Attribution – the \$X million question





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



By Unknown - Unknown, Public Domain, <u>https</u> From Wikipedia, th<mark>e f</mark>ree encyclop<mark>edi</mark>a

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



	Multi-Touch Attribution (MTA)	Media Mix Modeling (MMM)
Data:	Atomic, user-level data	Aggregated, granular data
Modeling approach:	Logistic regression/hazard models, Markov model, game theoretic	Regression-based approach
Data grain:	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
Result grain:	Enables effectiveness estimates at a more granular level	Holistic estimate across all channels
Purpose:	Determines credit allocation and therefore CPA	Calculates allocation and the marginal effect, the value of an incremental \$1 to a given channel or subchannel
Forecast:	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						
								first_touch_fractional	last_touch_fractional li	near_touch_fractional m	narkov_model_fraction			
-	ga_client_id	ga_timestamp	touch_num	touchpoint	custom_channel	custom_source	campaign	_value	_value	value	al_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 01C	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 01C	3		Paid Search - Brand	Google	Campaign name A	0	0	0.17	0.13			
	1000003111	2018-03-24 06:55:56 01C	2	Protocol	Paid Search - Brand	Google	Campaign name A	0	0	0.17	0.13			
	1000126400	2018-05-24 06:53:25 UTC	1	hirst touch	Organic Search	Google	(not set)			0.11	0.00			
	1000126400	2018-05-14 14:02:12 UTC	,	last touch	Display	Google	Campaign name B	0		0.14	0.08			
	1000126400	2018-03-29 19:10:51 UTC	0		Display	Google	Campaign name B	0	0	0.14	0.08			
	1000126400	2018-03-10 16:20:25 UTC	5		Display Daid Search Brand	Google	Campaign name B	0	0	0.14	0.08			
	1000126400	2018-03-15 02:02:10 01C	4		Paid Search Brand	Google	Campaign name C	0	0	0.14	0.13			
	1000126400	2018-03-15 00:57:51 UTC			Organic Soarch	Google	(not cot)	0	0	0.14	0.13			
	1000126400	2018-03-15 00:57:51 01C	2	first touch	Diganic Search Baid Search Brand	Google	Compaign name C	0		0.14	0.38			
	1000126400	2018-03-13 00:30:38 UTC	1	first touch	Paid Search Non Brand	Google	Campaign name D			0.14	0.13			
	1000120334	2018 05 01 14:05:26 UTC	1	last touch	Dicplay	Coogle	Campaign name E	1	1	0.25	1.00			
	1000145451	2018-03-01 14:03:20 UTC	2		Display	Google	Campaign name E	0	1	0.25	0.25			
	1000145451	2018-03-02 13:00:10 01C	3		Display	Google	Campaign name E	0	0	0.25	0.25			
	1000145451	2018-03-01 13:02:10 01C	2	first touch	Display	Google	Campaign name E	1	0	0.25	0.25			
	1000145451	2018-05-01 17:04:17 010	1	last touch	Organia Saarah	Google	(pot cot)	1	1	0.23	0.23			
	1000189009	2018-05-11 17:02:12 010	0 E	last touch	Organic Search	Google	(not set)	0	1	0.17	0.18			
	1000189009	2018-05-11 15:02:11 01C	3		Organic Search	Google	(not set)	0	0	0.17	0.18			
	1000189009	2018-05-10 19:45:42 01C	4		Organic Search	Google		0	0	0.17	0.18			
	1000189009	2018-03-10 17:41:25 01C	3		Direct	Direct	(not set)	0	0	0.17	0.18			
	1000189009	2018-03-03 14:52:19 010	2	first touch	Direct	Direct	(not set)	1	0	0.17	0.13			
	1000185005	2018-03-03 01:44:44 010	1	first touch	Direct Baid Search Brand	Coogle	Compaign name E	1	0	1.00	1.00			
	1000201233	2018-03-28 23:07:33 01C	2	last touch	Organia Search	Bing	(pot cot)	1	1	1.00	1.00			
	1000375842	2018-01-23 05:00:35 010	2	first touch	Organic Search	Bing	(not set)	1	1	0.50	0.50			
	1000384716	2018-02-28 13-04-29 UTC	1	last touch	Organic Search	Google	(not set)		1	0.30	0.30			
	1000384716	2018-02-20 13:04:29 0TC	3	ast touch	Organic Search	Google	(not set)	0	1	0.20	0.21			
	1000384716	2010-02-16 13:00:17 UTC	4		Organic Search	Google	(not set)	0	0	0.20	0.21			
	1000384716	2010-02-10 14:02:11 0TC	3		Organic Search	Google	(not set)	0	0	0.20	0.21			
	1000384716	2010-02-10 13:10:23 0TC	2	first touch	Direct	Direct	(not set)	1	0	0.20	0.21			
	1000384718	2018-01-17 13:47:08 0TC	3	last touch	Paid Search - Brand	Google	Campaign name G	0	1	0.20	0.13			
	1000402403	2018-04-04 15:02:10 UTC	3		Paid Search - Brand	Google	Campaign name G	0	1	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			
1	1000402405	2010-03-23 21.13.14 010	1	mist touch	raid Search - Drand	Google	Campaign name G	1	0	0.55	0.55			



How much lead credit re-attributed?

	Attribution Model - Total Fractional Credit								
	By Channel and 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

Journey Length

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By Channel and Journey Length

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%

Media Mix Modeling

- MMM grew out of econometric methods.
- Classical regression technique:

$$\begin{aligned} \mathsf{conv}_{\mathsf{t}} &= \beta_0 + \beta_m \cdot \mathsf{month}_{\mathsf{t}} + \beta_{dow} \cdot \mathsf{weekday}_{\mathsf{t}} + \\ &\beta_d \cdot \mathsf{display}_{\mathsf{t}} + \beta_v \cdot \mathsf{video}_{\mathsf{t}} + \beta_s \cdot \mathsf{search}_{\mathsf{t}} + \beta_{soc} \cdot \mathsf{social}_{\mathsf{t}} + \\ &\beta_{org} \cdot \mathsf{organic}_{\mathsf{t}} + \epsilon_t \end{aligned}$$

- 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.



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MMM Input and Output



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		# Spend Change 2	Sheet1 !20181017!USCA!sim!res	alts spend_change_2					
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File Data Worksheet Dashboard Story Analysis Map Format Server Window Help





File Data Worksheet Dashboard Story Map Format Server Window Help



Using the Models

Impact of Optimizing Spend

Leads

Day in Month

Optimizing Budget

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

Measuring Efficiency

Actual Leads Estimated

Optimal

- 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.