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Reward calculation based on quality of task completion

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Reward calculation based on quality of task completion

ABSTRACT

This disclosure describes techniques to incentivize higher quality in tasks performed by users as part of goal based advertising. Machine learning techniques are utilized to determine a quality score for tasks completed by users. Tasks are assigned in parallel to multiple users based on the quality score. The quality score is used to determine and provide rewards upon task completion.

KEYWORDS

- Advertising
- Quality score
- Crowdsourcing
- Paywall

BACKGROUND

Advertisers can employ goal-based advertising where users perform specified actions (tasks) in return for access to content or obtain services. However, the resultant quality of tasks performed by the users can vary widely. A mechanism that rewards users based solely on task completion without considering quality can incentivize users to prioritize quantity of tasks completed, compromising the quality, which can lead to poor results for an advertiser.

DESCRIPTION

This disclosure describes techniques to assign quality scores to user performed tasks. With user permission, tasks performed by a user are analyzed using machine learning techniques to determine the quality, and assign a corresponding quality score. The quality score is usable to incentivize users to perform higher quality work, e.g., by upgrading the reward based on the quality.

For example, a user task can be to categorize an object included in a photograph. A photo of a designer handbag, for instance, is displayed to the user. The task is for the user to either confirm or reject a statement such as “this photo displays a handbag.” Categorizing the photo correctly results in the user being rewarded with a bonus.

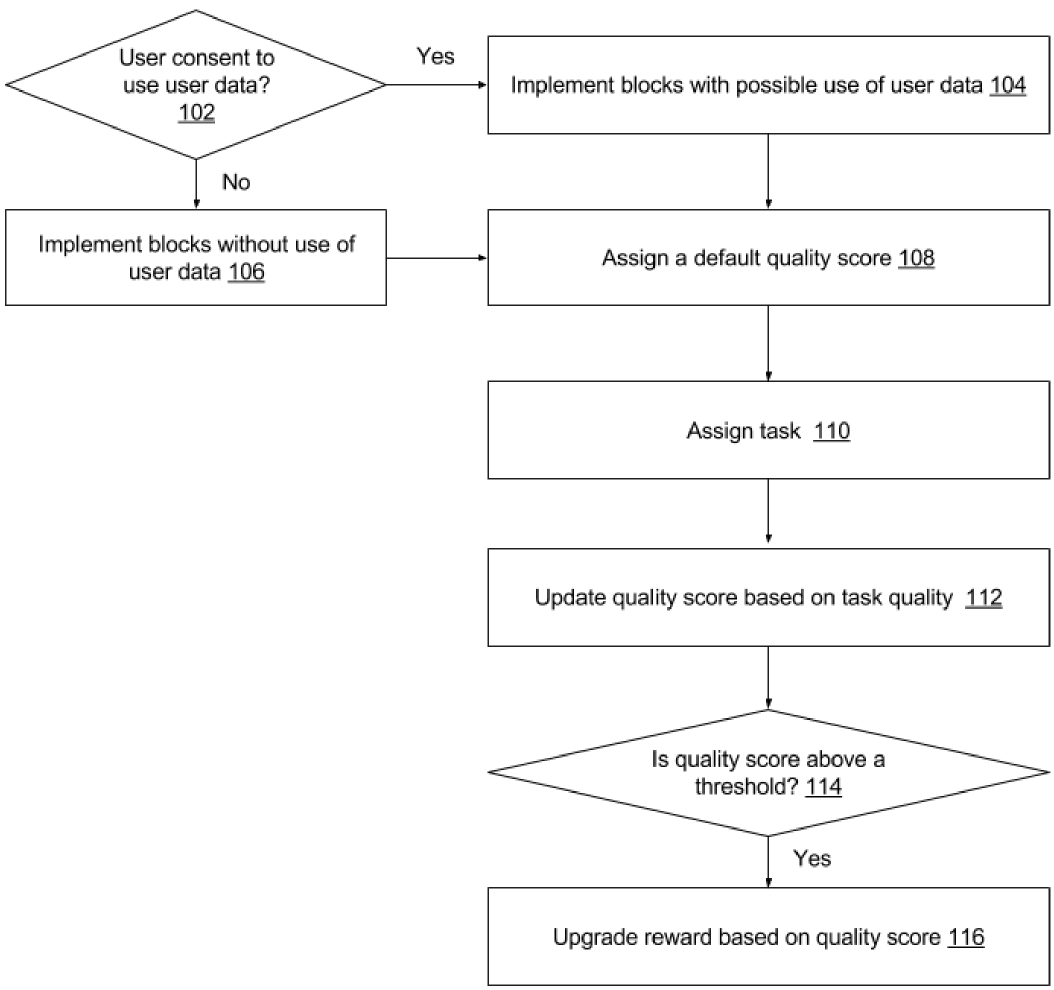

Fig. 1: Rewards based on the quality of actions

Fig. 1 illustrates an example of user reward calculation based on the determination of user task quality. It is first determined whether the user has provided consent for use of user data in the reward calculation (102). If consent is obtained, the calculation is performed with possible use of user data (104), e.g., data that the user has permitted for use for such calculation. Else the calculation is performed without use of user data, or may not performed at all, e.g., no quality-score is computed.

A new user is assigned a default quality score (108). The quality score is adjusted based on the quality of tasks performed by the user. To assess the accuracy with which a user performs a task, the task assigned to the user (110) is also assigned to multiple other individuals. The number of parallel assignments of the same task is dependent on the track record of the user and a confidence level in the quality score for that user.

For example, a machine learning model associates a higher confidence level to a user with a history of high quality work compared to a user who has completed fewer tasks or who has a history of poor task quality. The number of parallel assignments of the same task to others (redundancy) is reduced as a user performs a greater number of tasks, thereby improving cost efficiency of the process.

With user permission and express consent, the quality of the task performed by the user is determined, and the quality score is updated accordingly (112). If the quality score exceeds a predetermined threshold (114), the user is rewarded. The task completion reward is enhanced based on the improvement in the quality score (116). For example, the default reward is multiplied by the quality score to calculate and provide an enhanced reward for the task completion. As the quality score improves, the reward increases, thus incentivizing the user to perform better on tasks.

With user permission, the model uses one or more features such as the number of tasks performed by a user, past history of successful tasks, including assessments based on tasks performed outside of the core application for an independent third party, affinity of users to the task based on their interests, time spent by users on similar tasks in the past and the quality of completed tasks, time elapsed from previous user tasks, applications where the task was performed, local time of the day, etc. The machine learning model is updated as tasks are performed using the results of the tasks and feedback received with respect to their quality.

The quality scores are transparent to users to provide users an incentive to improve the quality of tasks. The described techniques incentivize users to perform tasks with progressively higher quality which can reduce attendant costs. Users that achieve a good quality score are awarded a bonus to reinforce quality improvement and create a positive feedback loop of encouragement. Users completing the task with inadequate or poor quality are not penalized but do not receive the bonus.

Users are provided feedback and an updated quality score upon task completion. The immediate feedback helps users approach future tasks based on past quality results. The reward structure, e.g., bonus, is determined to incentivize users to focus on quality instead of quantity. Users are rewarded only for tasks performed with adequate quality. The described techniques can be applied to various types of advertising, including mobile advertising, and crowdsourcing as well as cloud based advertising.

Further to the descriptions above, a user may be provided with controls allowing the user to make an election as to both if and when systems, programs or features described herein may enable collection of user information (e.g., information about a user's social network, social actions or activities, profession, a user's preferences, or a user's current location), and if the user is sent content or communications from a server. In addition, certain data may be treated in one or more ways before it is stored or used, so that personally identifiable information is removed. For example, a user's identity may be treated so that no personally identifiable information can be determined for the user, or a user's geographic location may be generalized where location information is obtained (such as to a city, ZIP code, or state level), so that a particular location of a user cannot be determined. Thus, the user may have control over what information is collected about the user, how that information is used, and what information is provided to the user.

CONCLUSION

This disclosure describes techniques to incentivize higher quality in tasks performed by users as part of goal based advertising. Machine learning techniques are utilized to determine a quality score for tasks completed by users. Tasks are assigned in parallel to multiple users based on the quality score. The quality score is used to determine and provide rewards upon task completion.