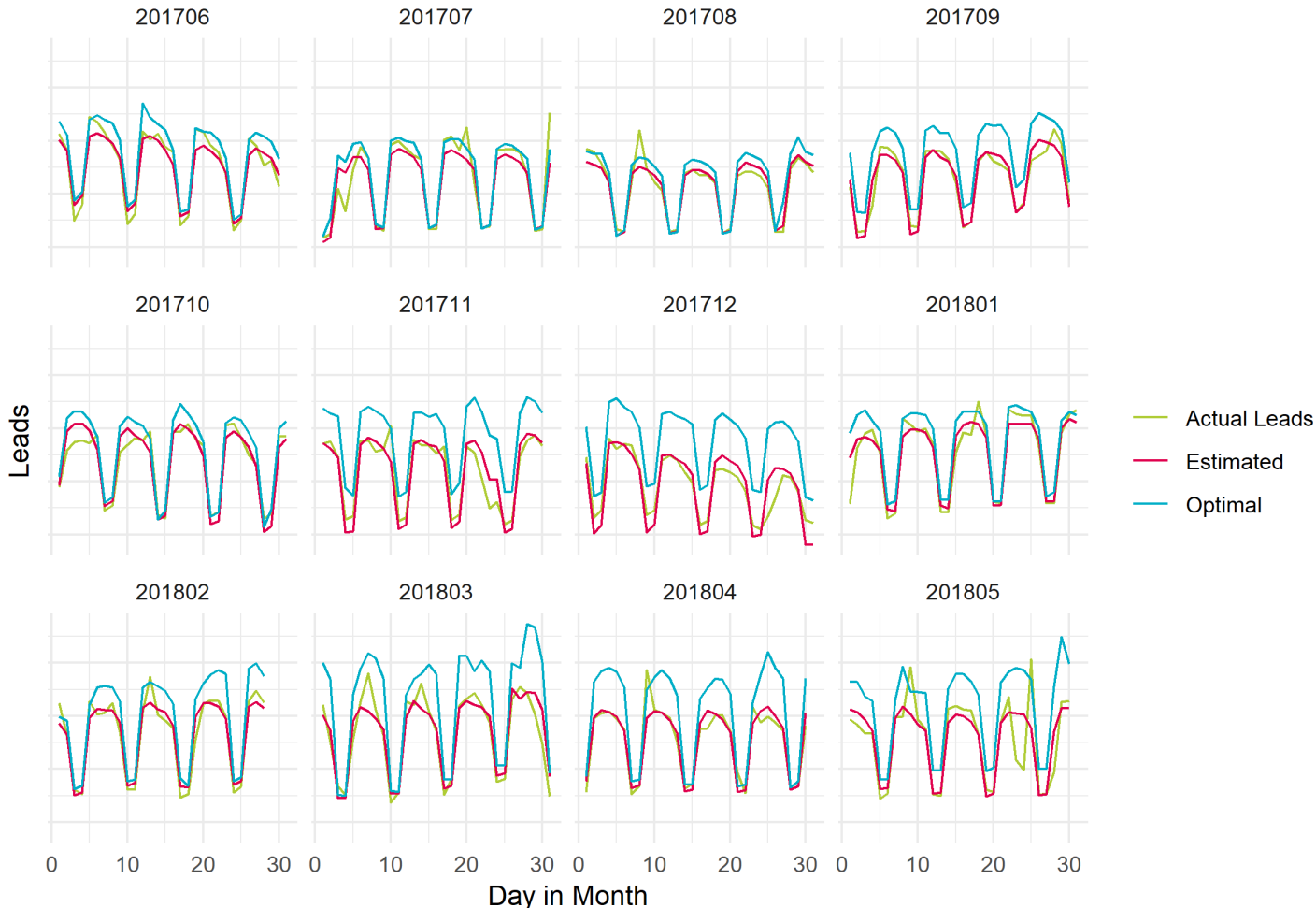
Note: Data is illustrative only. It resembles actual data but has been modified for confidentiality.



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# Using the Models

## Impact of Optimizing Spend



## Optimizing Budget

- Model allows exploration of budgeting scenarios.
- Keeping same spend as currently could yield **30%** more leads total.

## Measuring Efficiency

- Model shows us Paid Search incremental Cost-per-Lead (CPL) varies by **80%**.
- Most efficient incremental CPL at average spends can be **20x** more efficient than least efficient.