Marketing ROI with Oracle ML

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What Do We Do?

Now in our 5th year implementing Oracle Cloud Solutions - DXM provides growing companies affordable access to enterprise level data and analytics so they can execute digital marketing programs with greater confidence and compete more effectively.

Revealing greater insights that leverage more successful engagement.

We Focus on Episodic Business Verticals



What drives our DXM marketing platform?

OCI - ADW - OAC - OIC

Data Partners, Analytics & Customer Data Platform (CDP)



DXM

Oracle Data Cloud - ODC

Identity Graph/OnRamp



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90% of Online Identities

Oracle Data Cloud - ODC

Data Management Platform (DMP)



100's of data partners and millions of domain activity



Why Oracle Machine Learning is important to the data flow process

US Consumer Data



320 million records with over 3,000 variables **Client Data**



Client CRM data for profiles and analyses **Predictive Models**



Custom predictive models: Look-alikes

Campaign & Responder Data



KPI's and analyses from client transactional data and campaign logs



Some questions we're trying to answer with OML

Leveraging ADW/OAC's Explain Function

- Financial Svcs Identifying relevant behaviors from 70,000+ DMP data points.
- **Telecom** What consumer variables reflects better ability to pay?
- **Retail** What is the Quad relationship between performance and potential?
- **Real Estate** Does a click on the ad raise the propensity for a conversion?

• **Urgent Care** – Does distance to the clinic matter? What ads produce the most conversions? How do we prove it?

Urgent Care spatial analyses: hundreds of trade area distances correlated with



Health Care/Urgent Care

Correlation of distance traveled with optimal Return on Marketing Investment with modeled prospect audience

<u>\$16 to \$1 ROMI</u>

Optimizes at 5.91 Mile



Typical Attribution Method – Advertising Messages

Triggers are credited with one conversion if the converting prospect was served an ad based on the trigger

Trigger	Total Cost	Unique Prospects	Conversions	Conversions Conversion			СРС	ROM:
Back To School	\$13,277	145,070	3,298		2.27%		\$4.03	\$29.81
Contextual	\$1,574	38,104	334		0.88%		\$4.71	\$25.46
General	\$30,761	480,040	6,420		1.34%		\$4.79	\$25.04
Health Researchers	\$24,653	345,961	4,174		1.21%		\$5.91	\$20.32
Cold-Allergy-Sinus	\$27,322	335,518	4,559	/	1.36%		\$5.99	\$20.02
New Movers	\$28,269	314,094	4,133		1.32%	$\overline{\ }$	\$6.84	\$17.54
Total	\$129,560	675,413	7,076		1.05%		\$18.31	\$6.55

Prospects are served ads based on multiple triggers, so the sum of the conversions by trigger is greater than the actual number of conversions

All triggers appear to outperform the overall campaign

Prospect Journey 1: Trigger 1 + Trigger 2 + Trigger 3 Prospect Journey 2: Trigger 3 + Trigger 2 + Trigger 1 Prospect Journey 3: Trigger 1 + Trigger 3 + Trigger 2 Order and interaction of the triggers is not considered. Above prospect journeys may convert at a different rate, but they are all considered equal under the current method

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A prospect journey includes the triggers that resulted in an ad served to a prospect throughout the campaign in the order they were served and the result of the journey (conversion vs. no conversion)



Attribution Method Comparison – Easy Math – No ML

Heuristic Methods

First-Touch – All credit for the conversion goes to first ad on prospect journey **Last-Touch** – All credit for the conversion goes to last ad on prospect journey **Linear Touch** – Credit is split evenly between all ads on prospect journey

R Code

```
h_mod1 <- heuristic_models(PL_Final, var_path = 'path', var_conv = 'conv')
all_models <- merge(h_mod1, mod1$result, by.x = 'channel_name', by.y = 'channel_name')
colnames(all_models)[c(5)] <- c('markov_chain_method')</pre>
```

In R - the ChannelAttribution package uses the prospect journey data to calculate attribution based on heuristic methods

Attribution Method Comparison Output

channel_name	first_touch	last_touch	linear_touch	markov_chain_method
Back To School	1026	924	983.41837	887.88933
Cold-Allergy-Sinus	1169	1317	1254.24155	1438.68403
Contextual	64	90	79.96973	91.68422
General	2687	2460	2515.04961	1895.95623
Health Researchers	1092	1204	1169.12479	1387.90154
New Movers	1038	1081	1074.19596	1373.88465



ML Algorithm - Markov Chain – Evaluating the Prospect Journey

Markov Chain is a probabilistic method that begins by mapping the prospect journey. The simplified example below compiles several prospect journeys into a probabilistic model. The probability of conversion is calculated but adding up probabilities for each possible path to conversion.

Campaign Data

- 7,377,207 Impressions
- 675,560 Prospects
- 5 Triggers
- 236,055 Prospect Journeys
- 7,076 Conversions

While the concepts behind the Markov Chain method are relatively straight forward, applying the concepts and doing the math for a digital campaign with thousands of prospect journeys is not



Markov Chain Application - Results

While the <u>ranking</u> of ads is similar to the original method, the results are more comprehensive, intuitive and easier to interpret

- Sum of the conversions by trigger equals the total conversions
- Metrics can be evaluated in context with the campaign total
- Order and interaction of the triggers is considered in results
- Rotating ads is efficient and does produce positive ROMI CMO Confidence!

nanr	ielAttribut	ПопРаскад	e
	trigger	total_conversions	÷
	Back To School	887.88933	

1895.95623

1438.68403

1387.90154

1373.88465

91.68422

General

Cold-Allergy-Sinus

Health Researchers

New Movers

Contextual

Trigger	Total Cost	Unique Prospects	Conversions	Conversions %	СРС	ROMI	
Back To School	\$13,277	145,070	888	0.61%	\$14.95	\$8.02	
General	\$30,761	480,040	1,896	0.39%	\$16.22	\$7.40	
Contextual	\$1,574	38,104	92	0.24%	\$17.17	\$6.99	
Health Researchers	\$24,653	345,961	1,388	0.40%	\$17.76	\$6.76	
Cold-Allergy-Sinus	\$27,322	335,518	1,439	0.43%	\$18.99	\$6.32	
New Movers	\$28,269	314,094	1,374	0.44%	\$20.58	\$5.83	
Total	\$129,560	675,413	7,076	1.05%	\$18.31	\$6.55	



Attribution Method Comparison

DXM

Factoring in the amount spent on each trigger allows for a comparison of the efficiency of each trigger for each method



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URGENT CARE COVID-19 IMPACT SUMMARY

DXM

	COVID-19 Time Period Y-o-Y Visit Comparison 2019 Dates: 3/17/19 - 7/27/19 2020 Dates: 3/15/20 - 7/25/20											Monthly Visit Comparison 3/15-7/31																
																Ma	rch		April			May		Jui	ne		July	
Brand 1						-21	.%							Brand	1	-41	.%		-59%		-	41%		13	%		35%	
Brand 2						-29	%							Brand	2	-31	.%		-52%		-	21%		50	%		45%	
Brand 3						-38	3%							Brand	3	-45	5%		-56%		-	51%		-23	%		-8%	
Brand 4						-10)%							Brand	4	-39	1%		-57%		-	21%		29	%		36%	
Brand 5						-10)%							Brand	5	-30	1%		-53%		4	34%		39	%		34%	
										Y-	o-Y V	Veek %	ly Vis Diffe	it Co rence	mpai e	rison												
20% erence in Visits																				Brand 1 Brand 2 Brand 3 Brand 4 Brand 5								//
₩ 0 %																	4			2								-
	Week 2	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11	Week 12	Week 13	Week 14	Week 15	Week 16	Week 17	Week 18	Week 19	Week 20	Week 21	Week 22	Week 23	Week 24	Week 25	Week 26	Week 27	Week 28	Week 29	Week 30

Thank you for your time.

Ray Owens, Founder and CEO https://dxmarketing.com