June 20, 2018

Dormancy prediction and user equipment driven active-dormant transitions

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ABSTRACT

The decision to move a mobile device to dormant radio resource state is typically driven by the mobile network. For example, after a period of observed inactivity, the network may move the mobile device to dormancy. However, mobile applications may send data shortly after the mobile device is moved to dormancy which results in sub-optimal power and bandwidth use. This disclosure provides techniques that enable the mobile device to predict immediate data transmission requirements. The predictions are used by the mobile device to drive active-dormant transitions at the radio resource control (RRC) layer.

KEYWORDS

- Radio resource control (RRC)
- RRC Dormancy
- Dormancy prediction
- Machine learning
- UE power consumption
- Power saving
- Mobile device

BACKGROUND

The decision to move a mobile device to dormant radio resource state is typically driven by the mobile network. For example, after a period of observed inactivity, the network may move the mobile device to dormancy. However, mobile applications may send data shortly after the mobile device is moved to dormancy which results in sub-optimal power and bandwidth use.

Improperly timed active-dormant transitions can also reduce the responsiveness of the mobile device.

DESCRIPTION

This disclosure describes machine-learning techniques that enable a mobile device, e.g., a mobile phone, tablet, wearable device, etc. that communicates over a mobile network, to predict immediate data requirements. The predictions are used by the mobile device, also known as user equipment (UE), to drive active-dormant transitions at the radio resource control (RRC) layer.

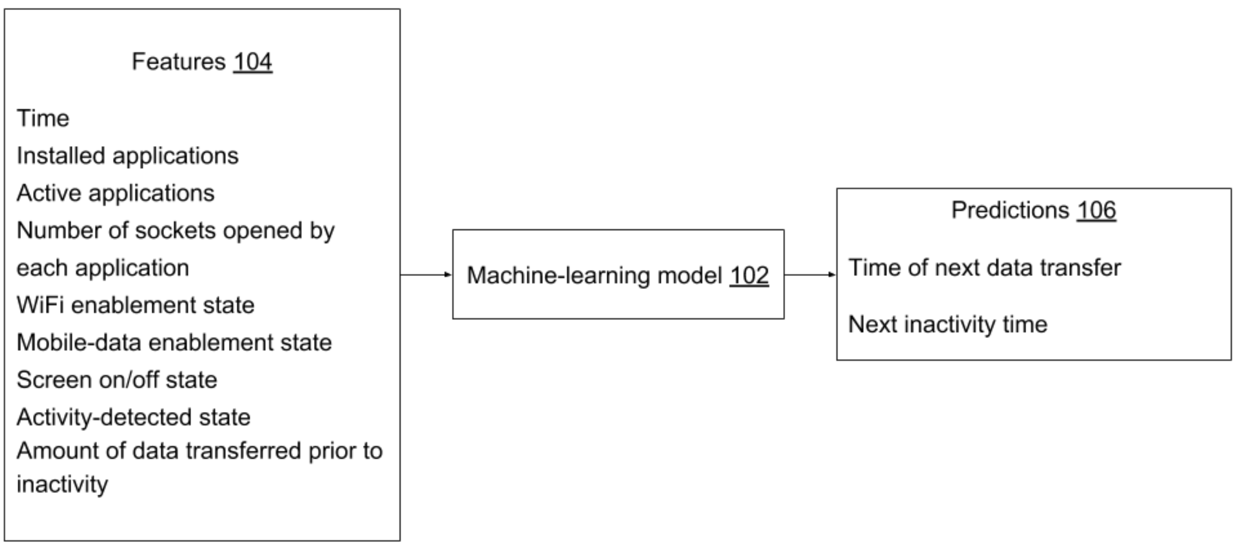

Fig. 1: Predicting the time-to-dormancy

Fig. 1 illustrates an example of application of machine learning techniques to predict the time to dormancy for a UE. A trained machine-learning model (102) accepts as input a number of features (104) relating to the state of the mobile device, and produces as output predictions (106) of time-to-dormancy. Features used as input to the machine-learning model can include, for example, time (e.g., of data transfer); applications installed on the UE; applications active on the UE; number of sockets opened by each application; Wi-Fi enablement state; mobile-data enablement state; screen on/off state; activity/inactivity detected state; amount of data transferred prior to inactivity; etc. Users are provided with options to enable or disable use of one or more of the features for use in such prediction. Users can also disable access to all the features and/or turn off the prediction. The machine learning model is implemented locally on the UE and the values of the features are utilized specifically for prediction. The output produced by the machine-learning model includes, for example, predicted time of next data transfer, predicted start of next inactive period, etc.

The machine-learning model is trained by use of training data that includes example pairs of input features and corresponding outputs. When users permit, the machine-learning model learns during operation, e.g., by comparing predicted and actual times of next data transfer/ start of next inactive period.

In this manner, the UE predicts the anticipated times of data transfer. The predictions are utilized at the UE to request or defer a transition to dormancy. For example, if it is anticipated that significant data transfer is expected in the near future, the UE requests the network to maintain the active RRC mode. If it is anticipated that significant data transfer is some distance away in the future, the UE requests the network to transition the UE to dormant RRC mode. In this manner, the UE drives its own active-dormant transitions, with such transitions based on anticipated data volume, rather than simply on the expiry of a timer.

The machine-learning model can be a regression-based model. Alternately, the model can be implemented as a multi-layer neural network, e.g., a long short-term memory (LSTM) neural network. Other types recurrent neural networks, and other models such as convolutional neural networks, and techniques such as support vector machines, random forests, boosted decision trees, etc., can also be used to implement the machine learning model.

CONCLUSION

The decision to move a mobile device to dormant radio resource state is typically driven by the mobile network. For example, after a period of observed inactivity, the network may move the mobile device to dormancy. However, mobile applications may send data shortly after the mobile device is moved to dormancy which results in sub-optimal power and bandwidth use. This disclosure provides techniques that enable the mobile device to predict immediate data transmission requirements. The predictions are used by the mobile device to drive active-dormant transitions at the radio resource control (RRC) layer.