Context-aware Interventions for Wellness

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• Introduction
  • What is context-aware interventions for wellness and why we need it?

• Context-aware intervention framework
  • Three main steps:
    • Perception
    • Identification
    • Intervention
  • Key technologies:
    • Multi-modal data representation
    • Knowledge-driven search & recommendation
    • Intent/situation understanding

• Summary
• Different types of interventions:
  • Screening
  • Vaccination
  • Supplementation (e.g. iodised salt to prevent goitre)
  • Behavior change (e.g. promotion of healthy behavior)

• Subject to:
  • Obesity
  • Drug, tobacco, and alcohol use
  • The spread of infectious disease

• **Long-term** effort aiming to improve mental and physical health on a **population level**

• With AI technology, we can deliver **real-time** context-aware interventions on an **individual level**
Goal: take right intervention actions for the right person at the right time and right situations to improve the individual’s wellness

Different ways of interventions:
- Context-aware recommendation
- Realtime nudge and notification
- Conversation with health-oriented chatbot

In different contexts:
- Personalization and user profiling
- Temporal and periodic context
- Location, activity, and health status
Framework for Context-aware Interventions

Perception

Intervention

Identification
Framework for Context-aware Interventions

Perception

Intervention

Identification
• Life Logging: Devices
  • Smartphones
    • GPS and Wifi
    • Foot Steps
    • Accelerometer
  • Wearable devices
    • Heart rate
    • Body temperature
    • Activity level
    • Autographer camera
    • …
• Sensing users’ physical activity in real-time
• NTCIR Lifelog Task:
  • http://ntcir-lifelog.computing.dcu.ie/index.html
  • Data: two months of rich lifelog data from two people,
    Including:
    • Autographer capturing two images per minute
    • Music listening history
    • heart rate, calorie burn, steps
    • Blood Sugar levels every fifteen minutes
    • locations visited
    • Physical activities

• Tasks:
  • LADT: Lifelog Activity Detection (sub) Task
  • LSAT: Lifelog Semantic Access (sub) Task
  • LIT: Lifelog Insight (sub) Task
• Food/nutrition recognition
• Through food image recognition wearable sensors

Figure 2: Food/ Nutrition Recognition Techniques
• DietLens: a mobile food App to recognize more than one thousand hawker and fast food dishes in Singapore (Ming et al., 2018)
• Log users’ online behavior
  • Activities on Social Networks
  • Activities on Search Engines
  • Activities on eCommerce Websites

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Framework for Context-aware Interventions

Perception

Intervention

Identification
• Music mood classification based on lifelog (Tong et al., 2018)
  • Collecting lifelog of 9 users
  • Label music mood on Thayers 2-D mood model
  • Predict music mood with lifelog and music features
  • Evaluation metric: Manhattan distance on 2-D mood coordinate

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• Identify pregnancy from Search Logs (Fourney et al., 2015)
  • Identify searchers experiencing pregnancy with queries like “I am N weeks pregnant”
  • Exploring the time-dependent concerns about pregnancy
  • Applications: Supporting mothers through personalized search and aggregation of pregnancy experiences

Histograms of query bigrams over 40 weeks of gestation

Histograms of query bigrams for the 24 weeks following inferred birth dates
• Identify depression using social network activities (Shen et al., 2017)
  • Identify depressed users by a strict pattern appeared in tweet:
    • (I’m/ I was/ I am/ I’ve been) diagnosed depression
  • Identify non-depressed users:
    • Never post a tweet containing the substring “depress”
  • Using multimodal features from social networks and a depressive dictionary learning method to predict whether a user is depressed or not
  • Performance: F1-score=85%
Framework for Context-aware Interventions

Perception

Intervention

Identification
Interventions: Recommendation

- Recommending product or food that will benefit user’s health condition
- Intervention when the user has an intention to buy product or food
- Personalized, explainable recommendation according to individual’s health condition

Recommendation for your health:
- Control calories intake
• Proactively prompt user with health suggestions at the right time

• For example:
  • To get people to be more active, set a reminder, “Remember to increase your number of foot steps today”
  • To ensure enough sleep, send a message at 11:00 PM, “It is time for bed, good night!”
  • To develop a healthy diet, promote healthy eating before lunch and prompt users to log food intake during the meal

• Anticipate users’ intention based on the current context

• Use reinforcement learning to test and learn how to effectively nudge the user to a healthier direction
• Chatbot technology can offer:
  • The most natural way to communicate with users
  • An highly interactive interface that encourage users to engage
  • Clarify user’s health related concerns and information needs

• Intervention at the right time in the conversation
  • To answer users’ health-related questions
  • To recommend healthy product and food
  • To educate and influence users with healthy life style
Framework for Context-aware Interventions: Key Technologies

Perception

Identification

Intervention

Multi-modal data representation

Knowledge-driven search & recommendation

Intent/situation understanding

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• Data collected in the perception step is multi-modal
  • Visual data from Autographer camera and food logging
  • Time-series data from wearable device
  • Structured and unstructured data from life and cyber logging

Figure 6: Prototype App Released to NUS community

Figure 7: Patient Mobile App: Lifestyle tracking functions

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• Modeling multi-modal data with unified representations

Food recognition model in (Chen et al., 2017)

Multimodal depressive dictionary learning framework in (Shen et al., 2017)
• Modeling multi-modal information with a tree based model
• CIKM2018 Best Overall Paper (Zhang et al., 2018)
• Knowledge-driven Search & Recommendation
  • Health constraints on search and recommendation models
  • Explainable search and recommendation

Explicit factor models for explainable recommendation (Zhang et al., 2014)

Tree-enhanced embedding model for explainable recommendation (Wang et al., 2018)
• To provide context-aware intervention, we need to detect user intent from the perception data

• Define user intent in product search (Su et al., 2018)
  • Three types of intent: Target Finding (TF), Decision Making (DM), and Exploration (EP)
  • Observe different user interaction patterns as well as perceived satisfaction under these three intents

• Characterize and predict user intent in image search (Xie et al., 2018)
  • Three types of intent: Explore/Learn, Locate/Acquire, and Entertain
  • Predict user intents with dwell time, click, query reformulation, and mouse movement features
Summary

Perception

Intervention

Identification

Multi-modal data representation

Knowledge-driven search & recommendation

Intent/situation understanding


