Analyzing Web Logs to Detect User-Visible Failures

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Road Map

I. Introduction

II. Technique

III. Model Training

IV. Evaluation

V. Discussion

VI. Conclusion

INTRODUCTION

- Web applications suffer from poor reliability
  - Top 40 Web sites about 10 days of downtime per year
  - 32% of shoppers experienced online shopping problems during the 2006 holiday season
  - 89% of all online customers experienced errors

Practitioners rely on fast failure detection and recovery to reduce the effects of failures on other users.

INTRODUCTION

- Early failure detection can mitigate about 65% of failures

- Failure detection is challenging
  - Requires up to 75% of failure recovery time

- User feedback has limited help for detecting failures
  - User survey of www.clinicalguard.com in 2008
    - 200 users
    - 9 responses
    - 1 specified the failure

Existing Detection Techniques

- Resource usages analysis
  - Constructing statistics using data of resources usage
    - Focusing on performance failures
    - Not on failures related to software bugs
- Runtime components interaction analysis
  - Detecting runtime execution path anomalies
  - Not always effective to software bugs
- User-behavior-based analysis
  - Analyzing request bursts to a URL/resource
    - Assume users refreshing browsers for failures
  - Users have different behavior than refreshing

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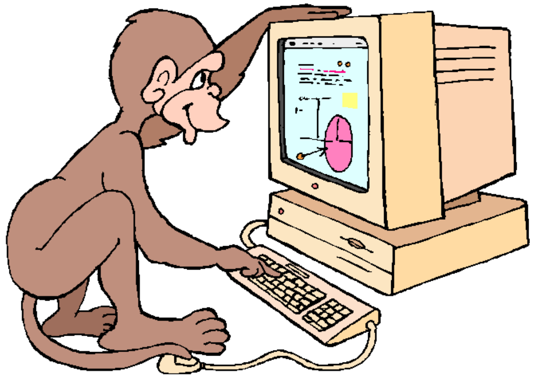
Overview

The Goal: Detecting failures caused by software bugs

Assumptions



HCI Rational Principle

Users must respond if the result of a sequence of interactions is not satisfactory

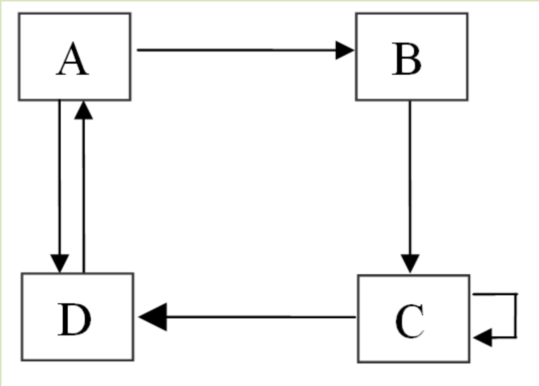
Navigation Patterns

- Web users follow certain navigation patterns
- Users' response to failures may break these patterns

The Idea: Detecting anomalous navigation paths as indications that users encountered failures

The Model

- A directed graph representing a Web site
  - Nodes are Web pages
  - Edges are users' navigation



S={A, B, C, C, D, A, D}

- A Markov model in the 1st order for estimating the probability of a navigation path
  - The transition probability to the next state is conditionally dependent on only the current state

P[AB]=P[A]P[B|A]

P[S]=P[A]P[B|A]P[C|B] P[C|C] P[D|C] P[A|D] P[D|A]

Transition Probability

- Two types of transition probability
  - Outgoing Transition Probability (OTP)
    The probability that users go from page A to page B
  - Incoming Transition Probability (ITP)
    The probability that users at page B coming from page A
- OTP usually is different from ITP
  - A user can navigate to the Home page from any page
  - But not vice versa

Occurrence Probability for Failure Detection

- Given a sequence of user requests
  - Compute the occurrence probability
  - Using 1st-order Markov model

- Outgoing Occurrence Probability (OOP)
  The occurrence probability computed using OTP

- Incoming Occurrence Probability (IOP)
  The occurrence probability computed using ITP

If *min* (OOP, IOP) < *threshold*
Raise a failure alarm

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Bayesian Learning

- Assume
  - The parameter to estimate is a random variable
- Estimate
  - The distribution of the parameter as a random variable
  - A statistic as the estimator
- Process
  - Assume a distribution of the parameter
  - Find a *conjugate prior distribution*
  - Compute the *posterior distribution*
    - Update the prior distribution using the training data
  - Decide an estimator
    - *posterior mean*: the mean of *the posterior distribution*

Bayesian Learning Transition Probability

- Bayesian Learning to train a First-order Markov Model
  - A Multinomial distribution
  - A Direchlet distribution as the conjugate prior

- Learn Outgoing/Incoming Transition Probability

- The learning process
  - A small amount of training data for setting prior
  - The rest training data for updating prior
  - *The posterior mean* as the estimator

Estimated Transition Probability

$$\hat{\theta}_{ij} = \frac{n_{ij} + \alpha q_j}{n_i + \alpha}$$

$\hat{\theta}_{ij}$	Estimated OTP from state *i* to state *j*
n_i	All hits on state *i* in data for setting the prior
n_{ij}	Transitions from *i to j* in data for setting the prior
α	All hits on state *i* in the rest training data
q_j	Transition frequency from *i to j* in the rest training data

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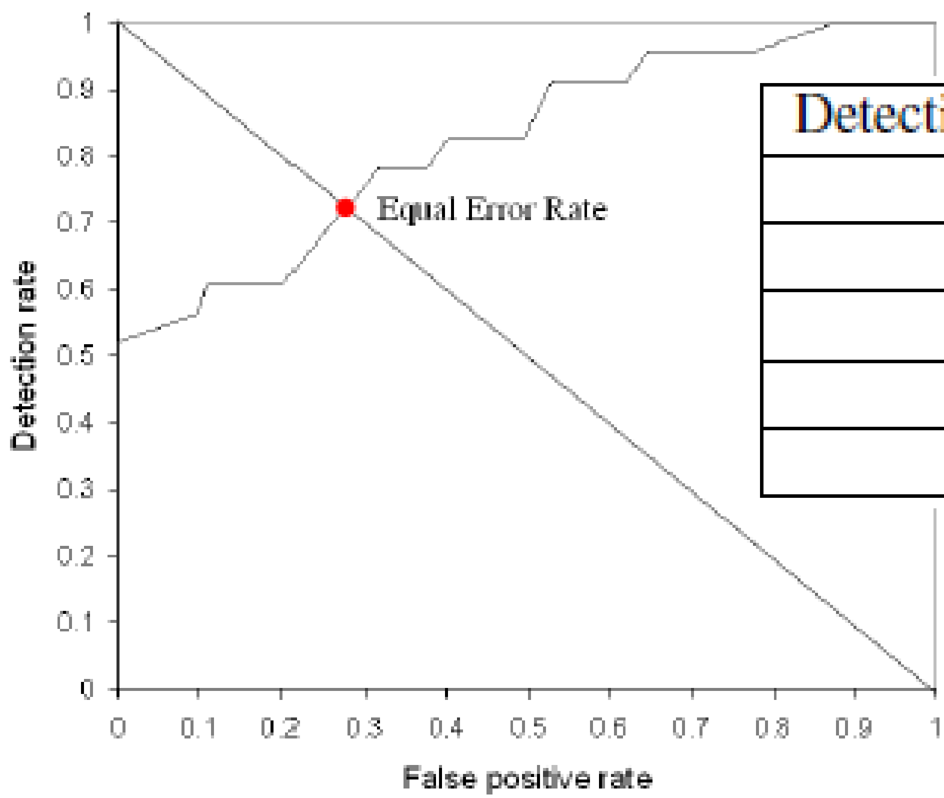
Subject

- NASA Web site
- Construct user-sessions using one month access log
  - 1,891,714 HTTP requests from real users
- Training data $\hat{\theta}_{ij} = \frac{n_{ij} + \alpha q_j}{n_i + \alpha}$
  - $n_i \; n_{ij}$ Prior: 572 user-sessions on 1st day
  - $\alpha \; q_j$ Learning: 2404 user-sessions on 2nd to 10th day
- Testing data
  - 7941 non-error sessions for detection
  - 500 error sessions for false positive

Result



Detection Rate	False-positive Rate
0.60	0.11
0.70	0.26
0.80	0.40
0.90	0.53
1	0.87

Equal Error Rate (i.e., EER): the decision boundary
when detection and false-positive have the same loss function.
Our model's EER=0.71/0.26

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Discussion

- Improving the detection power
  - Semi-Markov model (e.g., time)
  - Hidden state
- The “ground truth”
  - Error sessions as user-visible failures
- More case studies
  - Controlled environments
    - Recruit users
    - Instrument real-world Web sites

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Conclusion

- Detecting User-visible failures
  - Improving both reliability and user's satisfaction
- User's behavior changes when encounter failures
  - Breaking navigation patterns
- Our technique detects anomaly user navigation paths
- The experiment results demonstrate our technique can detect failures with reasonable cost
- Future work aims at model improvements and case studies

Thank You!