JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

ECOMMERCE WEBSITE PRODUCT RECOMMENDATIONS USING MACHINE LEARNING

Turangi Venkata Udayasri[1], Dr Y V Ramkumar, K ChandraSekhar[3]
[1]**PG Student,** Dept of CSE, Pragati Engineering College (Autonomous), Surempalem,AP
[2] **Associate professor,** Dept of CSE, Pragati Engineering College (Autonomous), Surempalem, AP
[3]**AssistantProfessor,** Dept of CSE, Pragati Engineering College (Autonomous), Surempalem,AP
Email: Turangi.udayasri@gmail.com[1], Chandrasekhar.koppireddy@gmail.com[3]

Abstract
Nowadays, the internet has been widely recognized as a huge data repository consisting of a variety of data kinds as well as vast quantity of unknown valuable information which may be found by a broad range of data mining or machine learning methods. Although the rise of e-commerce marketplaces leads in the development of search engines, consumers are still confronting a difficulty with accurate results. Instead, to accomplish this issue recommendation engines are primarily beneficial. Most e-commerce sites are creating recommendation systems evaluate a significant quantity of transaction data without having any understanding of what the items in the transactions represent or what they say about the people who bought or browsed things. Apparel fashion recommendation engine that employs deep convolutional neural networks utilizing Amazon API to propose goods and offer clients with information to assist them discover the products. Utilizing deep neural networks enable us to interpret such photos into a high dimensional feature representation that enables us to propose a pair from user preference tensor.
Keywords: Recommendation systems, e-commerce, CNN, feature extraction, machine learning

1. INTRODUCTION

In the mid-1990s, the concept of a recommendation system was originally floated. Recommendation systems provide intriguing suggestions for items based on the behaviour of consumers.. The increasing expansion of e-commerce necessitates the use of recommendation algorithms, which have attracted the attention of corporations like Amazon.com. Many organisations have found that these systems propose items that are appropriate for clients, have a significant impact on converting visitors into purchasers, and improve cross-sell opportunities. Recommendation algorithms have helped broaden the company's reach. Cosine/Jaccard-based product recommendations for apparel goods are prevalent in today's market, which is based on the consumers who saw and purchased such things, rather than the aesthetic characteristics or likeness of the items. Before making a purchase of clothing on the internet, most of us look at a number of different product details and reviews. Many details may be gleaned from product photographs, such as the colour, pattern, texture, and fabric of a product, among others. Images may be used to determine a product's transparency and overall condition.

An item's appearance is critical in the work of making wardrobe recommendations. ARS (Prevailing Apparel Recommendation Systems) utilises picture data with a variety of image attributes. Convolutional neural networks are used to extract these traits. Deep convolution neural networks are used to represent and predict features in the recommendation systems.

Types of recommendation systems:

A recommendation system may be classed into three types: content-based, collaborative, and hybrid systems.

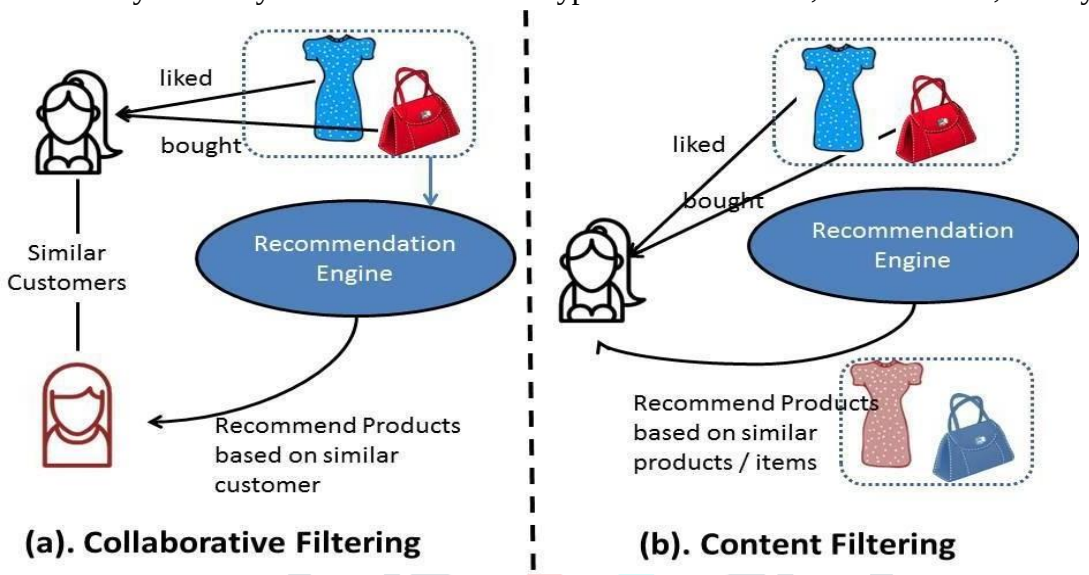

Fig 1: Types of recommendation systems

2. LITERATURE REVIEW

Lukas et al. primarily focused on the challenge of categorization, which is the difficulty of characterising what kind of outfit is worn in a picture. The study focuses on visual characteristics, which have grown in importance in recent years, and uses a multi-class learner based on Random Forest for type classification and Super Vector Machines for attribute classification. New deep model FashionNet was introduced by Ziwei et al., which learns clothing features by predicting landmarks and garment qualities. Their large-scale tests demonstrate the use of deep fashion and the efficacy of fashionNet. They analysed many building components of the proposed fashionNet and also reviewed the effectiveness of several approaches on category classification and attribute prediction. When human joints and poselets are used in lieu of fashionNet's garment landmarks, a 69%–91% decrease in performance is found. 76.4 percent of the time, this model is merely accurate. Using human landmarks rather than garment markers might have improved the model's accuracy. Structure of Interconnections Fashion-Net features a network topology similar to VGG-16, which has been shown to be powerful in a variety of visual tasks, including object detection and segmentation. VGG-16's convolutional layer structures are identical to those of FashionNet's lower convolutional layers, except for the final convolutional layer, which is specifically tailored to clothing. The last convolutional layer in VGG-16 is replaced with three branching of layers, shown in red, green, and blue. Branches in red and green represent global and local aspects of the clothing item, respectively. The branch in blue anticipates the landmarks' positions as well as their visibility (i.e. whether they have been occluded or not). In addition, the red and green branches' outputs are concatenated as in fc7 fusion to jointly predict clothing categories, characteristics, and model pairs of clothing.

3. PROPOSED SYSTEM

Deep conventional neural networks employing Amazon API are used to recommend items and offer clients with information on how to discover the things they are looking for. With the use of deep neural networks, it is possible to transform these photos into a high-dimensional feature representation, which may then be used to make recommendations from an individual's preferences. Our technique also enables us to explain the suggestions in terms of qualitative attributes, which we feel enriches the user experience and helps strengthen the user's trust in the recommendations.

DATASET

A data set is a collection of data that has been gathered together. Every column of the table or matrix represents one variable, and every row corresponds to one member of the dataset in issue. Each member of the data set has a value in the data set for each of the variables, such as their height and weight. It is referred to as a datum. The number of rows corresponds to the number of members in the dataset.

IMAGE COLLECTION

Many methods exist for gathering images for this dataset. There are a few examples of them: It is fairly uncommon for clothing datasets to be compiled using data gathered from shopping websites. In addition to this, pictures may also be gathered through image search engines, where the results originate from blogs, forums, and other user created material, which augment and expand the image collection obtained from shopping websites.

Fig 2: Dataset

It is also possible to gather relevant keywords for clothing photos from Google images. You'll need to go through the catalogues of a few online merchant businesses and gather the names of clothing products like an animal print dress to do this research. It's a total of 18 characteristics that we employ in our garment suggestion algorithm here. Here, we merely used the Amazon API fashion dataset to provide product recommendations and give client assistance in locating the items they want. Over one hundred eighty three thousand different photos of apparel make up the data set's vast majority. It has a wealth of information on various articles of apparel. There are 18 characteristics in each picture in this collection. The following are some of its unique characteristics:

S.NO	FEATURE	DESCRIPTION
1	Asin	Amazon standard identification number- ID of the product, e
2	Brand	Brand to which the product belongs to
3	Colour	Colour information of apparel, it can contain many colours as ared and black stripes
4	Product_type_name	Type of the apparel ex: SHIRT/TSHIRT
5	Medium_image_url	url of the image
6	Title	Title of the product

Table: Features of Dataset

4. ALGORITHM

Let m be the number of training data samples. Let p be an unknown point.

Store the training samples in an array of data points arr[]. This means each element of this array represents a tuple (x, y).

for i=0 to m: Calculate Euclidean distance d(arr[i], p).

Make set S of K smallest distances obtained. Each of these distances correspond to an already classified data point.

Return the majority label among S.

5. PROPOSED SYSTEM ARCHITECTURE

Machine learning is used by a wide range of industries to manage and enhance their processes. Even if the scope and complexity of ML projects varies, the basic framework remains the same. If a tiny data science team wanted to make one prediction, they would have to gather data, preprocess and convert it, then train, verify and (maybe) deploy a model. When it comes to providing individualised suggestions to Netflix's 100 million subscribers, data scientists would adopt a similar approach.

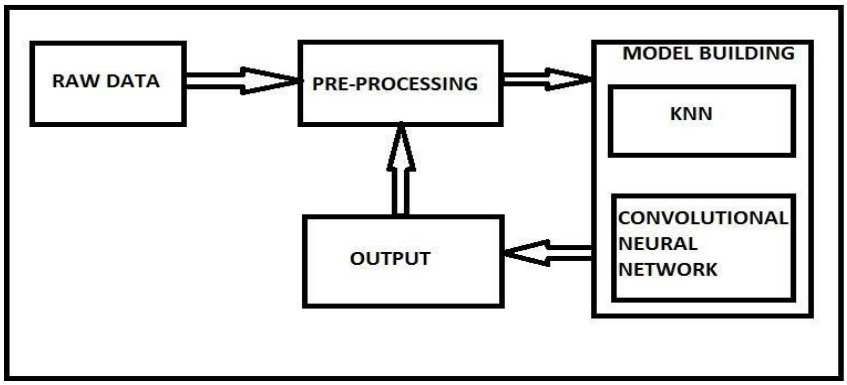

Fig : Architecture Of Apparel Recommendation Systems

Strategy: matching the problem with the solution

Strategic objectives are often outlined by corporate representatives during the first stages of a machine learning project. A solution is assumed, the scope of work is defined, and the development is planned. For example, sales at your online shop have been fewer than planned. As a result of this, you may be falling behind your competition.

Dataset preparation and pre-processing:

Any machine learning endeavour begins with data. Data collection, selection, preparation, and transformation are all included in the second phase of project execution. It's possible to break down each of these stages into many steps. The neural network model described above was used for the recommendation job. We feed the provided picture into our outfit suggestion algorithm. A random number generator is used to create outfits, which are then entered into our model to provide evaluations ranging from 0 to 1. Using these evaluations, we can come up with the top three best outfits.

6. EXPERIMENTAL RESULTS

Accordingly, we developed a neural network model that we used to make recommendations. If you'd like to use our outfit suggestion system, just upload a picture of yourself. A random number generator is used to create outfits, which are then entered into our model to provide judgements ranging from 0 to 1 for each of the outfits. There are three excellent outfits in the top three after sifting through these opinions.

Input

7. CONCLUSION

In order to target certain consumers, algorithms may be employed to create personalised shopping experiences. It is possible to use a good recommendation algorithm for large retailers like Amazon.com because it is scalable across very large customer bases and product catalogues, only requires sub-second processing time to generate online recommendations, and can react immediately to changes in a user's data. It also makes compelling recommendations for all users, regardless of the number of purchases and ratings. In contrast to previous methods, Item-to-Item Collaborative Filtering is able to address this issue.

REFERENCES

[1] J.B. Schafer, J.A. Konstan, and J. Reidl, ―E-Commerce Recommendation Applications,‖ Data Mining and Knowledge Discovery, Kluwer Academic, 2001, pp. 115-153.

[2] P. Resnick et al., ―GroupLens: An Open Architecture for Collaborative Filtering of Netnews,‖ Proc. ACM 1994 Conf. Computer Supported Cooperative Work, ACM Press , 1994, pp. 175-186.

[3] J. Breese, D. Heckerman, and C. Kadie, ―Empirical Analysis of Predictive Algorithms for Collaborative Filtering,‖ Proc. 14th Conf. Uncertainty in Artificial Intelligence, Morgan Kaufmann, 1998, pp. 43-52.

[4] B.M. Sa rwarm et al., ―Analysis of Recommendation Algorithms for E-Commerce,‖ ACM Conf. Electronic Commerce, ACM Press, 2000, pp.158-167.

[5] K. Goldberg et al., ―Eigentaste: A Constant Time Collaborative Filtering Algorithm,‖ Information Retrieval J., vol. 4, no. 2, July 2001, pp. 133-151.

[6] P.S. Bradley, U.M. Fayyad, and C. Reina, ―Scaling Clustering Algorithms to Large Databases,‖ Knowledge Discovery and Data Mining, Kluwer Academic, 1998, pp. 9-15.

[7] L. Ungar and D. Foster, ―Clustering Methods for Collaborative Filtering,‖ Proc. Workshop on Recommendation Systems, AAAI Press, 1998.

[8] M. Balabanovic and Y. Shoham, ―Content-Based Collaborative Recommendation,‖ Comm. ACM, Mar. 1997, pp. 66-72.

[9] G.D. Linden, J.A. Jacobi, and E.A. Benson, Collaborative Recommendations Using Item-to-Item Similarity Mappings, US Patent 6,266,649 (to Amazon.com), Patent and Trademark Office, Washington, D.C., 2001.

[10] B.M. Sarwar et al., ―Item-Based Collaborative Filtering Recommendation Algorithms,‖ 10th Int'l World Wide Web Conference, ACM Press, 2001, pp. 285-295.

[11] Bossard L., Dantone M., Leistner C., Wengert C., Quack T., Van Gool L. (2013) Apparel Classification with Style. In: Lee K.M., Matsushita Y., Rehg J.M., Hu Z. (eds) Computer Vision – ACCV 2012. ACCV 2012. Lecture Notes in Computer Science, vol 7727. Springer, Berlin, Heidelberg

[12] Hu, Xiaosong, Wen Zhu and Qing Li. ―HCRS: A hybrid clothes recommender system based on user ratings and product features.‖ *CoRR* abs/1411.6754 (2013): n. pag.

[13] Z. Liu, P. Luo, S. Qiu, X. Wang and X. Tang, "DeepFashion: Powering Robust Clothes Recognition and Retrieval with Rich Annotations," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, 2016, pp. 1096-1104.

[14] Yu, Wenhui, Huidi Zhang, Xiangnan He, Xu Chen, Li Xiong and Zheng Qin ―Aesthetic-based Clothing Recommendation.‖ *WWW* (2018).

[15] Hill, W., Stead, L., Rosenstein, M., & Furnas, G. Recommending and evaluating choices in a virtual community of use. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 194-201, 1995.

[16] Schafer, J. B., Konstan, J. A., & Riedl, J. E-commerce recommendation applications. In *Applications of Data Mining to Electronic Commerce*, pages 115-153, 2001.

[17] Laaksonen, J., Koskela, M., Laakso, S., & Oja, E. PicSOM–content-based image retrieval with self-organizing maps. *Pattern Recognition Letters*, 21(13): 1199-1207, 2000

[18] Breese, J. S., Heckerman, D., & Kadie, C. Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence*, pages 43-52, 1998.

[19] Kim, B. M., Li, Q., Park, C. S., Kim, S. G., & Kim, J. Y. A new approach for combining content-based and collaborative filters.*Journal of Intelligent Information Systems*, 27(1):79-91, 2006.