EARS: Collaborative Research: Intelligence Measure of Cognitive Radio Networks

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Motivation

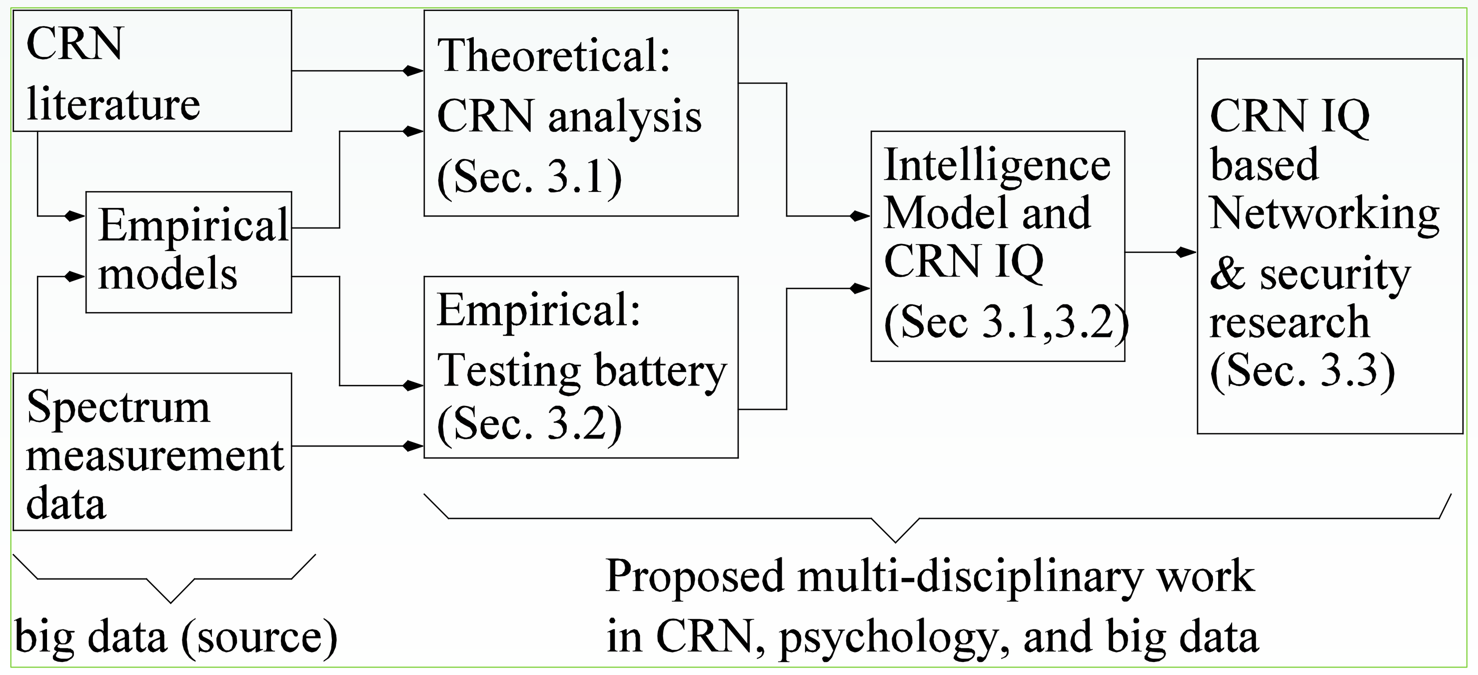
- Cognitive radio network (CRN) introduces cognitive capability into wireless operation
- Cognitive capability collectively is intelligence
- It is important but challenging to quantify cognitive capability and intelligence in CRN

Overall Objectives

Construct cognitive capability and intelligence models for CRN, develop CRN intelligence measure as CRN-IQ, take inspiration from human intelligence model (CHC model)

Research Tasks

- **Formulate theoretically CRN intelligence model based on performance analysis and common factor model**
- **Evaluate quantitatively the CRN intelligence model with empirical performance data**
- **Develop CRN IQ intelligence measure, and use it to guide CRN optimization**



Integrated Human Learning and Machine Learning

Motivation: Joint human/machine learning is highly needed for processing heterogeneous & error-prone CRN performance data in intelligence study

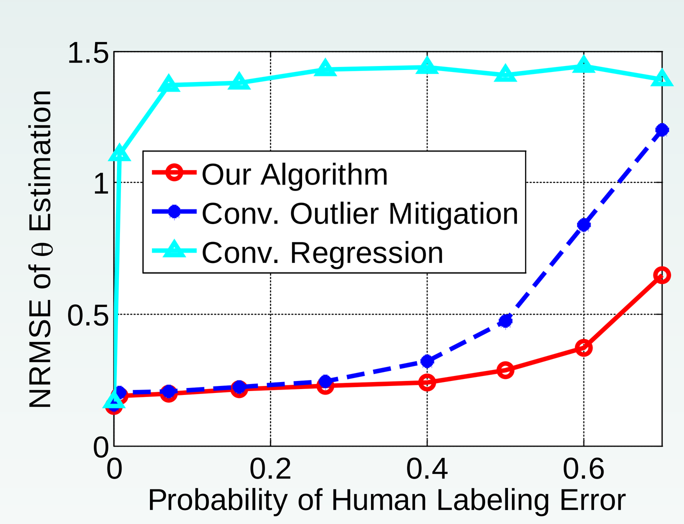
Model: Linear regression with outlier: $y_i = \mathbf{x}_i^T\theta + o_i + \epsilon_i$

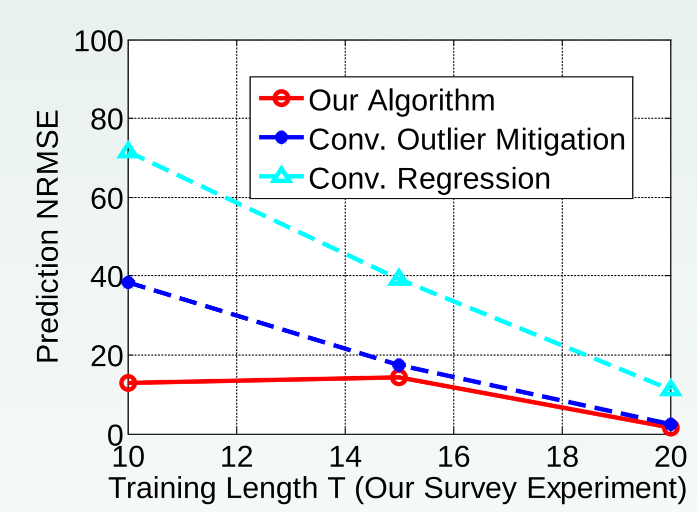
Outlier has probability: [item response theory (IRT)] $\mathbb{P}[o_i = 0] = \dfrac{1}{1+e^{\beta_i-\alpha}}$

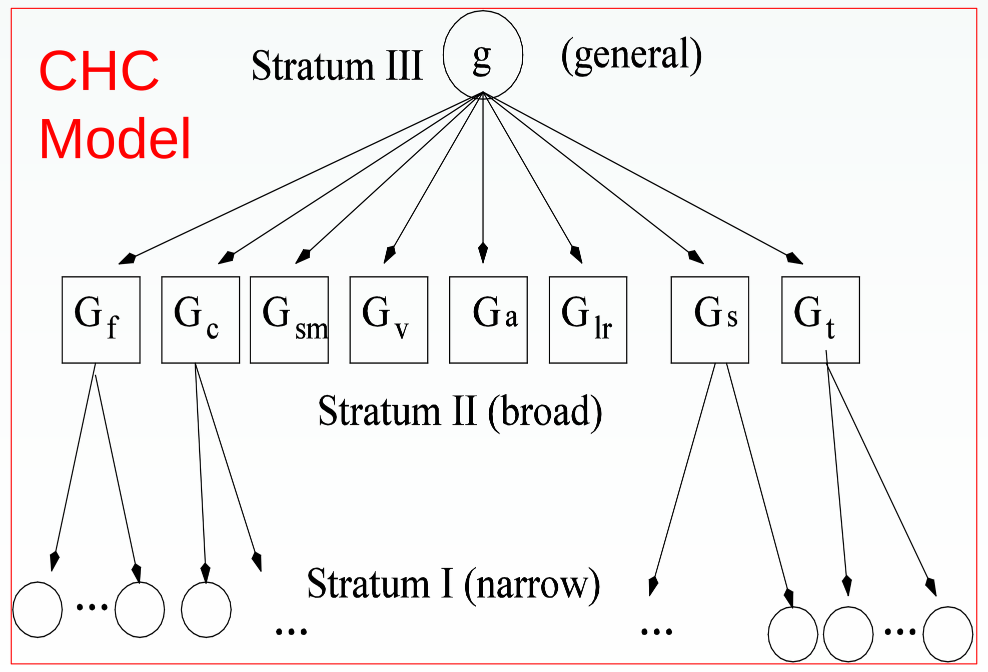
Techniques: Correlation matching (active learning), compressive sensing (outlier mitigation), and training data screening (guarantee sparsity in high error data)

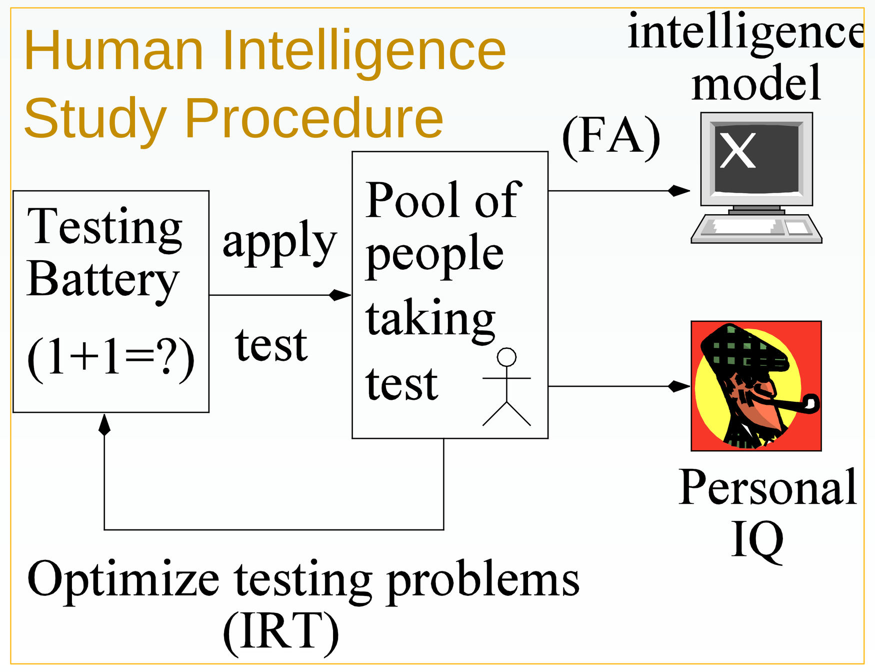
$$\begin{cases} \mathbf{x}_{t_j} = \arg\min\limits_{\mathbf{z}\in X_j} \left\| \dfrac{1}{j+1}\left(\mathbf{X}_{j-1}^T\mathbf{X}_{j-1}+\mathbf{z}\mathbf{z}^T\right)-\mathbf{R}\right\|^2 \\ \min\limits_{\theta,\mathbf{o}} \|\mathbf{y}_j - \mathbf{o} - \mathbf{X}_j\theta\| + \lambda_1\|\mathbf{o}\|_1 \\ \text{data screening threshold } \gamma: \dfrac{\mathbb{P}[|o_i+\epsilon_i|\le\gamma]}{\mathbb{P}[|\epsilon_i|\le\gamma]} \le \dfrac{\eta(1-\bar{P})}{1-\eta\bar{P}} \end{cases}$$

Results: Fast convergent active learning, robust to extremely high human error probability (non-sparsity). Demonstrated by simulations and real experiments.









Preliminary CRN Intelligence Study Results

Model: Common factor model $y_k(n) = a_{k,1}x_1(n) + \cdots + a_{k,l}x_l(n) + z_k(n)$

Method: Simulated three dynamic spectrum access algorithms: UCB1, EXP3, and RAN under 25 scenarios. Analyzed obtained data by factor analysis, and Identified two intelligence factors

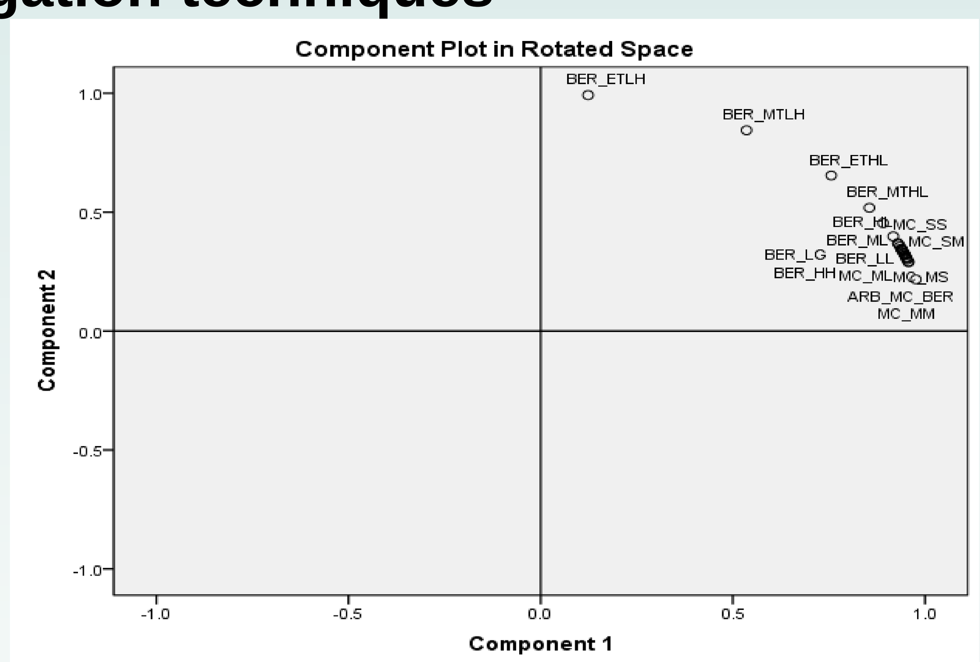
Factor 1: Capability of finding best channel

Factor 2: Capability of adapting to changing environment

Results: UCB1 is highly loaded in Factor 1, EXP3 is highly loaded in Factor 2, while RAN has low loading in both factors.

Results comply with the nature of these algorithms, thus validate the effectiveness of proposed CRN intelligence investigation techniques

Protocol	FAC1_1	FAC2_1
UCB1	0.93133	-0.68261
EXP3	0.12549	1.14786
RAN	-1.05682	-0.46525



Publications

1. X. Li, Y. Chen and K. Zeng, "Integration machine learning with human learning for linear regression," ICASSP, Mar. 2016.
2. X. Li and J. Zheng, "Joint machine learning and human learning design with sequential active…" CISS, Mar. 2016.
3. J. Xu, Q. Wang, K. Zeng, M. Liu, and W. Liu, "Sniffer channel assignment with imperfect monitoring for cognitive radio networks," IEEE Transactions on Wireless Communications, 2015