Reducing Distraction of Smartwatch Users with Deep Learning

Jemin Lee, Jinse Kwon, and Hyungshin Kim

Department of Computer Science and Engineering,

Chungnam National University, Republic of Korea







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- The smartwatch allows us to be aware of newly available notifications in real-time.
- But, users confront a huge variety of notifications.
 - SNS events (new post and location checkout), new application updates, won badges, or reminders.







Goal

 Design a system for intelligent notification delivery between smartphone and smartwatch.

 Define a important notification from real usage data and prior assumption.

 Build machine learning model and then deliver only a <u>important notification</u> to a smartwatch from a smartphone.



Definition of Important notification

 From prior research's results [Mehrotra et al. UbiComp'15], we assume that a important notification meets the following conditions:

• It triggers application launch to take further actions.

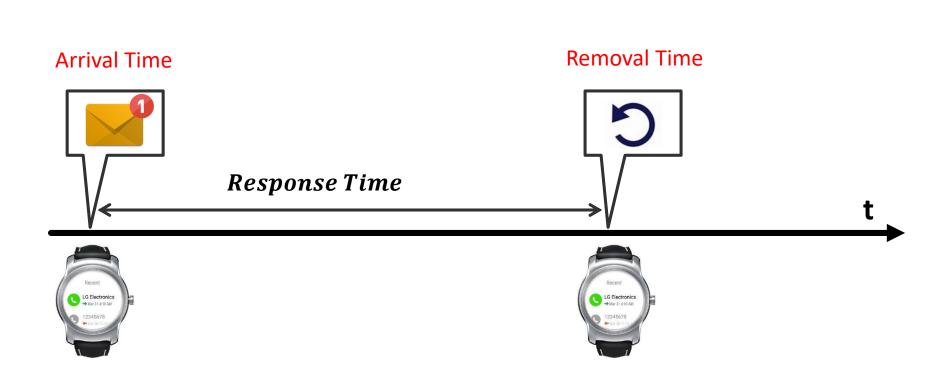
• The notification is reacted within 10 minutes.





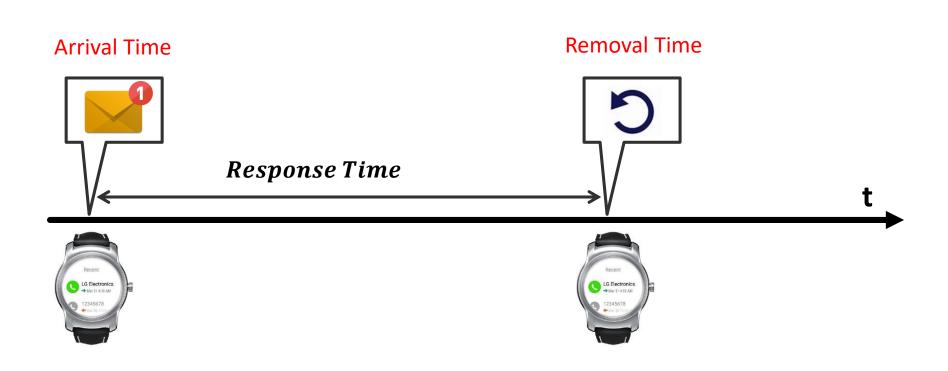


Response Time = Removal Time – Arrival Time



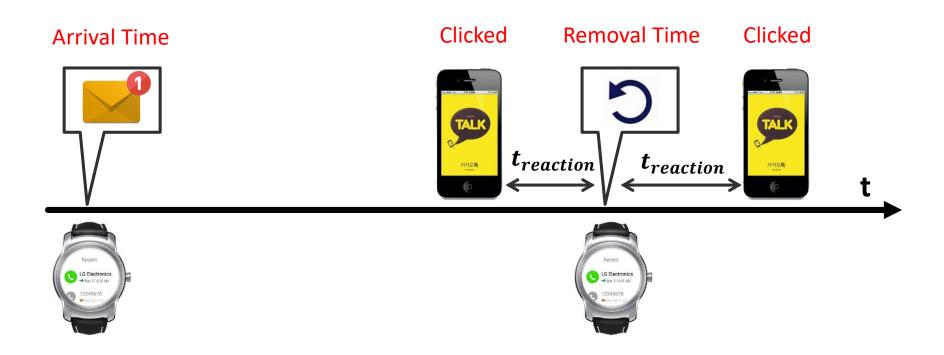


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- Check whether the application was launched.



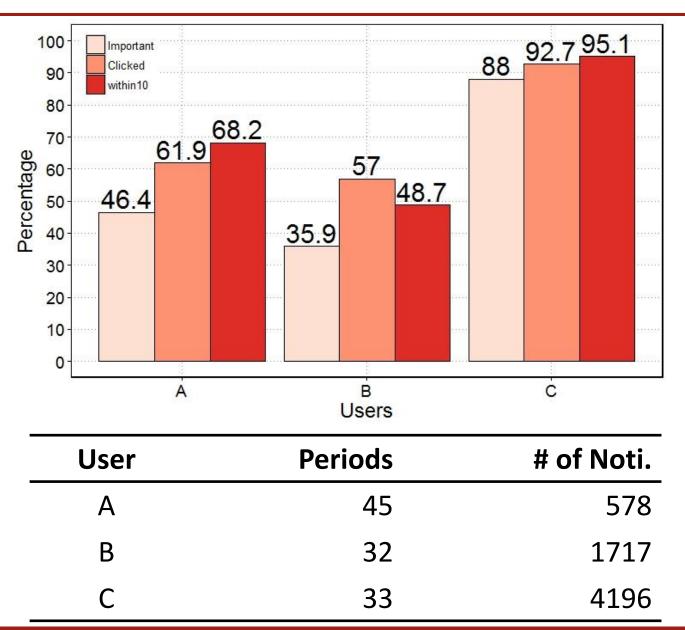


- Develop <u>nCollector</u> that can unobtrusively capture the notification labels and context data.
- LG Urbane W 150.
- Participants:3 (no monetary incentive)
 - 2 male and 1 female with the age span between 25 and 35 years.
- Collect total <u>6,491</u> notifications.

• Duration: 4 weeks on average.

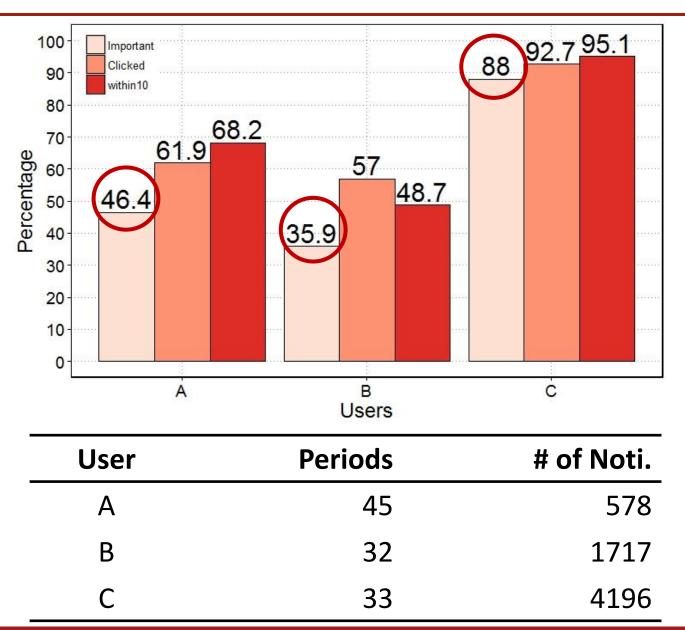


nCollector Dataset





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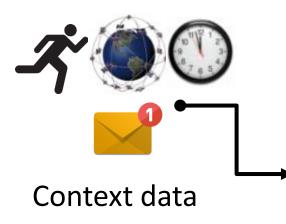
- Notification label: IsImportant = {TRUE, FALSE}
- Extract 8 features by using <u>R caret package</u>.
 - Sender application name
 - Notification Priority
 - Notification Title
 - Physical Activities: InVehicle, OnDicycle, OnFoot, Running, Still, Tilting, Walking, and Unknown
 - Time of day
 - Day of the week
 - Recent Phone Usage
 - Proximity



- Hypothesis: sensed context can identify the important notification.
- Training DNN with <u>TensorFlow (Supervised Learning)</u>

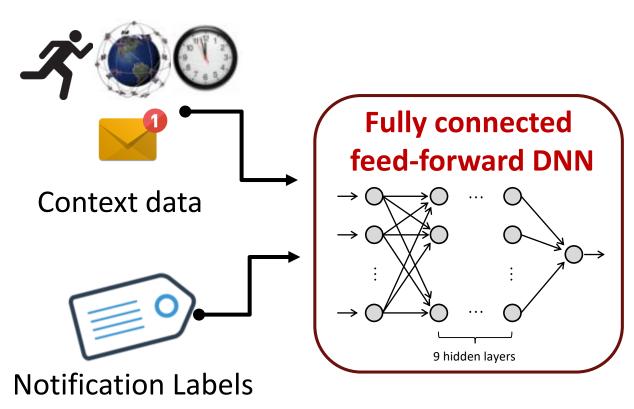


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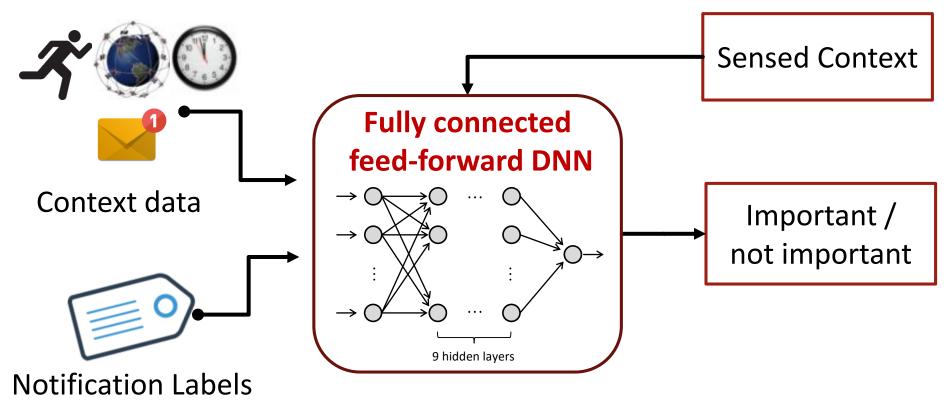


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- Users can check all the notifications on the smartphone.
- User B shows the worst precision and recall.
 - Using an desktop PC, rather than mobile devices.



Limitations and Discussion

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- Poor accuracy of prediction model.
 - The prediction model is trained by means of misclassified notification label.

Thank You

Questions?

Jemin Lee Email: leejaymin@cnu.ac.kr





Summary

 6,491 notifications and sensor data from three users were unobtrusively collected in the wild.

• A binary classifier, which identifies important notifications using deep learning, is implemented.

• The important notification can be predicted with an average precision of 74% and a recall of 72%.



- Smartphone, tablet and smartwatch are emerging and widely used.
- Users carry several mobile devices
- Our obsession with smartphones is a good example of what has been referred to as the "paradox of technology." The modern smartphone can free us to do things in places only dreamed of 20 years ago, but they also, in certain ways, enslave us. Has smartphone use reached a tipping point, where it's crossed the line from beneficial tool to detriment?

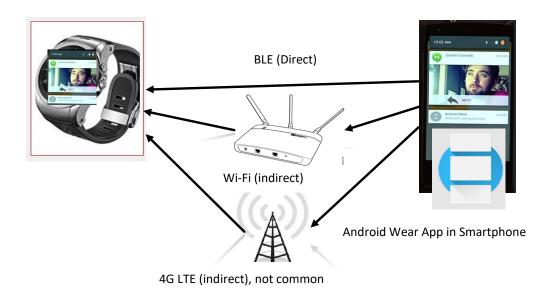
Key Benefits of Mobile Notifications

- A veracity of mobile devices, including smartphone, tablet, and smartwatch are emerging and widely used.
- They allow a recipient to be aware of newly available information in real-time.
- Also, They enable a sender to initiate a remote communication.
- Today, many users of mobile devices are continuously confronted with a huge variety of information.



Issues with Mobile Notifications

 Current notification delivery system pushes a notification all connected mobile devices like smartwatch.



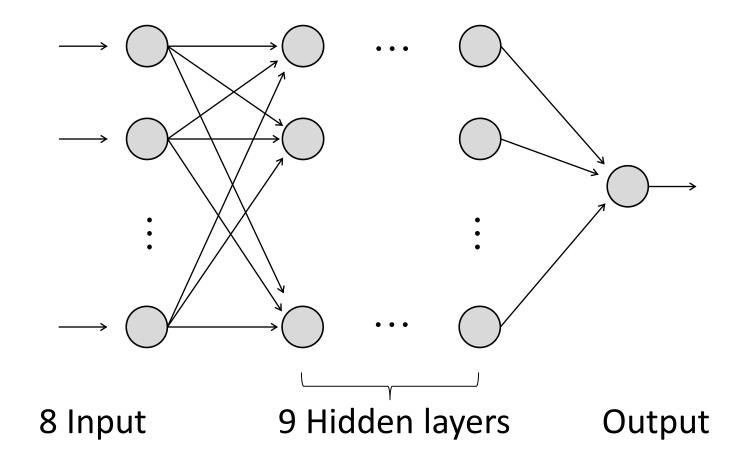
 For smartwatch, users can be much more distracted by the delivered notifications at the inopportune moments.



- HCI communities have proposed various techniques to remedy distraction issue.
- However, all prior works have focused on predicting opportune moment in a single device.
 - InterruptMe: designing intelligent prompting mechanisms for pervasive applications, UbiComp 2014.
 - Designing content-driven intelligent notification mechanisms for mobile applications, UbiComp 2015.
- Our work has concentrated on reducing notification delivery between a smartwatch and a smartphone.



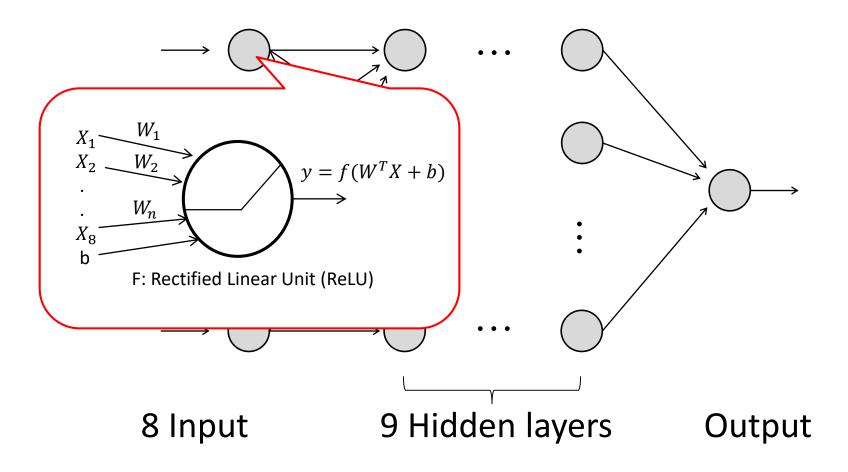
• Designed model is fully connected 11-layer feed-forward neural network, consisting of 9 hidden layers.







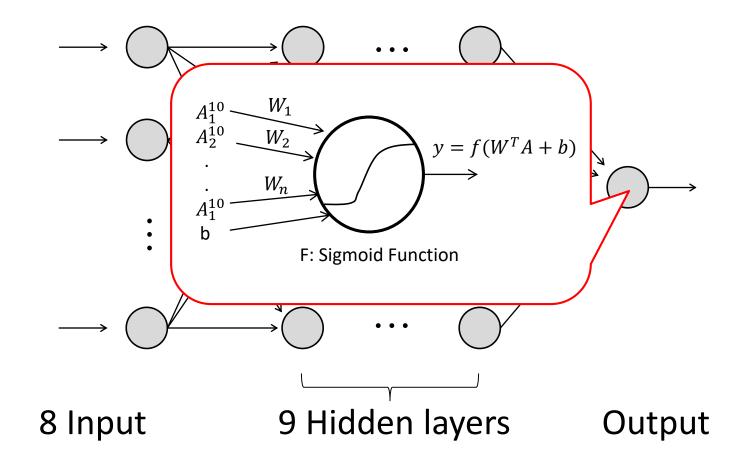
 For training, we selected <u>ReLU</u> as the activation function to avoid vanishing gradient problem







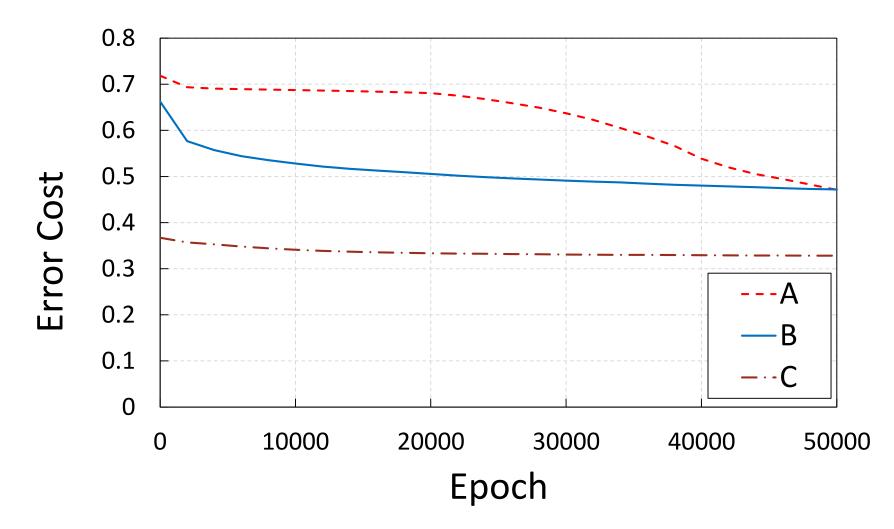
 To convert continuous data into nominal data, the final layer is interpreted as a logistic regression.







• Learning rate 0.001







- Split data into two sets: training(70%) and testing (30%).
 - Precision =
 # of important notific

of important notifications that are correctly predicted # of predictive important notifications

• Recall =

of important notifications that are correctly predicted # of notifications that are actually important

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А	71%	65%
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