Question Classification in English-Chinese Cross-Language Question Answering: An Integrated Genetic Algorithm and Machine Learning Approach

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Outline

- Introduction
- Research Background
- Methods
  - Hybrid GA-CRF-SVM Architecture
- Experimental Design
- Experimental Results and Discussion
- Conclusions

Introduction

- Question classification (QC) plays an important role in cross-language question answering (CLQA)
  - QC: Accurately classify a question in to a question type and then map it to an expected answer type
  - “What is the biggest city in the United States?”
  - Question Type: “Q_LOCATION_CITY”
  - Extract and filter answers in order to improve the overall accuracy of a cross-language question answering system

Introduction (cont.)

- Question informers (QI) play a key role in enhancing question classification for factual question answering
  - QI: Choosing a minimal, appropriate contiguous span of a question token, or tokens, as the informer span of a question, which is adequate for question classification.
  - "What is the biggest city in the United States?"
  - Question informer: "city"
  - "city" is the most important clue in the question for question classification.

Introduction (cont.)

- Feature Selection in Machine Learning
  - Optimization problem that involves choosing an appropriate feature subset.
  - Hybrid approach that integrates Genetic Algorithm (GA) and Conditional Random Fields (CRF) improves the accuracy of question informer prediction in traditional CRF models (Day et al., 2006)
- We propose an integrated Genetic Algorithm (GA) and Machine Learning (ML) approach for question classification in cross-language question answering.

Research Background

- Cross Language Question Answering
  - International Question Answering (QA) contests
    - TREC QA: 1999~
      - Monolingual QA in English
    - QA@CLEF: 2003~
      - European languages in both non-English monolingual and cross-language
    - NTCIR CLQA: 2005~
      - Asian languages in both monolingual and cross-language
- Question Classification
  - Rule-based method
  - Machine Learning based method

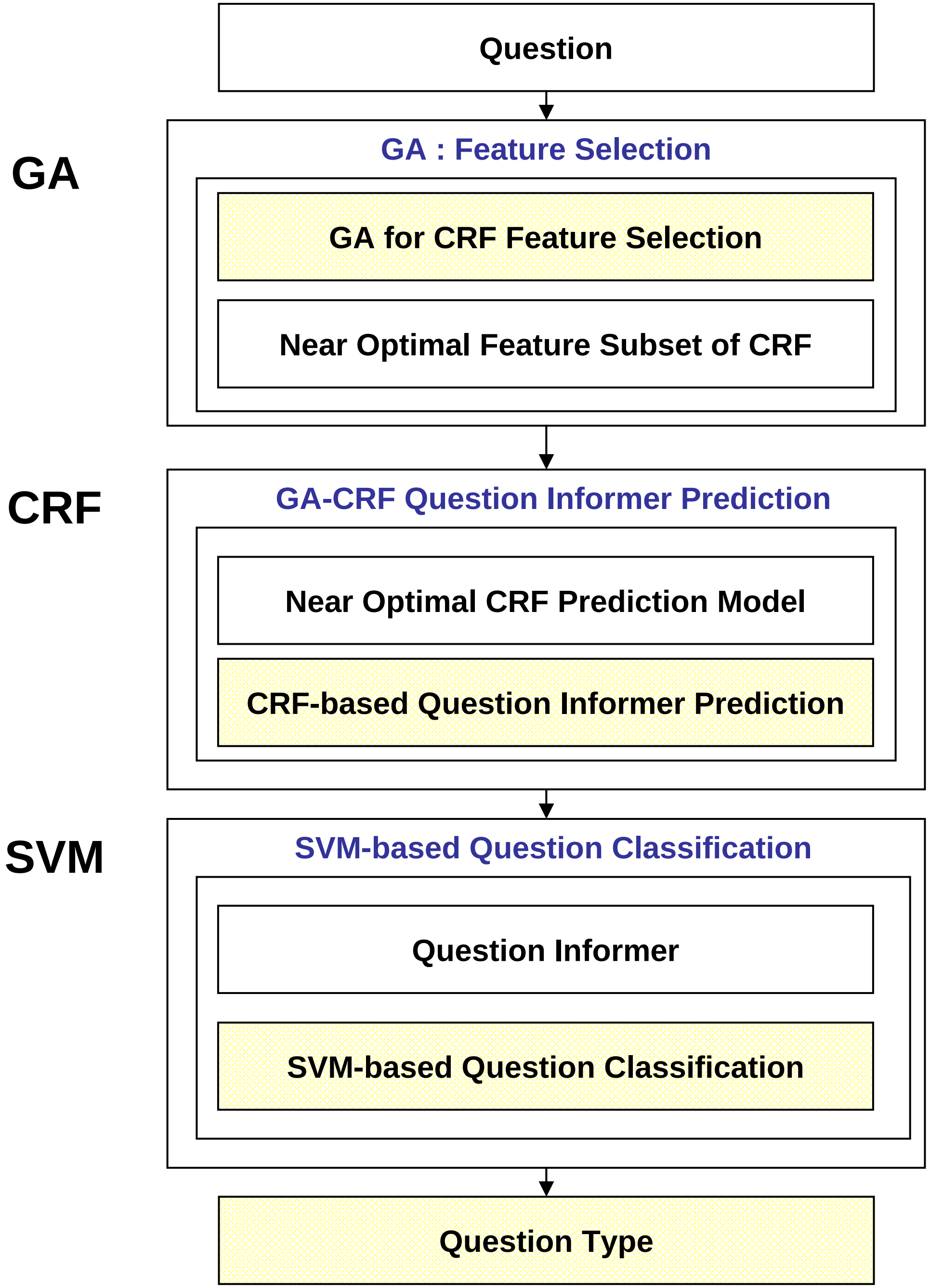
Research Background (cont.)

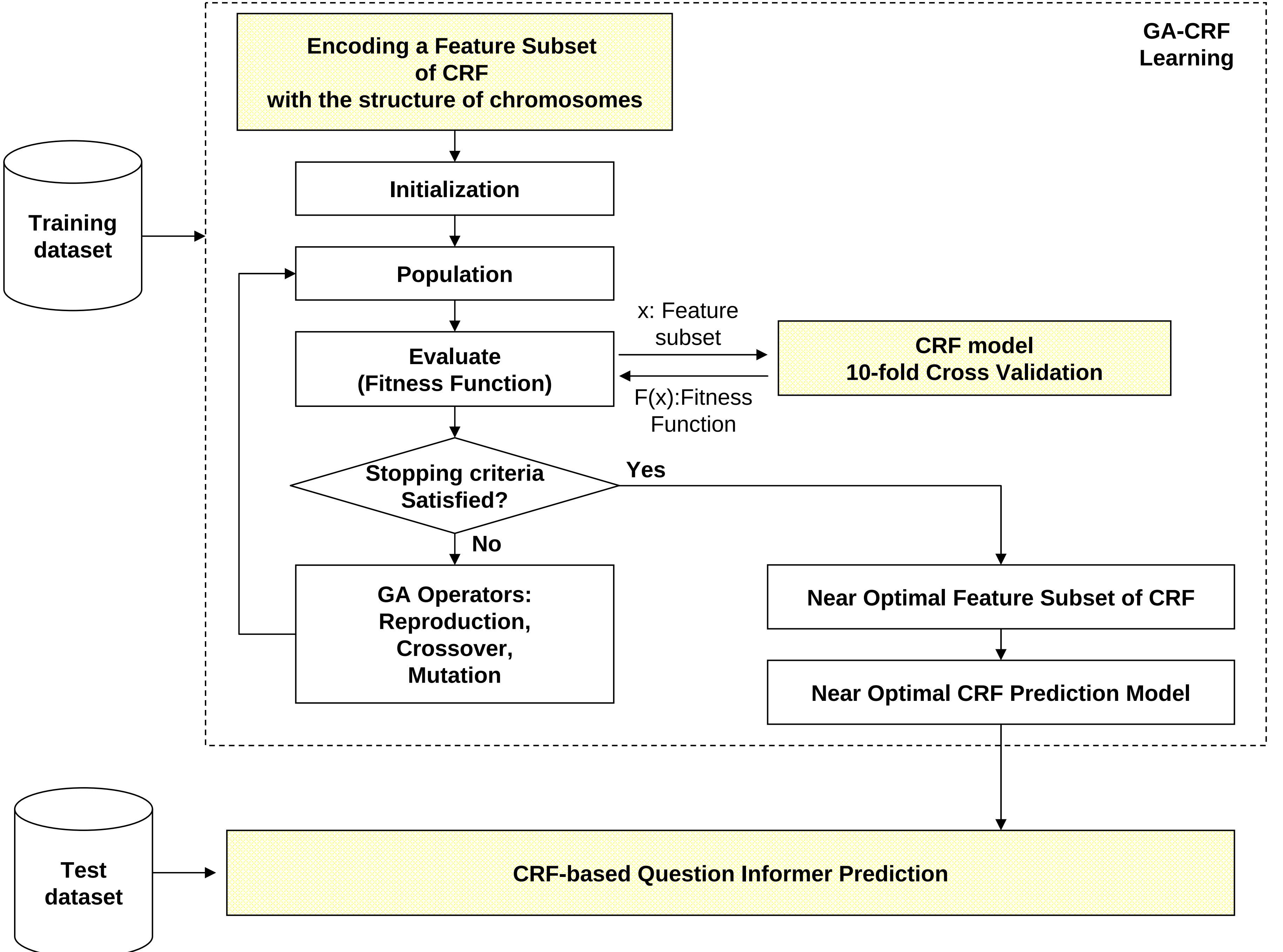
- Two strategies for question classification in English-Chinese cross-language question answering
  1) Chinese QC (CQC) for both English and Chinese queries.
     - English source language has to be translated into the Chinese target language in advance.
  2) English QC (EQC) for English queries and Chinese QC (CQC) for Chinese queries.
- We focus on question classification in English-Chinese cross-language question answering
  - Bilingual QA system for English source language queries and Chinese target document collections.

Methods

- Hybrid GA-CRF-SVM Architecture
  - GA for CRF Feature Selection
  - GA-CRF Question Informer Prediction
  - SVM-based Question Classification using GA-CRF Question Informer

Hybrid GA-CRF-SVM Architecture





GA-CRF Question Informer Prediction

Experiment Design

- Data set for English Question Classification
  - Training dataset (5288E)
    - 4,204 questions from UIUC QC dataset (E)
    - + 500 questions from the NTCIR-5 CLQA development set (E)
    - + 200 questions from the NTCIR-5 CLQA test set (E)
    - + 384 questions from TREC2002 questions (E)
  - Test dataset (CLQA2T150E)
    - 150 English questions from NTCIR-6 CLQA's formal run
- Data set for Chinese Question Classification
  - Training dataset (2322C)
    - 1238 question from IASL (C)
    - + 500 questions from the NTCIR-5 CLQA development set (C)
    - + 200 questions from the NTCIR-5 CLQA test set (C)
    - + 384 questions from TREC2002 questions (translated) (C)
  - Test dataset (CLQA2T150C)
    - 150 Chinese questions from NTCIR-6 CLQA's formal run

Experiment Design (cont.)

- Features for English Question Classification
  - Syntactic features
    - Word-based bi-grams of the question (WB)
    - First word of the question (F1)
    - First two words of the question (F2)
    - Wh-word of the question (WH)
      - i.e., 6W1H1O: who, what, when, where, which, why, how, and other
  - Semantic features
    - Question informers predicted by the GA-CRF model (QIF)
    - Question informer bi-grams predicted by the GA-CRF model (QIFB)

Experiment Design (cont.)

- Features for Chinese Question Classification
  - Syntactic features
    - Bag-of-Words
      - character-based bi-grams (CB)
      - word-based bi-grams (WB).
    - Part-of-Speech (POS)
  - Semantic Features
    - HowNet Senses
      - HowNet Main Definition (HNMD)
      - HowNet Definition (HND).
    - TongYiCi CiLin (TYC)

Experiment Design (cont.)

- Performance Metrics
  - Accuracy

$$Accuracy = \frac{Number\ of\ corrected\ question\ types}{Total\ number\ of\ questions}$$

  - MRR (mean reciprocal rank)

$$MRR = \frac{1}{M}\sum_{i=1}^{M}\frac{1}{rank_i}$$

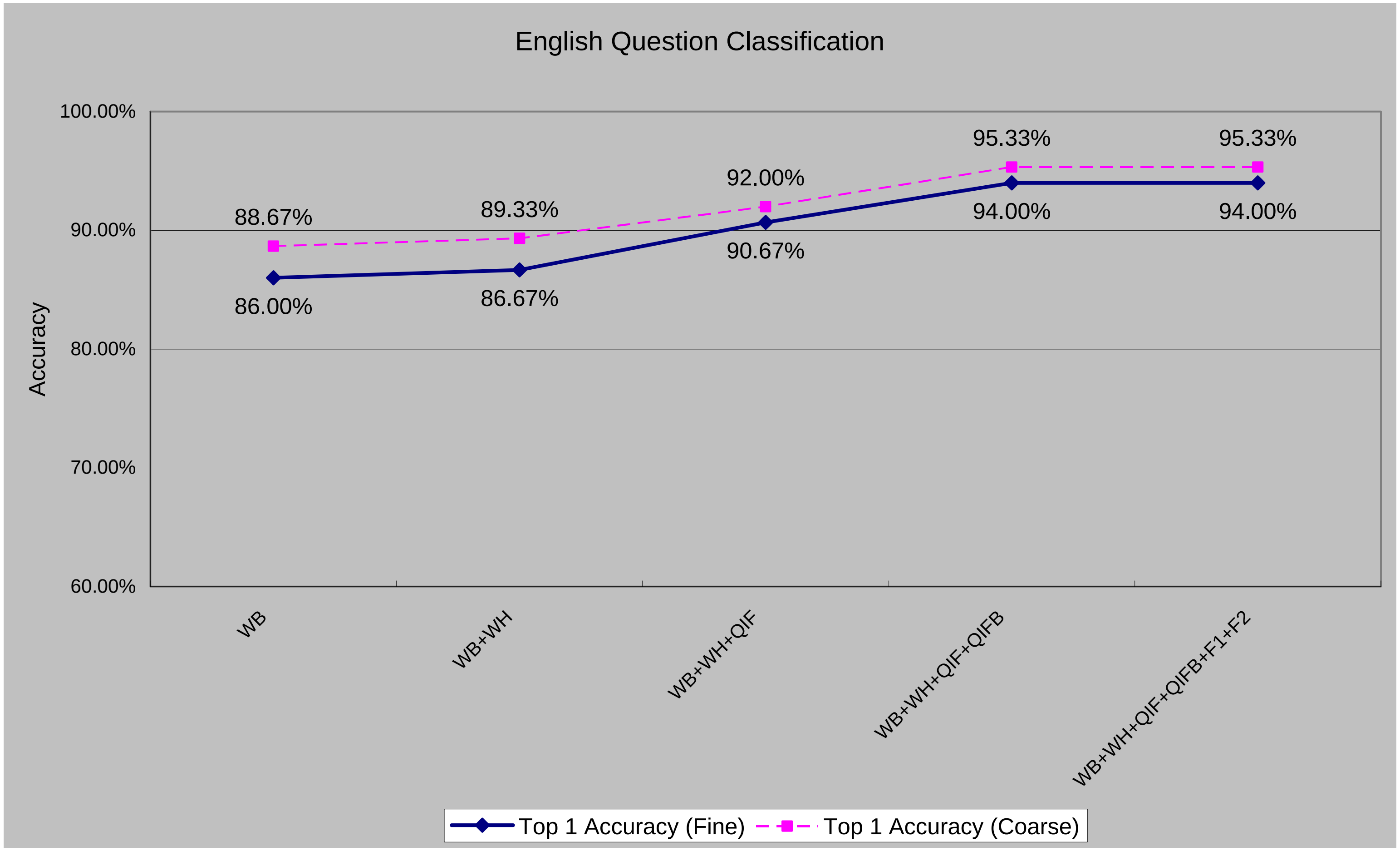
where $rank_i$ is the rank of the first *corrected* question type of the i^{th} question, and M is total number of questions.

Experimental Results

- Question informer prediction
  - Using GA to optimize the selection of the feature subset in CRF-based question informer prediction improves the F-score from 88.9% to 93.87%, and reduces the number of features from 105 to 40.
    - Training dataset (UIUC Q5500)
    - Test dataset (UIUC Q500)
  - The accuracy of our proposed GA-CRF model for the UIUC dataset is 95.58% compared to 87% for the traditional CRF model reported by Krishnan et al.(2005)
    - The proposed hybrid GA-CRF model for question informer prediction significantly outperforms the traditional CRF model.

Experimental Results

- English Question Classification (EQC) using SVM

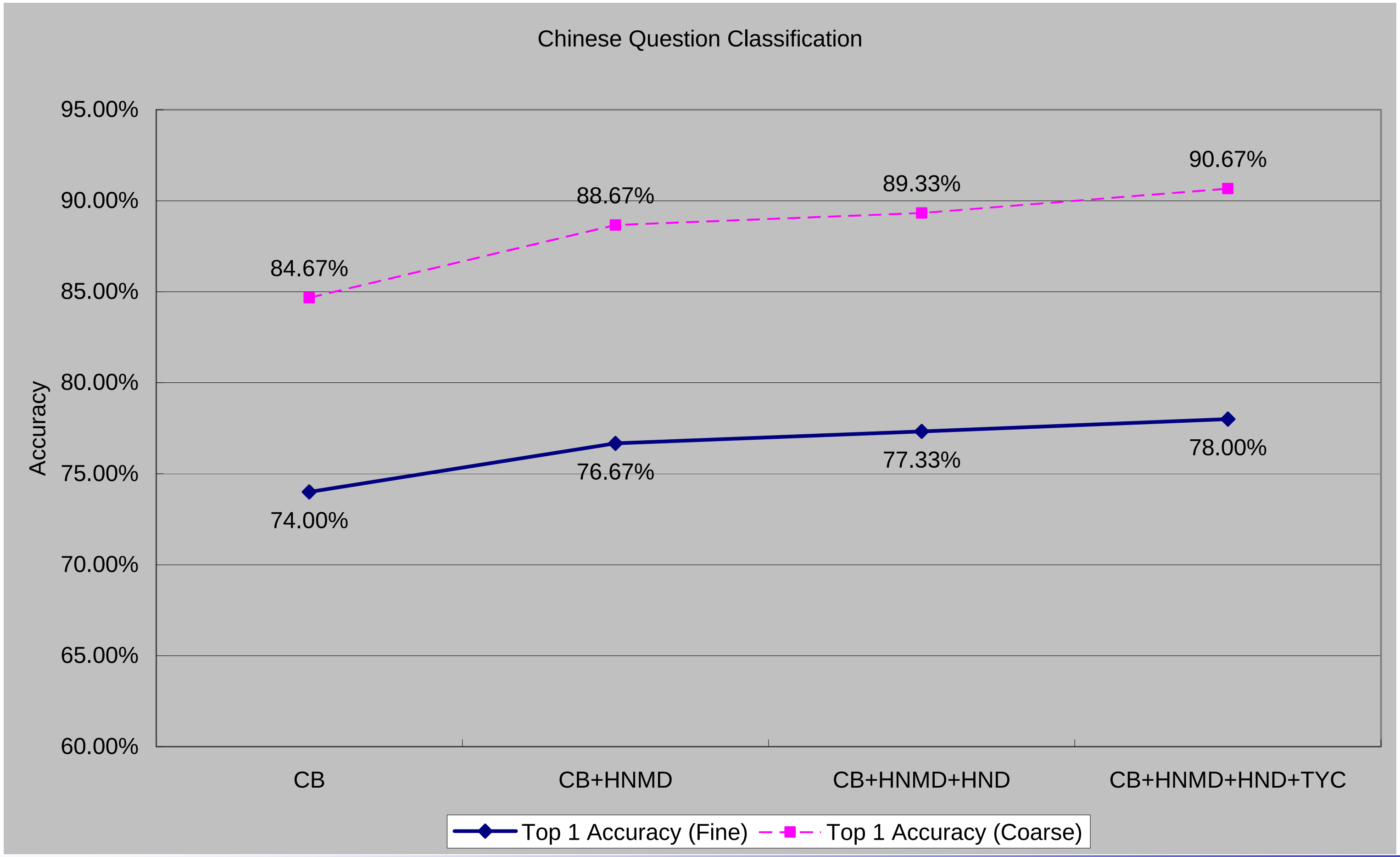


Experimental Results of Chinese Question Classification (CQC) using SVM with different features

Feature Used	Top 1 Accuracy (Fine)	Top 1 Accuracy (Coarse)	Top 5 MRR (Fine)	Top 5 MRR (Coarse)
POS	53.33%	65.33%	0.5732	0.7533
POSB	60.00%	74.00%	0.6469	0.7970
HNMD	71.33%	81.33%	0.7480	0.8832
CB	74.00%	84.67%	0.7934	0.9130
HNMDB	74.00%	86.00%	0.7916	0.9117
C	74.67%	84.67%	0.7979	0.9152
TYCB	74.67%	86.00%	0.7880	0.9062
HND	74.67%	86.67%	0.7860	0.9102
W	76.00%	88.00%	0.7901	0.9208
HNDB	76.67%	88.00%	0.8000	0.9162
WB	77.33%	88.00%	0.8067	0.9162
TYC	77.33%	88.67%	0.8019	0.9240

Experimental Results (cont.)

- Chinese Question Classification (CQC) using SVM



Conclusions

- We have proposed a hybrid genetic algorithm and machine learning approach for cross-language question classification.
- The major contribution of this paper is that the proposed approach enhances cross-language question classification by using the GA-CRF question informer feature with Support Vector Machines (SVM).
- The results of experiments on NTCIR-6 CLQA question sets demonstrate the efficacy of the approach in improving the accuracy of question classification in English-Chinese cross-language question answering.

Applications: ASQA (Academia Sinica Question Answering System)

http://asqa.iis.sinica.edu.tw

- ASQA (IASL-IIS-SINICA-TAIWAN)
  - ASQA is the best performing Chinese question answering system.
  - The first place in the English-Chinese (E-C) subtask of the NTCIR-6 Cross-Lingual Question Answering (CLQA) task.(2007)
  - The first place in the Chinese-Chinese (C-C) subtask of the NTCIR-6 Cross-Lingual Question Answering (CLQA) task.(2007)
  - The first place in the Chinese-Chinese (C-C) subtask of the NTCIR-5 Cross-Lingual Question Answering (CLQA) task.(2005)

Q & A

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