AI Product Business Proposal

Image identification and classification with convolutional neural networks in Ecommerce

BUSINESS GOAL

Project overview and goal

Today, almost every company is becoming more invested in E-commerce. Most fashion companies have websites on which they sell their products. When a customer signups and logs into the site he or she will want to find and purchase what he or she wants as fast as possible. To achieve this, they often go for the search box and write down whatever category of things they want.

In most E-commerce sites, this search is not optimized for example, when you search for women shoes and clothing, you might get limited information and at times a mixture of male attire. Customers get frustrated when they can't find what they need and end up leaving or not coming back to the site after the first purchase and thus the company keeps losing revenue.

Being able to classify products into their appropriate categories can be very helpful as it facilitates the time taken to provide results and providing the right result. Some companies rely on humans for categorization; for every new image, they are expected to put it under the respective class. This is a tedious process as it must be done for every incoming design, too time consuming and very much prone to errors.

To solve this problem, we use deep learning with convolutional neural networks and image processing. We use both ML/AI to label our data using image categorization with image annotation with a dynamic model which updates with new data. We build a model which can identity and classify our labelled data into various categories such as gowns, blazers, trousers, shoes and others. This model is trained and tested to automatically categorize any new data. This is an efficient method for our e-commerce search relevance. Being able to categorize our images into specific groups makes for an effective and efficient search functionality and customer satisfaction. The goal is to Provide better search results and product recommendations, for higher cart value and value-per-visitor.

Business case

Large online retailers typically use query-based search to help consumers find information/products on their websites. They are able to use technology to provide users with a better experience. This is because they apprehend the importance of search relevance, and that long and/or unsuccessful searches can turn their users away because users are accustomed to and expect instant, relevant search results like they get from Ebay and Amazon.

When applied to search engines, AI can solve concrete and specific problems and help business be more effective and efficient. Building this AI product for search relevance provides the following advantages;

- They enhance the quality of search results**,** providing high performance in terms of precision and recall and providing faster results.
- This AI product will improve user experience.
- Other than high search performance and user experience, this product will enhance the growth in company sales and revenue which is the prior motive of every ecommerce business.
- Using this AI product of search optimization increases the visibility of every product sold for a search, this facilitates product purchases and therefore higher revenue gain.
- Building an AI/ML model which provides efficient and effective searches provides user satisfaction. A customer is more satisfied when they can find exactly what they want in one go. This will intend create customer loyalty and a high lifetime value.
- In addition, this model will as well promote a higher churn rate.

- In the long run this AI/ML model provides cost savings. We will be automatically updating and optimizing our search function. This saves our income as we won't need to hire someone to do so.

Application of ML/AI

This problem of search optimization for an ecommerce company can be addressed using deep learning with convolutional neural networks. In our dataset we have images of different categories for example, blouses, blazers, jeans, gowns, jumpsuits. Using image annotation and classification we segment our images into the various categories, which are then fed into the model.

We annotate and label and our dataset (which is real, diverse, evenly distributed and large enough). Our data is split into training data and test data. After labelling our data we insert it into a model. Using convolutional neural networks to build our model, which is made up of several layers. Our training data should be made up of approximately similar amounts of each category to avoid data bias. This data goes into the network as pixels. We use transfer learning with some modifications to adjust our model, and at the end get an output, when training our model, we focus more on precision than recall and at the end we test our model with the test data.

Using AI/ML we should be able to correctly identify an image under a specific category of dresses under either jumpsuit, tops, gowns for example. Natural language processing is used to interpret a search which is not direct and help link it to the required category.

The objective of our trained model is to be able to automate and save cost, providing adequate user experience and satisfaction which will have added business advantages as seen above

Success Metrics

To evaluate the success of the product, I will use the following metrics;

Customer satisfaction: this is the measure of how the users find the system, how easily do they get the results the search for. I will get feedback from the customers as ratings as to how the platform works, comments as to why they like or do not like it. All this information gathered will provide us with an insight of how the product is fairing.

In addition, we could have a look at our revenue growth from when the product was implemented to a specific time frame. Increase in revenue will indicate a growing success in the product. In a time, however this revenue gain should be greater than the cost of the product in order to work on a profit.

Measuring the churn rate and customer retention rate is a valuable measure of success. If the number of customers who revisit the website for another purchase after their first purchase increases, then we have a positive measure of success.

DATA

1. **Data acquisition:** Data for this project is gotten somewhat quite easily at little or no cost. Data for this product was gotten from the Kaggle repositories of fashion mnist dataset which had 70,000 labelled designs and 10,000 test (Kaggle, fashion mnist n.d.) with a size of 69MB. Also we made use of the fashion product images dataset in Kaggle with 44,000 products with multiple category labels with a size of 12GB (Kaggle, fashion-product-images-dataset 2019). With the fashion industry keep coming up with new designs, we will need to update our model and datasets with new images. This data was not very sensitive and so less security issues.
2. **Data source**: we used grayscale and color images from Kaggle with sizes of 80,000 images associated with labels from 10 classes and 44,000 respectively to train our model. Also, we used the deep fashion database of over 800,000 diverse fashion images ranging from well-posed shop images to unconstrained customer photos (Large-scale Fashion (DeepFashion) Database n.d.). We eliminate data bias and

annotation bias by averaging the number of images for each category. For these data sets, 80 percent will be used as training data, 10% for test and the other 10 percent for validation.

3. **Data labels:** Working with images related to fashion, we annotate and label our data. various labels I came up with were; Tops, long dress, short dress, blazers, jeans, trousers, skirts, jumpsuits, jackets, crop tops. This is because these are the most popular categories of searches women use when looking for what they need.

MODEL

Model building

The model building and training will be done by an external platform, we will use AutoML build our model using transfer learning. Given that our data isn't highly sensitive, we can share it with the provider. This method is cheaper and support from the platform is always available.

Evaluating results

While evaluating or model we need sensible metrics of its performance. Given that our model is focused on being able to identity an image we will need a high model precision.

Our model is evaluated against a test set of data which was 10 percent of our balanced labeled data. Using the test data, we evaluate the precision and recall for each class in our model, here we guarantee success when we achieve an F1 score of 0.8.

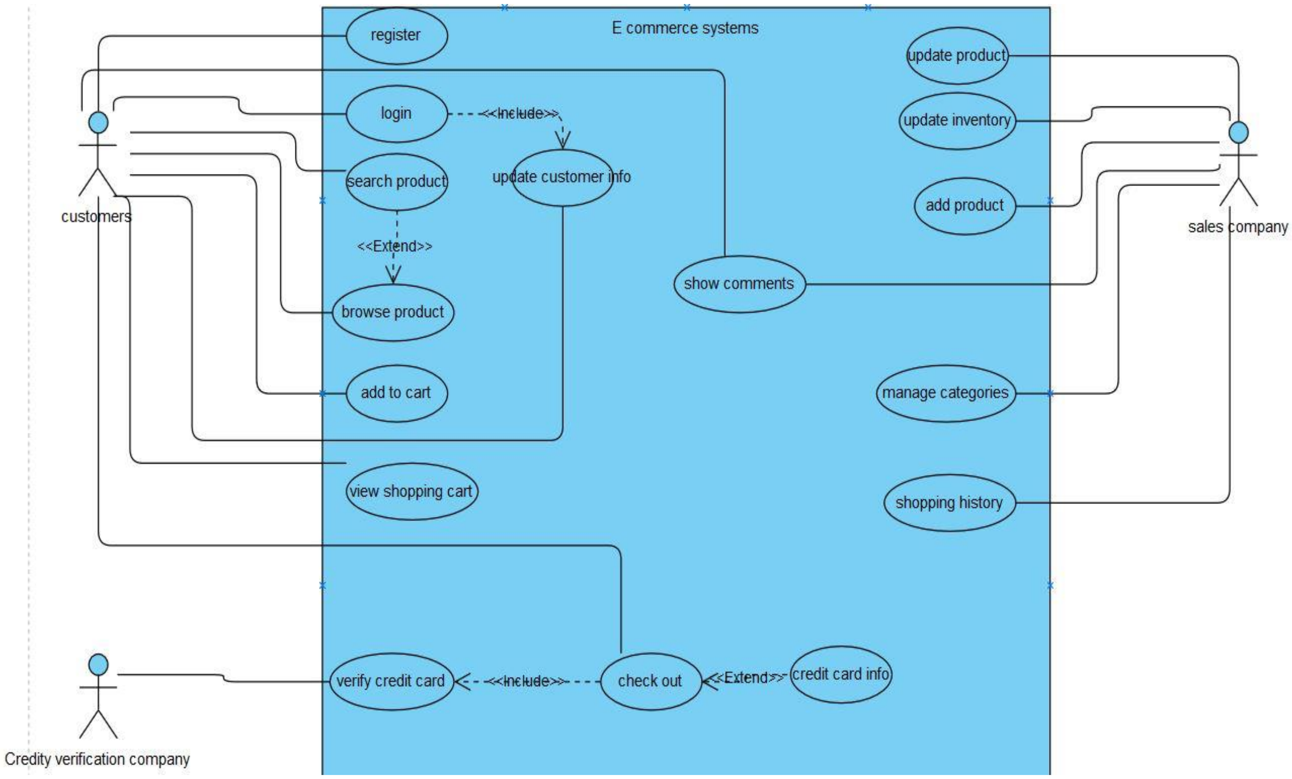
Minimum viable product

Design

The sample above represents a model of our minimum viable product. Here new images are uploaded, and model automatically categorizes them based on the training it got.

Use Cases

Taking a look at the sample use case below for an ecommerce website, our product is for both the customer and the company, statistics show that most users of ecommerce website range from 16 to middle aged (eurostat 2018). This product addresses the problem when the sales company intends to add new products to the ecommerce site. Here the AI system automatically identifies and manages the categorization. This facilitates the "search product" level for customers by providing adequate results (paradigm n.d.). Customers use this product without any knowledge of the product. The ecommerce uses this product when ever they want to update their inventory or goods. This AI product will categorize the image accordingly. In the case of new data, human annotators will need to classify the data and train the model to be able to carry out the task on its own later.



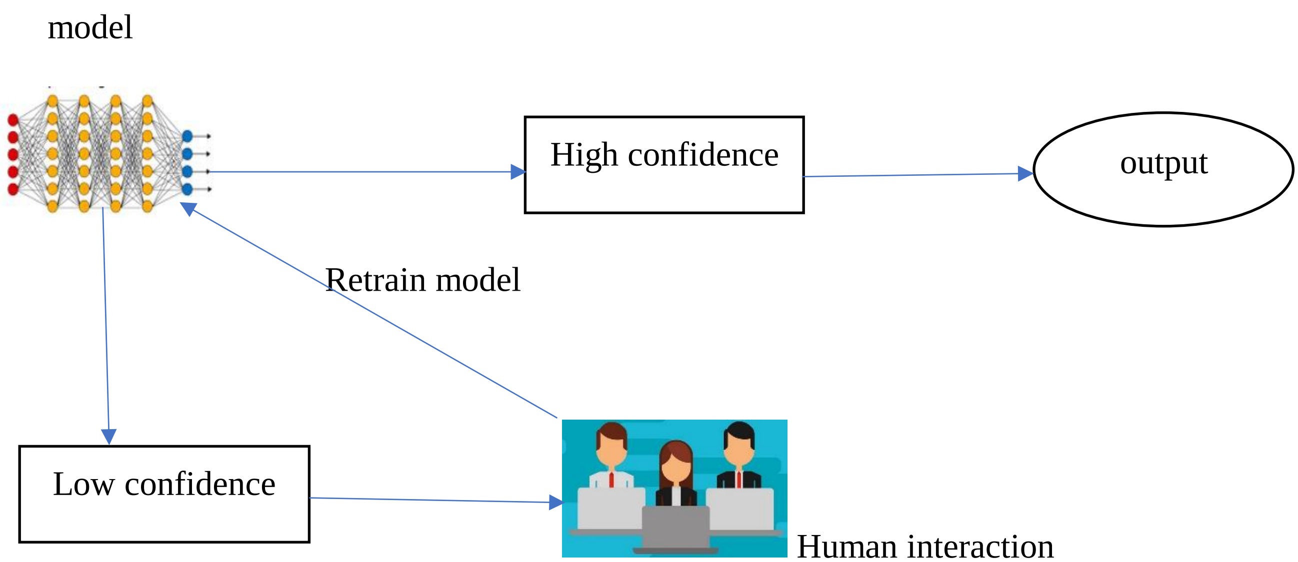
Roll-out

Our next phase will be measuring and updating the tool as we send it out to real world users. From our prototype, we provide our engineers with the requirements of security, operation and quality. Also, we pay attention to or updates and how they affect our system performance and user interaction while building our product we make room for easy iteration and monitoring. Once we've built our product and ready for launch, we make use of our success and performance metrics gotten from consistent testing of the model. At this point we collect feedback and act accordingly. With the feedback gotten we can work on optimizing our model to best suite customer satisfaction.

Post – MVP – Deployment

Designing for Longevity

With our product, we are working with data which is constantly being updated. We therefore use a dynamic model which is continuously trained on new data so it can keep learning. Our data used for training is real and our model will learn from new data by the continuous learning process as shown below;



Our model is used to predict a data set if it has a high confidence then it produces an output. When new data from an unknown category comes in, the model signifies a low confidence, and the data set is redirected to human annotators who annotate the data and retrain the model.

Furthermore, we need to constantly optimize our model to achieve success. We use AB testing to make data driven decisions to evolve and improve our product. To build our product, they will exist 2 models, on our well tested model we will traffic 75 percent of our customers and on our new model 25 percent to test the model. We test our new model against the performance metrics we chose, we as well make sure it is more cost effective in the long run than the previous model. We will run this model over a period to capture the seasons, maintenance and amount of investment required. After all the testing and monitoring we can make our decision as whether or not to improve our current model to the new version.

Monitor Bias

We constantly monitor and mitigate bias while we launch and scale our product.

To avoid data bias we make sure, we have diverse and large enough data from multiple sources. Also, data for each category is approximately equal so as to avoid the model from being bias in categorizing.

Handling annotation biases, we employ people of various cultures, gender and regions when dealing with annotation. Considering just people from one area will make the annotations bias to their opinions and therefore a bias model

References

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