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# Optimized Input Selection for Target Systems

Douglas Sanders

Dave Pang

Ying-hsiang Liao

Minh Nguyen

# OPTIMIZED INPUT SELECTION FOR TARGET SYSTEMS

## Introduction

Computer-implemented systems and methods are provided for leveraging data returned from a target system in response to known inputs to train an ML model that is used to optimize future target system inputs. For example, the trained ML model can be used to optimize image selection by automated product classifiers. Such a system provides higher quality listings to buyers, improved listing success for merchants and marketplaces, and increased consumer choice for users of marketing platforms.

With reference to FIG. 1, marketplaces (sometimes called aggregators) make products available to consumers, typically for purchase on the marketplace's storefront (via a website or app). Marketplaces aggregate products from third parties and may also sell products directly to consumers. Marketing platforms provide opportunities to advertise their products to prospective consumers. All parties involved are incentivized to make as many products available to as many prospective consumers as possible, as this increases consumer choice. The resulting increase in customer choice often yields more purchases and thus, sales for the marketplace.

Marketplaces often have unique listing requirements to ensure the consistency and quality of the listing on their platform. Further, the listing requirements of each marketplace may be different than those of marketing platforms, and each marketing platform may have different listing requirements from each other (and may even be in conflict). If requirements are not met, a product will typically be excluded from being offered to consumers (sometimes called "disapproved"). Many requirements are  rules that can be applied consistently. For text, for example, the rules may be easy to apply (e.g., the title is not written in all capital letters). However, some rules may be more difficult to apply (in particular, those that apply to media such as images or video). For example, a requirement may disallow images that contain promotional text.

Many small and medium-size merchants lack the resources to produce listings that meet the myriad requirements imposed upon them. While larger marketplaces and some merchants may have resources to manage their own listings, conflicting requirements may still be an issue.

Marketplaces are in a position to manage the product listings for the merchants that list on their platform, and are further incentivized to ensure that the listings provided to each marketing platform are optimal for that platform. Existing tools provide pre-submission filtering where remediations are fixed, such as the correction of a title in all caps by changing case. However, existing solutions do not provide variable remediations, such as the removal of "objectionable" content where the definition of "objectionable" is not clear or consistent.

**Summary**

Computer-implemented systems and methods are provided for optimizing inputs to target systems having unknown algorithms for generating outputs. The technology described herein can transform the non-fixed rules of marketing platforms or other target systems into a mechanism for optimizing the product for input to that platform. Listings can be remediated in a variable fashion so they are compliant with the unknown nature of rules being applied by the target system.

By way of example, the disclosed technology can optimize image selection for target systems such as automated product classifiers having non-fixed rules for accepting images or other inputs for listings on the target system. One or more models can be trained based on whether inputs such as images in a listing are approved or disapproved by a system. A database of images rejected and approved by a target system can be maintained. This database can be used

to train a model (e.g., analytical, heuristic, or machine-learning based) with the images and the target system outputs as the inputs. Once trained, the model may receive candidate images and generate a probability that one or more input images will or will not be approved by a third-party system, prior to uploading the one or more images to the system. This creates a model that is fundamentally different than the “black box” algorithms of the target system. Rather than determining which images contain forbidden or restricted content, the trained model determines which images will be approved by the black box algorithm and which will be disapproved. Once this model is trained, it can then be applied to images it has not yet seen. The resulting output is a score that identifies how likely the target system is to approve a prospective image.

In some examples, the model can also contain other information, such as how the image performs on the target system (e.g., which image yields the most purchases).

A model (e.g., machine-learned) can be trained using images intended for product listings on a system within a third-party marketing platform. The model may be trained using the approval of the images by the system. For example, a system within a marketing platform may contain proprietary algorithms for filtering images within a product listing and the proprietary algorithms may have no known documentation. The machine learned model may be trained on the output of the system such that its output provides an accurate prediction of whether an image will be allowed by the proprietary algorithms. Through this method, users that attempt to make listings are given information on whether their listings will be approved before providing images to the marketing platform.

**Description**

FIG. 2 depicts an example computing system 100 in which systems and methods in accordance with the present disclosure can be executed. The computing system comprises a user computing device 102 including one or more processors 112, memory 114 which may contain data 116 and instructions 118 configured to carry out the methods disclosed herein, and a user input component 122. The user input component can be, for example, a touch display or physical buttons within the user computing device 102. The computing system 100 further comprises a network 180 and a server computing system 130. The server computing system 130 comprises one or more processors 132, and memory 134 which may contain data 136 and instruction 138 configured to carry out the methods disclosed herein. For example, a user may send one or more images via the user input component 122 of the user computing device 102 and the one or more images are sent over the network 180 to the server computing system 130. A model is stored in memory 134 on the server computing system 130 where the one or more images are provided as input. The model will then output a score for each of the one or images that corresponds to a likelihood that the image will be approved (e.g., approved, rejected, promoted, etc.) by a target system. The scores are then sent back to the user computing device 102 via the network 180. In some embodiments the model will generate an ordering of the one or more images based on the score for each of the one or more images. Any combination or order of systems and methods disclosed herein can be performed on the user computing device, server computing system, or similar. For example, all processes may be performed on the user computing device 102 or the server computing system 130.

FIG. 2 depicts a system for training a machine learned model to determine a probability that an input such as an image will be approved, disapproved, etc. by a target system. Product images are provided at a marketplace system or other host system having a model for training to predict a likelihood or probability that an input such as an input image will be accepted by a target system (e.g., marketing platform). A response database stores images that are approved or rejected by the target system along with an annotation of whether the image was approved or rejected. The target system includes a black box including one or more non-fixed rules or other unknown algorithms for determining whether an input is acceptable or not by the target system.

Product images are provided as inputs to the target system. The target system generates an output for each target image indicating whether the image is approved or rejected by the target system. The marketplace system stores the product images and the corresponding response from the target system in the response database. The target images are then provided as input to the model (e.g., analytical, heuristic, or machine-learned). The model generates an output such as a prediction, score, classification, probability, or the like indicating whether the image will be accepted by the target system. The output may be one of a plurality of different labels such as, for example, approved, rejected, denied, or similar labeling that a marketplace may have for images. The output generated by the model is compared to the response generated by the target system. One or more parameters of the model can be modified or updated based on the comparison of the output generated by the model to the response generated by the target system. For example, one or more loss functions may be computed based on the response by the target system and the output generated by the model.

FIG. 4 depicts an example system including a trained model for optimizing image submissions to a target system. Product images are provided as input to the trained model which generates scores for each image and a sequence of images as an output. By way of example, two product images include restricted content. The product images are input to the trained model 304 which generate scores indicating a probability that the image will be approved (high score) or disapproved (low score) by the target system. The trained model may identify the restricted content present in the product images. Notably, the model is able to generate the scores without knowing the underlying algorithms or non-fixed rules applied by the target system to determine whether an image is approved or disapproved. The scores are used to generate an output including an ordered sequence of the product images based on their respective scores. The output may be ordered such that the image having the highest score is ordered first and the image having the lowest score is ordered last. Those that score best (i.e., are least likely to be disapproved) are placed first, while those that are more likely to be disapproved are deprioritized. The marketplace can then choose which of the images to submit to the target system. For example, the marketplace may select the highest scored image to be provided first so as to maximize the likelihood that the image will be selected by the target system.

In some examples, separate models can be trained for separate target systems, allowing the order for that system to be optimized (without requiring the merchant to create additional assets).

In other examples, a single model may be trained on a plurality of systems to provide a probability or scoring for an input image corresponding to each of the plurality of systems. The machine learned model may generate unique probabilities or scores for the input images corresponding to the different target systems. In other examples, a model may be trained for a plurality of target systems to generate an aggregated probability or score that represents the likelihood of an input image being ranked (e.g., approved, rejected, promoted, etc.) by any one of the plurality of systems.

**Drawings**

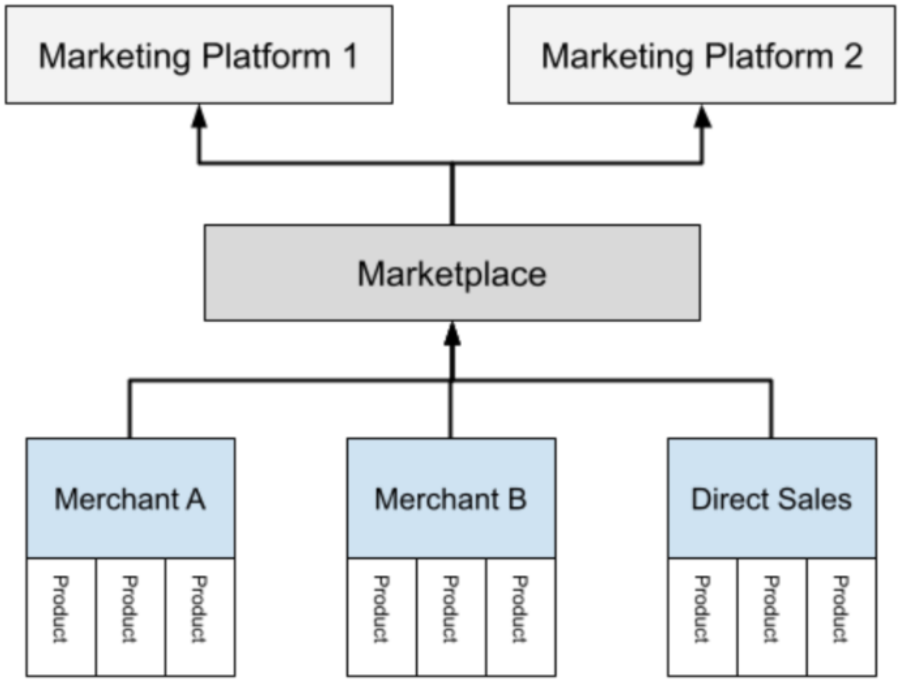


**FIG. 1**

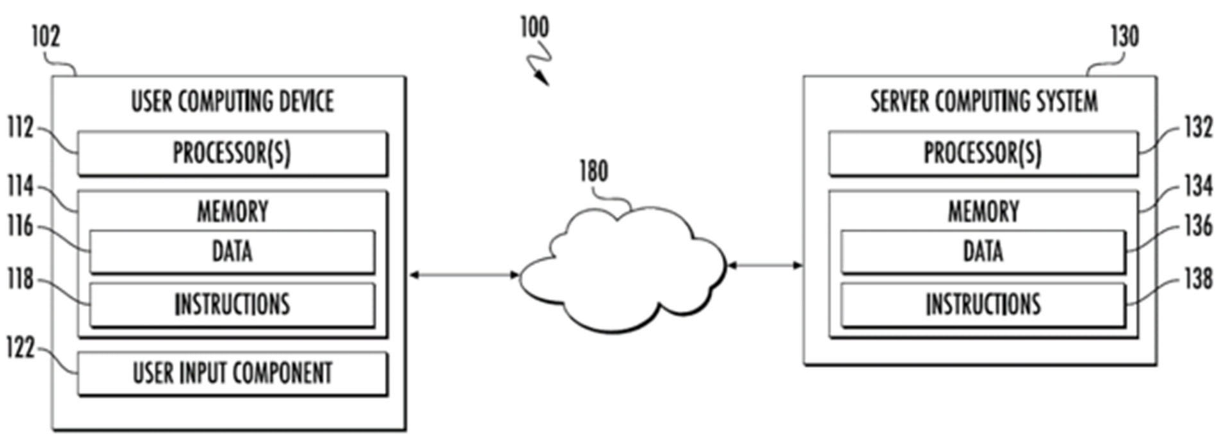


**FIG. 2**

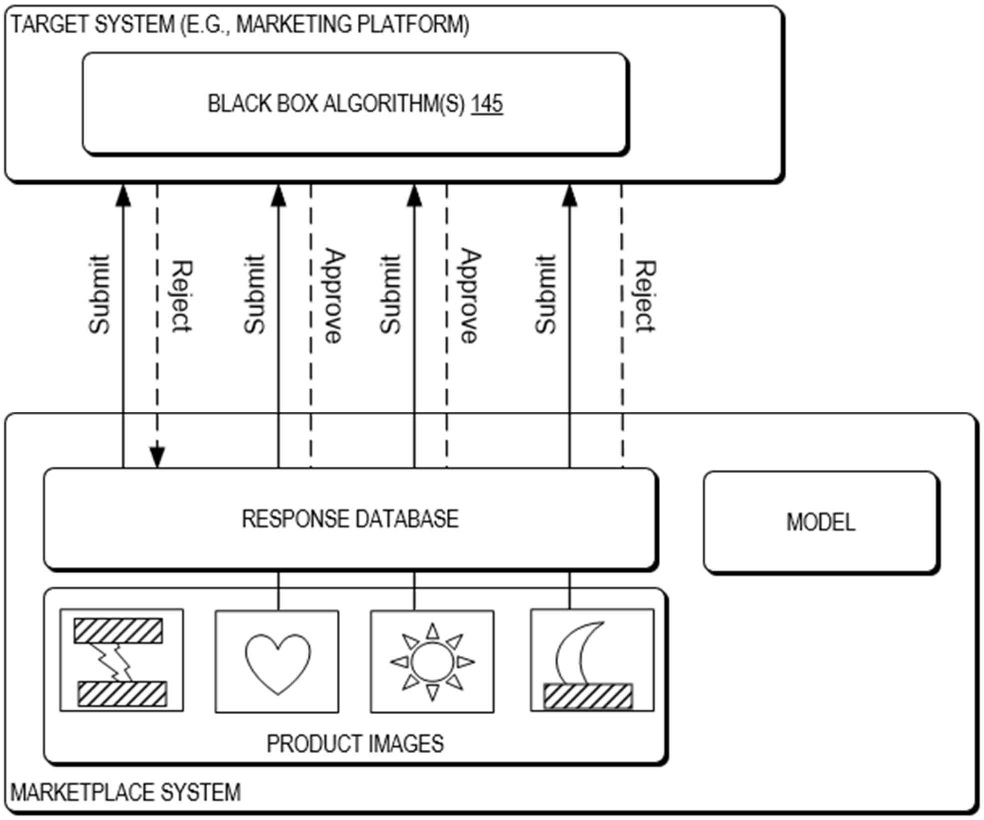
TARGET SYSTEM (E.G., MARKETING PLATFORM)
BLACK BOX ALGORITHM(S) 145
Submit
Reject
Submit
Approve
Submit
Approve
Submit
Reject
RESPONSE DATABASE
MODEL
PRODUCT IMAGES
MARKETPLACE SYSTEM

**FIG. 3**

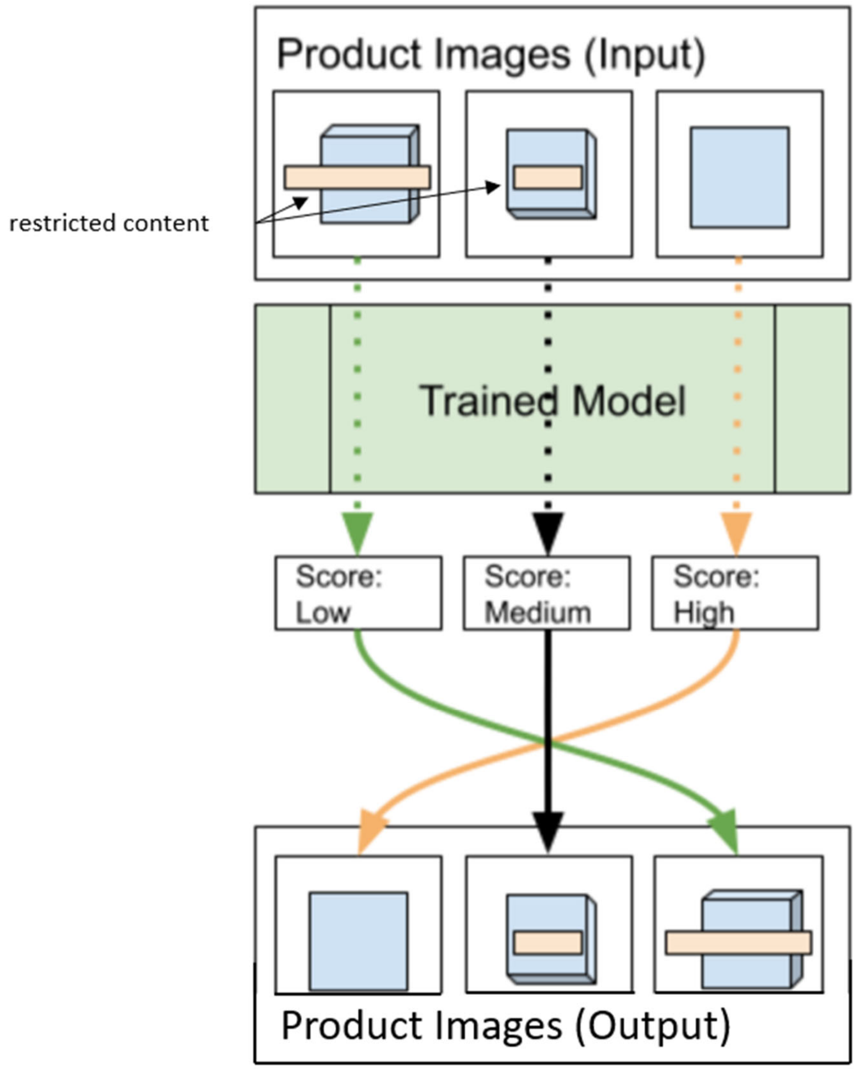
Product Images (Input)
restricted content
Trained Model
Score: Low
Score: Medium
Score: High
Product Images (Output)

**FIG. 4**

**Abstract**

Computer-implemented systems and methods for optimizing input selection for target systems such as automated product classifiers are provided. Such a system provides higher quality listings for buyers, more listing success for merchants and marketplaces, and increased revenue to marketing platforms. A model (e.g., analytical, heuristic, or machine-learned) is trained using an input such as images intended for product listings on a target system (e.g., marketing platform) and responses received from the target system. For future inputs (e.g., images), the model may generate an output such as a prediction, classification, or probability that an input will be accepted by the target system.