User Gender Prediction
Using Browser Interaction Pattern

Electrical and Computer Engineering | Carnegie Mellon University
Heng-Tze Cheng | Feng-Tso Sun

Motivation & Problem

Motivation

- User demographic profile (gender/age): important for customized web service / targeted advertising
- Hard to acquire labels directly through form-based survey: burden on users, security & privacy issues

Previous Work

- Use visited webpage/URL history, text features

Research Problems

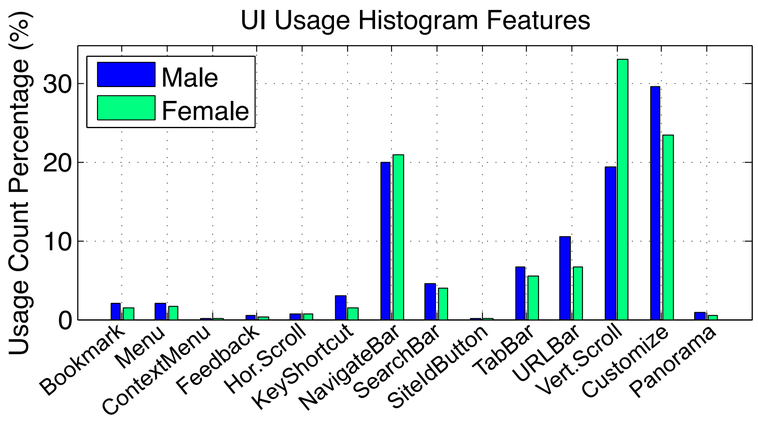
- How to predict a user's gender using browser UI interaction history?
- How to use the unlabeled data to improve the prediction accuracy?

Dataset

Firefox 4 Beta Interface Test Pilot dataset

- The history of browser UI interaction collected from 1,134 users (567 male, 567 female) within a test duration of 7 days
- Each sample X is in the format of (U, C, t)
  " User U used the UI component C at time t "
- Target gender label Y = {Male, Female}

Feature Extraction & Gender Classification



UI Usage Histogram Feature

- The percentage of time spent on each of the 14 UI categories
- The percentage of time spent on each of the 94 UI items

UI Item Transition Rate Feature

- Mean, median, and standard deviation of the time difference of successive UI item click

Within-Category UI Usage Interval Feature

- Mean, median, and standard deviation of the time interval within the same UI category identifier

Dimensionality Reduction

- Use Principle Component Analysis (PCA): Reduce 139 original feature dimensions to 20 dimensions

Supervised Learning

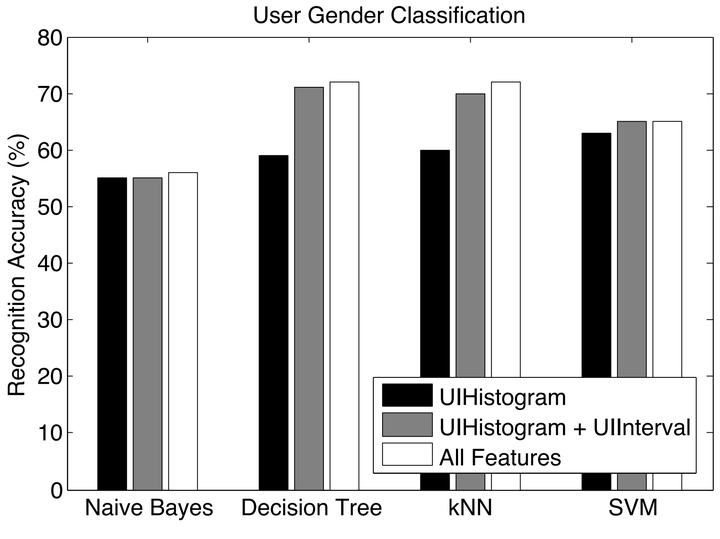
- Compare Naïve Bayes, Decision Tree, k-NN, and SVM
- Experiment setting: 10-fold cross validation

Semi-Supervised Learning

- Self-Training Algorithm
  - For each iteration train a classifier from labeled data L
  - Classify samples in unlabeled data U
  - Add m most-confident classifications to L (m = 10)
- Experiment setting: Initial |L| = 85, |U| = 766, |TestSet| = 283 (25%)

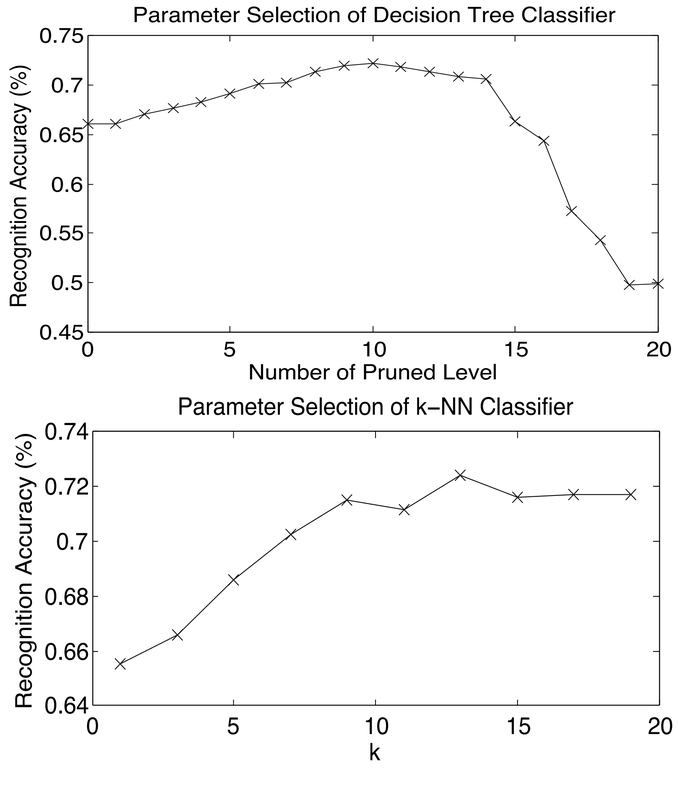
Experimental Results

Feature/Classifier Combinations

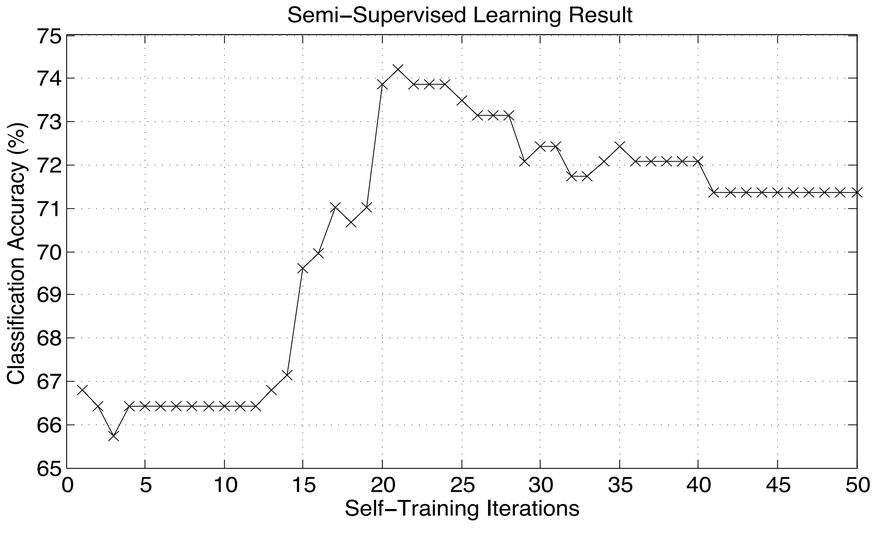


- k-NN and Decision Tree achieve 72% accuracy using all features
- UIHistogram & UIInterval more useful than UITransition

Parameter Selection



Semi-Supervised Learning Result



- 67% accuracy with initial 85 labeled data
- 766 unlabeled data were provided
- Converged to 72% after 50 iterations