

# Recognizing campaigns that cause cannibalization (presenting the results) Petra Huttunen 11.06.2018

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Työn saa tallentaa ja julkistaa Aalto-yliopiston avoimilla verkkosivuilla. Muilta osin kaikki oikeudet pidätetään.



#### Cannibalization

# A phenomenon where one product diverts sales from a substitute product, causing the sales of the substitute product to drop. (Copulsky, 1976)



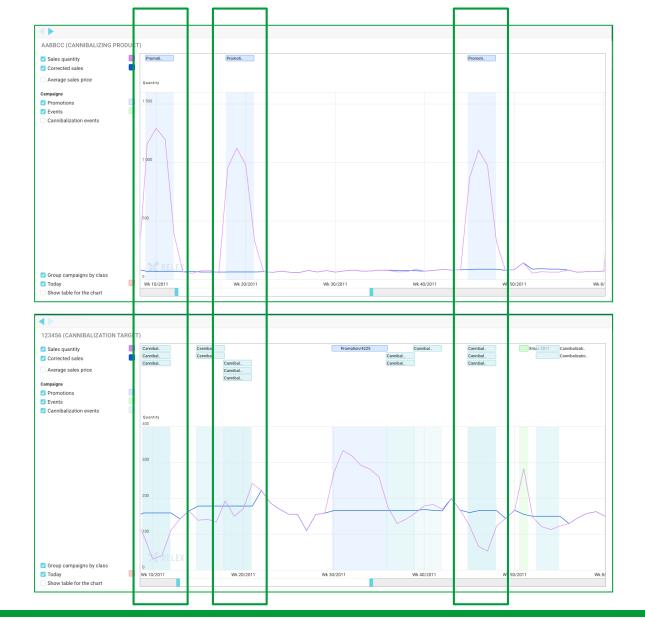


### **Research questions**

- Which promotions cause cannibalization?
- Can we predict before the product is promoted, whether that promotion will cause cannibalization or not?











# **Findings from literature**

- Products with similar attributes attract similar customers and can therefore divert sales from each other. (Mason and Milne, 1994)
- If one product is made more appealable to the customer because of a promotion, the customer can choose that product over another and cannibalization will occur. (Dawes, 2012)
- Promotions have different effects on product sales based on marketing, how good the offer is and how much the price is discounted. (González-Benito et al, 2010)





### Method

- Dataset contained information about the campaign and cannibalizing product, cannibalization event and cannibalization relationship
- The goal was to fit a regression model to the data
  - Dependent variable: additional sales of cannibalization event
- Data was real customer data from 2013 to 2016
  - 2013-2015 was used as analysis period
  - Data from 2016 was predicted by using the model fitted to analysis data
- Product groups used in analysis were beef, chicken, coca cola and frozen potatoes





## **Regression models in general**

- A regression model consists of three parts
  - Dependent variable y
  - Systematic part of the model  $f(x;\beta)$ 
    - Function of the independent variable(s) x
  - Residuals  $\varepsilon$  of the model
- The goal is to choose parameter  $\beta$  so that the residuals are as small as possible
  - One option is to use ordinary least squares method

$$y = f(x; \beta) + \varepsilon$$
$$\min_{\beta_0 \dots \beta_k} \sum_{i=1}^n \varepsilon_i = \sum_{i=1}^n (y - \beta_0 - \beta_1 x_{i1} - \dots - \beta_k x_{ik})^2$$



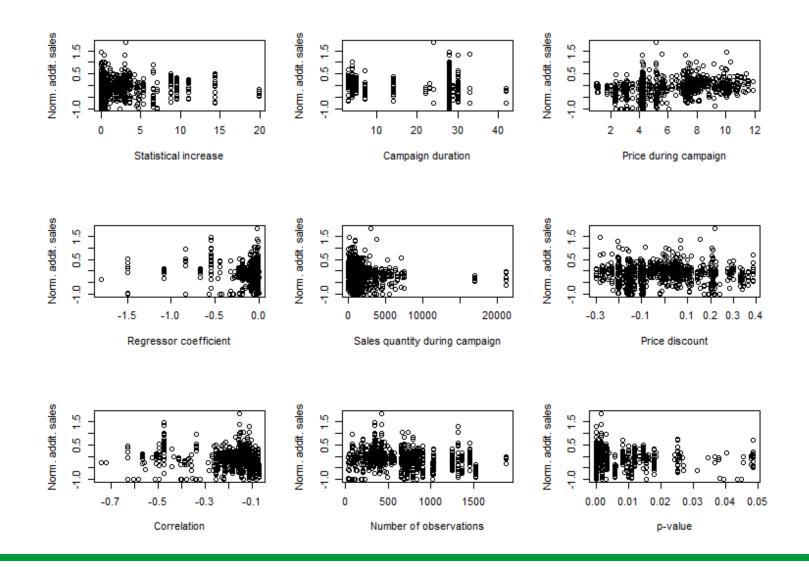


## **Independent variables**

- Product group
- Campaign types
  - Category, type, subtype
- Sales metrics
  - Sales quantity, baseline sales, additional sales
- Statistical increase of campaign (=relative sales increase)
- Campaign duration
- Price metrics
  - Price discount, price during campaign, price before campaign
- Information about the relationship
  - Regressor coefficient, correlation, p-value...







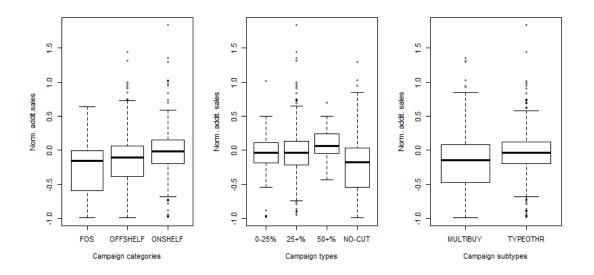




### **Categorical variables**

- Can we distinguish differences between campaigns in terms of cannibalization?
  - Campaigns seem to act in a very similar way

Additional sales divided by different campaigns

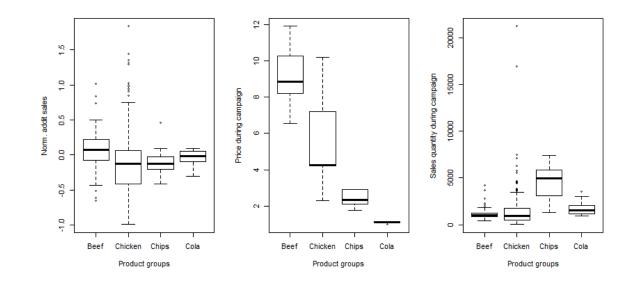




### **Categorical variables**

- How do the product groups differ in terms of sales and prices?
  - Chicken seems to have biggest variation

Values by subrgoup







## Fitting the regression model

- Model was first complied with all of the variables
  - Variables were eliminated based on significance and multicollinearity
- Linear variables and non-linear variables
- Log-model
- Normalised vs. real data





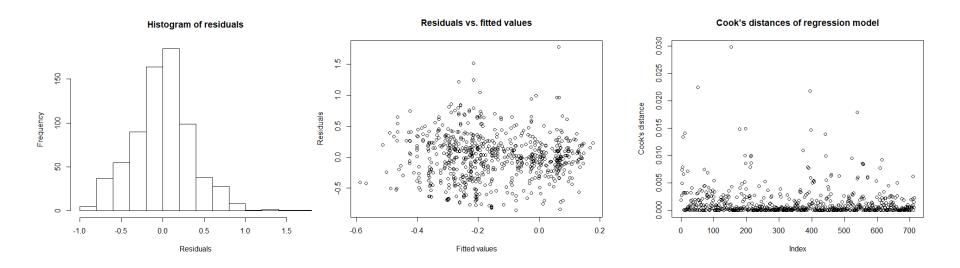
### **Fitted regression model**

Coefficient	Estimate	P-value
Intercept	0.25	0.0034
Category: offshelf	0.065	0.13
Category: onshelf	0.20	3.13e-5
Statistical increase	0.02	1.80e-6
Campaign duration	-0.0058	0.0010
Correlation	1.1	9.72e-7
Number of observations	-0.00029	2.44e-9
P-value	-3.4	0.036



### **Goodness of the model**

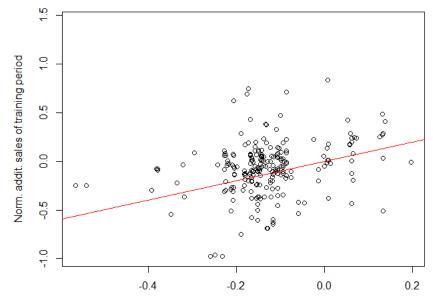
- Adjusted R-squared 15.63%
- All VIF-values were under 2
- No significant outliers (based on Cook's distance)





# **Prediction of the model**

- The model was used to predict the normalised additional sales of training data
- The results were compared with training data
- Dataset contained a lot of noise



Prediction vs. training data

Prediction





#### **Issues with dataset**

- Data contained noise and exceptions
- Exceptions were mostly caused by
  - Holiday events
  - Overlapping campaigns
  - Accuracy of baseline sales
    - Back-to-back campaigns
- Not all exceptions could be cleaned from the data





# Conclusions

- The regression model had a low coefficient of determination
  - The model build based on analysis data didn't explain the training data
- Confirmation that certain attributes do have an affect on cannibalization
  - Campaign categories
  - Strength of the cannibalization relationship
  - Statistical increase and campaign duration were interesting
- Other significant variables in various models
  - Price during campaign
  - Sales quantity
  - Subgroups





#### **Future prospects**

- Missing some possibly important information
  - Marketing plans for campaigns
  - Brand and quality of products
- Cannibalization was recognized only within product groups



### References

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