Towards a taxonomy of algorithmic attribution models – Which is the right model to measure, manage and optimize multiple campaigns?

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Abstract. Algorithmic attribution describes the attribution of marketing value to various channels in an algorithmic or statistical way. This discipline is growing in importance rapidly. This growth is due to an increasing number of potential advertising channels, with an increasing ability to track users along the whole customer journey. In this research in progress paper we develop a morphological box of the various algorithmic attribution models. This box is meant as a first step in the iterative development of a full taxonomy, which we intent to use to identify which models various attribution vendors use. This taxonomy will also be useful for the future development of marketing attribution solutions.

Keywords: Marketing Attribution, Taxonomy, Multichannel Marketing, Web Analytics, Multi-touch attribution

1 Introduction

It is expected that online advertisement will surpass TV commercials in terms of advertisement spending in 2017 for the first time [1]. With Google Adwords as one of the major providers being already for nearly 17 years on the market, online advertisement is not a new phenomenon [2]. However, the rapid growth of the market creates a highly versatile environment. Online marketers have a multitude of tools at their disposal, from which they can not only chose, but use many simultaneously. Additionally, in the digital environment, users can be tracked along the whole customer journey. Marketers know through which online channels customers came to the desired website. This data rich situation leads to new tasks for marketers. When a customer came to the website first through a search campaign, then a display campaign and lastly through e-mail advertisement to finally purchase, the marketer must decide to which of these channels the success should be attributed. Industry standard are heuristic attribution models like “last click wins” or “first click wins”. These attribute the success according to intuitive rules that don’t reflect the reality.

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Particularly, these models have no direct connection to the individual customer journey as they are based on assumptions rather than statistical analysis of each separate touch point [3]. In response to this lack of proper attribution, both academia and professionals started to develop algorithmic attribution models. This rather young trend caused, however, a lot of confusion. While there are already plenty of vendors who offer data driven attribution, most vendors stay purposely unprecise when describing their algorithmic attribution models, calling them data driven, algorithmic or artificial intelligence, expecting the customers to treat these algorithms as black boxes. For example they describe their approaches as follows:

- "Leverage advanced statistics and machine learning to objectively determine the impact of each marketing touch…" [4] or
- "AI-powered attribution attempts to fix this very problem using scientific and proprietary algorithms to allocate credit based on statistics and not human opinion. " [5]

Understandably, vendors try to obscure to some degree how exactly they attribute credit across the marketing channels as a good approach is a competitive advantage within this industry. However, it is a reasonable desire for researchers and for potential customers to get a better idea of what happens within those black boxes. This research attempts to build a taxonomy of algorithmic attribution models, based on academic literature and information attribution vendors share on their websites, technical documentation or other publically available marketing material. The developed taxonomy shall then help to identify the used approach of every vendor within our sample. As means to this end, we want to answer the following two research questions (RQ):

> RQ1: What are dimensions and respective characteristics that differentiate different algorithmic attribution models?

After the first question is answered we will use the created knowledge to answer

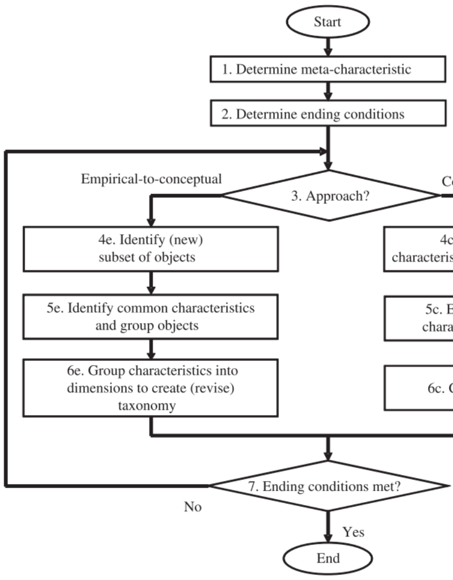
> RQ2: Which algorithmic attribution models do attribution vendors actually use to measure, manage and optimize multiple campaigns?

2 Building the taxonomy

2.1 Taxonomy Development

The taxonomy is developed, applying a structured approach developed by Nickerson et al.[6]. This is to our knowledge the first structured approach to taxonomy development within the IS community. Especially its iterative nature with clear ending conditions appeals to us as it has already been successfully applied by several researchers [7, 8]. Figure 1 shows a schematic description of the taxonomy development process.

Figure 1: Taxonomy development process [6]



Meta Characteristics. The first step is to define meta-characteristics. These should be defined based on the later use of the taxonomy. As mentioned earlier, this taxonomy is meant to help identifying which approach vendors use for their attribution modeling. To this end, we will try to identify what kind of data the vendors need to collect and what kind of data / information they provide as a result of their modeling. Respectively the meta characteristics will be the input and the output of the attribution approach.

Ending Conditions. The second step in the development process is the definition of ending conditions. We opt for two objective ending conditions

1. No new dimensions or characteristics were added in the last iteration
2. No dimensions or characteristics were merged or split in the last iteration

Approach. The third step is to decide whether to use the empirical-to-conceptual or the conceptual-to-empirical approach. In this research in progress we begin the development by applying the conceptual-to-empirical approach, building on the authors' knowledge and experience.

2.2 Academia as Data

To identify all models currently discussed in the academic literature, we performed a literature search, based on suggestions by Webster and Watson [9]. Therefore, we began with searching major databases (i.e. Google Scholar, Ebsco Host, Web of Science, ieeeXplore) for the search term "multi touch attribution" which lead to a total number of 78 results. After screening the abstracts for relevance for the taxonomy, we identified 27 papers. Papers that describe algorithmic attribution models in a detailed manner were included, while papers that rather discuss algorithmic attribution in general or the respective implications were excluded from the sample. In the second step, we performed a backward search by scanning the bibliographies of the identified articles and scanning forward with the help of Google Scholar. This way, we identified additional 10 papers, resulting in a total sample of 37 articles. All identified articles fall into the years 2010-2017. This was not set as a frame but happened due to the novelty of the topic. This novelty motivated us, not to limit the literature in terms of publication type, but rather make the inclusion - exclusion decision based on the papers content. Therefore three papers included are not peer reviewed, but published in the SSRN Electronic Journal [10–12]. Table 1 lists the proposed approaches with the respective references.

Table 1. Algorithmic attribution models derived from scientific literature

Approach	*Sources*
Time Series (Mutually exciting Point Process)	[13]
Time Series (Survival Theory)	[3, 14–17]
Time Series (Structured Autoregressive Model)	[18]
Counterfactual Framework	[19, 20]
Logistic regression	[21]
Bayesian statistics	[22]
Markov Model	[23–25]
Shapley Value	[12, 26, 27]
Sequence mining	[28]

2.3 Vendors

The vendors were identified using the business software review site G2 Crowd [29]. Within the category "Marketing Attribution Software" there was a total number of 32 vendors listed. To be listed on G2 Crowd vendors must "Use multiple attribution models like single touch attribution (when all attribution is assigned to only one event), fractional attribution (to include multiple events in the attribution, with equal or different weights), or algorithmic attribution (which uses data science for advanced attribution criteria and models)" [29]. However, for this research only vendors that offer algorithmic attribution are included in our sample. After screening their websites, we identified a total number of fourteen vendors that offer some form of algorithmic attribution. From those fourteen vendors five either explicitly or implicitly hint their approach, while the other nine keep their description rather vague.

Table 2 lists the fourteen vendors and when possible the most likely approach they apply.

Table 2. Attribution vendors with algorithmic attribution offers

Vendor	*Website*	*Approach*
Abakus	abakus.com	Shapley Value
Datalicious	datalicious.com	Hidden Markov Model
Optimine	optimine.com	Time Series Analysis
Neustar	neustar.biz	Logarithmic Regression
c3metrics	c3metrics.com	Bayesian Model
LeadsRX	leadsrx.com	-
OWOX	owox.com	-
VisualIQ	visualiq.com	-
Adinton	adinton.com	-
Converto	converto.com	-
Google Attribution	google.com/analytics/	-
Kvantum	kvantuminc.com	-
ConversionLogic	conversionlogic.com	-
ZetaGlobal	zetaglobal.com	-

2.4 First iteration and morphological box

For the first iteration we chose a conceptual-to-empirical approach, utilizing our knowledge of the topic. As a result of this first iteration, we identified five dimensions with two to three characteristics each. To validate the idea of this paper at an early stage, we built a morphological box to place three algorithmic attribution models therein. We opted for the development of a morphological box at this stage, as a method to foster creativity, given the less strict requirements towards a morphological box compared to a taxonomy.

Table 3: Morphological box (green: Shapley, red: Sequence mining, blue: Survival theory)

Dimension	*Characteristic*		
Time dependency	No time dependency		Time dependent
Granularity input	Touchpoints	Ordered touchpoints	Every single Journey
Granularity output	Channels	Sequences	Every single Journey
Prediction qualities	No prediction	Probability of conversion	Probability of every possible next step
Inclusion of additional Data	No inclusion		Inclusion

The lowest granularity means that all journeys with the same touchpoints are summed up, irrespective the order they occurred. Models that take ordered touchpoints as input, sum up all journeys that have the same touchpoints in the same order. Models that require the highest input granularity, need every single Journey and analyze them potentially with additional information.

3 Implications and Future Work

In this research in progress, we start to develop a taxonomy of algorithmic attribution models. As a firsts result in this iterative development process we present a morphological box and place three approaches that we identified within the academic literature. This box can already be used to differentiate between the various models and help deciding which model to focus on. From here, several more iterations have to follow to build a strict and clear taxonomy. With the results from the first iteration, we are confident that we will be able to build a comprehensive and useful taxonomy.

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