Intelligence Measure of Cognitive Radios with Learning Capabilities

Monireh Dabaghchian*, Songsong Liu*, Amir Alipour-Fanid*, Kai Zeng*, Xiaohua Li†, Yu Chen†
*Volgenau School of Engineering, George Mason University, Fairfax, VA 22030
*Email: {mdabaghc, sliu23, aalipour, kzeng2}@gmu.edu
†Electrical and Computer Engineering, Binghamton University, Binghamton, NY 13902
†Email: {xli, ychen}@binghamton.edu

***Abstract*—Cognitive radio (CR) is considered as a key enabling technology for dynamic spectrum access to improve spectrum efficiency. Although the CR concept was invented with the core idea of realizing "cognition", the research on measuring CR cognition capabilities and intelligence is largely open. Deriving the intelligence capabilities of CR not only can lead to the development of new CR technologies, but also makes it possible to better configure the networks by integrating CRs with different intelligence capabilities in a more cost-efficient way. In this paper, for the first time, we propose a data-driven methodology to quantitatively analyze the intelligence factors of the CR with learning capabilities. The basic idea of our methodology is to run various tests on the CR in different spectrum environments under different settings and obtain various performance results on different metrics. Then we apply factor analysis on the performance results to identify and quantize the intelligence capabilities of the CR. More specifically, we present a case study consisting of sixty three different types of CRs. CRs are different in terms of learning-based dynamic spectrum access strategies, number of sensors, sensing accuracy, and processing speed. Based on our methodology, we analyze the intelligence capabilities of the CRs through extensive simulations. Four intelligence capabilities are identified for the CRs through our analysis, which comply with the nature of the tested algorithms.**

I. Introduction

In order to resolve the imminent spectrum shortage problem, sharing spectrum with legacy systems has attracted intensive research during the past decade. Cognitive radio (CR), which has the capability to sense, learn, and adapt to the spectrum environment [1], [2], can significantly improve spectrum efficiency and guarantee the unharmful coexistence with the legacy systems [3]–[7]. Nevertheless, the complex and uncertain spectrum environment makes spectrum sharing extremely challenging. The uncertainty may come from the radio propagation environment, the legacy system activity, or the complex behavior of the CR itself.

Just like human being, sophisticated cognitive capabilities are essential for the CR to cope with the uncertainty of spectrum environment. The cognitive capabilities collectively define the intelligence of CR. Although the CR concept was born with the core idea of realizing cognition [8], the research on measuring CR intelligence is largely open.

Being able to quantitatively measure the intelligence of CR can bring us a lot of benefits. 1) With the intelligence model and measuring methodology, we will gain deeper insight about the key factors that affect the intelligence of a CR which can be used to guide the development of new CRs with high intelligence. 2) A CR vendor may advertise and price their CR products based on CR cognitive capabilities as a metric. A CR with higher loads on cognitive capabilities tends to achieve better performance in various spectrum environments, thus will be priced higher. 3) With the knowledge of intelligence capabilities of individual CRs, a service provider or network manager can better configure their networks by integrating CRs with different intelligence capabilities in a more cost-efficient way. For example, a CR with higher intelligence capabilities leading and networking with a set of CRs with low intelligence capabilities may achieve a desirable performance with low network deployment overhead. 4) Last but not the least, the investigation of CR cognitive capabilities will shed light on the intelligence measure and innovation of other smart systems, such as connected cars, unmanned aerial vehicles, smart grid, smart cities, etc.

In this paper, for the first time, we propose a data-driven methodology to derive the intelligence capabilities of CR. Following human intelligence theory, specifically the widely accepted Cattell-Horn-Carroll (CHC) intelligence model [9], we construct a CR intelligence model. Based on this model, we develop psychometric techniques to derive the CR intelligence capabilities. The basic idea of our methodology is to test different CRs in various spectrum environments under different settings. Based on the obtained performance results, we apply factor analysis (FA) [10] to extract and measure the intelligence capabilities of CR.

More specifically, we present a case study consisting of sixty three different types of CRs. We provide each CR different levels of capabilities including learning-based dynamic spectrum access algorithms which are based on the learning algorithms [11]–[13], number of sensors, sensing accuracy, and processing speed. Based on our methodology, we analyze the intelligence capabilities of the CRs through extensive simulations. Four intelligence capabilities are identified for the CRs through our analysis, which comply with the nature of the tested algorithms. This validates our proposed methodology of measuring CR intelligence.

We summarize the contributions of this paper as follows:

- We propose the idea of identifying the cognitive capabilities of CR, then propose an intelligence model for the CR (Section II).

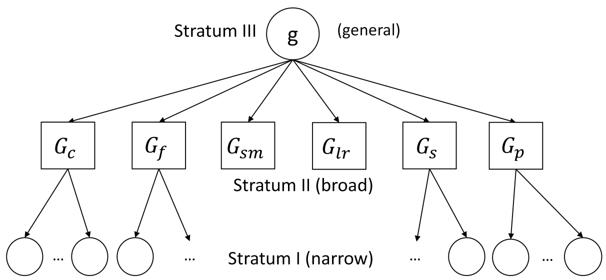

Fig. 1. Intelligence model for the cognitive radio

- We propose a methodology to extract the CR's cognitive capabilities.The theoretical framework applied is discussed in Section III.
- We present a case study in which we find the CR intelligence capabilities of learning-based CRs under dynamic spectrum access scenarios. Through extensive simulations our proposed methodology is verified. The case study is presented in section IV.

II. Quantitative Intelligence Model of CR

Motivated by the CHC model [9] that is widely used to describe human intelligence, we propose an intelligence model for the CR. Our model is structured with three strata (or stages) as shown in Fig. 1. At the top stage lies the stratum III, which defines a unique general intelligence factor g. CRs with high values in the g factor are more intelligent in general. That is, they tend to achieve better performance in various dynamic spectrum environments.

The stratum II represents more broad abilities in terms of cognition capabilities contributing to intelligence, which may be modeled as the following ones:

1) Comprehension-Knowledge (G_c): includes the breadth and depth of a CR's acquired knowledge and the ability to reason using previously learned experiences or procedures.
2) Fluid reasoning (G_f): includes the broad ability to reason, form concepts, and perform dynamic spectrum access using unfamiliar information or novel procedures.
3) Short-Term Memory (G_{sm}): is the ability to apprehend and hold information in immediate awareness and then use it within a short period (e.g., a few seconds or the time the CR is on).
4) Long-Term Storage and Retrieval (G_{lr}): is the ability to store information and retrieve it later in the process of communication or dynamic spectrum access.
5) Spectrum Sensing (G_s): is the ability to sense the spectrum environment, e.g., sensing the availability of white space or presence of primary users.
6) Processing Speed (G_p): measures the information processing time, which may include channel sensing, accessing and switching delay, computing, reasoning, and information retrieval delay, etc.

Within each stratum II broad ability, we can further define stratum I which is at the bottom with more narrow abilities.

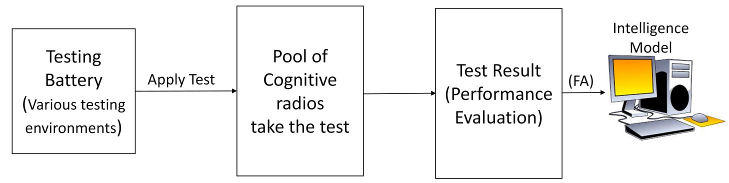

Fig. 2. A data-driven methodology to derive the intelligence capabilities of CR

These abilities are more specific cognition capabilities. For example, fluid reasoning can include inductive reasoning, sequential reasoning, deductive reasoning, and speed of reasoning. Spectrum sensing can include number of sensors and accuracy of sensing capability. Processing speed can include the speed of processing on the received data, the speed of reasoning and decision making, and the speed of switching among channels.

III. Proposed Methodology to Measure the intelligence capabilities of CR

In this section, we propose a data-driven methodology to derive the intelligence capabilities of cognitive radios. The basic idea of our methodology is illustrated in Fig. 2.

As shown in the figure, for a pool of N different CRs, say CR_1, CR_2, ..., CR_N, we design a battery consisting of K tests to evaluate the cognitive capabilities of CRs. Through the tests, we obtain a vector of performance, $\boldsymbol{Y}_k(n)$, for each CR_n ($1 \leq n \leq N$) at each test scenario k ($1 \leq k \leq K$). Then we apply FA method [10] on the measured output to derive the cognitive capabilities called latent factors.

The performance of a test taker can be modeled as a general intelligence factor called $g(n)$ in the stratum III of the intelligence model, as shown in Fig. 1. The $g(n)$ is called the "common factor". In other words, all other cognitive capabilities in stratum II and I regress to $g(n)$. Equation (1) shows how cognitive applicabilities can be modeled by the common factor $g(n)$ [10].

$$y_k(n) = a_k g(n) + z_k(n) \tag{1}$$

where $y_k(n)$ and a_k are the measured performance and the weight respectively. Also $z_k(n)$ is unique to the specific performance measurement called the unique factor. In all the terms above, n and k indicate the CR and testing scenario indices.

Similar relation holds between the performance measurement and the broad cognitive capabilities in stratum II. We substitute $g(n)$ by $x(n)$ to distinguish between the general capability and the broad capabilities. Also since in stratum II we are measuring multiple capabilities, we indicate them by $x_1, ..., x_I$ called the group of latent factors. Since it is possible to measure several metrics, the single value $y_k(n)$ is substituted by the vector performance measurement $\boldsymbol{Y}_k(n)$.

Equation (2) shows the relation between measured metrics and the broad cognitive capabilities in stratum II used to identify the group of latent factors [10].

$$\boldsymbol{Y}_k(n) = \boldsymbol{a}_{k,1} x_1(n) + \boldsymbol{a}_{k,2} x_2(n) + ... + \boldsymbol{a}_{k,I} x_I(n) + \boldsymbol{Z}_k(n) \tag{2}$$

Where $\boldsymbol{a}_{k,1}$,...,$\boldsymbol{a}_{k,I}$ and $\boldsymbol{Z}_k(n)$ are the weights and the unique factor respectively.

We apply FA technique [10] to extract the group of latent factors and then construct the CR intelligence model. In order to apply the FA method, first we write the equation (2) in the matrix format [10].

$$\boldsymbol{Y} = \boldsymbol{\Lambda X} + \boldsymbol{\Psi} \tag{3}$$

Where $\boldsymbol{X}$ and $\boldsymbol{\Psi}$ are the common and the unique latent factors matrices respectively. The $\boldsymbol{\Lambda}$ is the matrix of weights, $\boldsymbol{a}_{k,I}$ and $\boldsymbol{Y}$ is the performance matrix.

According to the expected-value theory, we obtain

$$\boldsymbol{\Sigma} = \boldsymbol{E}\left(\boldsymbol{YY'}\right) = \boldsymbol{\Lambda\Phi\Lambda'} + \boldsymbol{E}\left(\boldsymbol{\Psi\Psi'}\right) \tag{4}$$

Where $\boldsymbol{\Phi} = E\left(\boldsymbol{XX'}\right)$. The equation (4) is derived based on the assumption that the common factor and unique factor are uncorrelated which yields $E\left(\boldsymbol{X\Psi'}\right) = 0$. $\boldsymbol{E}\left(\boldsymbol{\Psi\Psi'}\right)$ is also substituted by the diagonal, positive definite matrix $\boldsymbol{\Gamma^2}$. Therefore, the Equation (4) can be rewritten as

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda\Phi\Lambda'} + \boldsymbol{\Gamma^2} \tag{5}$$

It is postulated the common factors are orthogonal or uncorrelated in the model. As a result $\boldsymbol{\Phi} = \boldsymbol{I}$. Then we subtract $\boldsymbol{\Gamma^2}$ from both sides of Equation (5) to derive $\boldsymbol{\Lambda}$:

$$\boldsymbol{\Sigma} - \boldsymbol{\Gamma^2} = \boldsymbol{\Lambda\Lambda'} \tag{6}$$

In this model, $\boldsymbol{\Sigma} - \boldsymbol{\Gamma^2}$ is called "the reduced correlation matrix" [14]. As mentioned above, the next step is to determine the $\boldsymbol{\Gamma^2}$ and $\boldsymbol{\Lambda}$. Since $\boldsymbol{\Lambda\Lambda'}$ is the diagonal matrix, in order to calculate these two matrices, we treat $\boldsymbol{\Lambda}$ as the matrix $\boldsymbol{\Lambda} = \boldsymbol{AD^{\frac{1}{2}}}$, where $\boldsymbol{A}$ is the eigenvector matrix and $\boldsymbol{D}$ is the diagonal eigenvalue matrix of the matrix $\boldsymbol{\Sigma} - \boldsymbol{\Gamma^2}$. For $\boldsymbol{\Gamma^2}$ we have

$$\boldsymbol{\Gamma^2} = \boldsymbol{\Sigma} - \boldsymbol{\Lambda\Lambda'} \tag{7}$$

Equation (7) can be solved through three steps as follows.

1) Find the eigenvector and eigenvalue matrices $\boldsymbol{A}$ and $\boldsymbol{D}$ of "the reduced correlation matrix": $\boldsymbol{\Sigma} - \boldsymbol{\Gamma^2} = \boldsymbol{ADA'}$
2) Find $\boldsymbol{\Lambda} = \boldsymbol{AD^{\frac{1}{2}}}$
3) Find $\boldsymbol{\Gamma^2} = \boldsymbol{\Sigma} - \boldsymbol{\Lambda\Lambda'}$

According to [14], this procedure will be iterative computation until the maximum difference of the last two round of $\boldsymbol{\Gamma^2}$ is less than 0.001. Let $\boldsymbol{S} = \boldsymbol{\Sigma} - \boldsymbol{D}$, then $\boldsymbol{\Sigma} - \boldsymbol{S}^2$ will generate the unrotated factors matrix. Normally, we will pick up factors whose eigenvalues are greater than 1. In the practical analysis, we use principal component analysis [14], which just considers the common factors influencing the performance and ignores the unique factors.

IV. Case Study: Intelligence Measure of CR with Learning Capabilities

In this section, we present a case study consisting of different types of CRs. By designing a set of testing environments, we apply our methodology presented in section III to derive the cognitive capabilities or latent factors contributing to the CR intelligence.

Fig. 3. Time slot structure applied by the CR

A. Settings

We consider a basic single hop scenario where there is only one CR and one primary user (PU). Therefore, we can focus on each CR's ability without considering channel contention. There are several channels in the network. The PU can appear on some or all of the channels simultaneously. We also assume a time slot based network. Fig. 3 shows the time slot structure used by the CR.

As shown in the figure, the first part of the time slot is assigned for channel sensing. During this period, the CR senses the chosen channel and at the end of this period decides whether the channel is idle or not. If the CR finds the channel is idle, it begins data transmission. Otherwise, it keeps silent to not interfere with the PU.

During the third part of the time slot, the CR learns from its observation. Whether the channel was idle or busy, both of them are useful information for the CR to learn and optimize its decisions in the future. The last part is the switching period which indicates the amount of time that it takes the CR to switch from one channel to another one.

We have conducted extensive simulations in which there are $N = 63$ different types of CRs. 10 channels are considered in the network. $K = 18$ testing scenarios are designed, such that each CR can perform on all of them. We run the simulations in MATLAB. For each CR performing in one single testing scenario we run the algorithm 10000 times and get the average.

B. Cognitive Radio Capabilities

The different features of CRs are described as follows.

- Channel access strategy employed by the CR to learn and adapt to the environment. It can be a learning-based method or just a random strategy. We consider two types of learning-based access strategies known as UCB1 [11] and EXP3 [12] and one random access strategy. The latter as the name suggests is based on a random access and does not utilize any learning-based algorithm.
- Sensing accuracy which indicates the detecting probability when the PU is present. There are several methods of channel sensing including energy detection and feature extraction [15]–[17]. We consider three values of 1, 0.9, 0.8 as the probability of the correct sensing. The values are relatively large because in practice, the CRs usually have high sensing accuracy.
- Number of sensors. Possessing more sensors, the CR observes more channels at each time slot. Then depending on the reasoning it employs, the CR may adapt better to the environment. This is probably equal to higher loads

TABLE I
DESIGNING TEST SCENARIOS

PU Activity	PU Load	Channel Rate	FDR
i.i.d./ on-off	High Load	100 Mbps	1
Markovian Chain	Medium Load	50 Mbps	0.75
Transition/ Arbitrary	Low Load	10 Mbps	0.5
-	Large gap	-	-
-	random at each time	-	-

in cognitive capabilities. In this case study, we consider the number of sensors (m) to be either 1 , 2, or 6.

- Delay is another feature of a CR that occurs during sensing, learning, and switching parts of the time slot. We consider all the delays occurred as one single total delay. We assume the total delay to be either 0, $0.1t_s$, or $0.3t_s$ in which t_s indicates the time slot duration.

Considering all the combinations of the features above, we can generate eighty one types of CRs. However, when the access strategy is random, no learning capability is utilized; so the number of channels being observed will have no impact on the CR's performance. By removing eighteen redundant combinations, 63 CRs remain.

C. Testing Scenarios

We consider several parameters to design the testing scenarios:

- Type of PU activity. We consider three types of activities for the PU: I.i.d. distribution, Markovian Chain, and arbitrary where no well defined distribution exists.
- PU Load which indicates the probability of the PU to be active on each channel. PU may have a high load on all the channels or may have a light load on only one channel and a heavy load on all other channels (Large gap). This testing scenario can discriminate among learning and nonlearning-based access strategies. We have considered several combinations of PU activity on the channels.
- Channel Rate. Three different values are considered as channel rates as shown in Table I. If we assume all other characteristics of the channels to be identical, a CR that learns the high rate channel may be considered as having high load in the corresponding cognitive capability.
- Frame delivery ratio (FDR) which includes the impact of channel quality and noise on a given channel. Three possible values for FDR are considered in this case study.

Table I shows a summary of the parameters considered.

D. Measured Outputs

We measure the performance of the CRs based on the three different metrics:

- Throughput which is stored at $y_{1k}(n)$ where k and n indicate the testing scenario and the CR indices respectively and the 1 at $y_{1k}(n)$ indicates that the throughput is the first metric measured.

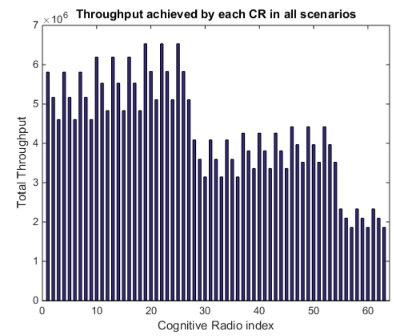

Fig. 4. Total throughput of each CR achieved from all testing scenarios

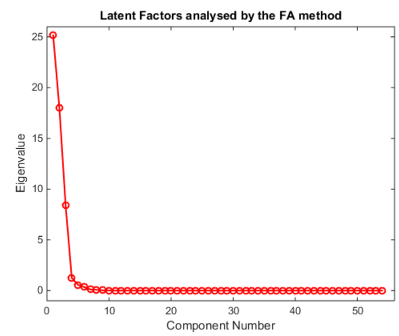

Fig. 5. Latent Factors achieved by using FA

- Delay which indicates total delay occurred in the time slot and is stored as $y_{2k}(n)$. The number 2 indicates the delay is considered as the second metric.
- Violation ratio which represents the average number of times the CR interfered with the PU due to wrong sensing result called miss detection. It is assumed if the CR interferes with the PU, there will be a penalty for the CR and its data will be blocked, so there will be no throughput for the CR. Violation ratio is stored in $y_{3k}(n)$. The number 3 indicates the third metric that we measure.

The performance measure $\boldsymbol{Y}_k(n)$ is a vector equal to $\boldsymbol{Y}_k(n) = [y_{1k}(n)\ y_{2k}(n)\ y_{3k}(n)]$ for $n = 1, \ldots, 63$ and $k = 1, \ldots, 18$. The simulation result of the first metric, throughput, is shown in Fig. 4. This is the total throughput obtained by aggregating the throughput achieved from all the testing scenarios for each CR.

As is shown in this figure, three clusters can be identified in the graph. The first cluster (index 1 up to 27) represents CRs employing UCB1 learning-based access strategy. The second cluster (index 28 up to 54) belongs to the CRs employing EXP3 learning-based access strategy. The last cluster (index 55 up to 63) represents CRs utilizing random access strategies.

One observation is that, among each cluster, as the number of sensors increases, the overall throughput increases as well. Next, the total throughput of CRs employing UCB1 is higher than those employing EXP3 since most of the testing scenarios designed are well behaved (stochastic) in which UCB1 performs better [11], [12]. The third cluster illustrates those CRs employing random access methods. Since random

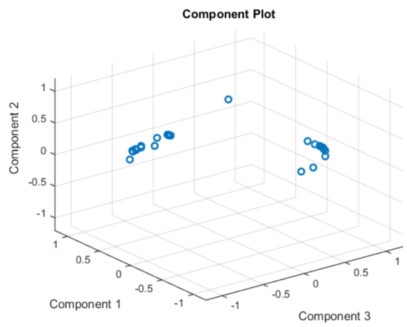

Fig. 6. Component plot achieved by using FA

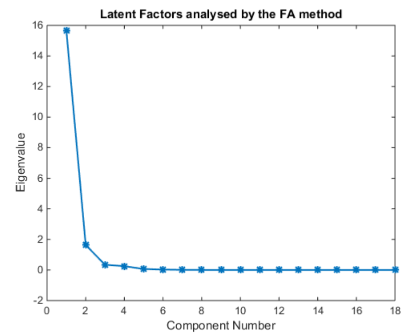

Fig. 7. Latent Factors achieved by using FA for the throughput metric

strategy never utilizes the previous observations, it achieves the lowest throughput among others. We can also observe from the graphs that, for each three consecutive CRs (bars) in the graph, the throughput is decreasing since the sensing accuracy is decreasing.

In the next step, we apply FA technique. Based on the simulations, three 63 by 18 matrices are generated for three metrics we measure. They all together create the $\boldsymbol{Y}_k(n)$ with the dimension of 63 by 54. FA technique is applied on this matrix using the software IBM SPSS [18].

The analysis identifies four latent factors shown in Fig. 5. As is shown in the figure, only four factors are distinguishable and the rest are negligible, almost zero. Due to limited apace we omitted the detailed output data corresponding to the FA results. Eventhough the number of cognitive capabilities are identified but it is not yet clear which cognitive broad capabilities these factors correspond to. We need to examine the data thoroughly and by matching them to the concepts, to find out the corresponding intelligence capabilities.

By examining the data, four latent factors (cognitive capabilities) are found as the following: Spectrum sensing capability, processing speed capability, environment recognition capability, and environment adaptation capability. The results are summarized in Table II.

The data of the factor one provides information on the violation ratio which is impacted by the sensing accuracy and the number of sensors. As a result we conclude that the first factor corresponds to the spectrum sensing capability. It is easy to see that the second latent factor is addressing the delay. Delay is associated with the processing speed capability. The third factor is related to the learning capability. As a result environment recognition is the third latent factor . The forth factor shows a better performance for EXP3 and random access strategy than the UCB1 when the sensing accuracy decreases. The same thing happens when the environment is not well behaved. This indicates that the EXP3 and random access strategy adapt better to non-well behaved environments. The reason is because they are utilizing randomness in their access strategy. As a result this latent factor is addressing the environment adaptation capability.

Comparing to the intelligence model proposed in section II, processing speed capability matches broad capability G_p, spectrum Sensing matches G_s, and the two others can correspond to G_c or G_f factors as shown in Table II. Also, all the CRs used in this case-study have high load on the G_{sm} factor.

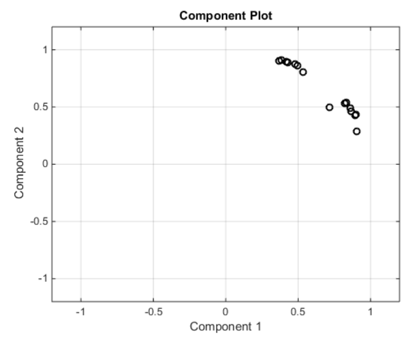

Fig. 8. Component plot achieved by using FA for the throughput metric

TABLE II
LATENT FACTORS IDENTIFIED THAT CONTRIBUTE TO INTELLIGENCE

Factor I	Sensing Capability, G_s
Factor II	Processing Speed Capability, G_p
Factor III	Environment Recognition Capability, G_c or G_f
Factor IV	Environment Adaptation Capability, G_c or G_f

Next we plot the components achieved in the analysis. Component plot shows how the scenarios in the case study belong to each of the four latent factors. Since it is not possible to plot four dimensional figures, we plot the components for factors 1, 2 and 3 as shown in Fig. 6. The whole data is divided into three clusters, each corresponding to one latent factor.

In order to get a deeper insight from the results, we can also apply the FA technique to one of the measured outputs, throughput. In this case two factors are identified as shown in Fig. 7. One of them corresponds to the learning capability and the other one corresponds to the environment adaptation capability. Fig. 8 shows the components of the analyzed data in which the whole data is divided into two clusters, each corresponding to one latent factor.

V. Related Work

The cognitive capabilities and the intelligence model of human beings is studied in psychology [19]. Human cognition capabilities include sensing, learning, memory, problem solving, etc. And intelligence is defined as the ability to learn and perform cognitive tasks [19]. Cattel-Horn-Carrot [9] is the most widely accepted model of human intelligence used to model and analyze the human being intelligence capabilities [7], [19].

The practical measurement of mental abilities has been considered as a pivotal development in the behavioral sciences and the theories and techniques formed a field called phychometrics. The first attempts of mathematically more rigorous study of intelligence measure occurred in 1940s, with statistical techniques such as correlation and FA. Overall, FA is used in multiple areas including psychology and economics.

There have been some efforts trying to develop comprehensive benchmark frameworks to evaluate the cognitive radio network (CRN) performance [20], or to evaluate the performance of more general wireless networks [21]–[23]. However, since benchmarking wireless network is a challenging task, simulation/experimentation has been adopted widely as a tool and in the literature benchmark is not used to test CR intelligence, but performance.

It is useful to identify the differences between human and CR intelligence capabilities. One is that for human beings, the age of the test taker is an important factor that needs to be considered when designing the test questions; Specially at the childhood stages in which the brain is still developing. However, with respect to the CRs, a testing scenario can be tested by all types of CR.

Another important difference is that a human being can get tired by the long duration of the test or may not be in mood on the test day. This can make the test results unreliable. However, the benefit of cognitive engines as machines is that they never get tired and the test results can always be correct, unbiased and reliable.

VI. Conclusion and Future Work

In this paper, for the first time, we have proposed the idea of deriving the intelligence capabilities of the CR. First, an intelligence model is proposed for the CR. Then a data-driven methodology which applies FA on the measured output, is proposed to extract the cognitive capabilities. A case study is presented in which through out the extensive simulations, four latent factors are identified for the CR which comply with the nature of our tested algorithms.

In the future, we will measure the intelligence quotient (IQ) for each CR. IQ can be considered as a general intelligence capability indicating how well a CR performs in different environments. We will also expand our methods to measure CR intelligence in multi-user and multi-hop networks.

Acknowledgment

M. Dabaghchian, S. Liu, A. Alipour-Fanid, and K. Zeng are partially supported by the NSF under grant No. CNS-1502584 and CNS-1464487. X. Li and Y. Chen are supported by NSF via grant CNS-1443885.

References

[1] H. Li and Z. Han, "Dogfight in spectrum: Combating primary user emulation attacks in cognitive radio systems; part ii: Unknown channel statistics," *Wireless Communications, IEEE Transactions on*, vol. 10, no. 1, pp. 274–283, January 2011.

[2] M. Dabaghchian, A. Alipour-Fanid, K. Zeng, and Q. Wang, "Online learning-based optimal primary user emulation attacks in cognitive radio networks," in *Communications and Network Security, 2016 CNS 2016. IEEE*, Oct 2016.

[3] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey," *Computer Networks*, vol. 50, no. 13, pp. 2127 – 2159, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389128606001009

[4] Q. Zhao and B. M. Sadler, "A survey of dynamic spectrum access," *IEEE Signal Processing Magazine*, vol. 24, no. 3, pp. 79–89, May 2007.

[5] K. G. Shin, H. Kim, A. W. Min, and A. Kumar, "Cognitive radios for dynamic spectrum access: from concept to reality," *IEEE Wireless Communications*, vol. 17, no. 6, pp. 64–74, December 2010.

[6] M. J. Marcus, "Spectrum policy for radio spectrum access," *Proceedings of the IEEE*, vol. 100, no. Special Centennial Issue, pp. 1685–1691, May 2012.

[7] S. D. R. Forum, "Cognitive radio definition and nomenclature," *SDRF-06-P-0009*, 2008.

[8] I. C. A. Organization, "potential for radio frequency interference to aeronautical surveillance systems for new terrestrial communications," *Montreal, Canada*, Apr. 2012.

[9] K. S. Mcgrew, "Editorial: Chc theory and the human cognitive abilities project: Standing on the shoulders of the giants of psychometric intelligence research," *Intelligence*, p. 10, 2009.

[10] H. KESTELMAN, "The fundamental equation of factor analysis," *British Journal of Statistical Psychology*, vol. 5, no. 1, pp. 1–6, 1952. [Online]. Available: http://dx.doi.org/10.1111/j.2044-8317.1952.tb00106.x

[11] P. Auer, N. Cesa-Bianchi, and P. Fischer, "Finite-time analysis of the multiarmed bandit problem," *Mach. Learn.*, vol. 47, no. 2-3, pp. 235–256, May 2002. [Online]. Available: http://dx.doi.org/10.1023/A:1013689704352

[12] P. Auer, N. Cesa-Bianchi, Y. Freund, and R. E. Schapire, "The nonstochastic multiarmed bandit problem," *SIAM J. Comput.*, vol. 32, no. 1, pp. 48–77, Jan. 2003. [Online]. Available: http://dx.doi.org/10.1137/S0097539701398375

[13] M. Dabaghchian, A. Alipour-Fanid, K. Zeng, and Q. Wang, "Optimal online learning with partially observable graphs: Random graphs," in *arXiv Aug. 2016*, 2016.

[14] S. A. Mulaik, *Foundations of factor analysis*. CRC press, 2009.

[15] S. Atapattu, C. Tellambura, and H. Jiang, "Energy detection based cooperative spectrum sensing in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 10, no. 4, pp. 1232–1241, April 2011.

[16] W. Zhang, R. K. Mallik, and K. B. Letaief, "Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 8, no. 12, pp. 5761–5766, December 2009.

[17] W. l. Chin, H. c. Kuo, and H. h. Chen, "Features detection assisted spectrum sensing in wireless regional area network cognitive radio systems," *IET Communications*, vol. 6, no. 8, pp. 810–818, May 2012.

[18] IBM SPSS. [Online]. Available: http://www.ibm.com/analytics/us/en/technology/spss/

[19] R. J. Sternberg and S. B. Kaufman, Eds., *The Cambridge Handbook of Intelligence*. Cambridge University Press, 2011, cambridge Books Online. [Online]. Available: http://dx.doi.org/10.1017/CBO9780511977244

[20] Y. Zhao, S. Mao, J. O. Neel, and J. H. Reed, "Performance evaluation of cognitive radios: Metrics, utility functions, and methodology," *Proceedings of the IEEE*, vol. 97, no. 4, pp. 642–659, April 2009.

[21] N. Patwari and S. K. Kasera, "Crawdad utah cir measurements," http://crawdad.cs.dartmouth.edu/meta.php?name=utah/CIR.

[22] S. Rehman, T. Turletti, and W. Dabbous, "A roadmap for benchmarking in wireless networks," Technical Report, INRIA, 2011.

[23] G. Jourjon, T. Rakotoarivelo, C. Dwertmann, and M. Ott, "Executable paper challenge: Labwiki: an executable paper platform for experiment-based research," Procedia Computer Science, 2011.