Linking Multi-Category Purchases to Latent Activities of Shoppers: Analysing Market Baskets by Topic Models

By Harald Hruschka

We investigate the application of two topic models, latent Dirichlet allocation (LDA) and the correlated topic model (CTM), to market basket analysis. Topic models measure the association between observed purchases and underlying latent activities of shoppers by conceiving each basket as random mixture of latent activities. We explain the structure of the two topic models used. We discuss estimation of LDA models by blocked Gibbs sampling. In addition, we show how to evaluate the performance of topic models on estimation and holdout data. In the empirical study, we analyse a total of 18,000 purchases made at a medium-sized supermarket which refer to 60 product categories. The LDA model performs better than the CTM in terms of log likelihood values. Latent activities inferred by these models are intuitive and interpretable, e.g., related to shopping of beverages or personal care, to baking or to an inclination towards luxury food. To illustrate the managerial relevance of estimated topic models we sketch the core of a recommender system which ranks purchase probabilities of other product categories conditional on the basket of a shopper.

1. Introduction

In text mining, the use of topic models is widespread and quite successful (Sun/Deng/Han 2012). We investigate the application of topic models to market basket analysis. Consistent with extant work on analysing cross-category purchases we look at purchases of product categories made by individual customers. The overwhelming majority of relevant contributions in the marketing literature are based on either multivariate logit models (e.g., Boztug/Hildebrandt 2008; Boztug/Reutterer 2008; Dippold/Hruschka 2013; Russell/Petersen 2000) or multivariate probit models (e.g., Chib/Seetharaman/Strijnev 2002; Duvvuri/Ansari/Gupta 2007; Manchanda/Ansari/Gupta 1999). These models consider pairwise relations between product categories only. In logit models, these relations are reproduced by cross-category coefficients. In probit models, pairwise residual correlations serve the same purpose.

Using topic models we do not restrict attention to pairwise relationships between categories. Instead we focus on the association between observed purchases and underlying latent activities of shoppers. Activities constitute a major element in definitions of consumer behaviour. For example, consumer behaviour is equated with “activities people engage in when searching for, selecting, purchasing, using, evaluating, and disposing of products and services so as to satisfy their needs and desires” (Belch/Belch 2003, p. 105). Topic models applied to market basket data infer latent activities from observed purchases, i.e., they only need data which are available to many firms. This way, additional costs of primary research by, e.g., surveys, may be avoided. Topic models conceive a basket which consists of the categories purchased by a shopper as random mixture of latent activities. Latent activities are distributed over product categories and reflect co-occurrence of categories in shoppers’ baskets. In a grocery retailing context, for example, a latent activity may alternatively indicate which product categories are more important if a shopper wants to prepare a breakfast, intends to bake a cake or does the weekly purchase of beverages or personal care products, etc.

Our study is related to a paper of Boztug/Reutterer (2008) who determine basket prototypes using purchase data for 65 product categories using an online version of K-means. Topic models differ from K-means and similar clustering techniques in several respects. Firstly, K-means associates each basket with a single prototype, whereas topic models sample the latent variable repeat-
edly within a basket. Therefore topic models allow that a basket may be linked to several latent activities and reflect that a shopper may pursue several activities at the same time (e.g., that a shopper both prepares breakfast and does the weekly purchase of personal care products).

Secondly, in contrast to most clustering techniques, topic models are based on a statistically defined objective function, e.g., a log likelihood function. Thirdly, topic models can be extended to measure the effect of predictors (e.g., socio-demographic or marketing variables), whereas clustering techniques exclude predictors.

Our main research goal consists in assessing whether basic topic models are appropriate tools for market basket analysis. To this end we use a data set which encompasses purchases referring to 60 categories. This number is much higher than the about five categories found in most multivariate logit and probit models estimated on market basket data sets.

We continue by explaining the structure of the two topic models, latent Dirichlet allocation (LDA) and the correlated topic model (CTM), by which we analyse market basket data. We discuss estimation of LDA models by blocked Gibbs sampling. Then we show how to evaluate the performance of topic models with respect to estimation and holdout data. The next section deals with the empirical study. It provides descriptive statistics, presents estimation results and gives an illustration of the managerial relevance of an estimated topic model. In the final section, we summarise results, indicate advantages of topic models and discuss both limitations of our study as well as possibilities for future research.

2. Topic Models

In text mining applications, topic models as a rule serve to relate words appearing in documents to discrete latent variables which are called topics. To the benefit of readers with a marketing background we will in the following only refer to product categories, market baskets and latent activities which take the place of words, documents and topics, respectively. We present and apply two topic models, latent Dirichlet allocation (LDA) and the correlated topic model (CTM). Comprehensive descriptions of LDA and typical applications can be found in the text mining literature (e.g., Blei 2012; Blei/Ng/Jordan 2003; Steyvers/Griffiths 2007; Sun/Deng/Han 2012). Tirumailai/Tellis (2014) present a marketing-related text mining study in which they extract latent dimensions of consumer satisfaction by LDA using consumers’ online product reviews.

According to LDA the product categories contained in each basket are generated by a mixture of latent activities. All baskets share the same latent activities, but their proportions are specific to each basket and randomly drawn from a Dirichlet-basket-activity distribution. For each activity assigned to a basket this way a product category is chosen randomly from its corresponding distribution. LDA forms activities in such a way that categories with higher conditional probabilities for an activity frequently co-occur with each other in baskets (Crain et al. 2012, p. 143).

Let $I$, $J$ and $K$ denote the number of baskets, product categories and latent activities, respectively. Random parameters in a $(J,K)$ matrix $\phi$ and a $(K,I)$ matrix $\theta$ indicate the importance of categories for activities and the importance of activities for baskets, respectively. The $k$-th column of $\phi$ holds the conditional probability of the categories conditional on latent activity $k$ and therefore sums to one.

The probability $p_j$ that basket $i$ contains category $j$ is related to the importance of this category for activities and the importance of activities for this basket in the following manner (Griffiths/Steyvers 2004, p. 5228):

\[ p_j = \sum_{k=1}^{K} \phi_{jk} \theta_{ki} \]

$\theta$ and $\phi$ are smoothed by Dirichlet hyperparameters $\alpha$ and $\beta$. $\alpha$ can be interpreted as prior count of the number of times any latent activity is assigned to a basket, before having observed any category contained in the basket. Low values of $\alpha$ lead to sparse distributions favouring a low number of activities. $\beta$ on the other hand can be seen as prior count of the number of times that categories are sampled from a latent activity before the purchase of any category is observed. Each category $j$ in a market basket $i$ is linked to activities by integer random variables $z_j = 1,...,K$ which give the index of the generated activity.

We estimate LDA models by blocked Gibbs sampling, i.e. marginalizing out parameters in $\phi$ and $\theta$. Blocked Gibbs sampling determines the posterior distribution over latent variables $z_j$ (the assignment of categories to topics), given the observed categories. For each basket $i$, the Gibbs sampling procedure considers each category $j$ purchased in turn, and determines the probability of assigning the current category to each activity, conditioned on the activity assignments of all other categories. From this conditional distribution an activity is sampled and stored as the new activity assignment for this category.

We denote this conditional distribution as $P(z_j = k | z_{-j}, \neg j, -i)$. $z_j = k$ represents the topic assignment of category $j$ to activity $k$, $z_{-j}$ the topic assignments of all other categories, $-j$ and $-i$ are indices of all other categories and all other baskets, respectively. This conditional probability is proportional to (Griffiths/Steyvers 2004, p. 5229):

\[ p(z_j = k | z_{-j}, \neg j, -i) \propto \max(n_{ijk} - 1, 0) + \beta \\
\max(n_{ijk} - 1, 0) + \sum_{j'} n_{j'k} + J\beta \\
\max(n_{jik} - 1, 0) + \alpha \\
\max(n_{jik} - 1, 0) + \sum_{k'} n_{j'k'} + K\alpha \]

Count variables $n_{ijk}$ and $n_{jik}$ contain the number of times category $j$ is assigned to activity $k$ and the number of times activity $k$ is assigned to the categories of current

https://doi.org/10.15358/0344-1369_2014_4_267

Das Erstellen und Weitergeben von Kopien dieses PDFs ist nicht zulässig.
basket $i$, respectively. The terms $\max(n_{jk} - 1, 0)$ and $\max(n_{ki} - 1, 0)$ in expression (2) show that the current category and the current basket are not relevant for computing this conditional probability.

The left part of expression (2) equals the probability of category $j$ under activity $k$. Its right part equals the probability of activity $k$ under the current distribution of activities for basket $i$. Once a category has been frequently assigned to activity $k$ across all baskets, it will increase the probability of assigning any instance of that category to activity $k$. At the same time, if activity $k$ has been used many times in a basket, it will increase the probability that any category in that basket will be assigned to activity $k$. Therefore, categories are assigned to activities depending on how likely the category is for an activity, as well as on how important an activity is in a basket.

Based on count variables $n_{jk}$ and $n_{ki}$ posterior estimates of parameters $\phi_{jk}$ and $\theta_{ki}$ can be computed as (Griffiths/Steyvers 2004, p. 5230):

$$\phi_{jk} = \frac{n_{jk} + \beta}{\sum_{j=1}^{J} n_{jk} + J\beta}$$

$$\theta_{ki} = \frac{n_{ki} + \alpha}{\sum_{i=1}^{I} n_{ki} + K\alpha}$$

The correlated topic model (CTM) allows for arbitrary correlations between activities which may be of advantage if activities are highly correlated (Blei/Lafferty 2007). In this respect, the CTM differs from LDA which implies very small negative correlations between activities (Blei/Lafferty 2007, p. 21).

The generation of baskets according to the CTM occurs in the same way as for the LDA except that activity proportions are drawn from a logistic normal (Aitchison/Shen 1980) rather than from a Dirichlet distribution. For each basket, a $K - 1$ dimensional vector of random variables $\mu_{1}, \ldots, \mu_{K-1}$ is drawn from a multivariate normal distribution with complete $(K - 1, K - 1)$ covariance matrix. The latter allows for correlations between activities.

Activity proportions result from the following multiple logistic transformation of these random variables (similar to Blei/Lafferty 2007, p. 20):

$$\theta_{ki} = \begin{cases} \frac{\exp \mu_{ki}}{1 + \sum_{i=1}^{K} \exp \mu_{ki}} & \text{for } k = 1, \ldots, K - 1 \\ \frac{1}{1 + \sum_{i=1}^{K} \exp \mu_{ki}} & \text{for } k = K \end{cases}$$

Like for LDA models we estimate CTM models by blocked Gibbs sampling, but to this end we have to add an appropriate data augmentation step for Bayesian logistic regression developed by Polsen/Scott/Windle (2013). We do not explain the CTM in more detail because its estimation is technically more involved and in the empirical study CTM models did not perform better than their LDA counterparts.

We evaluate the performance of topic models by log likelihood values both for estimation and for holdout data. We apply models determined on the basis of estimation data to holdout data to assess whether models are prone to overfitting.

The log likelihood $LL_e$ across baskets and categories for the estimation data is defined as (Newman et al. 2009, p. 1811):

$$LL_e = \frac{1}{S} \sum_{i=1}^{S} \sum_{j=1}^{J} y_{ij} \log \frac{\sum_{k=1}^{K} \phi'_{jk} \theta_{ki}}{\theta_{ki}}$$

$I_e$ is the number of baskets in the estimation data set. $y_{ij}$ is a binary indicator variable which equals one if basket $i$ contains category $j$, otherwise it is zero. The log likelihood is defined as average across $S$ parameter samples ($\phi'_{jk}$ and $\theta_{ki}$ denote parameter samples with $s = 1, \ldots, S$).

The log likelihood $LL_h$ for the holdout data set is computed in an analogous manner:

$$LL_h = \frac{1}{S} \sum_{i=1}^{S} \sum_{j=1}^{J} y_{ij} \log \frac{\sum_{k=1}^{K} \phi'_{jk} \theta'_{ki}}{\theta'_{ki}}$$

$I_h$ is the number of baskets in the holdout data set. To evaluate the holdout data the category-activities distribution remains constant by setting $\phi'_{jk}$ parameters to their average sampled values for the estimation data. For blocked Gibbs sampling on the holdout data therefore the left part of expression (2) is replaced by the corresponding constant estimate of $\phi_{jk}$. Only the $\theta_{ki}$ parameters which describe the activities to basket distribution are estimated according to equation (4).

3. Empirical Study

3.1. Data

The data of the empirical study consist of 18,000 market baskets of purchases made at a medium-sized supermarket. The median number of categories purchased per basket equals four. 25% of the baskets contain eight or more product categories. Out of a total of 209 categories, we analyse the 60 categories with the highest univariate purchase frequencies (see Tab. 1). We randomly divide the 18,000 baskets into two data sets and estimate topic models using the larger data set of 12,600 markets baskets. The remaining 5,400 baskets serve as holdout data.

3.2. Estimation Results

For each model, the respective blocked Gibbs sampler performs 4,000 iterations for the estimation data and 400 iterations for the holdout data, respectively. Note that one iteration includes a complete pass over all market baskets in the estimation and holdout data set, respectively. The first half of these iterations is used for burn-in. Log likelihood values and parameter estimates are arithmetic averages across iterations of the second half.

For Gibbs sampling, we set the hyperparameters $\alpha = .4$ and $\beta = .01$ after trial runs with several values. Especial-
higher values for $\beta$ (e.g., $\beta = .1$) lead to much lower log likelihood values. These results are in accordance with the study of Asuncion et al. (2009) who investigate how sensitive the performance of topic models is with respect to values of hyperparameters.

Tab. 2 gives the log likelihood values of LDA and CTM models with a minimum of two and a maximum of eleven latent activities both for the estimation and holdout data. These models all perform better than the independent model which is based on marginal frequencies only and attains log likelihood values of -123,056 and -52,035 for the estimation and holdout data, respectively. We obtain the best log likelihood values both for estimation and holdout data for the LDA with ten latent activities. Results turn out to be quite robust as the ranking of models with different numbers of latent activities for the estimation data set does not change if these models are applied to the holdout data. At each of the investigated number of latent activities the CTM model attains lower log likelihood values than the corresponding LDA models. This result is in agreement with the very low estimated correlations between latent activities estimated for the CTM models. With respect to correlations of latent activities LDA and CTM do not really differ and LDA has the advantage of a lower number of parameters (e.g., for ten latent activities LDA has 36 parameters less). In view of its superior performance we only present and discuss estimation results of the LDA model with ten latent activities in the following.

Tab. 3 gives importances of the product categories (i.e., the estimated $\phi_{jk}$ parameters) which are at least equal to .05. Most of the inferred latent activities are well defined and different from each other. In addition, the latent activities of Tab. 3 are intuitive and interpretable.

Activity 1 focuses on beverages and also includes periodicals and cigarettes, activity 3 focuses on milk and pasta. Activity 6 refers to various products appropriate for baking. Activity 7 comprises bread and dairy products which are often purchased for breakfast. Activity 8
is related to purchasing personal care products. Cigarettes, periodicals, bread, and sparkling wine are important categories for activity 9. Activity 10 shows an inclination towards luxury food, i.e., sweets, chocolate, confectionary, and cigarettes.

Several of the important categories for activities 2, 4, and 5 are identical, namely vegetables, tropical fruits, and fruits. On the other hand activity 5 reflects a much broader assortment of shoppers as it also includes dairy products. Overall the latent activities inferred turn out to be more distinctive than the 14 prototypes chosen in Boztug/Reutterer (2008). Five of their 14 prototypes focus on dairy products, three on beverages and one prototype on personal care categories.

### 3.3. Managerial Relevance

To illustrate the managerial relevance of topic models we sketch the core of a recommender system which processes estimated parameters of a LDA. Recommendations to a shopper are based on the categories already purchased and consist of categories with higher conditional probabilities. Such a system is of obvious interest for cross-selling programs of online retailers (see, e.g., Mild/Reutterer 2003 for an overview of recommender systems), but could also be used by brick-and-mortar retailers if they get online information about market baskets of shoppers via electronic cash registers. In such a situation, product recommendations may be added to the receipt printed out at the POS.

We explain the working of such a recommender system for initial baskets of two categories $j_1$ and $j_2$, the extension to baskets of larger size being rather straightforward. The purchase probability of any other category $j_3 \neq j_1, j_2$ conditional on purchases of categories $j_1$ and $j_2$ is defined as:

$$\text{pr}(j_3 | j_1, j_2) = \frac{\text{pr}(j_3, j_1, j_2)}{\text{pr}(j_1, j_2)}$$

$\text{pr}(j_3, j_1, j_2)$ and $\text{pr}(j_1, j_2)$ symbolize joint probabilities of the given three and two categories, respectively. For the LDA, we finally obtain with $\text{pr}_k$ denoting the probability of latent activity $k$:

$$\text{pr}(j_3 | j_1, j_2) = \frac{\sum_{k=1}^{K} \phi_{j_1 k} \phi_{j_2 k} \phi_{j_3 k} \text{pr}_k}{\sum_{k=1}^{K} \phi_{j_1 k} \phi_{j_2 k} \text{pr}_k}$$

Expression 9 shows that the conditional purchase probability of category $j_3$ increases if $j_3$, $j_1$, $j_2$ have high(er) importances for the same latent activities. On the other hand, if these categories are related to different activities, a low conditional probability of category $j_3$ results.

The fact that after estimation such conditional probabilities can be computed based on $K - 1 + KJ$ parameters constitutes a big advantage of LDA. An alternative direct approach needs $J \binom{J}{2}$ and $J \binom{J}{3}$ univariate, bivariate and trivariate frequencies, respectively. For ten latent activi-

---

Tab. 3: Product categories’ importances for latent activities 1–10

<table>
<thead>
<tr>
<th>Product Category</th>
<th>Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beer</td>
<td>.284</td>
</tr>
<tr>
<td>Soft drinks</td>
<td>.240</td>
</tr>
<tr>
<td>Water</td>
<td>.235</td>
</tr>
<tr>
<td>Juices</td>
<td>.071</td>
</tr>
<tr>
<td>Periodicals</td>
<td>.063</td>
</tr>
<tr>
<td>Cigarettes</td>
<td>.061</td>
</tr>
<tr>
<td>Vegetables</td>
<td>.143</td>
</tr>
<tr>
<td>Tropical fruits</td>
<td>.117</td>
</tr>
<tr>
<td>Milk</td>
<td>.041</td>
</tr>
<tr>
<td>Fruits</td>
<td>.171</td>
</tr>
<tr>
<td>Sugar</td>
<td>.096</td>
</tr>
<tr>
<td>Fat &amp; oil</td>
<td>.091</td>
</tr>
<tr>
<td>Flour</td>
<td>.050</td>
</tr>
<tr>
<td>Cheese</td>
<td>.050</td>
</tr>
<tr>
<td>Chocolate</td>
<td>.103</td>
</tr>
<tr>
<td>Confectionary</td>
<td>.058</td>
</tr>
<tr>
<td>Dairy</td>
<td>.077</td>
</tr>
<tr>
<td>Pasta</td>
<td>.117</td>
</tr>
<tr>
<td>Milk</td>
<td>.050</td>
</tr>
<tr>
<td>Yogurt</td>
<td>.066</td>
</tr>
<tr>
<td>Fruits</td>
<td>.057</td>
</tr>
<tr>
<td>Milk</td>
<td>.050</td>
</tr>
<tr>
<td>Baking ingredients</td>
<td>.127</td>
</tr>
<tr>
<td>Yogurt</td>
<td>.085</td>
</tr>
<tr>
<td>Body care</td>
<td>.066</td>
</tr>
<tr>
<td>Dental care</td>
<td>.073</td>
</tr>
<tr>
<td>Milk</td>
<td>.050</td>
</tr>
<tr>
<td>Fruits</td>
<td>.073</td>
</tr>
<tr>
<td>Bread</td>
<td>.081</td>
</tr>
<tr>
<td>Periodicals</td>
<td>.060</td>
</tr>
<tr>
<td>Milk</td>
<td>.053</td>
</tr>
<tr>
<td>Bread</td>
<td>.096</td>
</tr>
<tr>
<td>Gifts</td>
<td>.058</td>
</tr>
<tr>
<td>Chocolate</td>
<td>.120</td>
</tr>
<tr>
<td>Sliced cheese</td>
<td>.068</td>
</tr>
<tr>
<td>Cigarettes</td>
<td>.051</td>
</tr>
<tr>
<td>Rusk</td>
<td>.075</td>
</tr>
<tr>
<td>Sweets</td>
<td>.089</td>
</tr>
<tr>
<td>Periodicals</td>
<td>.091</td>
</tr>
<tr>
<td>Cheese</td>
<td>.050</td>
</tr>
<tr>
<td>Fruits</td>
<td>.073</td>
</tr>
<tr>
<td>Hair care</td>
<td>.067</td>
</tr>
<tr>
<td>Periodicals</td>
<td>.060</td>
</tr>
<tr>
<td>Milk</td>
<td>.050</td>
</tr>
<tr>
<td>Fruits</td>
<td>.073</td>
</tr>
</tbody>
</table>

contains all $f_{jk} \geq .05$
ties and 60 categories, this amounts 609 parameters for LDA versus 36,050 frequencies for the direct approach. In addition, the sparseness of higher order frequencies causes the direct approach to provide unstable estimates of conditional probabilities, LDA is free of these problems because it smooths low frequencies by means of hyperparameters.

Tab. 4 lists five recommended other categories for each of twelve selected baskets with two categories each. Six of these baskets contain either bread or chocolate. The recommendations are ranked according to conditional probabilities computed on the basis of the LDA model with ten latent activities (rank 1 gives the category with the highest conditional probability).

### 4. Conclusions

Our main research goal consists in assessing whether basic topic models are appropriate tools for market basket analysis. A LDA model with ten latent activities performs much better in terms of log likelihood values both for estimation and holdout data than the CTM with a maximum of eleven latent activities. Most of the inferred latent activities by this LDA model are well defined and different from each other. In addition, the latent activities are intuitive and interpretable, e.g., related to shopping of beverages or personal care, to various products appropriate for baking or to a tendency towards luxury food. To illustrate the managerial relevance of estimated topic models we sketch the core of a recommender system which ranks purchase probabilities of other product categories conditional on the basket of a shopper.

In addition to interpretability, we notice two important advantages of topic models compared to other models of market basket analysis, namely parsimony and scalability. Topic models are more parsimonious than logit and probit models with pairwise coefficients and correlations, respectively. For our data constellation of 60 product categories, topic models with ten latent activities require about 1,100 parameters less than the multivariate logit and probit models often applied in marketing. Scalability means that topic models are capable to deal with a very large number of product categories. Text mining studies with topic models which process a vocabulary of several thousand words provide clear evidence for this property (e.g., Blei/Lafferty 2007, pp. 27; Blei/Ng/Jordan 2003, pp. 1008).

We see our paper as a first attempt to use topic models in market basket analysis. That is why we note several limitations of this study which on the other hand indicate interesting avenues of future research. The data set investigated refers to individual market baskets, but does identify individual shoppers. Therefore the topic models estimated here take latent heterogeneity across baskets into account, but cannot consider latent heterogeneity across shoppers. The data set also does not contain shoppers’ attributes (e.g., socio-demographics) and marketing variables (e.g., price and sales promotion). Though such a data constellation can be found frequently in grocery retailing, we think that future research efforts should extend basic topic models by including latent heterogeneity of shoppers and by measuring the effects of predictors on latent activities.
References


Keywords

multi-category buying behaviour; market basket analysis; topic models
Das internationale Standardwerk.

**Dieser Klassiker**


**Die Schwerpunkte**

- Entwicklung, Herausforderungen und Trends
- Aktivierende Prozesse
- Kognitive Prozesse
- Das Kaufentscheidungsverhalten der Konsumenten
- Das System der Umweltvariablen
- Konsumentenverhalten in unterschiedlichen Lebensphasen
- Konsumentenverhalten am Point-of-Sale
- Wirkungsmuster der Medien und der Massenkommunikation
- Wirkung von klassischer Werbung, Alternativen und Werbevermeidung
- Virtuelle Welten und Social Media
- Die mehrfach erfahrene Umwelt
- Zum Problem der Konsumentensouveränität und Verbraucherdemokratie
- Verbraucherpolitik und Verbraucherschutz

»... für Studenten, Dozenten, aber auch für Führungskräfte im Marketing ein zentrales Fundament für das Verständnis des Konsumentenverhaltens und somit den erfolgreichen Umgang mit (potenziellen) Kunden«

V. Walter, in: Marketing Review St. Gallen, zur Vorauflage
Sicher gestalten.

Von Dr. Michael Fammler, LL.M., RA
3. Auflage. 2014. XV, 205 Seiten. Kartoniert € 37,90
ISBN 978-3-406-66581-3

In deutscher und englischer Sprache
bietet dieser bewährte Band ein umfassendes Vertragsmuster für die Ausgestaltung moderner Markenlizenzverträge. Rechtlich einwandfrei können Sie damit sowohl im nationalen wie auch im internationalen Geschäftsverkehr operieren.

Ein Mustervertrag steht zum Download zur Verfügung und lässt sich in beiden Sprachen individuell anpassen.

Die 3. Auflage
- berücksichtigt die Änderungen der GMVO und der MarkenRL
- enthält die zum 1. Mai 2014 in Kraft getretene neue GruppenfreistellungsVO zu Technologietransferverträgen
- ergänzt das Vertragsmuster um neue Klauseln, beispielsweise zu Domains, einschließlich der neuen »gTLD«, und zu Change-of-Control Bestimmungen.

Einzelheiten finden Sie unter:
beck-shop.de | Verlag C.H. BECK oHG · 80791 München | bestellung@beck.de | Preise inkl. MwSt. | 163409

Know-how für erfolgreiche Verkäufer.

Von Christine Behle und Renate vom Hofe.
ISBN 978-3-8006-4773-6

Portofrei geliefert: vahlen.de/13172229

Die Kunst des Verkaufens

Die Schwerpunkte
- Kundengewinnung und Kundenbindung,
- Gebietsmanagement und Verkaufsstrategien,
- Verkaufspsychologie und Preisgespräche.

Einzelheiten finden Sie unter:
vahlen.de | Verlag Franz Vahlen GmbH · 80791 München | bestellung@vahlen.de | Preise inkl. MwSt. | 163059

Erhältlich im Buchhandel oder bei:
beck-shop.de | Verlag C.H. BECK oHG · 80791 München | bestellung@beck.de | Preise inkl. MwSt. | 163409

Vahlen
Bestens vernetzt im Vertriebsrecht.

**Gebündeltes Know-how**

Die weit verstreuten Rechtsgrundlagen des Vertriebsrechts fasst dieser neue Kommentar praktisch und übersichtlich in einem Band zusammen. Erläutert werden die relevanten Vorschriften u. a. aus dem ■ BGB ■ HGB ■ Strafrecht ■ Kartellrecht ■ Wettbewerbsrecht ■ Verbraucherschutzrecht ■ Arbeits- und Sozialrecht.

Dabei geht das Werk ganz neue Wege in punkto Struktur der Kommentierung: Basierend auf der einschlägigen Vorschrift, werden die verschiedenen Vertriebsformen konkret erläutert.

Der Kommentar berücksichtigt auch das internationale Vertriebsrecht. Erstmalig werden auch die Beschlüsse der Schweizerischen Wettbewerbskommission und deren Bedeutung für Vertriebsverträge allgemein erläutert.

**Die wichtigsten Vertriebswege**

Alle praxisrelevanten Vertriebsarten werden ausführlich kommentiert:

■ Handelsvertretervertrag
■ Vertragshändlervertrag
■ Franchisevertrag
■ Kommissionsagenturvertrag.

**Die Experten**

Herausgeber RA Prof. Dr. Eckhard Flohr und RA Dr. Ulf Wauschkuhn sowie das gesamte Autorenteam sind ausgewiesene Fachkenner des Vertriebsrechts mit langjähriger Erfahrung aus Anwaltschaft und Industrie.
Das aktuelle Wissen zum B2B-Marketing.

Das Industriemarketing
bereitet dieses Werk didaktisch schlüssig auf und befasst sich neben den Grundlagen insbesondere mit den Schwerpunkten:

- Besonderheiten des Industriegütermarketings
- Bestimmung der Wettbewerbsposition: Organisa-
  tionales Beschaffungsverhalten, relative Konkurrenz-
  und Ressourcenanalyse
- Geschäftstypenspezifisches Marketing im Produkt-, Projekt-, System- und Integrationsgeschäft
- Geschäftstypenwahl und -wechsel.

Die 10. Auflage
enthält zahlreiche neue und aktuelle Beispiele. Ins-
bondere die Kapitel zum Organisationalen Be-
 schaffungsverhalten, zum Brand Management sowie
die Ausführungen zu den Geschäftstypen wurden
überarbeitet und erweitert. Ein Kapitel zur Geschäfts-
typenwahl wurde ergänzt.

»Insgesamt gelingt es den Autoren hervorragend, aus
dem Standardwerk eine echte Marke zu machen (...) Das Buch sichert sich somit die führende Stellung als Standardwerk zum Industriegütermarketing.«
In Thexis 1/2008 zur 8. Auflage
Die Erfolgsrezepte für integriertes Kommunikationsmanagement.

Effizient kommunizieren

Der Inhalt im Überblick
- Bedeutung und Stellung der Kommunikationspolitik
- Strategische Ausrichtung der Unternehmenskommunikation
- Einsatz kommunikationspolitischer Instrumente
- Rechtliche Rahmenbedingungen der Kommunikationspolitik

Die aktuelle 3. Auflage
wurde vollständig überarbeitet und berücksichtigt die Neuerungen und Veränderungen des Social Media und des Mobile Marketing als Kommunikationsmedien.

Das Handbuch
für Praktiker, Wissenschaftler und Studierende im Fachbereich Marketing, Werbung und Vertrieb.

Bruhn
Unternehmens- und Marketingkommunikation
Gebunden € 89,--
ISBN 978-3-8006-4858-0
Neu im Oktober 2014
Portofrei geliefert:
vahlen.de/13694775