Customer Purchase Behavior Prediction in E-commerce: Current Tasks, Applications and Methodologies

Douglas Cirqueira[1*], Markus Hofer[2], Dietmar Nedbal[3], Markus Helfert[1], Marija Bezbradica[1]

[1] Dublin City University, Dublin, Ireland
douglas.darochacirqueira2@mail.dcu.ie
[2] Raiffeisenlandesbank Obersterreich, Linz, Austria
[3] University of Applied Sciences Upper Austria, Steyr, Austria

Abstract. Digital retailers have experienced a high influx of big data coming from their consumers' interactions online, a consequence of the convenience in buying goods via E-commerce platforms. Such interactions compose complex behavioral patterns which, when analyzed, can provide businesses with opportunities to understand their consumer needs and improve their satisfaction. That can be achieved by the application of behavior or predictive analytics, specifically customer purchase prediction approaches. There is a diversity of proposals employing machine learning and probabilistic models aiming to predict the next steps of customers on their online journeys. However, a systematic classification of this literature is lacking. Therefore, this paper presents a literature review of recent research dealing with customer purchase prediction in the E-commerce context. The main contribution is a conceptual framework of analysis, which systematically maps this current literature in three main tasks as the prediction of buying sessions, purchase decisions, and customer intents. It also provides the applications enabled by those tasks, as well as the predictive features and analytics models adopted in those, classified in supervised and unsupervised learning techniques. Finally, it is discussed existing issues worth investigating in the field of purchase behavior prediction online.

Keywords: Consumer Behavior, Purchase Prediction, Behavior Analytics, Machine Learning, Data Mining, E-commerce, Digital Retail.

1 Introduction

Online activities generate daily a big data of opportunities for businesses to understand their consumer behavior in E-commerce platforms [1]. Indeed, consumers around the globe purchased $2.86 trillion on the web in 2018, up from $2.43 trillion in the previous year, which represents an 18% growth[1] in online sales. According to predictions of the purchasing behavior of customers, companies would be able to anticipate their needs and provide personalized services [2,3].

* This research was supported by the European Union Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No. 765395; and the industry partner Raiffeisenlandesbank Oberösterreich AG.

However, consumer behavior itself is well known as a complex pattern among the data mining community [4]. To analyze such pattern, researchers have been working with behavior and predictive analytics, which includes machine learning (ML) and statistical models. Those were applied to historical online customer's transactions to predict their next steps [5, 6]. Nevertheless, a mapping and classification of this recent literature are missing. Therefore, this paper aims to provide a systematic literature review into recent proposals performing purchase behavior prediction in E-commerce platforms. We propose a conceptual framework of analysis, which systematically maps this literature and provides guidelines on how to deal with customer behavior online. The main tasks aimed are illustrated, as well as predictive methodologies and guidelines for their application.

The rest of this paper is organized as follows: Section 2 describes the research methodology of the literature review; Section 3 presents results and the main contributions, followed by final remarks in Section 4.

2 Research Methodology

The review methodology has followed systematic guidelines and steps from Watson (2002) [7] and Kitchenham, et al. (2009) [8]. Inspired by [9], a search query was created to collect comprehensive literature within the research scope of purchase prediction in E-commerce. Then, it was applied in the following scientific databases: Scopus, Web of Science, Science Direct, EBSCO Host (Business Source Complete and Academic Search Complete), Emerald, IEEE Xplore and Association of Information Systems (AIS) library.

- **Search Query**: "(consumer or customer) AND (purchas* OR buy* OR sale* OR shop* OR behavi*) AND (predict* OR forecast*)"

The searches were performed in the abstract field, except for the Web of Knowledge (abstract title and keywords were used) and AIS libraries (full text was used), due to the characteristics of their search engines. The search period has covered papers from 2014 to 2019, only in the English language, which has provided a total of 9705 exported proposals. The next step removed duplicates and included the inclusion filter only to retrieve papers focused on the problem of consumer purchase behavior prediction. That has provided a total of 420 papers.

Next, the exclusion criteria were applied to remove papers not focused on the E-commerce context. At this stage, the total of papers kept was 28. Based on those proposals, backward and forward (using Google Scholar) searches were conducted, adding 18 and 10 papers respectively. The final number of papers for extraction and mapping steps was 56. All those results are available at an extra material repository (https://bit.ly/2TUkMB6).

[1] Digital Commerce 360, Global E-commerce Sales 2019. https://www.digitalcommerce360.com/article/global-ecommerce-sales/

3 Results

Table 1 presents all the papers obtained from the literature review. The primary grouping factor and contribution of this table is to classify the existing literature according to the predictive task targeted, which will be detailed next. Some authors focused on evaluating multiple algorithms. Those receive the label "Multiple" in the *Algorithm* column. Abbreviations are adopted for some algorithms, such as Gradient Boosting Decision (GB), Random Forest (RF), Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM). It is also decided to report the best performance achieved by each author. An abbreviation is used for the metric Area Under the Curve (AUC). However, some papers did not explicitly mention their method's performance, or focused mostly on evaluating their tools in competitions with specific scores. In those cases, the performance column has the value NA (Not Available).

3.1 RQ 1. What tasks and applications have been addressed in the problem of consumer purchase behavior prediction in E-commerce?

The literature shows proposals targeting three main tasks within the online purchase prediction problem. Every task has a different prediction subject, which is described below.

- **Predict Buying Session (PBS):** Predict if a current user online session or visit will end up with a purchase or not.
- **Predict Purchase Decisions (PPD):** Predict customers purchase behavior concerning their buying decisions. For instance, to foresee what product or category a customer will buy; to predict the time or period likely to witness a purchase; to predict the next amount customers are likely to spend in their purchases.
- **Predict Customer Intent (PCI):** Predict the intention of customer visits online. The types of intentions reported in the literature are purchase oriented or general [51]. It has also been categorized within the types browsing, searching, purchasing, and bouncing [53].

Those three identified tasks enable a variety of business intelligence applications for online retailers, such as: **A)** Product Recommendations [12, 66, 51]; **B)** Targeted Marketing [15, 51, 59, 63]; **C)** Layout Personalization of E-commerce Landing Pages [11, 16, 25, 67]; **D)** Load balance Optimization to Prioritize Quality of Service for Likely Buyers [11, 15, 18, 29]; **E)** Stock Management Optimization of Products [11, 48, 49]; **F)** Real-time Customer Service [66]; **G)** Purchase Trends Discovery [12]; **H)** Offers Awareness Based on Detected Intention of Consumers [51].

Table 1 also brings the business intelligence applications that were the focus of authors in the literature, according to their main prediction tasks. That is reported in the column *Focused Business Intelligence Applications*.

Table 1. Proposals collected in this literature review (Ref = Reference; Y = Year; C = Customer; P = Product; T = Time; Ch = Channel; L = Location; S = Supervised; U = Unsupervised)

Ref	Y	Task	Focused Business Intelligence Applications	Predictive Feature Dimensions					Algorithm Methodology		Algorithm	Performance Reported by Authors
				C	P	T	Ch	L	S	U		
[10]	2018	Buying Session (PBS)	B,C,D,F	x	x	x			x		GB	68.78% Recall
[11]	2018			x	x	x			x		Logistic Regression	75% AUC
[12]	2017			x	x				x		Multinomial Naïve Bayes	82.91 F1
[13]	2017			x	x	x			x		Multiple (GB)	34% F1
[14]	2017			x	x	x			x		Multiple (RF)	99.53% Accuracy
[15]	2017			x	x		x			x	Association Mining	92% Confidence
[16]	2017			x	x	x			x		Multiple (GB)	34% F1
[17]	2017			x	x	x	x		x		Multiple (RF)	76% Accuracy
[18]	2017			x		x	x		x		MLP	99.6% Accuracy
[19]	2016			x		x	x			x	Bayesian Probability Model	91% True Negative
[20]	2015			x	x		x		x		SVM	84% AUC
[21]	2014			x	x	x			x		Ensemble	97.2% F1
[22]	2018			x		x	x	x	x		Multiple (GB)	37% AUC
[23]	2017			x	x	x		x	x		Decision Tree	57.89% Recall
[24]	2017			x		x			x		RF	97.3% Accuracy
[25]	2016			x	x	x			x		Multiple (GB)	94% Recall
[26]	2017			x	x		x		x		Firthlogit Regression	NA
[27]	2016			x	x	x			x		Multiple (Bagging with 1R)	92.9% F1
[28]	2015			x		x	x		x		K-Nearest Neighbor	99.85% Accuracy
[29]	2015			x	x	x	x		x		SVM	99.94% Accuracy
[30]	2014			x		x			x		K-Nearest Neighbor	72.4% Accuracy
[31]	2018			x		x	x	x	x		Neural Network	87.94% F1
[32]	2017			x	x	x			x		SVM	76.73% Accuracy
[33]	2018			x	x	x			x		LSTM	83.9% AUC
[34]	2016	Product (PPD)	A,B,C,E,F,G	x	x	x			x		Logistic Regression	32% F1
[35]	2016			x	x	x			x		Gradient Boosting Decision	8.66% F1
[36]	2014			x	x	x				x	HMM and K-Means	14% Error Rate
[37]	2017			x	x	x			x		Deep Feed Forward-MLP	53% Hit Ratio
[38]	2016			x	x				x		Logistic Regression	67.6% AUC
[39]	2015			x	x	x			x	x	Multiple	NA
[40]	2015			x	x	x			x	x	Multiple	NA
[41]	2015			x	x					x	Collaborative Filtering MF	12.5% F1
[42]	2015			x	x	x		x	x		Gradient Boosting Decision	8.318% F1
[43]	2014			x	x				x		Logistic Regression	85% Hit Ratio
[44]	2018			x	x					x	Latent Factor Model	53% F1
[45]	2017			x	x	x	x	x	x		SVM	96.5% Accuracy
[46]	2019			x	x	x			x		Logistic Regression	32% F1
[47]	2017			x	x					x	Collaborative Filtering MF	87.94% AUC
[48]	2016			x		x			x		Logistic Regression	43.62% F1
[49]	2018			x	x	x			x	x	Multiple (Expected Maximi-zation)	42% F1
[50]	2019			x	x				x		LSTM	67% AUC
[51]	2018	Purchase Intent (PCI)	B,D,H	x	x	x			x		Gradient Boosting Decision	75% Recall
[52]	2017			x						x	Ant Colony Optimization	60% Accuracy
[53]	2017			x	x	x	x			x	K-Means Clustering	NA
[54]	2016			x		x	x			x	K-Means Clustering	NA
[55]	2015	Buying Session And Product (PBS & PPD	A,B	x	x	x			x		GB	85% AUC
[56]	2015			x	x	x			x		RF	75% Recall
[57]	2015			x	x	x			x		LSTM	NA
[58]	2015			x	x	x				x	Deep Networks and Autoen-conders	86% AUC

Table 1 Cont. Proposals collected in this literature review (Ref = Reference; Y = Year; C = Customer; P = Product; T = Time; Ch = Channel; L = Location; S = Supervised; U = Unsupervised)

Ref	Y	Task	Focused Business Intelligence Applications	Predictive Feature Dimensions					Algorithm Methodology		Algorithm	Performance Reported by Authors
				C	P	T	Ch	L	S	U		
[59]	2017	Product and Time (PPD)	A,E	x	x	x			x		Naive Bayes Regression	NA
[60]	2015			x	x			x	x		Gradient Boosting Decision	8.64% F1
[61]	2015			x	x	x			x		Ensemble	4.18% F1
[62]	2014			x	x	x			x		Ensemble	6.11% F1
[63]	2016	Time (PPD)	E	x	x	x			x		Ensemble	70% AUC
[64]	2016	Time and Amount (PPD)	B,E	x	x	x		x		x	Bayesian Probability Model	62% AUC
[65]	2014	Buying Session and Amount (PBS & PPD)	A,B,E	x		x				x	Bayesian Probability Model	NA

3.2 RQ 2. What methodologies have been adopted to predict consumer purchase behavior online?

Researchers have been working with machine learning and statistical methods to model the complex customer purchase behavior online [5]. Predictive models generally work by: 1) Identifying underlying patterns based on descriptive features in datasets, and 2) creating a model able to identify those patterns in new instances [68]. The answer to this research question is provided through Figure 1, which brings a conceptual framework of analysis to summarize the behavior and predictive analytics literature for customer purchase prediction online.

A Conceptual Framework of Analysis for Customer Purchase Prediction Online. The framework starts with the data layer, illustrating how consumer behavior is modeled to predictive analytics. In the data preprocessing layer, it is highlighted the pros and cons of adopting each of the identified strategies to preprocess consumer data. The predictive layer shows when to adopt each of the identified methodologies for the main tasks of predicting customer behavior. The penultimate layer shows which tasks enable what business intelligence applications, as identified in Subsection 3.1.

Data Layer. Customer behavior in E-commerce is captured through datasets of past online sessions, shopping logs, and click-stream records. Those are transformed into transactions from which researchers derive descriptive features to explain the complex user behavior online. To provide a systematic view on that, we provide a data layer classifying those features, inspired by [2], in dimensions and sub-dimensions. Every dimension supports in explaining and predicting customer behavior from different perspectives, which bring some benefits for predictive tasks on that data.

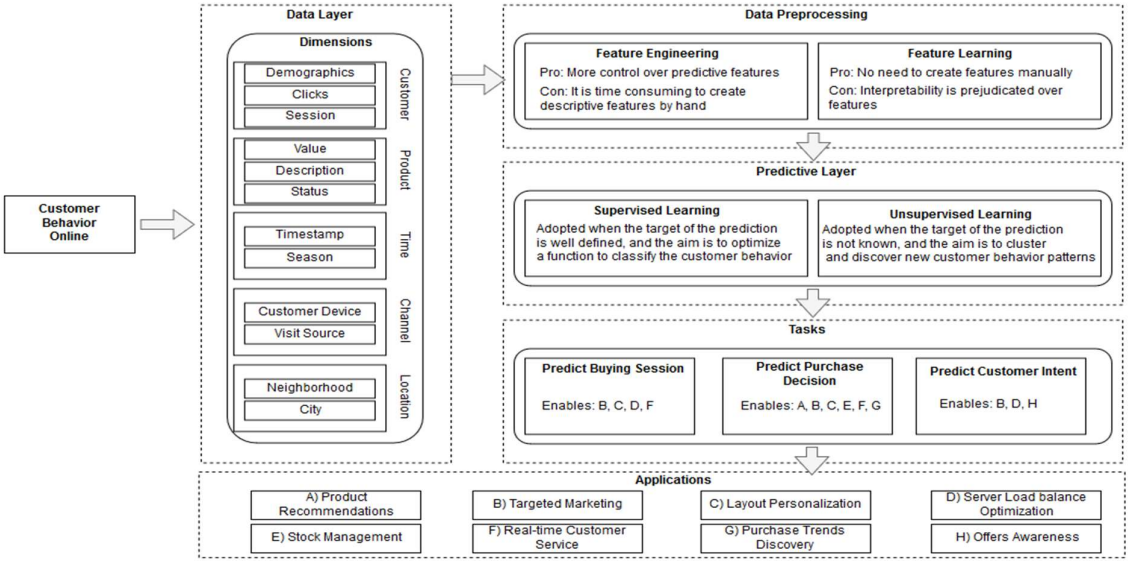

Fig. 1. A conceptual framework of analysis for the literature in behavior and predictive analytics for customer purchase prediction online. (Legends for applications enabled by tasks: A = Product Recommendations; B = Targeted Marketing; C = Layout Personalization; D = Server Load Balance Optimization; E = Stock Management; F = Real-time Customer Service; G = Purchase Trends Discovery; H = Offers Awareness)

- ***Customer***: reveals the profile of every consumer, and enables their segmentation by demographics and clicking behavior within their visiting sessions online. **Benefit**: can support in tackling the cold start problem, and in predictions for customers without purchase history by clustering them according to their similarities.
- ***Product*:** relates to the raw characteristics of products which consumers buy online. **Benefit**: supports the detection of what are their interests regarding prices and tastes, narrowing down potential recommendations, and targeted marketing campaigns.
- ***Time***: timestamps of consumer transactions. **Benefit:** supports the prediction of when events can happen based on previous timestamps and seasonal patterns, optimizing the decision for the best moment to target a customer.
- ***Channel***: relates to characteristics of accessing devices and touchpoints between consumers and an E-commerce platform. **Benefit:** enables the assessment of what factors influence customer purchase likelihood when adopting different channels to reach out an online shop, such as mobile and online, or organic and paid marketing campaigns.
- ***Location***: contains information about the location of consumers. **Benefits:** helps in identifying patterns according to the spatial placement of consumers. For instance, in [42, 45, 60, 64] the authors adopt customers location in order to capture underlying relationships between their purchases and the influence of their zip code, city or state location level.

Data Preprocessing. In order to derive predictive features out of those dimensions, researchers adopt Feature Engineering or Feature Learning modeling strategies.

- **Feature Engineering**: refers to researchers and experts applying aggregating functions such as counting and ratios to create further explanatory variables. For example, [35] counts user clicks in specific product categories and input that to an ML model, so to detect the most likely item a customer will buy. The advantage of Feature Engineering is the interpretability of the variables created. On the other hand, the con is the usual time-consuming task of creating those variables.
- **Feature Learning**: relates to automatically deriving new explanatory variables from raw features. In this literature, researchers have achieved that through the application of Recurrent Neural Networks, LSTMs, and Autoencoders [33, 50, 57]. From raw features, those models generate embeddings, which are vectors of real numbers learned from the hidden relationships between features and their correlation to a target variable. For instance, [57] adopts a bidirectional recurrent neural network based on LSTM, so their model can learn session features directly from the raw variables in those sessions. The advantage of Feature Learning tackles the con of Feature Engineering, as it reduces the time of manually creating explanatory features. Moreover, Feature Learning enables the discovery of hidden correlations and relationships between variables, which is not possible through the engineering strategy. The human behavior is already a complex pattern, which supports the potential adoption of this approach for preprocessing it. On the other hand, the interpretability of the features learned gets compromised. However, it is observed Feature Learning for consumer behavior online is still a little explored area, and it should be further investigated due to its potential well noted for other domains with complex patterns, such as computer vision and natural language processing [70].

Predictive Layer. It was detected two main approaches for consumer purchase behavior in E-commerce. The first, supervised machine learning, is adopted by the majority of researchers. Authors here focused on providing labeled past instances of buying sessions, purchase decisions, or intents as described in Subsection 3.1, along with descriptive features for training a predictive model. It then learns to output those labels for new instances [46]. The second approach is unsupervised machine learning, where unlabeled sessions and purchase transactions are given to a model which will discover patterns in similar instances and group them for providing predictions. For instance, in [53, 54], the authors successfully employed the K-means algorithm to segment customers based on variables regarding their clickstream behavior. After obtaining those segments, similar customers were closer regarding their search patterns as buying, searching, browsing, or bouncing.

It is also possible to deeply discuss the methods adopted in this literature from different perspectives, such as modeling and interpretability.

- **Modeling**: Another insight is the major focus of researchers on static machine learning algorithms. Those learn and deal with every transaction from customers independently. The most used algorithms in this literature fit into this category, such as Logistic Regression [11, 13, 14, 16, 17, 63, 35, 21, 23, 25, 36, 26, 44, 46, 48, 49, 38, 39, 58, 62, 43], Gradient Boosting Decision [10, 51, 13, 16, 63, 35, 22, 25, 50, 40, 55, 62], Random Forest [10, 14, 17, 34, 63, 21, 22, 24, 56, 61, 58, 62], Multilayer Perceptron [18, 21, 37, 31, 39] and Support Vector Machines [20, 21, 45, 32, 29]. On the other hand, there is sequential machine learning, which explicitly models the dependency between past customer transactions and current events.

Examples are recurrent neural networks, which are only adopted in three proposals [33, 50, 57]. This sort of algorithm is interesting as it has the capacity of naturally capturing the evolving consumer behavior over time. However, this aspect is still not widely explored in this literature.

- **Example:** When adopting sequential models, the aim is to capture patterns in consumer transactions such as "She is buying a phone case after purchasing a smartphone". Literature reports the potential of investigating successive customer interactions, respecting the order of their previous records, as it gives clues on their next steps [71].

- **Interpretability**: Finally, it is noticed the majority of authors reporting higher performances as those applying supervised learning algorithms, which also have a black-box nature. Examples are Support Vector Machine for PBS and PPD tasks (99.94% and 96.5% Accuracy, respectively) and Gradient Boosting Decision Trees for PCI (75% Recall). In unsupervised settings, Deep Networks & Autoencoders are the highlights for PBS & PPD (86% AUC). It is not possible to interpret the decisions of those models. Indeed, interpretability seems not to be the focus on this recent literature. It would be interesting to carry on more research on such aspect, given the rise of privacy policies with the General Data Protection Regulation (GDPR) in Europe, which demands explanations even from machine learning models for decisions involving consumer's data.
  - **Example:** When enabling interpretability from models with high performance, it is possible to benefit both retailers and customers. Retailers get the benefit of understanding particular aspects influencing customer behavior, which can help them in improving their models. Customers will receive explanations for their recommendations, which can support in the convincement and provision of personalized services to match their needs. For instance, a retailer would be able to identify if the location, time, or previous products purchased are influencing the current order of a customer. The customer would better understand his purchase behavior, and optimize future decisions for deals and bundles.

4 Final Remarks

This study has provided a systematic literature review of recent proposals in consumer purchase prediction in E-commerce. It was noticed that each author provides its particular strategy to predict consumer behavior online, but a general framework for that is lacking. We provide a conceptual framework of analysis as a first approach in this direction. Researchers and practitioners can now better visualize how to systematically manage and analyze the complex behavior of their customers in E-commerce.

This framework presents the consumer behavior classified in five contextual dimensions, and few authors have been working with all those contexts, which can be further investigated in this field. Moreover, feature learning for behavior analytics online is an ongoing area and needs further investigation due to its promising results in different fields with complex patterns.

Future Research Directions. The adoption of benchmark datasets for a performance evaluation of the methodologies identified in every task. We aim to provide recom-

mendations for techniques according to the complexity of the three prediction tasks revealed by this review. Another little explored area and future aim is the evaluation of predictive methodologies in multi-task settings, such as to forecast the next product, purchase time, or amount a customer will likely buy. There is also the possibility of profoundly exploring sequential machine learning to capture the evolving consumer behavior, and the assessment of interpretability for purchase predictions. That would also enable the optimization of predictive models and improved human-computer interaction, as customers would visualize the reasons for why they are being recommended or targeted special services.

References

1. Agnihotri, R., Dingus, R., Hu, M.Y., Krush, M.T.: Social media: Influencing customer satisfaction in b2b sales. Industrial Marketing Management 53 (2016) 172– 180
2. Bradlow, E.T., Gangwar, M., Kopalle, P., Voleti, S.: The role of big data and predictive analytics in retailing. Journal of Retailing 93(1) (2017) 79–95
3. Le, D.T., Fang, Y., Lauw, H.W.: Modeling sequential preferences with dynamic user and context factors. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases, Springer (2016) 145–161
4. Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. Journal of Business Research, 69(2), 897-904.
5. Shmueli, G., et al.: To explain or to predict? Statistical science 25(3) (2010) 289–310
6. Martens, D., Provost, F., Clark, J., de Fortuny, E.J.: Mining massive fine-grained behavior data to improve predictive analytics. MIS quarterly 40(4) (2016)
7. Webster, J., Watson, R.T.: Analyzing the past to prepare for the future: Writing a literature review. MIS quarterly (2002) xiii–xxiii
8. Kitchenham, B., Brereton, O.P., Budgen, D., Turner, M., Bailey, J., Linkman, S.: Systematic literature reviews in software engineering–a systematic literature review. Information and software technology 51 (1) (2009) 7–15
9. Akter, S., Wamba, S.F.: Big data analytics in e-commerce: a systematic review and agenda for future research. Electronic Markets 26(2) (2016) 173–194
10. Hou, C., Chen, C., Wang, J.: Tree-based feature transformation for purchase behavior prediction. IEICE TRANSACTIONS on Information and Systems 101(5) (2018) 1441–1444
11. Zeng, M., Cao, H., Chen, M., Li, Y.: User behaviour modeling, recommendations, and purchase prediction during shopping festivals. Electronic Markets (2018) 1–12
12. Jia, R., Li, R., Yu, M., Wang, S.: E-commerce purchase prediction approach by user behavior data. In: 2017 International Conference on Computer, Information and Telecommunication Systems (CITS), IEEE (2017) 1–5
13. Chen, C., Hou, C., Xiao, J., Wen, Y., Yuan, X.: Enhancing purchase behavior prediction with temporally popular items. IEICE TRANSACTIONS on Information and Systems 100(9) (2017) 2237–2240
14. Parkhimenka, U., Tatur, M., Zhvakina, A.: Heuristic approach to online purchase prediction based on internet store visitors classification using data mining methods. In: 2017 International Conference on Information and Digital Technologies (IDT), IEEE (2017) 304–307
15. Suchacka, G., Chodak, G.: Using association rules to assess purchase probability in online stores. Information Systems and e-Business Management 15(3) (2017) 751–780
16. Chen, C., Xiao, J., Hou, C., Yuan, X.: Improving purchase behavior prediction with most popular items. IEICE TRANSACTIONS on Information and Systems 100(2) (2017) 367–370

17. Niu, X., Li, C., Yu, X.: Predictive analytics of e-commerce search behavior for conversion. In: Twenty-third Americas Conference on Information Systems. (2017)
18. Suchacka, G., Stemplewski, S.: Application of neural network to predict purchases in online store. In: Information Systems Architecture and Technology: Proceedings of 37th International Conference on Information Systems Architecture and Technology–ISAT 2016–Part IV, Springer (2017) 221–231
19. Park, C.H., Park, Y.H.: Investigating purchase conversion by uncovering online visit patterns. Marketing Science 35(6) (2016) 894–914
20. Lee, M., Ha, T., Han, J., Rha, J.Y., Kwon, T.T.: Online footsteps to purchase: Exploring consumer behaviors on online shopping sites. In: Proceedings of the ACM Web Science Conference, ACM (2015) 15
21. Boroujerdi, E.G., Mehri, S., Garmaroudi, S.S., Pezeshki, M., Mehrabadi, F.R., Malakouti, S., Khadivi, S.: A study on prediction of user's tendency toward purchases in websites based on behavior models. In: 2014 6th Conference on Information and Knowledge Technology (IKT), IEEE (2014) 61–66
22. Baumann, A., Haupt, J., Gebert, F., Lessmann, S.: Changing perspectives: Using graph metrics to predict purchase probabilities. Expert Systems with Applications 94 (2018) 137–148
23. Bansal, S., Gupta, C., Sinha, A.: Clickstream & behavioral analysis with context awareness for e-commercial applications. In: 2017 Tenth International Conference on Contemporary Computing (IC3), IEEE (2017) 1–6
24. Huang, W., Li, L.: Predicting purchase proneness of anonymous user in mobile commerce. In: WHICEB. (2017) 29
25. Chen, C., HOU, C.y., XIAO, J.k., YUAN, X.j.: Predicting purchase behavior of ecommerce customer, one-stage or two-stage? DEStech Transactions on Computer Science and Engineering (aics) (2016)
26. Kai Sun, B.Z., Zuo, M.Y.: Who will buy in the next visit? In: PACIS 2017 Proceedings. Volume 99. (2017)
27. Bogina, V., Kuflik, T., Mokryn, O.: Learning item temporal dynamics for predicting buying sessions. In: Proceedings of the 21st International Conference on Intelligent User Interfaces, ACM (2016) 251–255
28. Suchacka, G., Skolimowska-Kulig, M., Potempa, A.: A k-nearest neighbors method for classifying user sessions in e-commerce scenario. Journal of Telecommunications and Information Technology (2015)
29. Suchacka, G., Skolimowska-Kulig, M., Potempa, A.: Classification of e-customer sessions based on support vector machine. ECMS 15 (2015) 594–600
30. Pai, D., Sharang, A., Yadagiri, M.M., Agrawal, S.: Modelling visit similarity using clickstream data: A supervised approach. In: International Conference on Web Information Systems Engineering, Springer (2014) 135–145
31. Sakar, C.O., Polat, S.O., Katircioglu, M., Kastro, Y.: Real-time prediction of online shoppers purchasing intention using multilayer perceptron and lstm recurrent neural networks. (2018) 1–16 Exported from https://app.dimensions.ai on 2019/04/03.
32. Tang, L., Wang, A., Xu, Z., Li, J.: Online-purchasing behavior forecasting with a firefly algorithm-based svm model considering shopping cart use. Eurasia Journal of Mathematics, Science and Technology Education 13(12) (2017) 7967–7983
33. Sheil, H., Rana, O., Reilly, R.: Predicting purchasing intent: Automatic feature learning using recurrent neural networks. CoRR abs/1807.08207 (2018)
34. Zhao, Y., Yao, L., Zhang, Y.: Purchase prediction using tmall-specific features. Concurrency and Computation: Practice and Experience 28(14) (2016) 3879–3894
35. Li, Q., Gu, M., Zhou, K., Sun, X.: Multi-classes feature engineering with sliding window for purchase prediction in mobile commerce. In: 2015 IEEE International Conference on Data Mining Workshop (ICDMW), IEEE (2015) 1048–1054

36. He, M., Ren, C., Zhang, H.: Intent-based recommendation for b2c e-commerce platforms. IBM Journal of Research and Development 58(5/6) (2014) 5–1
37. Jannach, D., Ludewig, M., Lerche, L.: Session-based item recommendation in ecommerce: on short-term intents, reminders, trends and discounts. User Modeling and User-Adapted Interaction 27(3-5) (2017) 351–392
38. Kazmi, A.H., Shroff, G., Agarwal, P.: Generic framework to predict repeat behavior of customers using their transaction history. In: 2016 IEEE/WIC/ACM International Conference on Web Intelligence (WI), IEEE (2016) 449–452
39. Chen, W., Li, Z., Zhang, M.: Linear and non-linear models for purchase prediction. In: Proceedings of the 2015 International ACM Recommender Systems Challenge, ACM (2015) 9
40. Pálovics, R., Szalai, P., Kocsis, L., Szabó, A., Frigó, E., Pap, J., Nyikes, Z.K., Benczúr, A.A.: Solving recsys challenge 2015 by linear models, gradient boosted trees and metric optimization. In: RecSys Challenge. (2015) 4–1
41. He, T., Yin, H., Chen, Z., Zhou, X., Luo, B.: Predicting users purchasing behaviors using their browsing history. In: Australasian Database Conference, Springer (2015) 129–141
42. Yi, Z., Wang, D., Hu, K., Li, Q.: Purchase behavior prediction in m-commerce with an optimized sampling methods. In: 2015 IEEE International Conference on Data Mining Workshop (ICDMW), IEEE (2015) 1085–1092
43. Huang, B.C.L., Xiang, Y., Huang, Z.H.: Use logistic regression to predict userbehaviors. In: Applied Mechanics and Materials. Volume 651., Trans Tech Publ (2014) 1695–1698
44. Jia, R., Li, R.: Modeling user purchase preference based on implicit feedback. In: CSCWD, IEEE (2018) 832–836
45. Yehezki, S., Dhini, A.: Classifying purchase decision based on user clickstream in ecommerce using web usage mining. In: Proceedings of the International Conference on Business and Information Management. ICBIM 2017, New York, NY, USA, ACM (2017) 57–61
46. Dong, Y., Jiang, W.: Brand purchase prediction based on time-evolving user behaviors in e-commerce. Concurrency and Computation: Practice and Experience 31(1) e4882 e4882 cpe.4882.
47. Park, C., Kim, D.H., Yang, M., Lee, J., Yu, H.: Your click knows it: Predicting user purchase through improved user-item pairwise relationship. CoRR abs/1706.06716 (2017)
48. Iwanaga, J., Nishimura, N., Sukegawa, N., Takano, Y.: Estimating product-choice probabilities from recency and frequency of page views. Knowl.-Based Syst. 99 (2016) 157–167
49. Nishimura, N., Sukegawa, N., Takano, Y., Iwanaga, J.: A latent-class model for estimating product-choice probabilities from clickstream data. CoRR abs/1612.06589 (2016)
50. Singhal, R., Shroff, G., Kumar, M., Choudhury, S.R., Kadarkar, S., Virk, R., Verma, S., Tewari, V.: Fast online 'next best offers' using deep learning. In: Proceedings of the ACM India Joint International Conference on Data Science and Management of Data. CoDS-COMAD '19, New York, NY, USA, ACM (2019) 217–223
51. Zheng, B., Liu, B.: A scalable purchase intention prediction system using extreme gradient boosting machines with browsing content entropy. In: 2018 IEEE International Conference on Consumer Electronics (ICCE), IEEE (2018) 1–4
52. Minjing, P., Xinglin, L., Ximing, L., Mingliang, Z., Xianyong, Z., Xiangming, D., Mingfen, W.: Recognizing intentions of e-commerce consumers based on ant colony optimization simulation. Journal of Intelligent & Fuzzy Systems 33(5) (2017) 2687– 2697
53. Schellong, D., Kemper, J., Brettel, M.: Generating consumer insights from big data clickstream information and the link with transaction-related shopping behavior. In: Proceedings of the 25th European Conference on Information Systems (ECIS). (2017)
54. Schellong, D., Kemper, J., Brettel, M.: Clickstream data as a source to uncover con-sumer shopping types in a large-scale online setting. In: ECIS. (2016) Research Paper 1

55. Romov, P., Sokolov, E.: Recsys challenge 2015: ensemble learning with categorical features. In: Proceedings of the 2015 International ACM Recommender Systems Challenge, ACM (2015) 1
56. Esmailian, P., Jalili, M.: Purchase prediction and item suggestion based on http sessions in absence of user information. In: Proceedings of the 2015 International ACM Recommender Systems Challenge, ACM (2015) 6
57. Wu, Z., Tan, B.H., Duan, R., Liu, Y., Mong Goh, R.S.: Neural modeling of buying behaviour for e-commerce from clicking patterns. In: Proceedings of the 2015 International ACM Recommender Systems Challenge, ACM (2015) 12
58. Vieira, A.: Predicting online user behaviour using deep learning algorithms. arXiv preprint arXiv:1511.06247 (2015)
59. Yeo, J., Kim, S., Koh, E., Hwang, S.w., Lipka, N.: Predicting online purchase conversion for retargeting. In: Proceedings of the Tenth ACM international conference on web search and data mining, ACM (2017) 591–600
60. Li, D., Zhao, G., Wang, Z., Ma, W., Liu, Y.: A method of purchase prediction based on user behavior log. In: 2015 IEEE International Conference on Data Mining Workshop (ICDMW), IEEE (2015) 1031–1039
61. Dong, H., Xie, L., Zhang, Z.: Research on statistics-based model for e-commerce user purchase prediction. In: 2015 10th International Conference on Computer Science & Education (ICCSE), IEEE (2015) 553–557
62. Zhang, Y., Pang, L., Shi, L., Wang, B.: Large scale purchase prediction with historical user actions on b2c online retail platform. arXiv preprint arXiv:1408.6515 (2014)
63. Liu, G., Nguyen, T.T., Zhao, G., Zha, W., Yang, J., Cao, J., Wu, M., Zhao, P., Chen, W.: Repeat buyer prediction for e-commerce. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM (2016) 155–164
64. Kooti, F., Lerman, K., Aiello, L.M., Grbovic, M., Djuric, N., Radosavljevic, V.: Portrait of an online shopper: Understanding and predicting consumer behavior. In: Proceedings of the ninth ACM international conference on web search and data mining, ACM (2016) 205–214
65. Panagiotelis, A., Smith, M.S., Danaher, P.J.: From amazon to apple: Modeling online retail sales, purchase incidence, and visit behavior. Journal of Business & Economic Statistics 32(1) (2014) 14–29
66. Tang, L., Wang, A., Xu, Z., Li, J.: Online-purchasing behavior forecasting with a firefly algorithm-based svm model considering shopping cart use. Eurasia Journal of Mathematics, Science and Technology Education 13(12) (2017) 7967–7983
67. Schellong, D., Kemper, J., Brettel, M.: Clickstream data as a source to uncover con-sumer shopping types in a large-scale online setting. In: ECIS. (2016) ResearchPaper1
68. Martínez, A., Schmuck, C., Pereverzyev Jr, S., Pirker, C., Haltmeier, M.: A machine learning framework for customer purchase prediction in the non-contractual setting. European Journal of Operational Research (2018)
69. Peker, S., Kocyigit, A., Eren, P.E.: A hybrid approach for predicting customers individual purchase behavior. Kybernetes 46(10) (2017) 1614–1631
70. Wang, L., Li, Y., & Lazebnik, S. (2016). Learning deep structure-preserving image-text embeddings. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 5005-5013).
71. Huang, Jin, et al. "Taxonomy-aware multi-hop reasoning networks for sequential recommendation." Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining. ACM, 2019.