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Customized dynamic application delivery based on user need

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ABSTRACT

Presently, user devices download and install entire software applications even when only a part of the application functionality is used by a user of the device. As a result of the presence of functionality that is unlikely to be needed, download of the application likely uses more bandwidth. Further, the application code takes up more storage space on the device and uses more memory during runtime. This disclosure utilizes dynamic assembly to deliver an application package that includes only the functionality that fits user's needs, device configuration, and context, as determined by a trained machine learning model.

KEYWORDS

- Application delivery
- Application customization
- Dynamic application assembly
- Application parts
- Application components
- Mobile apps
- Application feature recommendation

BACKGROUND

The manner in which a software application is used differs across users. These differences stem from differences in user preferences. For example, some users of a messaging application may prefer texting over calling, some users of a content delivery application may choose to download only books while others download only videos. Similarly, users who do not possess a credit card do not utilize the corresponding payment functionality within an application. Differences in application usage may also result from regional variations. For instance, in places where mobile Internet access is expensive, users may prefer offline content.

Presently, a user must download and install the entire application on a user device, e.g., a smartphone, tablet, laptop, wearable device, etc. even when only a part of the application functionality is likely to be used. As a result of the presence of functionality that is unlikely to be used by the user, download of the application uses more download bandwidth, and the application code takes up more storage space on the device, and uses more memory during runtime.

DESCRIPTION

Many operating systems (OSs) provide features that allow a larger application to be broken down into smaller pieces based on the functionality. The functional pieces can be selectively assembled and packaged to generate a customized version of the application. This disclosure utilizes such dynamic assembly of application code to deliver an application package that includes only the functionality that fits the expected needs, device configuration, and context of a user. A trained machine learning model is applied to predict the parts of the application of relevance to the user.

If the user permits, the model takes as input various factors, e.g., the usage of a given application or a similar application by the user, to predict the likelihood for the use of one or more individual functional components of the application by the user. Additionally, if the user permits, the model can incorporate the consideration of other user-specific features, such as the user’s characteristics, prior usage of the device, and current context. Based on user permission, such information is obtained from one or more of: metadata in the user’s account, sensors on the user’s device, logs of the user’s interactions with various applications, etc.

In addition to the relevant information of the user, the model can also utilize pertinent aggregated information of other users with their permission. For example, the model can utilize factors such as geographic proximity of the other users, similar use of an application by other users, etc. as indicators for similarity between users. The model is trained to predict the likelihood of different parts of an application being of likely interest to the user based on a comparison with the interests and behaviors of similar users based on the various similarity indicators. For example, users that are close in geographic location are likely to utilize the same atomic application parts related to the locale, language, currency, etc.

The model outputs probability scores for different application parts based on corresponding user need for the respective part. The output is utilized to select application parts for delivery to the user device, e.g., based on whether the probability score associated with each respective part exceeds a threshold value. A version of the application customized for the user is generated by assembling the selected parts and is provided to the user for downloading and installation.

Alternatively, the selected parts are made available for prefetching when the user is on an unmetered network, thus making it faster and free to install the application upon selection by the user. Further, the model output can serve as a recommender system to show the user suggestions for additional features of likely interest in applications that are already requested or installed on the user device. With user permission, user selections in response to the recommended functionality can be used as a training signal to improve and refine the machine learning model.

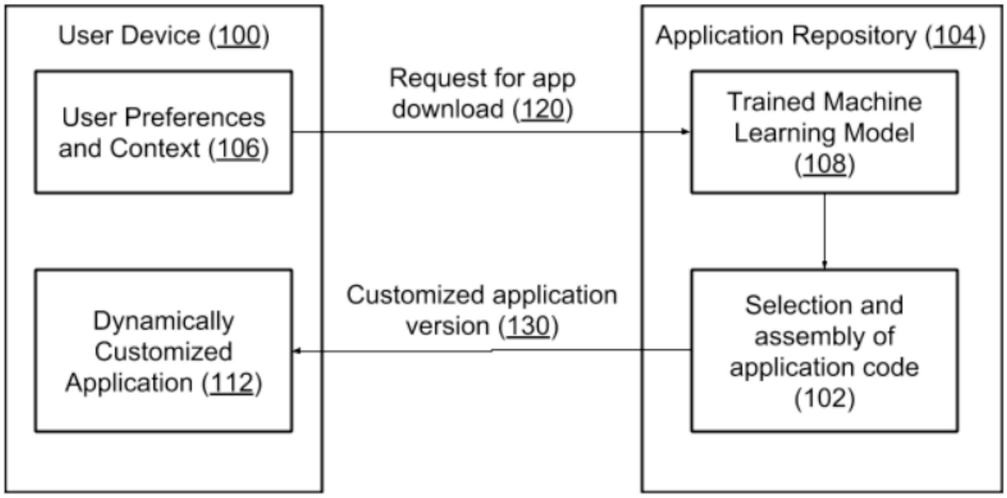

Fig. 1: Customized dynamic delivery of a software application

Fig, 1 shows an example implementation of the techniques of this disclosure. The user of a device (100) requests the download (120) of an application (102) from an application repository (104), such as an online application store or website that provides application downloads. The request includes information about the user's preferences and context (106), as permitted by the user. The information is provided as input to a trained machine learning model (108). Description and metadata regarding the atomic functional parts of the application, stored in the repository, serve as an additional input to the model.

The output of the model indicates the parts of the application determined by the model as likely to be utilized on the user device. The output of the model is utilized to select the parts and assemble application code (102) to generate and deliver (130) a customized version of the application (112) to the user device. By such customization, parts of the application that are indicated by the ML model as unlikely to be utilized by the user are excluded, thereby reducing the overall size of the application as downloaded to the user device, and the storage space/ memory utilized to store and execute the application on the user device. When the same application is requested by a different user of a different device, a different version of the application, customized for the different user is generated and provided.

The threshold values used to select the parts of the application relevant to the user can be specified by application developers, configurable by the user, or be determined dynamically. The threshold values may differ for different applications and may be different for different parts of the same application.

The machine learning model used to implement the techniques of this disclosure can be any of the models commonly utilized by recommender systems. Examples of such models include matrix factorization with a large matrix of users and application functionality that could encode preferences for inferring missing values and end-to-end neutral networks. Parts of the machine-learned components could be replaced by manually specified heuristics, with a possible loss of generalizability. The model complements and improves upon heuristics based approaches for application customization, such as those based on language or hardware components. The model can be utilized to deliver software applications to any OS or platform that supports splitting applications into components and by any services that provide such applications.

Example of use

- Consider two users - Alice and Bob - of a messaging application. Alice uses the application to make paid phone calls while Bob never does so. Using the techniques of this disclosure, Alice receives a version of the application with the functionality for paid phone calls included, while Bob is provided a different version that excludes this feature. User preferences for phone calls may be determined from user-permitted factors, including use of other applications on respective user devices.

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 utilizes dynamic assembly to deliver an application package that includes only the functionality that fits user's needs, device configuration, and context, as determined by a trained machine learning model. A version of the application customized for the user is generated by assembling the selected parts and provided to the user for downloading and installation. Further, the model output can also serve as a recommender system to show the user suggestions for additional features of potential interest in the applications that are already requested or installed. The techniques can reduce bandwidth consumption for application delivery and the storage space/ memory used on the user device to store and execute the application.

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