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ISMS Marketing Science Conference 2018  
14.06.2018
Motivation

- ‘research shopper’ phenomenon.” (Verhoef et al., 2007)
- crossdevice path to purchase data is necessary to get an accurate picture of the device attributions”
- The more pressing of an issue is attributing the offline conversions.” (Kannan et al., 2016)
- GDPR?
- Compared to the multichannel phase, omni-channel thus involves more channels. An important additional change is that the different channels become blurred as the natural borders between channels begin to disappear.” (Verhoef et al., 2015)
From Channel Addition Challenges…

<table>
<thead>
<tr>
<th>Brick &amp; Mortar</th>
<th>Online</th>
<th>e.g., Pauwels et al., 2011; van Nierop et al., 2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Catalog</td>
<td>Online</td>
<td>e.g., Ansari et al., 2008; Gensler et al., 2007</td>
</tr>
<tr>
<td>Brick &amp; Mortar</td>
<td>Online</td>
<td>e.g., Dholakhia et al., 2005; Avery et al., 2012; Pauwels and Neslin, 2015</td>
</tr>
<tr>
<td>Online</td>
<td>Mobile</td>
<td>e.g., Bang et al., 2013; Huang et al., 2015</td>
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</tbody>
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…to Omni-Channel Challenges

Challenges for Omni-Channel Studies:

- Visits and sales, online and offline
- Interrelated channels, same-day effects
- State-dependent effects
- Channel system embedded in larger system

- Aggregate time-series data from all channels
- Endogeneous, co-varying effects
- Dynamic model
- Unobserved variables
### A Short History of Empirical Dynamic Models (EDM)

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Theoretical and Methodological Basis</th>
<th>EDM Methodology for Ecosystems (e.g., Predator–Prey Foodwebs)</th>
<th>Applied to Climate Systems and Retailing Related Settings</th>
</tr>
</thead>
</table>
| Late 20th Century | - Chaotic dynamics in deterministic systems: *Lorenz 1963.*  
- Multivariate embeddings / attractor reconstruction: *Packard et al. 1980*  
- Time-delay embedding theorem: *Takens, 1981*  
- Detecting optimal embeddings and forecasting: *Sugihara & May 1990  
Kantz & Schreiber 1997* | - Causality-tests: *Sugihara et al., 2012  
Ma, Aihara & Chen 2014*  
- Non-linear estimation: *Deyle et al., 2013, Ye et al., 2015, Deyle et al., 2016a* | - Causal feedbacks in climate systems: *van Nes et al. 2015*  
- Global drivers of influenza: *Deyle et al. 2016b*  
- Assessment of impact of e-commerce on energy consumption: *Dost & Maier 2017* |
| 2012 - 16 | | | |
| 2015 - | | | |

**References:**
- Chaotic dynamics in deterministic systems: *Lorenz 1963.*
- Multivariate embeddings / attractor reconstruction: *Packard et al. 1980*
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- Global drivers of influenza: *Deyle et al. 2016b*  
- Assessment of impact of e-commerce on energy consumption: *Dost & Maier 2017*
EDM Basics: Time Series as Attractor Manifolds

2D-example from our data:

A: System attractor manifold

B: Time series variables

3D-example with Lorenz system (Sugihara et al 2012):

\[ m(t) = [X(t), Y(t), Z(t)] \]
EDM Basics: Embeddings / Shadow Manifolds

2D-example from our data:

A: System attractor manifold

B: Time series variables

C: Embedding (shadow manifold)

3D-example with Lorenz system (Sugihara et al 2012):

\[ m(t) = [X(t), Y(t), Z(t)] \]
Prediction and Cross-Prediction in EDM

A: Univariate prediction embedding (e.g. simplex projection of point P)

B: Cross-prediction embedding X (driving variable: App Visits)

C: Cross-prediction embedding Y (forced variable: Store Visits)
Study with a Three-Channel System (B&M, Web, Mobile)

Modeling steps:

1) Establish embeddability for variables
   - Simplex projection
     (Sugihara and May 1990)
2) Derive and test interrelated (causal) network
   - Convergent Cross-Mapping
     (Sugihara et al. 2012)
3) Build multivariate EDM model
   - S-Maps (Sugihara 1994)
4) Estimate marginal effects (Jacobian) at each state
   - Multivariate S-Maps
     (Deyle et al 2016a)

Data:

- Visit and sales time series from large European fashion retailer
  that operated three channels: brick-and-mortar stores as the dominant channel, an online store, and an app store
- Period 39 weeks of daily data
Results: Embeddings and Omnichannel Consumer Flow Network

- Brick & Mortar Offline Store Visits (E = 7)
- Web / Online Store Visits (E = 3)
- Mobile (App) Visits (E = )
- Total System Revenue (E = )

Correlation Coefficients:
- ρ = .41***
- ρ = .35***
- ρ = .34***
- ρ = .92***
- ρ = .95***
- ρ = .19*
- ρ = .26***
- ρ = .39***
- ρ = .23***
- ρ = .39***
Results: Marginal Effects as Contributions to System Revenues

Marginal Effects Distribution: \( \frac{d_{TotalRevenue}}{d_{OfflineVisits}} \)

- mean: 5.634
- sd: 17.815
- mode: 11.679

Marginal Effects Distribution: \( \frac{d_{TotalRevenue}}{d_{OnlineVisits}} \)

- mean: 5.698
- sd: 12.649
- mode: -0.91

Marginal Effects Distribution: \( \frac{d_{TotalRevenue}}{d_{MobileVisits}} \)

- mean: -34.454
- sd: 220.065
- mode: 116.575
Results: Marginal Effects as Contributions to System Revenues – Higher Variance in Mobile Channel Effects

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Results: Marginal Effect Interactions – Channel Conversion Tradeoffs
Results: State-dependencies – From Increasingly Saturating to Strangely Nonlinear Webrooming
Speculation: Consumer Flows in Omnichannel Systems as Hub-and-Spoke System?

### Two-channel models
- **C** (Ansari et al., 2008)
- **O** (Gensler et al., 2007)
- **B** (Pauwels et al., 2011)
- **O** (van Nierop et al., 2011)
- **O** (Bang et al., 2013)
- **O** (Huang et al., 2015)

- **Channels always integrate, irrespective of the channel combination**

### Traditional three-channel models
- **B**
- **C** (Omni-channel theory, e.g., Verhoef et al., 2015)
- **O**
- **B** (Dholakia et al., 2005)
- **O**
- **B** (Avery et al., 2012)
- **O**
- **B** (Pauwels et al., 2015)

- **Research finds that some channels integrate, but others—shown to integrate in 2-channel models—do not**
- Only dominant channel always integrated
- This contrasts with the expected full channel integration in the omni-channel paradigm

### Current three-channel models
- **B**
- **O**
- **M** (Omni-channel theory, e.g., Verhoef et al., 2015)

- **Our prediction**

- **O**
- **B**
- **M**

- **Our empirical finding**

### Legend:
- **B**: Brick & mortar
- **O**: Online
- **M**: Mobilo
- **C**: Catalog
- **Integration**
- **New channel**

- **Peripheral channels always integrate with the dominant channel, but not as strongly among themselves**
Questions, please

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About:
Interrelated Visits and Sales in an Omni-Channel System: An Empirical Dynamic Modelling Approach