Machine Learning for Big Data Systems Acquisition

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Motivation

Acquisition Aspiration

• “Choose a modern technology stack” (playbook.cio.gov)

Acquisition Reality

• “The subject matter competencies for successful enterprise IT system acquisition are often missing in government” (GAO)

Trusted knowledge bases are part of the solution

• In FY14 we built knowledge base for NoSQL technology
  • Quality at Scale for Big Data – QuABaseBD
  • [http://quabase.sei.cmu.edu](http://quabase.sei.cmu.edu)
  • Knowledge model – categories, features, allowable values
• Expensive to curate - populate and maintain knowledge as products evolve
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Research Question:
Can we automatically identify relevant document pages that contain the knowledge required for a curator to populate the knowledge base for a product feature?

Approach:
- 2-level supervised machine learning classifier
  - Document model
  - Sentence model
- Train using QuABaseBD contents
- Assess classifier precision, simultaneously extend training set with labeled documents and passages
- Measure classifier improvement
Challenges of Technical Knowledge Curation

Quantity of Information and Diversity of Structure

• Oracle NoSQL – 1000s of fine-grained pages, multiple “volumes”
• Accumulo – single web page with all documentation topics

Ambiguous Terminology

• CAP – fundamental quality tradeoff in distributed systems
  • Consistency – Replica or transactional?
  • Availability – System property or semantic dependency (“feature X is available only when configuration flag Y is enabled”)
  • Partition – network failure or database shard?

Unsupported Features

• Rare to find explicit statement that a feature is not supported
• Closed-world assumption requires rich feature dependency model
Experiment Approach

1. Explore Database Technologies and Features
   - Extract Features, Feature Values, Curated URLs for Database Collection #1
     - Initial Classifier

2. Seed URLs for database collection #2
   - Documentation URL
     - Recommended URLs for each Feature
       - Ranked Lists
       - Security – Comparing Precision for Non-Features against Features
         - Security - All
         - Security - Non-Features Excluded

3. Ranked Lists
   - Passage level labeling
     - Improved Classifier
     - Documentation URL for database collection #3
     - Ranked Lists
     - Precision assessment by curators
Results Towards Automation

Precision better for supported features (Orange bars) (p=0.03)

Sensitive to
- Documentation structure
- Product feature-richness

Classifier performance improved as training set was extended
Future Work

Classifier performance was limited by available training data
  • Extend training sets and identify limit of classifier performance
  • Assess classifier performance on other knowledge base feature categories
Systematically investigate performance sensitivities to develop confidence measures
  • Quantify differences in document structure and writing style, product feature-richness, other heuristics
Assess classifier performance on new versions of product/documentation
  • Knowledge base evolution/maintenance scenario may be more automate-able
Research Team

Principal Investigator: Prof. Ian Gorton (Northeastern U., ex-SEI)

Classifier Development: Prof. Yiming Yang
   (CMU Language Technology Institute)

Domain Experts: Soumya Simanta
   (SEI)  John Klein