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Event Creator Advisor Based on Deep Learning

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Class
Collaborative Systems

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Abstract

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Content: In a social involvement field, the main focus is oriented on people and their degree of participation in a community or a society. In this paper, we try to propose a supporting system that would increase the amount of individuals being interested in social activities such as going to various events, meetings, participating in communities or groups etc. As a team of international students studying in Germany, we could use our experience in an environment with different mental paradigms to help us understand the problems better, thus possibly find a feasible solution. Based on our efforts to raise an awareness of this matter of subject in a few communities, we were eventually advised on proposing a more complex idea and to come up with something that could benefit people on a large scale. Finally, we thought about devising an Event Creator Advisor (ECA) utilizing deep learning technology with the combination of recommender systems. In the next pages, we offer a holistic view on the matter of subject in regards to the current technological solution, as well as to the status quo, eventually proposing an innovative system based on artificial neural networks, that would boost the degree of participation of people in regards to the social involvement field.

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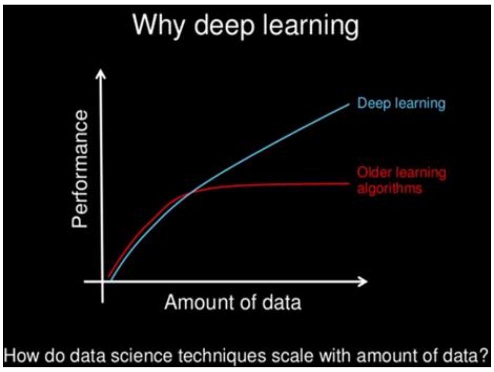
Introduction

In a social involvement field, the main focus is oriented on people and their degree of participation in a community or a society. In this paper, we try to propose a supporting system that would increase the amount of individuals being interested in social activities such as going to various events, meetings, participating in communities or groups etc. As a team of international students studying in Germany, we could use our experience in an environment with different mental paradigms to help us understand the problems better, thus possibly find a feasible solution. Based on our efforts to raise an awareness of this matter of subject in a few communities, we were eventually advised on proposing a more complex idea and to come up with something that could benefit people on a large scale. Finally, we thought about devising an Event Creator Advisor (ECA) utilizing deep learning technology with the combination of recommender systems. In the next pages, we offer a holistic view on the matter of subject in regards to the current technological solution, as well as to the status quo, eventually proposing an innovative system based on artificial neural networks, that would boost the degree of participation of people in regards to the social involvement field.

Deep Learning

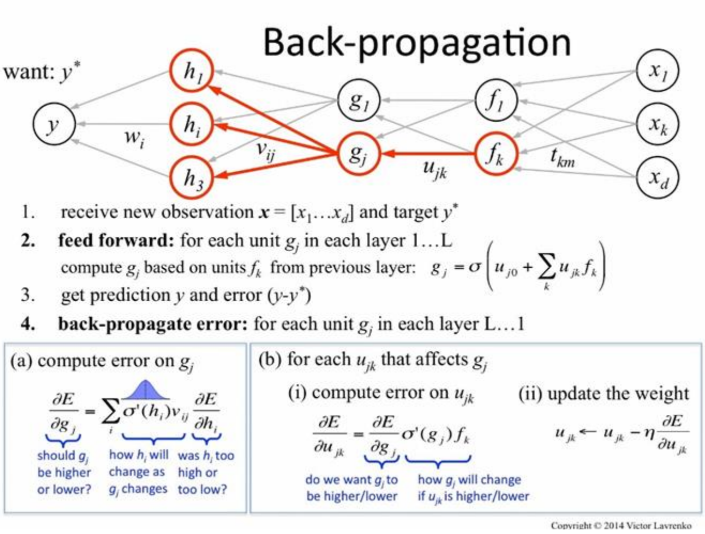
Deep learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. It works with algorithms in order to classify input of data in order to get a pattern result for the input given. Neural networks are computing systems inspired by the biological neural networks that constitute animal brains. Such systems learn to do tasks by considering examples, generally without task-specific programming. This means that it is working “like a brain”, meaning that the system will learn from errors until it reaches “perfection” in its classification and will be getting better results, this terminology is call to “train” the network for better results. It is certainly not an easy task, due to the fact, that depending on the complexity of the system it can create a really big network (the node tree), with so many neurons and edges that it will result in a challenging task to train it. This is because to train a network, the algorithm uses something call “gradient”, which means to the rate in which cost changes with respect to weight or bias (D.Hof). But there is a conflict with this concept, when the gradient in the network is large the network tends to be trained fast. The problem comes when the gradient is small - the network would tend to be trained relatively slow. A network normally tends to have a small gradient at the beginning of it (making it to be trained slow at the first layer), causing a problem because the beginning of a network has a crucial job on detecting the simplest patterns and the building blocks, so if this layers malfunction the result won’t be the expected.



Why deep learning

Backpropagation

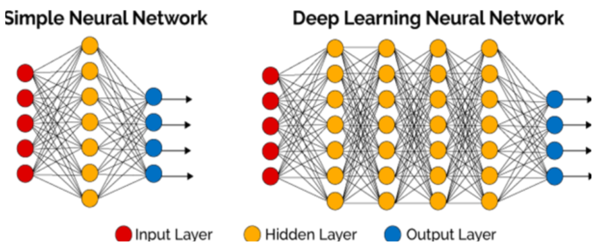
The process to train correctly is the process of backpropagation, which calculates the gradient of the network from right to left; every time it calculates a gradient it uses all the previous gradients up to that point. This process gets to be complex because the gradient at any layer is the multiplication of gradients at prior layers. It is commonly used as a part of algorithms that optimize the performance of the network by adjusting the weights (Wikipedia, 2017).



Backpropagation algorithm

Neural Network

The structure of a neural network is basically a complex node tree divided into layers, the first layer is the input layer, the second layer is the hidden layer and the third layer is the output layer. The nodes from the network are call neurons which serve during the process of the calculations and classifications in order to get the output that will solve a specific problem. The input layer of the network, as its name says, works as the layer that receives all the inputs for the system and distributes them into the next layer, hidden layers, depending of the classifiers that the neurons have due to the input. The hidden layers from the network work as the “engine” from the system, where all the neurons process the input data depending of the classifiers of all the neurons in the layers and distribute the results with the corresponding edges paths. And at the last we have the output layer where it receives the results from the hidden layers and with these results you can find the solution to the problem you are looking for (UFLDL Tutorial).



Nerual network structure

Deep Learning in the Real World

There are different big and prestigious companies that are using deep learning algorithms in order to fulfill functions or features from their products. Google, Facebook and other cellphone companies have been using this concept in order to enhance their features and functions in their products. For example, they have been enhancing the text processing, image recognition, object recognition and speech recognition from their products. For text processing and speech recognition, recurrent net is often used, which is a type of neural network where connections between the items create a directed cycle (Kapathy, 2015). This allows it to exhibit dynamic temporal behavior. They can use their internal memory to process arbitrary sequences of inputs. This makes them applicable to tasks such as unsegmented connected handwriting recognition or speech recognition. In image recognition and object recognition, the often used network is convolutional net (CNN), which is a class of deep, feed-forward artificial neural network that has successfully been applied to analyzing visual imagery. CNNs use a variation of multilayer neurons designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks, based on their shared-weights architecture and translation invariance characteristics. These two types of networks are crucial for the new concept of deep learning in future devices, applications, etc.

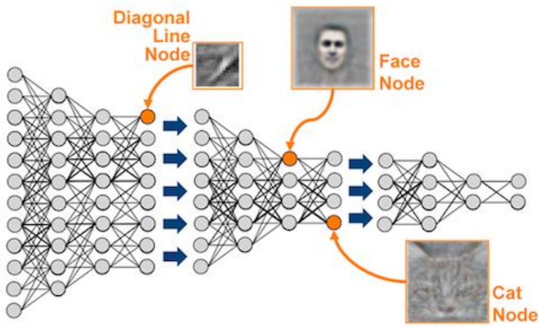
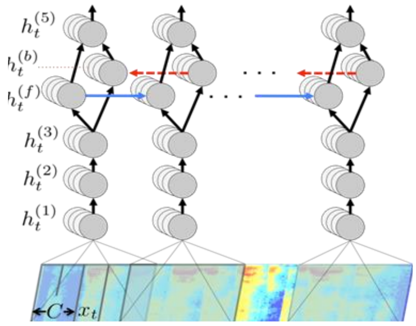


Image recognition



Speech recognition

Unlabeled Data

Unlabeled data consists of samples of natural or human-created artifacts that are obtain normally in the world. Some examples of unlabeled data might include photos, audio recordings, videos, news articles, etc. There is no extra information for each piece of unlabeled data, they contain just the data without any type of classification.

Labeled Data

Labeled data usually uses a set of unlabeled data and enhances each element of that unlabeled data with some sort of meaningful "tag," or "class" that inform about it. For example, labels for the above types of unlabeled data might be whether this photo contains a horse or a cow, which words were heard in this audio recording, what type of action is being performed in this video, what the topic of this news article is, etc. Labels for data are often obtained by asking humans to make judgments about a given piece of unlabeled data and are significantly more expensive to obtain than the raw unlabeled data. After obtaining a labeled dataset, machine learning models can be applied to the data so that new unlabeled data can be presented to the model and a likely label can be guessed or predicted for that piece of unlabeled data. When working with labeled data, usually they are working with text processing, image recognition, object recognition or speech recognition. For this, it is common to use a classifier because working with labeled data the correct thing to do is to do a classification of it to get a common result.

Recommenders and understanding users

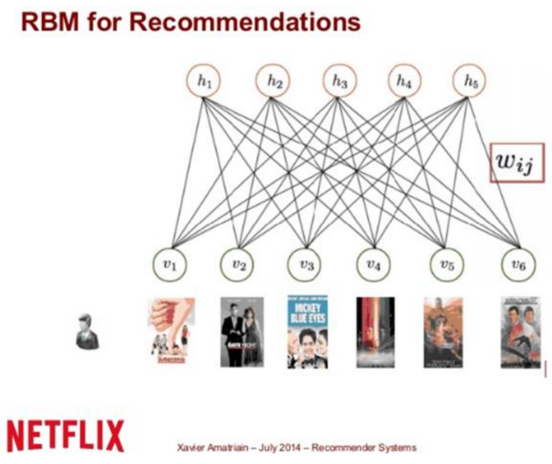
Based on deep learning, we suggest creating an event advisor that would autonomously propose events that people might be interested in. This tool could be used for communities and groups of any kind of size and background. Firstly, we will have a look at the currently existing ideas and solutions related to influencing people's behavior at engagement in some kind of activity. Later, we will discuss the event advisor, mechanics behind it as well as its business model, future applications and possible difficulties such as data acquisition.

Understanding and Influencing Users

The basic idea of understanding people – their needs, interests, behavior etc. in the context of deep learning is to use collections of users' data and run them through a deep learning algorithm such as CNN for data classification (Gamboa, 2017). In this instance, we are looking at sets of labeled data. If we focus more on users' behavior, prediction in time-series (data over time) can be done with RNNs (Gamboa, 2017). The input of these nets is unlabeled data. In our Event Creator Advisor (ECA) idea proposition, we will discuss utilization of both CNNs and RNNs or alternatively use autoencoders capable of solving our problem.

Recommenders

If you want to apply the results of ANNs for influencing people's behavior and actions, it's highly probable you will make a use of recommenders. Recommenders are systems that seek to predict rating or preference a user would give to a particular item. They are vastly used in e-commerce for recommending items the user is likely to buy/click on/engage in. Even though recommenders are relatively still in a research stage (Vorhies, 2017), they have already been a great success. Many informed sources estimate that for the major ecommerce platforms like Amazon and Netflix, recommenders may be responsible for as much as 10% to 25% of incremental revenue (Vorhies, 2017).



Deep learning and recommenders

Basic Approaches

There are 3 major kinds of approaches used in recommender systems: collaborative filtering, content-based filtering and hybrid approaches (Jones, 2013).

Collaborative Filtering

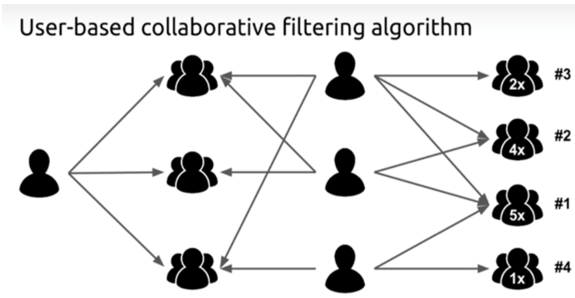
Collaborative filtering (CF), also referred to as social filtering, filters information by using the recommendations of other people. It is based on the idea that people who agreed in their evaluation of certain items in the past are likely to agree again in the future (Recommender Systems, 2012). For example, Facebook or LinkedIn recommend new friends, groups or pages based on examination of network of connections between a user and their friends.

Content-Based Filtering

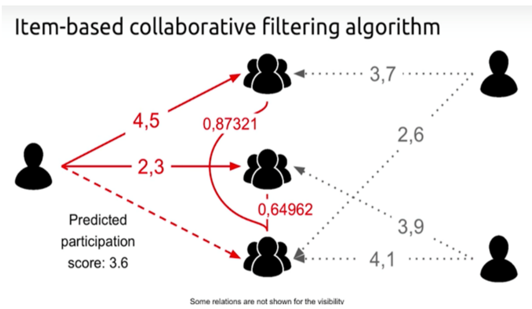
Content-based filtering (CBF), also referred to as cognitive filtering, recommends items based on a comparison between the content of the items and a user profile (Recommender Systems, 2012). For instance, movie ratings by users in movie databases such as Rotten Tomatoes or Internet Movie Database would be an example that utilizes this approach.

Hybrid Approaches

Hybrid recommender systems combine features of CF and CBF. This approach can be in some cases more effective. Netflix is a good example. The website makes recommendations by comparing the watching and searching habits of similar users (i.e., CF) as well as by offering movies that share characteristics with films that a user has rated highly (CBF) (Recommender Systems, 2012).



Collaborative Filtering



Content-based filtering

Deep Learning in Recommenders

It's important to mention, that recommenders are systems based on machine learning, however, not necessarily on deep learning algorithms. For each of the presented approaches exist shallow structures working with k-means, Pearson correlation, Bayesian Classifiers, cluster analysis or decision trees among others. A major task in the previous years has been to improve on these algorithms and replace them with superior deep learning algorithms such as CNNs and RNNs incorporating LSTM (Long short-term memory) (Vorhies, 2017). Neural nets have already been able to significantly outperform the former systems.

One Step Further

With the basic knowledge acquired about recommenders and their importance, usage and functionality explained, we want to propose an idea of a kind of advisor that will be able to help in the field of social involvement. The system will be able to autonomously suggest and possibly devise events. Its foundations and ideas are in recommenders and the similarities are strong enough that we will classify it as a kind of recommender system. The difference is in what way how it operates.

Event Creator Advisor

Building an event creator advisor will be another step in increasing effectiveness of the concurrent platforms or systems that aim to provide people with relevant events that they can attend.

Functionality of Current Systems

Existing event recommenders (just as any items recommender) proposal direction is from existing items being presented to a user. Those items (in our case events) can be either created by other users or by an administrator of a given website. For instance Facebook recommends to a user events they might like, based on the user data provided (both explicit and implicit data). The nets can be implemented in various ways with different artificial nets, for example using the hybrid recommender approach based on autoencoders (Florian Strub, 2016) or CNNs incorporating VBPR (Visual Bayesian Personalized Ranking) (Ruining He, 2015). Also these kinds of event recommender systems, just as any others, can be created without the need of any deep learning algorithm and can simply work with shallow structures. ANNs basically improve on their effectiveness. E-commerce and websites utilizing these features opt for having at least some kind of a system running, since any improvement is converted into more customer satisfaction, hence profit.

Our Proposal of the System

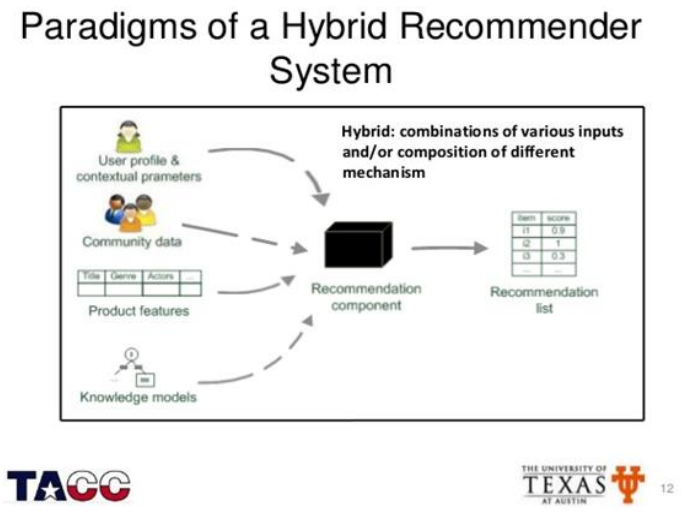
With our recommender, we aim to increase the effectiveness even more. The main difference between the event creator advisor and concurrent systems lies in the proposal direction. Unlike the other recommenders, our solution's flow is from the system to administrators, not users. The advisor will be able to autonomously propose events to organizations, institutions or groups that will interest their audience. Simply put, the system will act as a highly intelligent individual understanding the community on such level it will have the potential to increase its social involvement. With the latest advances in deep learning and its performance, this will slowly become possible. The nets will have to be truly sophisticated and reach a degree of understanding surpassing humans' EQ (Emotional Quotient) (Goleman, 1995) to be effective enough.

Technological Solution

In order to materialize the idea, we will propose a rough model of the system along description of the way in which it will function.

Recommender Basis

As the advisor is a type of recommender, its underlying mechanics will be the same – a recommender system utilizing the hybrid approach (CF and CBF). CF takes care of pattern recognition in unlabeled data, whereas CBF analyses labeled data. We propose to use a hybrid system because CF is able to recognize patterns and assumes dependencies (between user data) and is able to create future predictions, which means in our case, proposal of events based on user behavior over time (time-series analysis). On the other side, CBF will consider metrics such as user rating, rankings and preferences. This will make the advisor more effective and more importantly, it will make the system training possible, resulting in a fine-enough starting point. This is a common problem in recommenders referred as the cold start or sparsity problem (Vorhies, 2017). CBF won't be initially experienced enough and it will take some time until it will produce satisfying results that can positively influence the system. Until then, the net will be highly reliable on CF.



Hybrid recommender system basis

Applicable Models

For the hybrid approach based on deep learning, there are a few existing solutions the advisor could potentially utilize. One possibility is to use a kind of modified CNN inspired by Hybrid Music Recommender (Paulo Chiliguano, 2017). Another option would be to use autoencoders, proposed in 2016, that feature a way of dealing with sparse inputs (sparsity problem) (Florian Strub, 2016). If we consider the model's functionality, more in particular the net learning abilities, we come to an idea of training our system with CBF and in the later stages rely solely on CF incorporating for instance a CNN aided with an additional denoising autoencoder (Xin Dong, 2017).

Frontend Structure

On the backend, we have a deep learning system. Regarding the frontend, let us briefly discuss a possible model of ECA. Based on the set of user data, systems learning (implicitly set) and given options (explicitly set by a user of the system) such as target audience, location, age or hobbies, the system would generate a list of events that can be successful and “increase social involvement". With the knowledge acquired, the user can more effectively choose an event she wants to organize. Ideally, data from the event – number of participants, satisfaction, overall event success, profit etc. will be provided to the system back serving as a feedback, thus ultimately as data ECA can learn from. An exact solution of collection of the data exceeds scope of the paper and can be a subject for further research. We can only point out the solution might increase complexity of the overall system by introducing a very sophisticated and innovative way of data acquisition.

Business Model

In this paper, we will also propose how the system could be applied instead of only designing the technological solution, since we are looking at the problem of social involvement from more of a holistic point of view.

More Distanced-Future Solution

Having more advanced technology, one can consider having a system creating events on its own. Its understanding would be sophisticated enough to take care of organization completely autonomously. However, with this idea arise many problems and complications, such as who would physically manage the events. This could be realizable with robots serving as organizers, making this application feasible not earlier than in 50 years. Therefore, we decided to "lower the bar" and opt for another solution.

Feasible Near-Future Solution

As we need someone physically being present (in most cases) and able to organize events, we need to take advantage of already existing social structures that will enable the system to be used. On that account, we propose a B2B, B2A (Business to Administrator), or possibly a B2G business model. The system will be offered to smaller social units that will be able to materialize the events with their own (private) resources. ECA will provide them with ideas what kind of events will interest their target audience or community. The tool can be used both for profit as well as for non-profit purposes. Ultimately, the system will bring value for all 3 parties involved – for the company selling the solution, administrative units using it and for the end-users. The company will profit, the administrative units can monetize it and/or increase social involvement in their community and the end-users will enjoy company of other people and events fitting their interests.

Data Acquisition

Performance and accuracy of ECA will depend on the data collection available to it. The system that we are proposing is aiming to utilize data of a relatively big size and will require large training set. The more data is fed to the net, the better proposals it will generate. Currently, only companies such as Google, Amazon or Facebook possess such quantities of holistic data to make the ECA effective and universal enough (Marr, 2015). For example, there is even an option (considering the problematic regarding this kind of big data acquisition), that the aforementioned companies could offer ECA as one of their services. Other solutions may be a task for another research and further elaboration on the matter of subject is out of scope of this paper.

Other Utilization of the System

We focused more on a relatively niche problem in regards to the deep learning technology. If we generalize the concept of the system we proposed, it's clear it can be applied to other fields and not only to events creation. Once the net is inputted enough (valid) data, it will be able to “predict” other things, as well. For instance, this system could have a huge impact in real estate, e-commerce, education or health. Looking more in the future, it's very probable systems will gain marginally more understanding of humans than we can do by ourselves. Hence, their value will skyrocket.

Conclusion

In this paper, we proposed a rather unconventional solution focused on a social involvement problem of people not being engaged in communities or events outside of their homes as much as they could be. On a micro-scale, our team firstly tried to understand and solve the problematic by engaging with people in small communities. Later, we came up with an idea of using deep learning to tackle the problem on a macro-scale by introducing Event Creator Advisor. After a brief intro into the technology, we covered already existing solutions and our idea in regards to the status quo. Later, we described a model proposition of the system as well as its prospective business model. We also pointed out a potential data acquisition issue and the idea's analogical use in various different fields. Real implementation of the model will mean to start working with ANNs and use training data sets to train the nets to test their usability and effectiveness. Tweaks and adjustments of the model will be necessary. Nevertheless, we believe our system will eventually yield positive results in the field of social involvement, thus making individuals, society and after all, the whole environment better.

Acknowledgement

We would like to thank our project coordinator Prof. Dr. Achim P. Karduck for seeding the idea of using deep learning for introducing an innovative solution in the matter of subject.

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Images

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