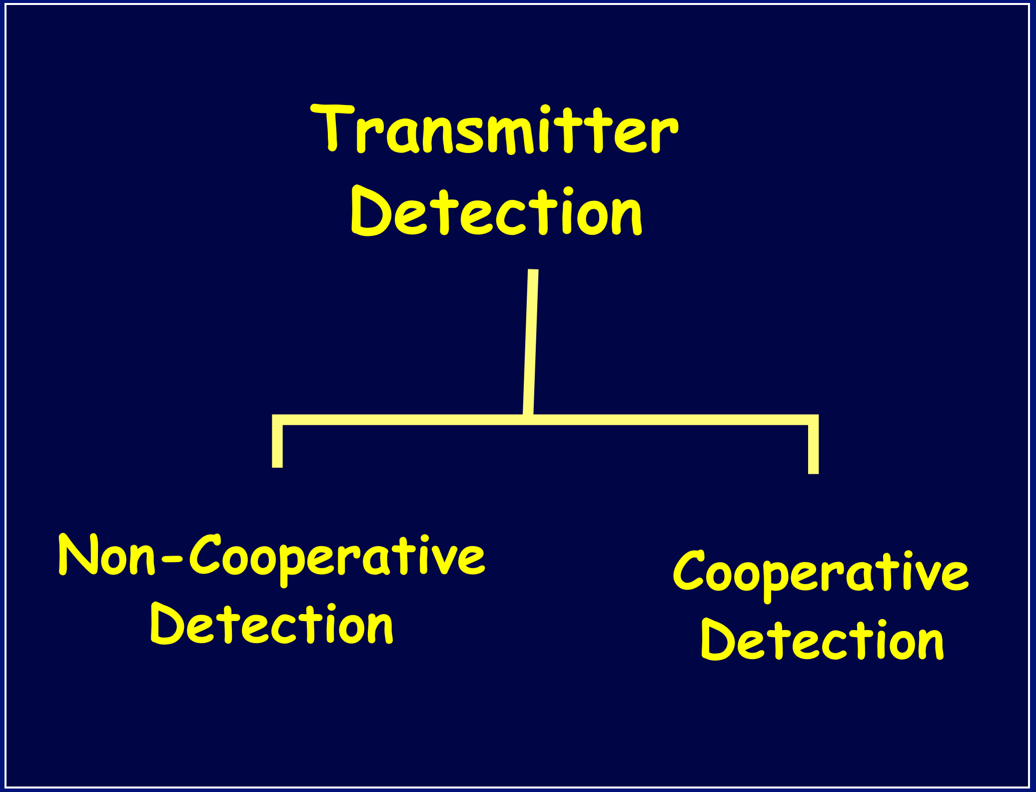
CHAPTER 5.2.
COOPERATIVE SPECTRUM SENSING

I. F. Akyildiz, B. F. Lo, R. Balakrishnan

“Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey”

Physical Communication (Elsevier) Journal, Vol. 4, pp. 40–62, 2011♪

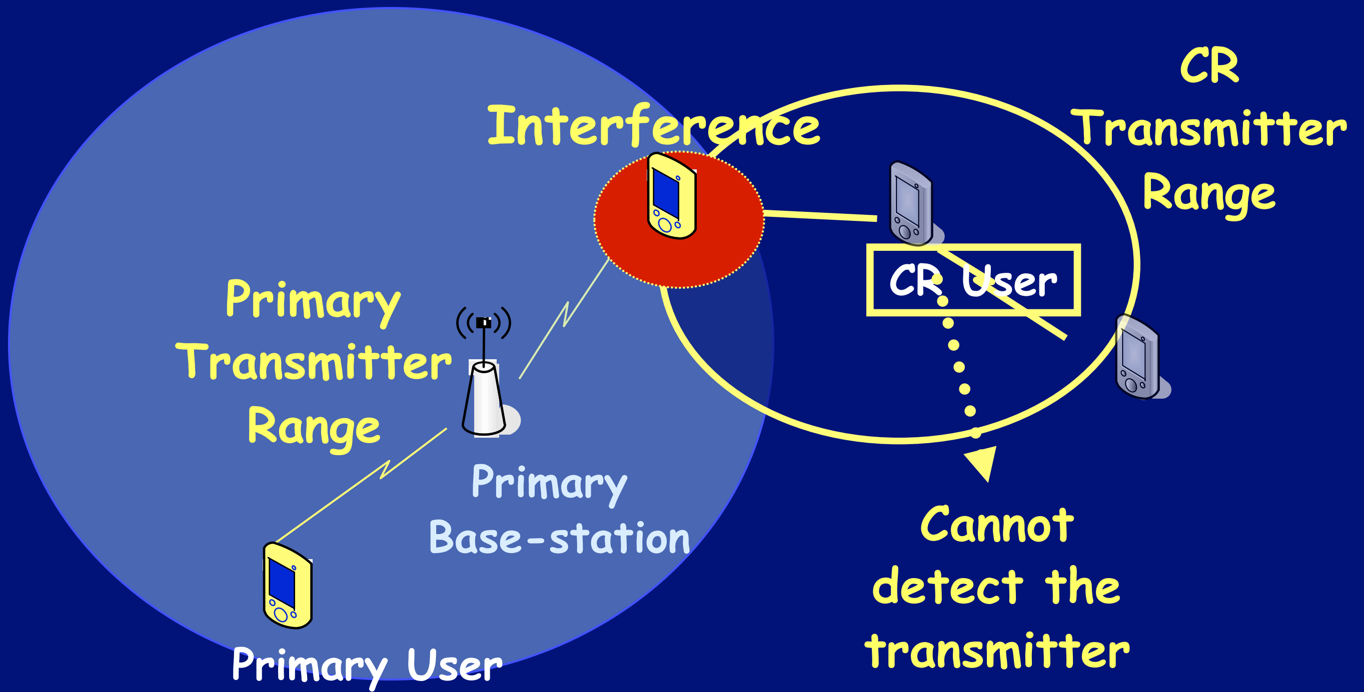
Transmitter Detection



Why Cooperative Sensing?

- Receiver Uncertainty Problem
- Shadowing Problem
- Multi-path Fading Problem

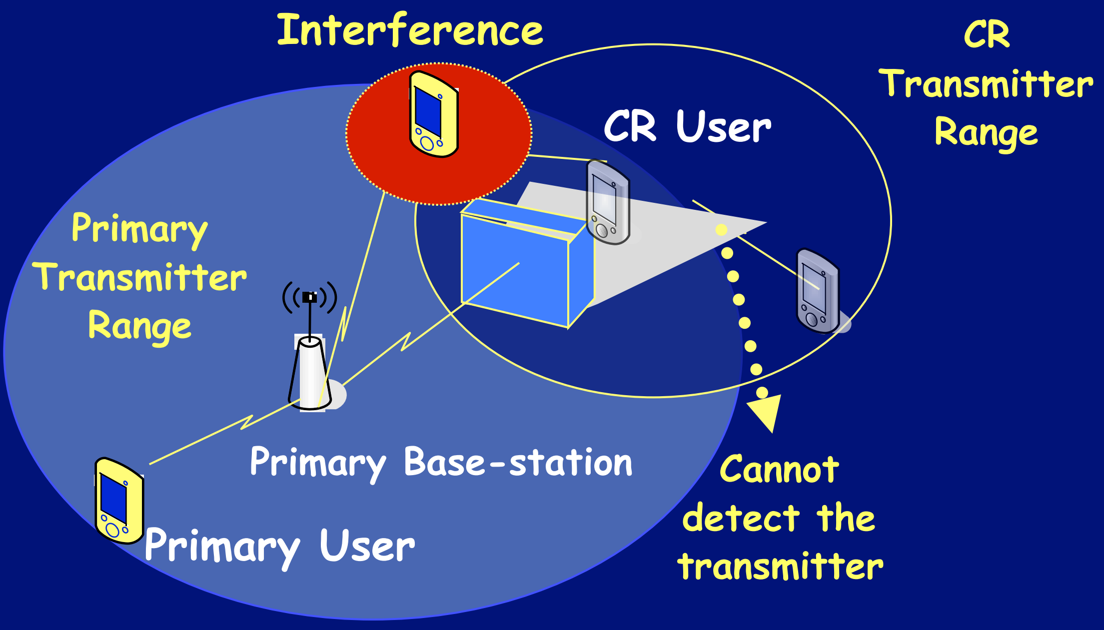
Receiver Uncertainty Problem



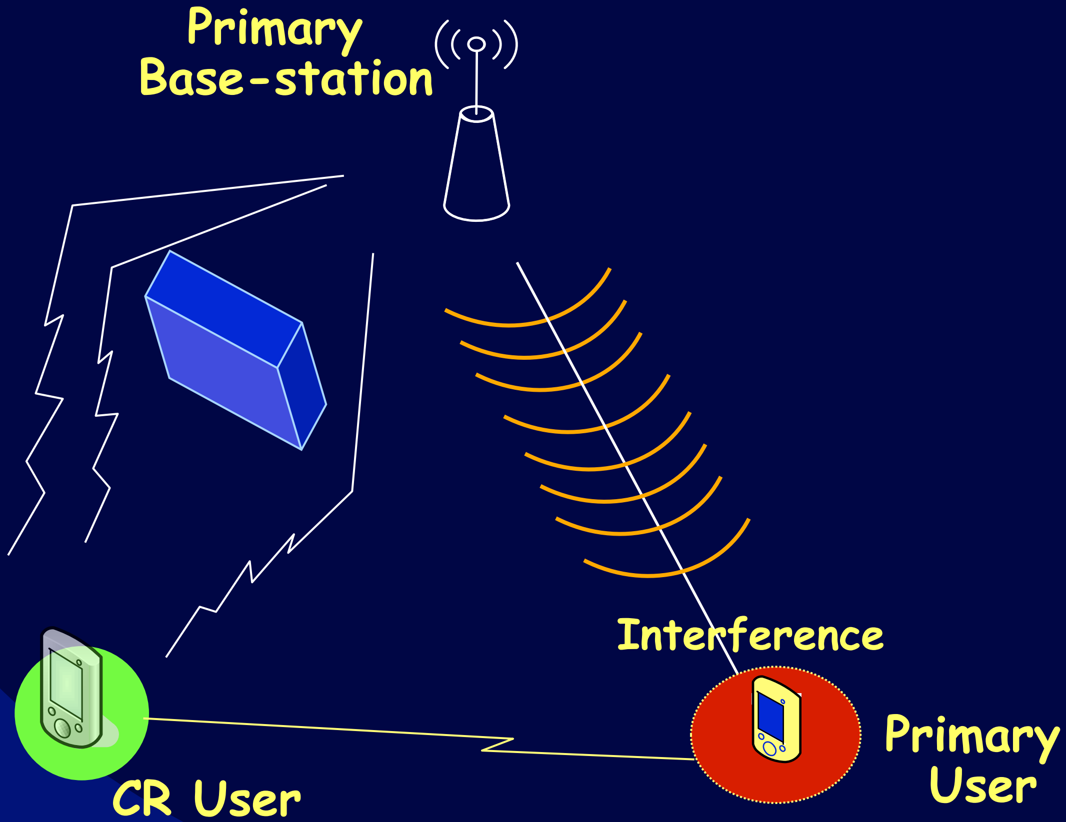
Interference due to uncertainty of receiver location

Shadowing Problem

Hidden Terminal Problem due to Shadowing



Multi-path Fading Problem



Multi-path fading

Weak signals are received due to the multi-path fading
→ may not detect the primary user

Non-Cooperative vs Cooperative Detection

- **Non-Cooperative Detection**
  - CR users detect the PU signal independently through their local observations.

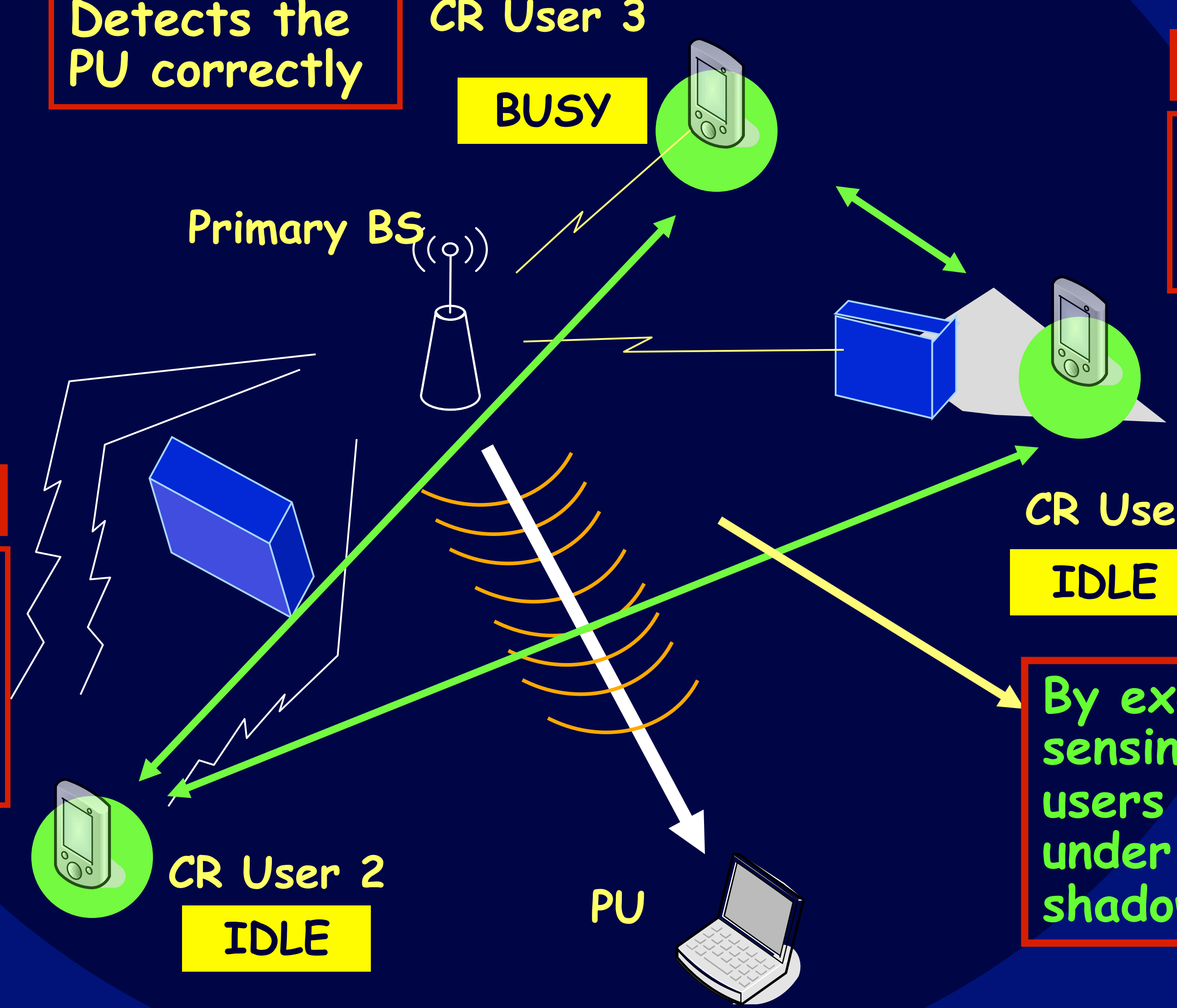
- **Cooperative Detection**
  - Information from multiple CR users are utilized for PU detection.
  - Mitigates multi-path fading and shadowing effects → improves the detection probability in heavily faded/shadowed environments.

Cooperative Spectrum Sensing

CR users cooperatively perform spectrum sensing to explore spatial diversity of primary signal observation for achieving high primary detection performance

Cooperative Sensing

Detects the PU correctly



Shadowing

Cannot detect the PU due to the obstacles

Multi-path fading

Weak signals are received due to the multi-path fading
→ may not detect the PU

By exchanging their sensing information, CR users can detect the PU under fading and shadowing environments

THREE BUILDING BLOCKS

D. Cabric, S. Mishra, R. Brodersen,
"Implementation Issues in Spectrum Sensing for CRs",
Proc. of ASILOMAR Conf. on Signals and Systems and Computers, 2004.

- How can CRs cooperate?
  (COOPERATION METHOD)
- How much can be gained from cooperation?
  (COOPERATIVE GAIN)
- What is the overhead associated with cooperation?
  (COOPERATION OVERHEAD)

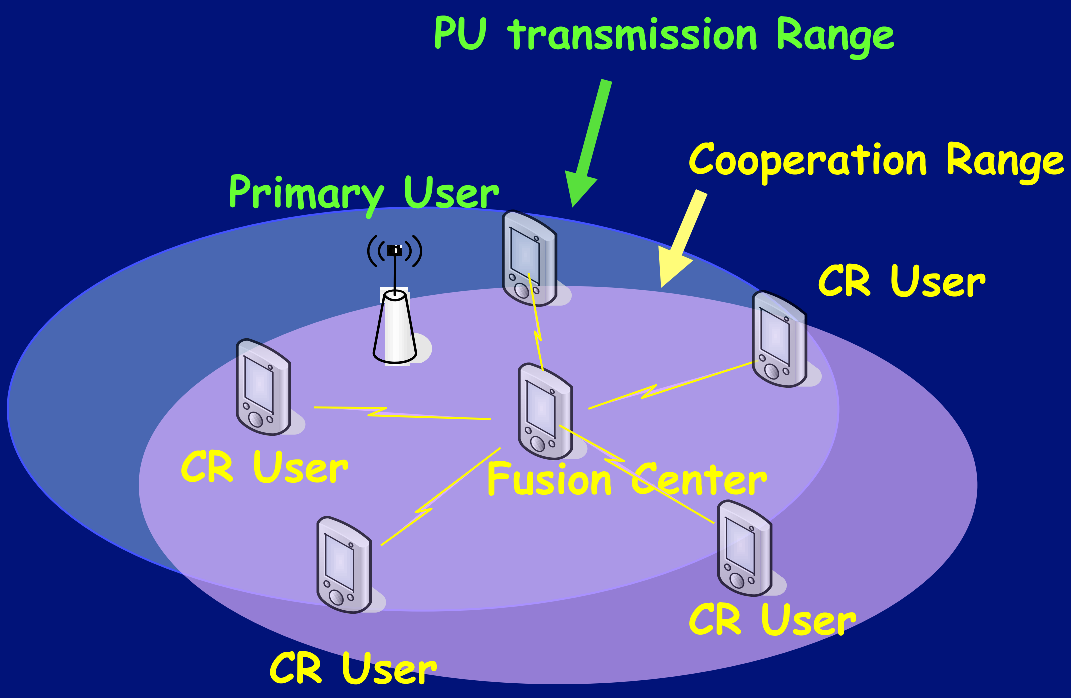
Classification of Cooperative Sensing

I. F. Akyildiz, B. F. Lo, and R. Balakrishnan,
"Cooperative Spectrum Sensing in Cognitive Radio Networks: A Survey",
Physical Communication (PHYCOM) (Elsevier) Journal, Febr. 2011.

- Centralized Cooperative Sensing
- Distributed Cooperative Sensing
- Relay-assisted Cooperative Sensing

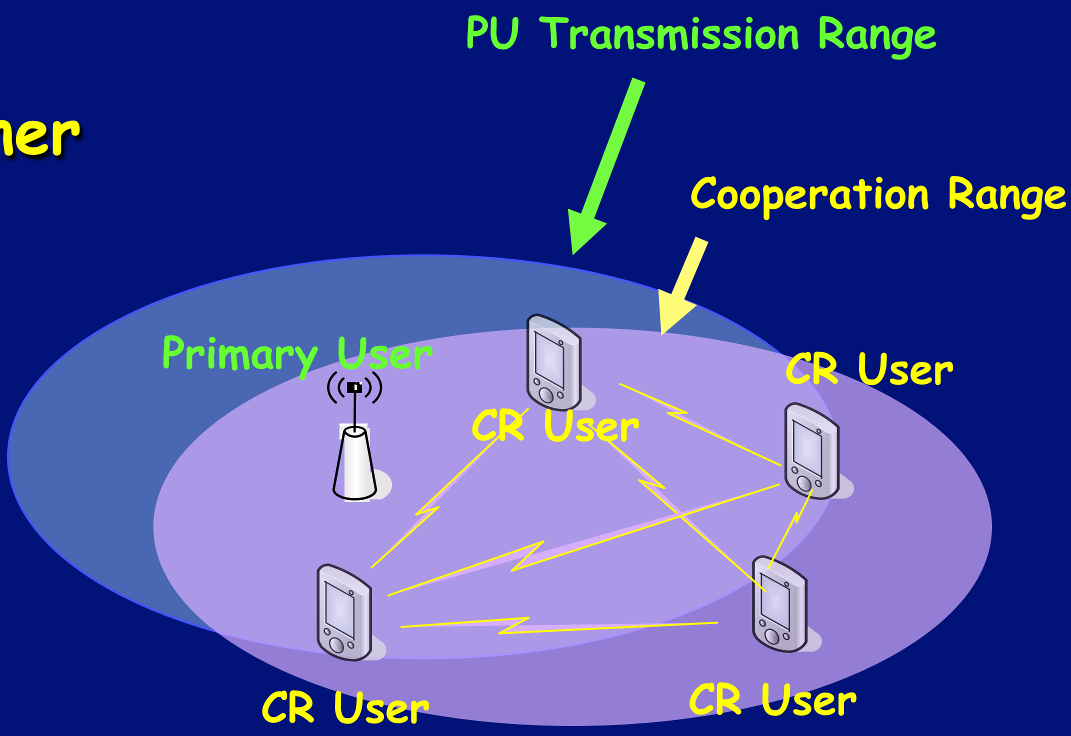
Centralized Cooperative Sensing

- CR users perform local sensing of the PU signal and send the sensed data or local decisions to the FC.
- FC is a BS (in CENTRALIZED NWs) or simply a CR user (IN CR AD HOC NETWORKS) acting as data collector and collecting local sensing data from cooperating CR users
- FC fuses data & determines the presence or absence of PUs and sends the decision back to all CR users



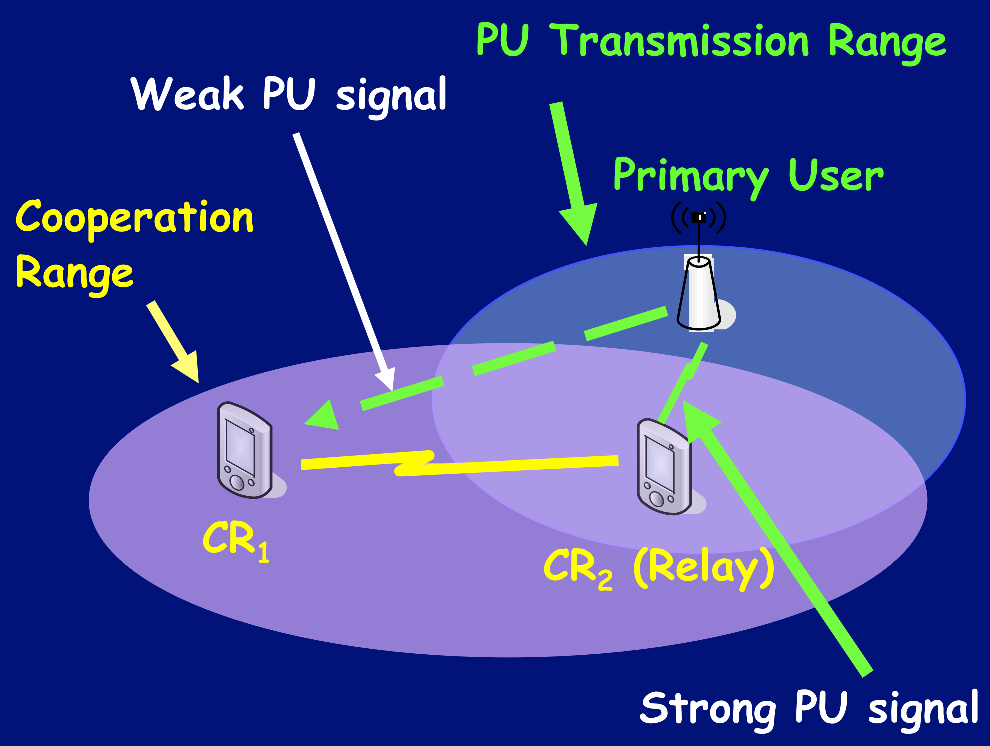
Distributed Cooperative Sensing

- CR users exchange sensing information among each other in a distributed manner
- CR users gradually agree upon the presence or absence of PU after iterations of sharing individual sensing data

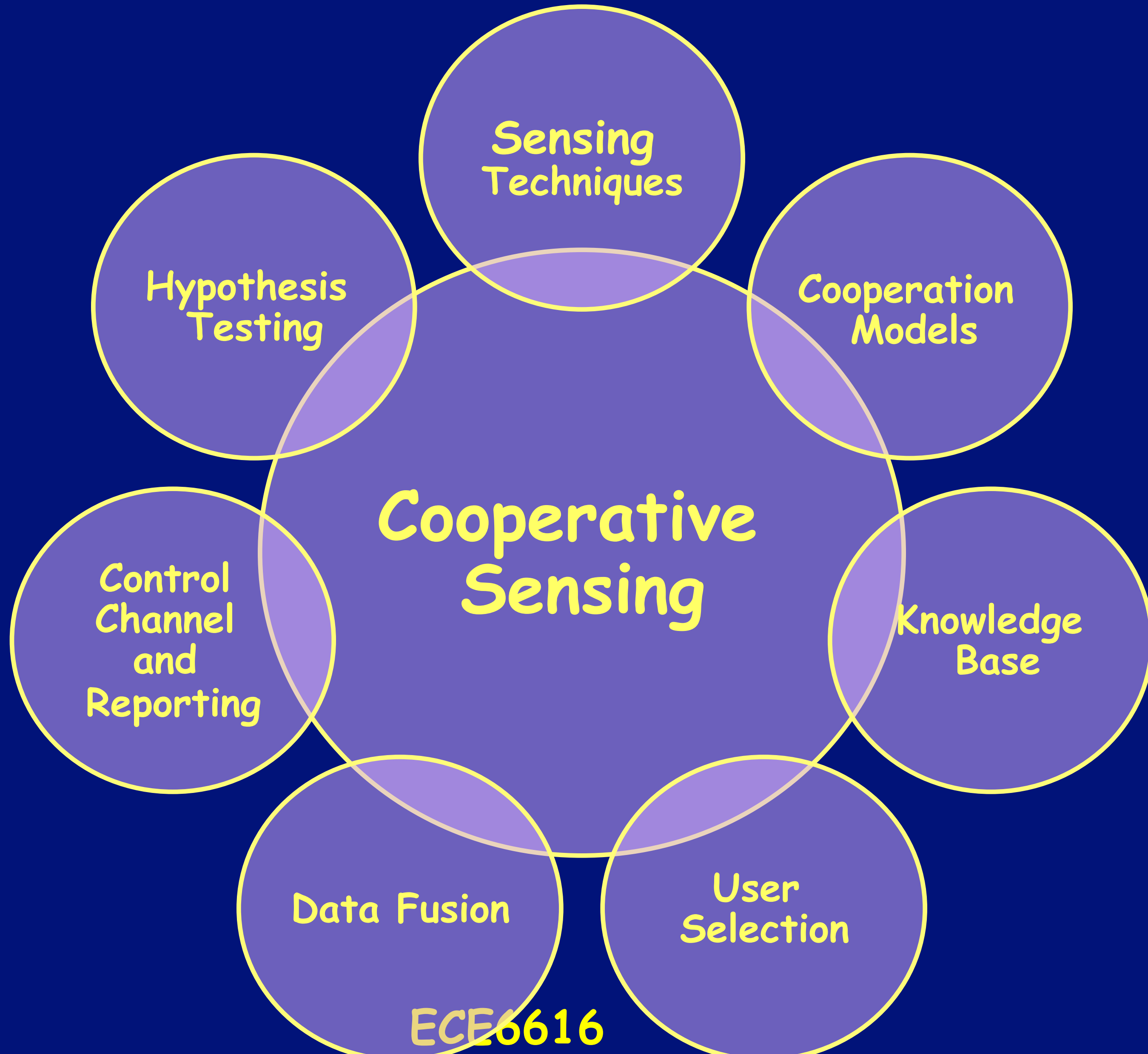


Relay-Assisted Cooperative Sensing

- CR users can act as relays to assist with the spectrum sensing of other CR users
- CR user with the lowest miss detection probability can be selected as a relay to forward the sensing information
- CR_1 observes weak PU signal while CR_2 with strong PU observation relays the sensing information to CR_1

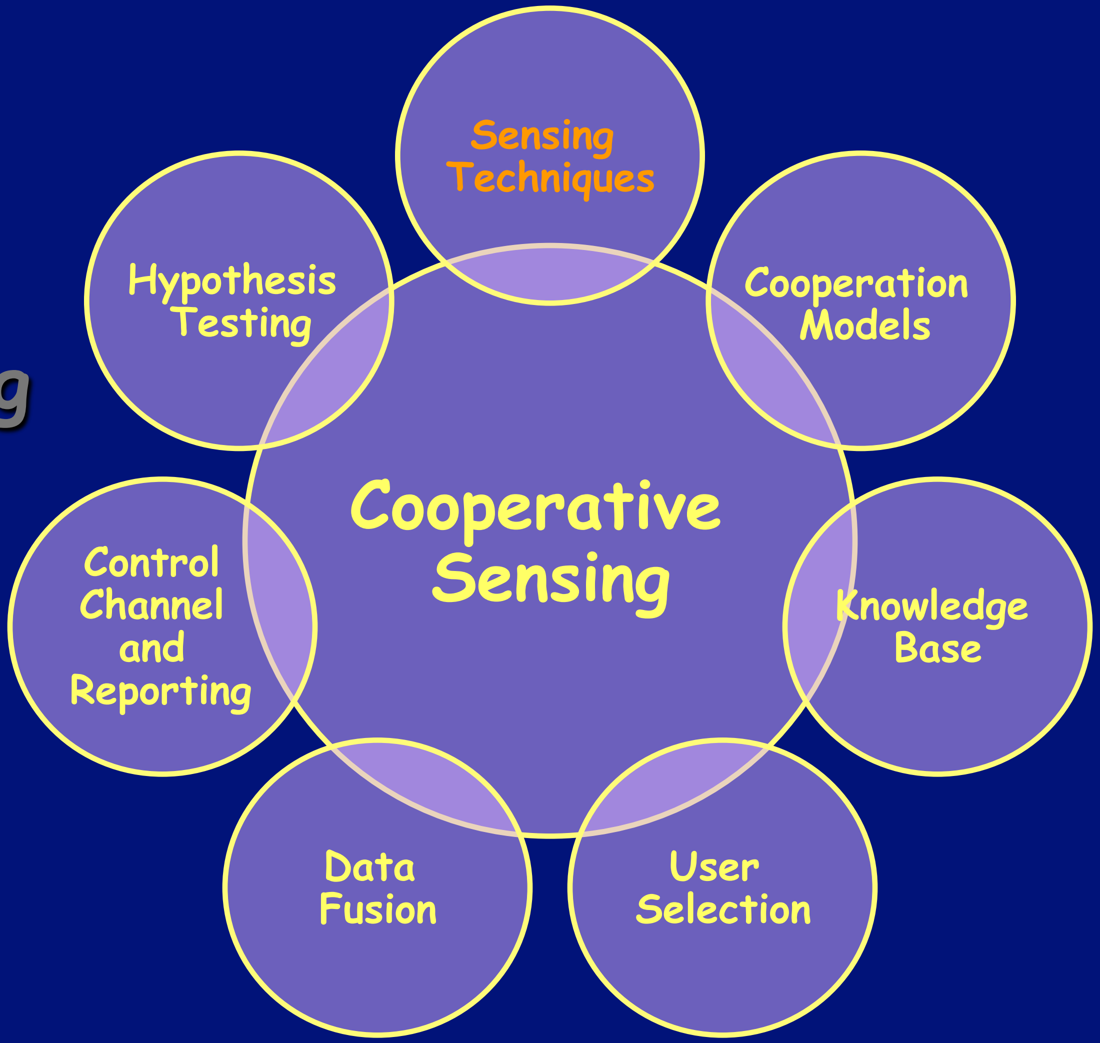


Elements of Cooperative Sensing



Elements of Cooperative Sensing

- Sensing Techniques
- Hypothesis Testing
- Control Channel/Reporting
- Data Fusion
- User Selection
- Knowledge Base
- Cooperation Models



Elements: Sensing Techniques (Section 5.1)

COHERENT DETECTION:

Primary signal can be coherently detected by comparing the received signal or the extracted signal characteristics with a priori knowledge of primary signals.

NON-COHERENT DETECTION:

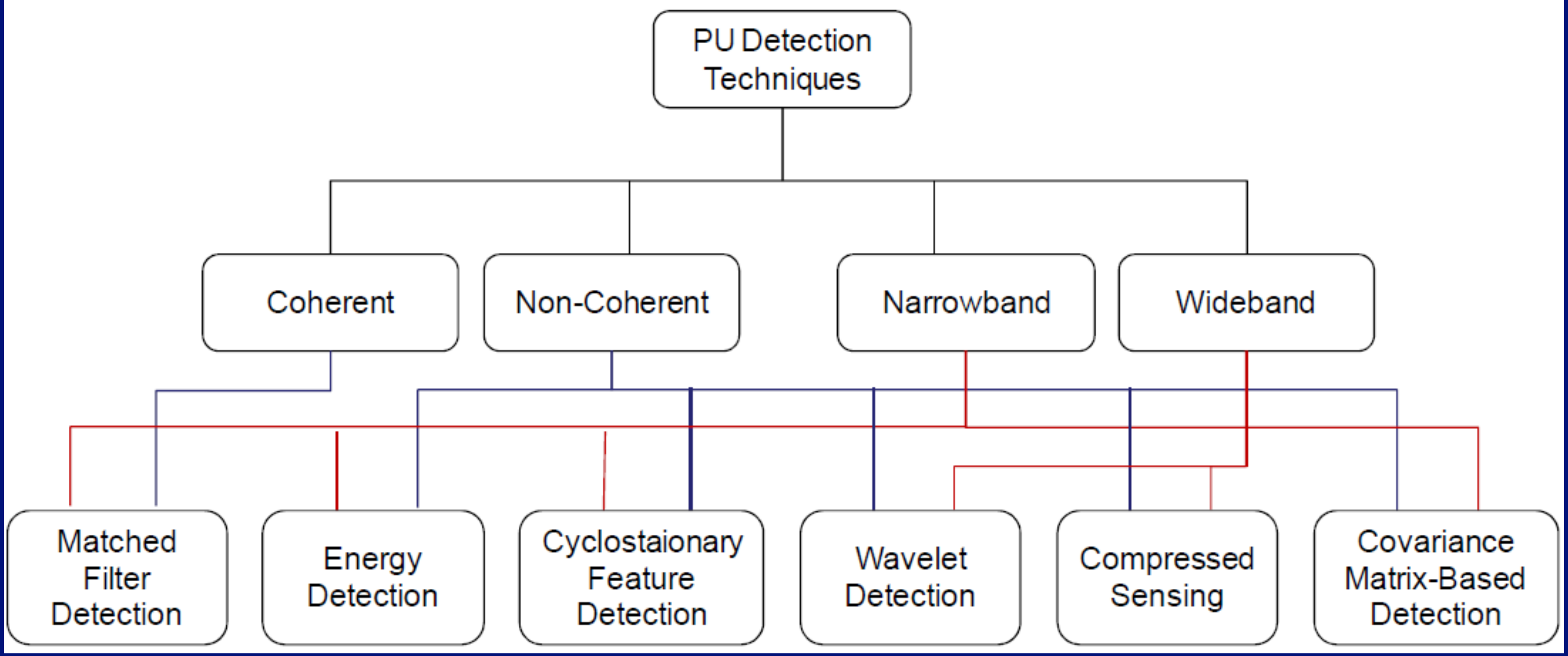
No a priori knowledge of primary signals is required for detection.

Elements: Sensing Techniques

NW Band vs Wideband

* Energy Detection → NW Band Sensing
* Cyclostationary Feature Detection → NW Band Sensing
* Compressed Sensing → Wideband Sensing

Elements: Sensing Techniques



Elements of Cooperative Sensing

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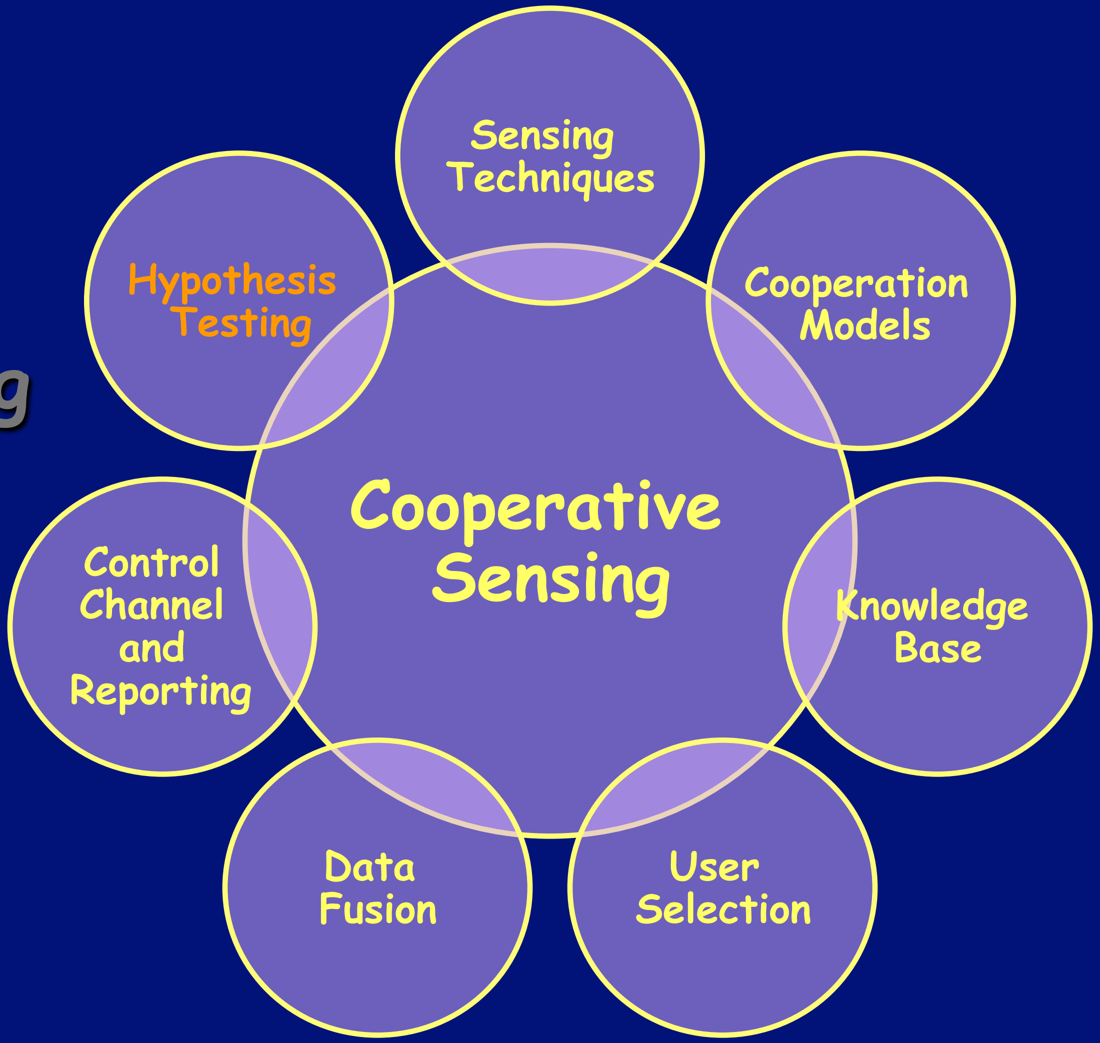


Elements: Hypothesis Testing

- PU signal statistics are generally not available
- Determine the hypothesis from a large number of observations in the absence of PU information

DETECTION OF SPECTRUM HOLES

If PU is absent → pdf is a noise-only distribution

If PU is active → pdf is signal + noise distribution

According to a CRITERION (THRESHOLD),
the SU determines if PU is present or not!

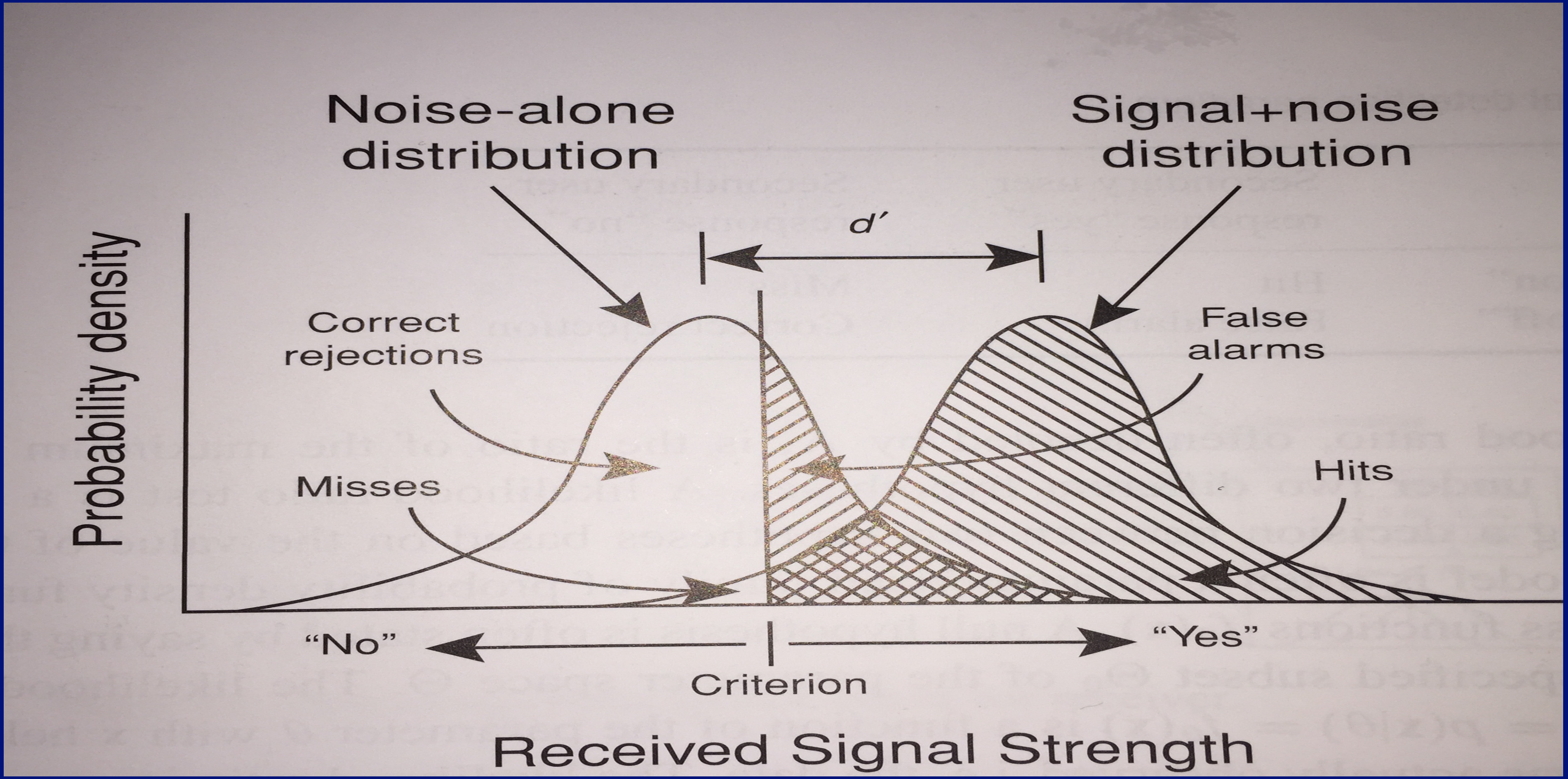
There are 4 possibilities !

HYPOTHESIS TESTING: DETECTION OF SPECTRUM HOLES

	SU Detects "YES"	SU Detects "NO"
PU "ON"	HIT	MISS (type II Error)
PU "OFF"	FALSE ALARM (type I Error)	CORRECT (REJECTION)

QUESTION: These probabilities for all 4 cases highly depend on the THRESHOLD?
HOW TO SELECT THE OPTIMAL THRESHOLD?

DETECTION OF SPECTRUM HOLES



DETECTION PROBABILITIES

$P_d = \text{Prob}\{\text{Decision} = H_1 | H_1\}$ → Prob of Correct Detection

$P_f = \text{Prob}\{\text{Decision} = H_1 | H_0\}$ → Prob of False Alarm

$P_m = \text{Prob}\{\text{Decision} = H_o | H_1\}$ → Prob of Miss Detection

Rewritten:

$P_d = P(H_1 \mid H_1)$; $P_f = P(H_1 \mid H_0)$; $P_m = 1 - P_d = P(H_0 \mid H_1)$

Detection Probabilities (Reminder)

$$P_d = P\{Y > \lambda \mid H_1\} = Q_m(\sqrt{2\gamma}, \sqrt{\lambda})$$
$$P_f = P\{Y > \lambda \mid H_0\} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)}$$

Non-Fading Environment

where γ is the SNR

m = TW is the (observation/sensing) time bandwidth product

$\Gamma(\cdot)$ and $\Gamma(\cdot,\ \cdot)$ are complete and incomplete gamma functions

$Q_m(\ )$ is the generalized Marcum Q-function

λ is the threshold value

$$P_d = \int_x Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) f_\gamma(x) dx$$

Fading Environment

f_γ is pdf of SNR

Detection and False Alarm Probability for Cooperative Detection

A. Ghasemi and E. S. Sousa, "Collaborative Spectrum Sensing for Opportunistic Access in Fading Environment," in Proc. IEEE DySPAN, pp. 131-136, Nov. 2005

* Assume n CR users have the same sensing capabilities (same P_d and P_f)

* All CR users assume a channel to be occupied even if at least one CR user detects a PU in that channel.

  →

  - Increases the cooperative detection probability Q_d
  - Suitable for a highly faded/shadowed radio environments

Detection and False Alarm Probability for Cooperative Detection

Cooperative detection also increases the probability of false-alarm

Q_d = 1 – Pr{all n CR users miss the detection} = $1 - (1 - P_d)^n$

Q_f = 1 – Pr{all n CR users detect the spectrum hole correctly} = $1 - (1 - P_f)^n$

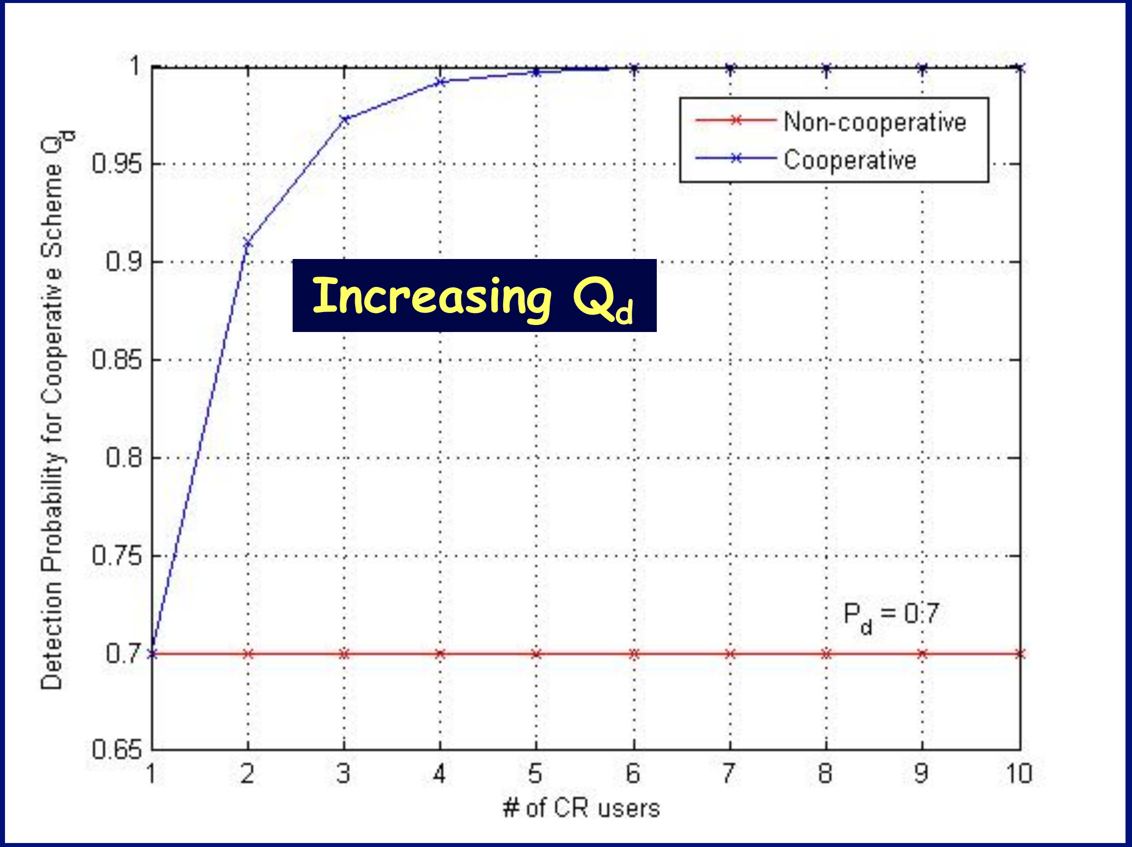
Q_d → cooperative detection probability

Q_f → cooperative false alarm probability

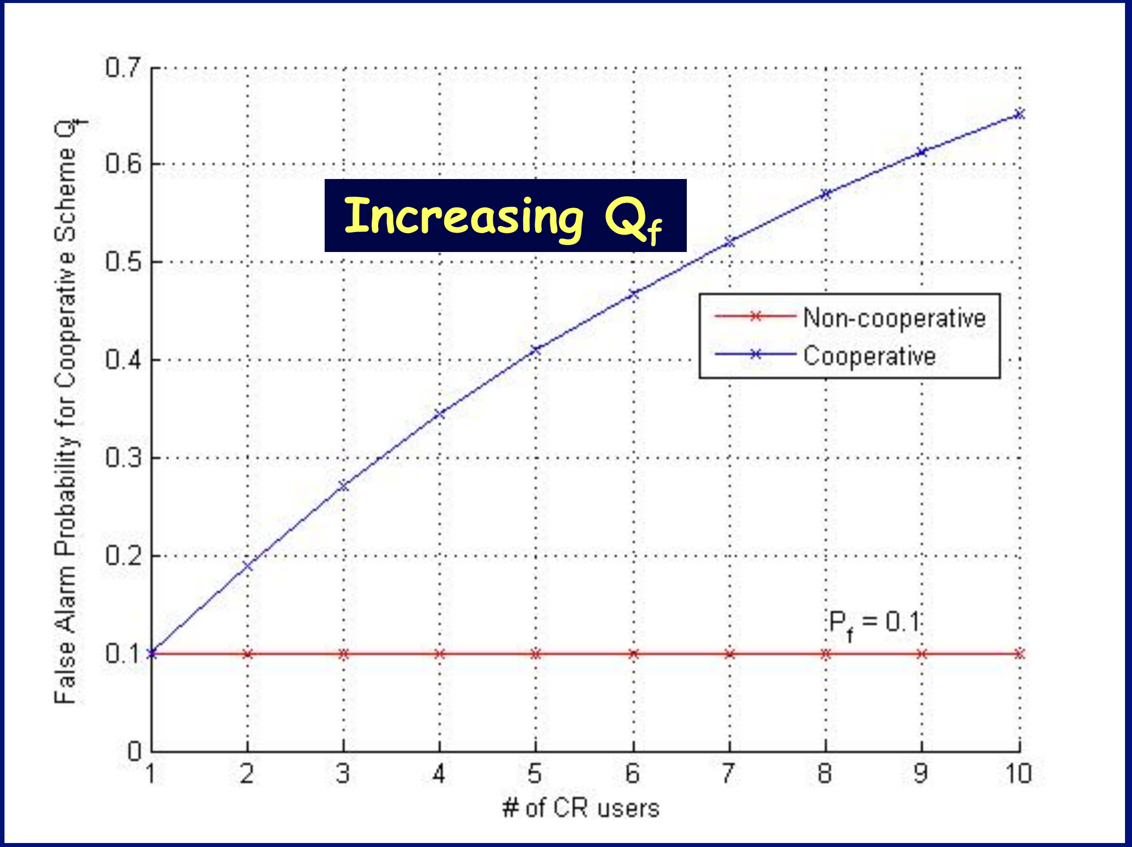
P_d → non-cooperative (individual) detection probability

P_f → non-cooperative (individual) false alarm probability

Detection and False Alarm Probability for Cooperative Detection



Cooperative Detection Probability



Cooperative False Alarm Probability

Cooperative Sensing

- Provides more accurate sensing performance
- However →

  Overhead traffic and power consumption
  for exchanging sensing information

HOW TO SELECT OPTIMAL THRESHOLD?

- Likelihood Ratio Test
- Neyman-Pearson Lemma and
- Bayesian Testing

LIKELIHOOD RATIO TEST

A statistical test: Make a decision about 2 competing hypotheses, e.g., Null Hypothesis (H_0) and Alternative Hypothesis (H_1).

Likelihood Functions:

$L(H_0|y)$: *(NULL HYPOTHESIS)*

Probability of observations y, given that H_0 is true, i.e., $p(y|H_0)$

$L(H_1|y)$: (ALTERNATIVE)

Probability of y, given that H_1 is true, i.e., $p(y|H_1)$

The likelihood of the Null Hypothesis over the Alternative is

$$\Lambda(\mathbf{Y}) = \frac{L(H_0 \mid \mathbf{y})}{L(H_1 \mid \mathbf{y})}$$

LIKELIHOOD RATIO TEST

Do not reject H_0 if $\Lambda(\mathbf{Y}) > \lambda$

Reject H_0 if $\Lambda(\mathbf{Y}) < \lambda$

Likelihood Ratio Test

Decision threshold needs to be determined based on experiments (empirically) to satisfy **miss-detection and false alarm constraints.**

$$\Lambda(\mathbf{Y}) = \frac{L(H_1 \mid \mathbf{y})}{L(H_0 \mid \mathbf{y})} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$$

Accept H_1
Reject H_0

NEYMAN PEARSON LEMMA

$$\Lambda(\mathbf{Y}) = \frac{L(H_1 \mid \mathbf{y})}{L(H_0 \mid \mathbf{y})} \geq \lambda$$

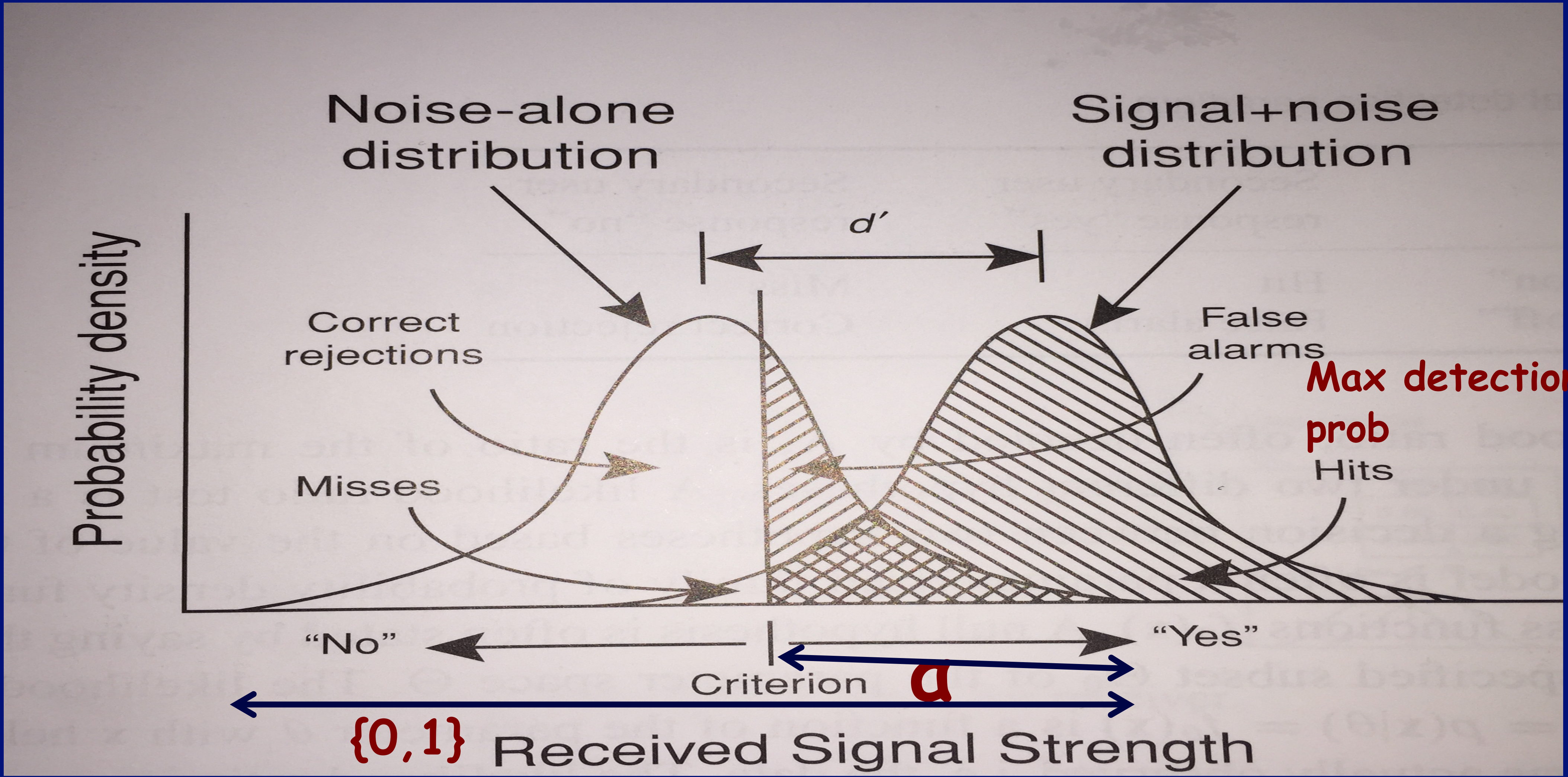
Given $P(\Lambda(\mathbf{Y}) \geq \lambda \mid H_0) = \alpha$, then $\Lambda(\mathbf{Y}) \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$ is

the most powerful test (max. detection probability {0,1}) of size α.

Note that α is the false alarm probability!

Interpretation: Thanks to NP lemma, λ can be adjusted to satisfy a false alarm prob. with maximum detection probability!

DETECTION OF SPECTRUM HOLES



Example

Basketball players seem to be taller than average

- Use this observation to formulate our hypothesis H_1:
  "Tallness is a factor in the recruitment of KU basketball players"
- The null hypothesis, H_0, could be:
  "Players on KU's team are a just average height compared to the population in the U.S."
  "Average height of the team and the population in general is the same"

Example

Setup:

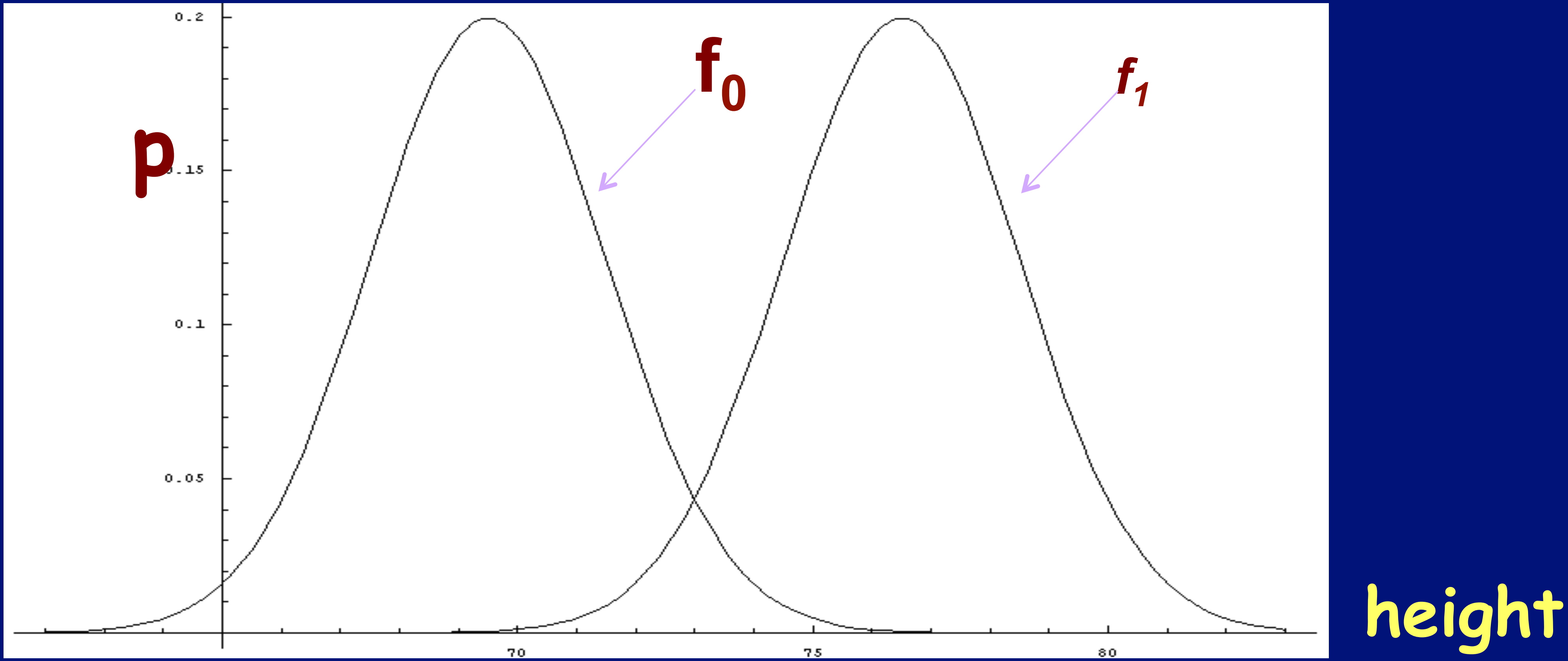
- Average height of males in the US: 5'9 ½"
- Average height of KU players in 2008: 6'04 ½"
  - Assumption: both populations are normal-distributed centered on their respective averages (μ_0 = 69.5 in, μ_1 = 76.5 in) and σ = 2
  - Sample size: 3

$$f_0(x) = \frac{e^{-\frac{(x-69.5)^2}{8}}}{2\sqrt{2\pi}} \qquad f_1(x) = \frac{e^{-\frac{(x-76.5)^2}{8}}}{2\sqrt{2\pi}}$$

- Choose α: 5%

Example

Two populations:



Example

Our test statistic is the Likelihood Ratio, LR

$$\Lambda(x)=\frac{f_1(x_1)f_1(x_2)f_1(x_3)}{f_0(x_1)f_0(x_2)f_0(x_3)} = \frac{\frac{e^{-\frac{(x_1-76.5)^2}{8}}}{2\sqrt{2\pi}}\frac{e^{-\frac{(x_2-76.5)^2}{8}}}{2\sqrt{2\pi}}\frac{e^{-\frac{(x_3-76.5)^2}{8}}}{2\sqrt{2\pi}}}{\frac{e^{-\frac{(x_1-69.5)^2}{8}}}{2\sqrt{2\pi}}\frac{e^{-\frac{(x_2-69.5)^2}{8}}}{2\sqrt{2\pi}}\frac{e^{-\frac{(x_3-69.5)^2}{8}}}{2\sqrt{2\pi}}}$$

$$= e^{\frac{1}{8}\sum_{i=1}^{3}(x_i-69.5)^2-(x_i-76.5)^2}$$

Now we need to determine a threshold λ at which we can reject H_0, given a = 5%

$P(\Lambda(x) \geq \lambda |\ H_0$ is true) = 0.05, determine λ

Example

So we just need to solve for λ' and calculate λ:

$$\int_{\lambda_1'}^{\infty}\int_{\lambda_2'}^{\infty}\int_{\lambda_3'}^{\infty} f_0(x_1) f_0(x_2) f_0(x_3)\, dx_1\, dx_2\, dx_3 = 0.05$$

How to solve this?

Well, we only need one set of values to calculate λ, so let us pick two and solve for the third:

$$\int_{68}^{\infty}\int_{71}^{\infty}\int_{\lambda_3'}^{\infty} f_0(x_1) f_0(x_2) f_0(x_3)\, dx_1\, dx_2\, dx_3 = 0.05$$

We get one result: λ_3' =71.0803

Example

Then we can just plug it in to Λ and calculate λ:

$$\lambda = e^{\frac{1}{8}\sum_{i=1}^{3}(\lambda_i^{'}-69.5)^2-(\lambda_i^{'}-76.5)^2}$$

$$= e^{\frac{1}{8}\left((68-69.5)^2-(68-76.5)^2+(71-69.5)^2-(71-76.5)^2+(71.0803-69.5)^2-(71.0803-76.5)^2\right)}$$

$$= 1.663 * 10^{-7}$$

Example

With the significance point λ = 1.663*10^-7^ we can now test our hypothesis based on observations:

E.g.: Sasha = 83in, Darrell = 81in, Sherron = 71in

$$\Lambda(X=\{83,81,71\})=e^{\frac{1}{8}\sum_{i=1}^{3}(X_i-69.5)^2-(X_i-76.5)^2}$$

$$\Lambda(83,81,71)=1.446*10^{12}$$

$1.446*10^{12} > 1.663*10^{-7}$

Therefore, our hypothesis that *tallness is a factor in the recruitment of KU basketball players* is true.

Likelihood Ratio Testing for AWGN Channel

Consider AWGN case to statistically model the received signal:

Assume PU transmits a constant level pulse.
CR user knows this level and tries to detect it via its observations:

Signal Model

$$y = \xi + n$$

- n is the AWGN with mean μ_0 and variance σ^2
- ξ is the PU signal level (deterministic) to be detected by the receiver
- y is the vector of the received signals

Likelihood Ratio Testing for AWGN Channel

Likelihood Function for H_0

$$L(H_0|\mathbf{y}) = f(\mathbf{y}|H_0) \tag{3.2}$$

$$= f(y_1|H_0)\, f(y_2|H_0) \cdots f(y_N|H_0) \tag{3.3}$$

$$= \prod_i^N \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y_i-\mu_0)^2}{2\sigma^2}} \tag{3.4}$$

$$= \frac{1}{(\sqrt{2\pi})^N \sigma^N} e^{-\frac{\sum_i (y_i-\mu_0)^2}{2\sigma^2}} \tag{3.5}$$

$$= \frac{1}{(\sqrt{2\pi})^N \sigma^N} e^{-\frac{\sum_i (y_i-\mu_0)^2}{2\sigma^2}} \tag{3.6}$$

$$= \frac{1}{(\sqrt{2\pi})^N \sigma^N} e^{-\frac{N\mu_0^2}{2\sigma^2}} e^{-\frac{-N\mu_0 \bar{y}}{\sigma^2}} e^{-\frac{\sum_i y_i^2}{2\sigma^2}} \tag{3.7}$$

Note that:

$$\bar{y} = \frac{1}{N}\sum_i y_i$$

Sample Average

Likelihood Ratio Testing for AWGN Channel

Likelihood Function for H_1

$$L(H_1|\mathbf{y}) = f(\mathbf{y}|H_1) \tag{3.8}$$

$$= f(y_1|H_1) f(y_2|H_1) \cdots f(y_N|H_1) \tag{3.9}$$

$$= \prod_i^N \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y_i-\xi)^2}{2\sigma^2}} \tag{3.10}$$

$$= \frac{1}{(\sqrt{2\pi})^N \sigma^N} e^{-\frac{\sum_i (y_i-\xi)^2}{2\sigma^2}} \tag{3.11}$$

$$= \frac{1}{(\sqrt{2\pi})^N \sigma^N} e^{-\frac{\sum_i (y_i-\xi)^2}{2\sigma^2}} \tag{3.12}$$

$$= \frac{1}{(\sqrt{2\pi})^N \sigma^N} e^{-\frac{N\mu_1^2}{2\sigma^2}} e^{-\frac{-N\xi\bar{y}}{\sigma^2}} e^{-\frac{\sum_i y_i^2}{2\sigma^2}} \tag{3.13}$$

Likelihood Ratio Testing for AWGN Channel

- Likelihood ratio for AWGN channel becomes

$$\Lambda(\mathbf{y}) = \frac{f(\mathbf{y}|H_1)}{f(\mathbf{y}|H_0)} = Ke^{-\frac{-N(\xi-\mu_0)\bar{y}}{\sigma^2}}$$

which can be used to compare with the threshold

$$\Lambda(\mathbf{y}) \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$$

where λ can be optimized using Neyman-Pearson criterion $P(\Lambda(\mathbf{Y}) \geq \lambda \mid H_0) = \alpha$ using numerical techniques

Neyman-Pearson Testing RECAP

Objective:

Max. P_d given the constraint P_f<=a (a is the max. P_f)

Neyman-Pearson test is equivalent to the foll. Likelihood Ratio Test (LRT):

$$\Lambda(\mathbf{Y}) = \frac{f(\mathbf{y} \mid H_1)}{f(\mathbf{y} \mid H_0)} = \prod_{k=1}^{N} \frac{f(y_k \mid H_1)}{f(y_k \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$$

$\Lambda(Y)$ is the likelihood ratio

$f\,(y|H_j)$ is the distribution of observations $y = \{y_k\}^N$ (iid) under hypothesis H_j, $j \in \{0, 1\}$,

λ is the detection threshold,

y_k is the decision received at the FC from CR users

N is the number of samples (cooperating CR users)

- The right hand side is the product of the likelihood ratios of a priori probabilities for k independent cooperating CR users

Example
Neyman-Pearson Testing

- Consider the following binary hypothesis test on whether or not a primary signal $s(t)$ exists in a particular channel, which is performed on the received signal $y(t)$:

H_0: $y(t) = n(t)$, no primary signal
H_1: $y(t) = s(t) + n(t)$, there is a primary signal

where $s(t)$ is the primary signal (non-deterministic), and
$n(t)$ is the ambient (AWGN) noise.

Example
Neyman-Pearson Testing

K samples are obtained from the received signal $y(t)$, denoted by $y = \{y_k\}$, $k = 1,...,K$.

Assume that $s_k \sim N(\mu_1, \sigma_s^2)$, $k = 1,...,K$, are independent and identically distributed (i.i.d.), and $n_k \sim N(0, \sigma^2)$.

The noise and the primary user signal are independent.

Example
Neyman-Pearson Testing

What are the distributions of y under H_i, $p(y|H_i)$, $i = 0,1$?

$$p(\mathbf{y}|H_0) = p(y_1, \dots, y_K|H_0) = \prod_k p(y_k|H_0) = \prod_k \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{y_k^2}{2\sigma^2}\right) = \frac{1}{(2\pi\sigma^2)^{K/2}} \exp\left(-\frac{\sum_k y_k^2}{2\sigma^2}\right)$$

Similar to H_0, for H_1 :

$$p(\mathbf{y}|H_1) = \prod_k p(y_k|H_1) = \prod_k \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(y_k - u_1)^2}{2(\sigma^2 + \sigma_s^2)}\right) = \frac{1}{(2\pi(\sigma^2 + \sigma_s^2))^{K/2}} \exp\left(-\frac{\sum_k (y_k - u_1)^2}{2(\sigma^2 + \sigma_s^2)}\right)$$

Example
Neyman-Pearson Testing

Derive the log-likelihood ratio (LLR) function

$$\log \Lambda = \log \frac{p(\mathbf{y}|H_1)}{p(\mathbf{y}|H_0)}$$

$$= \log\left(\frac{(\sigma^2)^{K/2}}{(\sigma^2+\sigma_s^2)^{K/2}}\exp\left(-\frac{\sum_k (y_k-u_1)^2}{2(\sigma^2+\sigma_s^2)}+\frac{\sum_k y_k^2}{2\sigma^2}\right)\right)$$

$$= \frac{K}{2}\log\frac{\sigma^2}{\sigma^2+\sigma_s^2}-\frac{\sum_k (y_k-u_1)^2}{2(\sigma^2+\sigma_s^2)}+\frac{\sum_k y_k^2}{2\sigma^2}$$

Neyman-Pearson test:

$$\Lambda(\mathbf{Y}) \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$$

Example
Neyman-Pearson Testing

- **Special cases:**
  - If $u_1=0$, we can combine the last two terms:

$$\log \Lambda = \frac{K}{2}\log\frac{\sigma^2}{\sigma^2+\sigma_s^2} + \frac{\sigma_s^2}{2(\sigma^2+\sigma_s^2)\sigma^2}\sum_k y_k^2 > \log\lambda$$

  - log-likelihood ratio (LLR) function can be arranged for the given problem such that the detection is equivalent to detecting the energy:

$$\sum_k y_k^2 > \frac{2(\sigma^2+\sigma_s^2)\sigma^2}{\sigma_s^2}\left(\log\lambda - \frac{K}{2}\log\frac{\sigma^2}{\sigma^2+\sigma_s^2}\right)$$

$$= 2\sigma^2((\sigma/\sigma_s)^2+1)\left(\log\lambda + \frac{K}{2}\log(1+(\sigma_s/\sigma)^2)\right)$$

BAYESIAN TESTING

Objective:

Minimize the expected cost called the Bayes Risk given by

$$R = \sum_i \sum_j C_{ij}\, P(H_i|H_j)\; P(H_j) \qquad \text{for } i=0,1 \text{ and } j=0,1$$

where

C_{ij} and $P(H_i \mid H_j)$ are the cost and the probability, respectively, of declaring H_i when H_j is true, for $i, j \in \{0, 1\}$ and

$P(H_i)$ is the a priori probability of hypothesis H_i, for $i \in \{0, 1\}$.

$P(H_0)+P(H_1) = 1$

Elements: BAYES TESTING

Here $P_d = P(H_1 \mid H_1)$; $P_m = 1 - P_d = P(H_0 \mid H_1)$ and $P_f = P(H_1 \mid H_0)$.

In other words, the Bayes risk to be minimized is the sum of all possible costs weighted by the probabilities of two incorrect detection cases (false alarm and miss detection) and two correct detection cases.

H_o H_o → C_{oo} → (=0 for no cost for correct detection)

H_1 H_o → C_{10} → (=1 equal cost for missed detection)

H_o H_1 → C_{01} → (=1 equal cost for false alarm detection)

H_1 H_1 → C_{11} → (=0 no cost for correct detection)

Thus, if the value of $P(H_1)$ is not known, it may make sense to select a decision rule that minimizes the maximum value taken by the risk as $P(H_1)$ ranges in [0, 1] .

Elements: BAYES TESTING

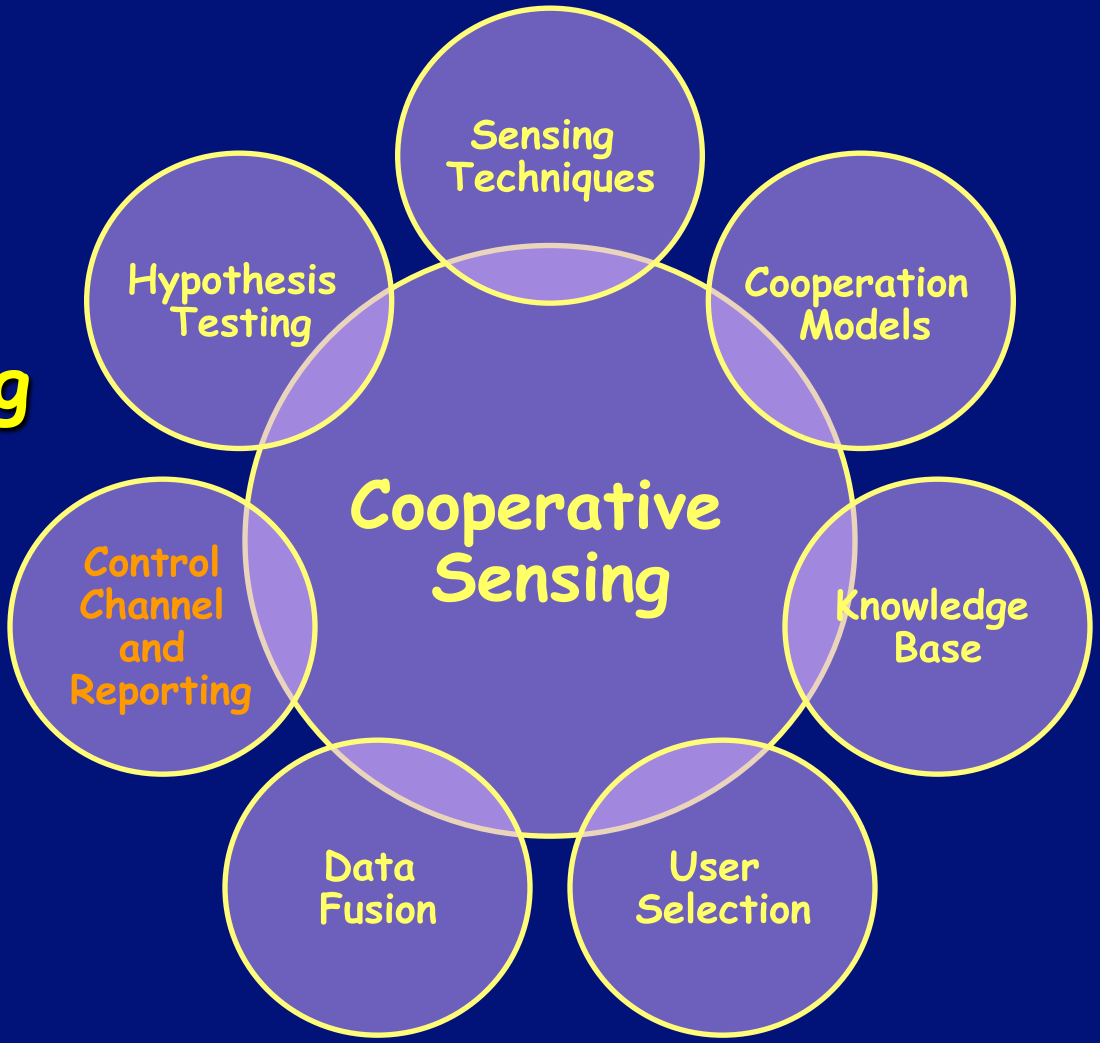
With the knowledge of a priori probabilities $P(H_i)$, the LRT of a Bayes test can be represented as

$$\Lambda(\mathbf{y}) = \frac{f(\mathbf{y}|H_1)}{f(\mathbf{y}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{P(H_0)(C_{10} - C_{00})}{P(H_1)(C_{01} - C_{11})} = \lambda.$$

Thus, the detector or the FC can minimize the Bayes Risk by declaring H_1 if $\Lambda(y) > \lambda$ and declaring H_0 otherwise.

Elements of Cooperative Sensing

- Sensing Techniques
- Hypothesis Testing
- **Control Channel/Reporting**
- Data Fusion
- User Selection
- Knowledge Base
- Cooperation Models



Elements:
Control Channel and Reporting

- CR users use control channel to report local sensing data to FC or share with other CR users

- Allocation of Control Channel

  Dedicated channel in licensed or unlicensed bands (most popular in coop sensing) or

  - Dynamic in-band channel (same as data channel) or

- MAC needed for accessing the control channel by cooperating CR users

- Control channel in cooperative sensing is assumed to exist in the literature

Elements:

Control Channel and Reporting Sensed Data:

REQUIREMENTS

- Bandwidth
- Reliability
- Security

Elements:
Control Channel and Reporting: BW Requirement

BW of the control channel determines the level of cooperation

because the amount of local sensing data that can be transmitted to the FC or shared with the neighbors is limited by the control channel BW.

Problem is addressed by censoring and quantizing local sensing data.

Each cooperating CR user performs the censoring by reporting the result only if the local decision is determined by the SPRT (sequential probability ratio test).

Thus, censoring reduces the unnecessary reporting and the usage of control channel BW.

Elements:
Control Channel and Reporting: RELIABILITY

- Like data channels, the control channel is susceptible to Gaussian noise, multipath fading, and correlated shadowing

- Channel impairments can compromise the reliable delivery of sensing data on control channel

Research Challenges:
Control Channel and Reporting: RELIABILITY

- How to design a control channel resilient to

    * channel impairments,
    * robust to PU activity, and
    * bandwidth-efficiency

for delivering sensing data is a nontrivial task

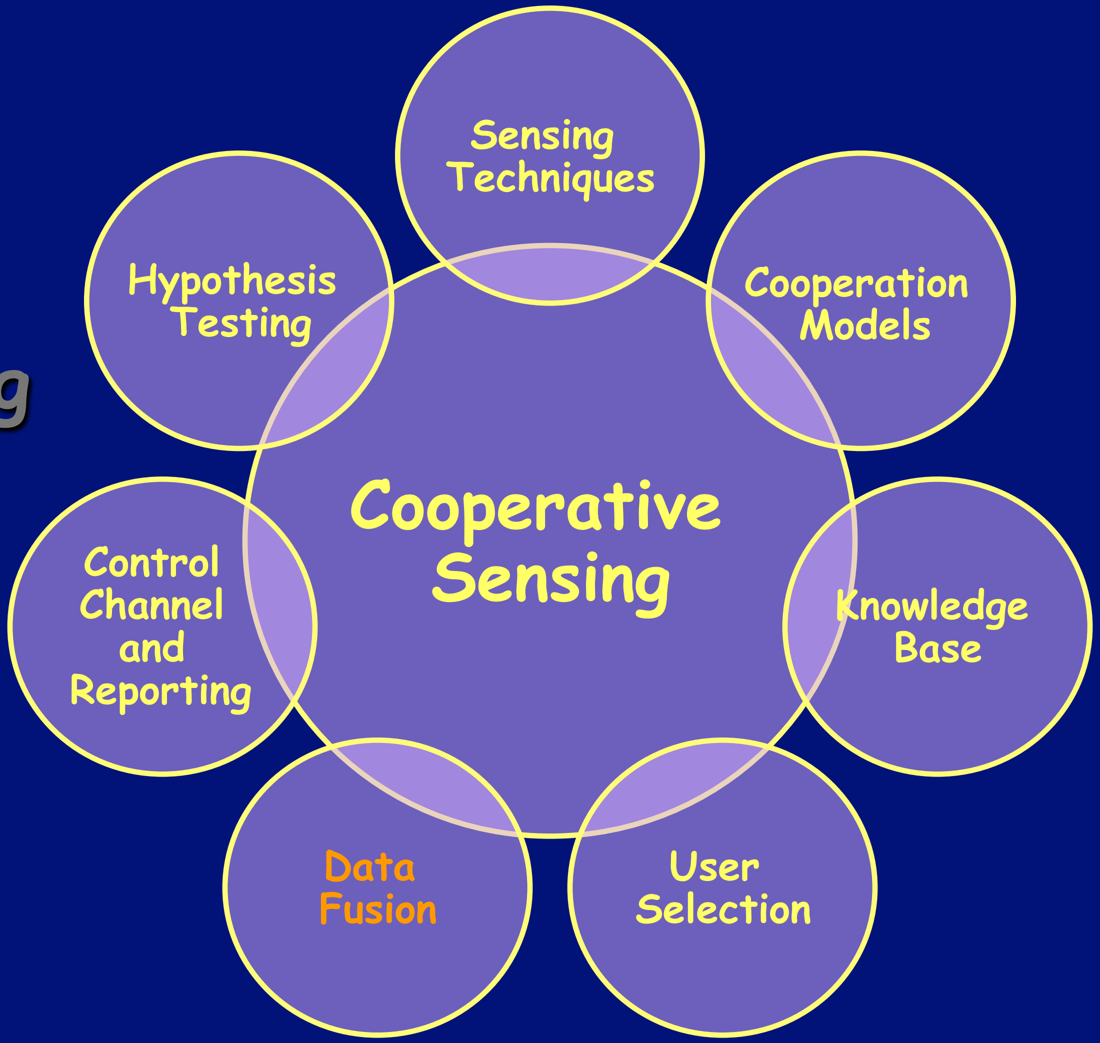
Research Challenges:
Control Channel and Reporting:
Dynamic Control Channel Allocation

- Most existing cooperative sensing schemes assume a dedicated control channel for data reporting

- Dynamic control channel allocation according to PU activity, channel availability and network topology significantly increases the difficulty for CR user cooperation and data reporting

Elements of Cooperative Sensing

- Sensing Techniques
- Hypothesis Testing
- Control Channel/Reporting
- **Data Fusion**
- User Selection
- Knowledge Base
- Cooperation Models



Elements: Data Fusion

- A process of combining local sensing data for hypothesis testing
- Depending on the control channel BW requirement, reported sensing results may be of different forms, types, and sizes.
- Sensing results reported to the FC or shared with neighboring users can be combined in three different ways in descending order of demanding control channel BW:

Elements: Data Fusion

- Soft Combining
  - CR users can transmit the entire local sensing sample or the complete local test statistics for soft decision.
- Quantized Soft Combining

  CR users can quantize the local sensing results and send only the quantized data for soft combining to alleviate control channel communication overhead.

  (Signal statistics such as mean, variance, histograms, etc)
- Hard Combining
  - PU decisions obtained locally by CRs
  - 1-bit decision (present or not present) reported

Elements: Data Fusion

- Soft Combining
  → the best detection performance → but control channel overhead

- Quantized soft combining and hard combining
  → much less control channel BW
  → but degraded performance due to the loss of information from quantization

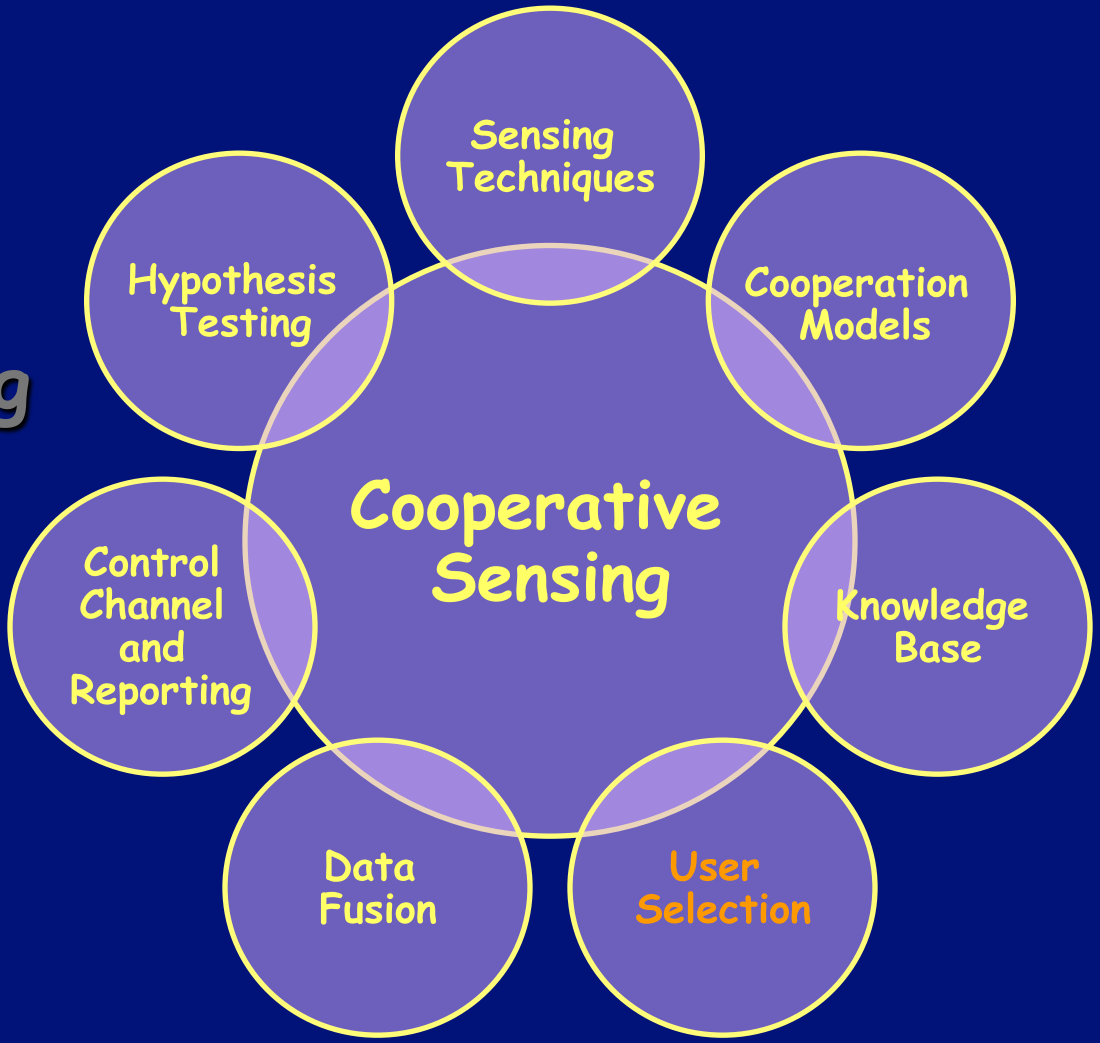
Elements: Data Fusion

- Fusion rules are mainly used for combining binary decisions (Hard Combining or Decision Fusion)

  - AND rule (N out of N rule)
  - OR rule (1 out of N rule)
  - Generalized K out of N rule
    - Declare the presence of PU when K out of N CR users say so
  - Majority rule (K > N/2)

Elements of Cooperative Sensing

- Sensing Techniques
- Hypothesis Testing
- Control Channel/Reporting
- Data Fusion
- **User Selection**
- Knowledge Base
- Cooperation Models



Elements: User Selection

- User selection determines
  - Who will cooperate ?
  - How many will cooperate ?
  - How to cooperate ?
- Range of cooperation needs to be determined along with the user selection schemes
- Popular user selection schemes
  - Centralized Location-based
  - Distributed Cluster-based

Elements: User Selection: Centralized Location-based

Y. Selen, H. Tullberg, and J. Kronander,
"Sensor Selection for Cooperative Spectrum Sensing,"
Proc. of IEEE DySPAN 2008.

ALGORITHM 1: Correlation Measure-based Sensor Selection

Selects a set of cooperating CR users with the minimum correlation measure among them by a greedy approach.

CR users with the largest summed correlation with respect to the remaining CR users are successively removed one at a time from the set until the desired number of CR users for cooperation is reached.

Based on the knowledge of CR user locations, the correlation can be evaluated by the distance between two CR users.

Algorithm 1: Example

Choose K=6 out of N=10

Initial: Candidate Set C = {0,1,2,3,4,5,6,7,8,9}

Active Set A = ∅

Remove the CR user with the largest summed correlation from C in each iteration

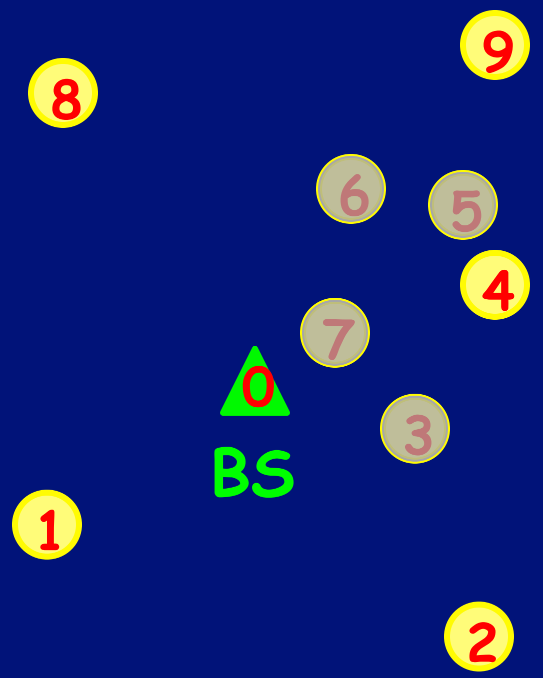
Remove 7 → C = {0,1,2,3,4,5,6,8,9} → K = 9

Remove 5 → C = {0,1,2,3,4,6,8,9} → K = 8

Remove 3 → C = {0,1,2,4,6,8,9} → K = 7

Remove 6 → C = {0,1,2,4,8,9} → K = 6

Final: A = {0,1,2,4,8,9}



ALGORITHM 2:
Iterative Partitioning based on CR users Position Estimates

Select CR users by successively adding uncorrelated users to the set if the selected CR users are located at a distance greater than the decorrelation distance d_0 from all existing members of the set.

Algorithm 2: Example

Choose K=6 out of N=10 using CR user positions x

Initial: Candidate Set $C = \{1,\ldots,9\}$

Active CR set $A = \{0\}$, $j \in A$ → K=1

Pick one CR user randomly from C each time

Select 9 → $||x_9-x_j||>d_0$ → $A=\{0,9\}$ → K=2

Select 7 → $||x_7-x_j||<d_0$ → $A=\{0,9\}$ → K=2

Select 1 → $||x_1-x_j||>d_0$ → $A=\{0,1,9\}$ → K=3

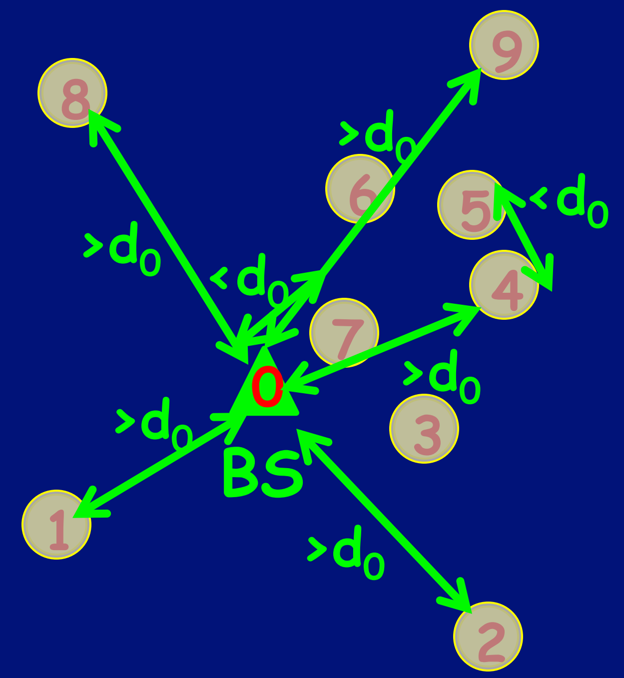
Select 4 → $||x_4-x_j||>d_0$ → $A=\{0,1,4,9\}$ → K=4

Select 5 → $||x_5-x_j||<d_0$ → $A=\{0,1,4,9\}$ → K=4

Select 2 → $||x_2-x_j||>d_0$ → $A=\{0,1,2,4,9\}$ → K=5

Select 8 → $||x_8-x_j||>d_0$ → $A=\{0,1,2,4,8,9\}$ → K=6

Final: $A = \{0,1,2,4,8,9\}$



d_0: de-correlation distance

ALGORITHM 3: Sensor Selection Based on Radius Information

Finds K cooperating CR users within the radius r of the BS that satisfy the desired probability of uncorrelated K CR users with only the radius information from the BS to users.

Algorithm 3: Example

Initial: Candidate Set C={1,…,9}, Active Set A={0}
Set target λ=Pr{Corr}=0.3, d_0 known

Set $r=r_1$ ➔ Find the largest K that satisfies s.t.

$$\Pr\{K\ uncorrelated\ CRs\} = \prod_{k=1}^{K}\left[1-(k-1)\Pr\{\mathrm{Corr}\}\right] \geq \lambda$$

➔ K=2

➔ Add 2 CRs with highest radii ≥r ➔ A={0,1,4}

Compute r' ➔ $r'=r_2$ ➔ $r_2-r_1<d_0$ (r_2 not valid)

$$\Pr\{\mathrm{Corr}\} = \frac{1}{\pi}\cos^{-1}\left(\frac{r^2+(r')^2-d_0^2}{2rr'}\right)$$

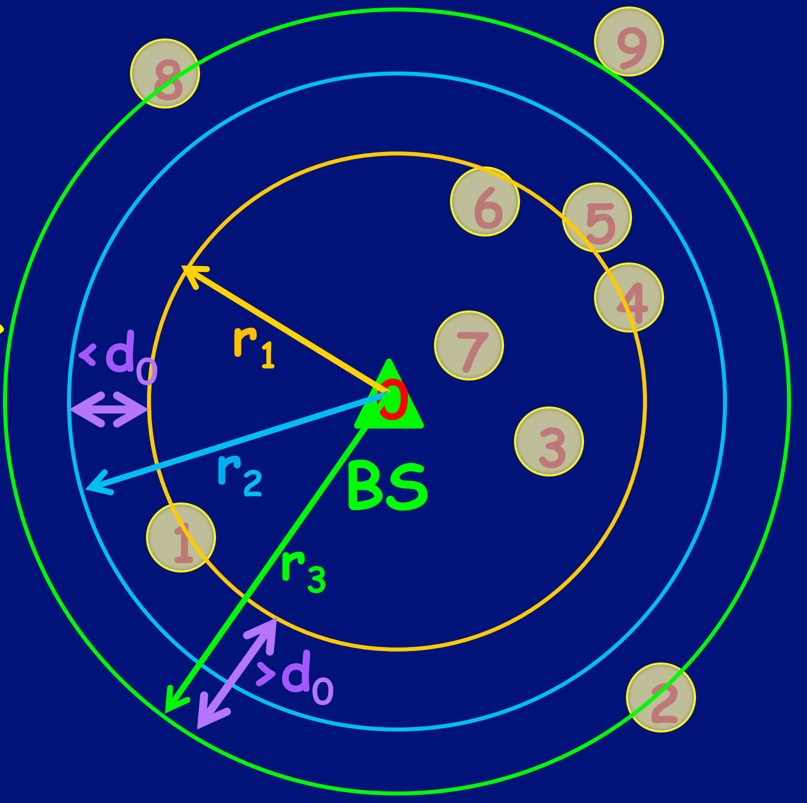
Adjust λ=Pr{Corr}=0.25 ➔ recompute r'

➔ $r'=r_3$

$r=r_3$ ➔ Find the largest K that satisfies λ ➔ K=3

➔ Add 3 CRs ➔ A={0,1,2,4,8,9}

Final: A = {0,1,2,4,8,9}



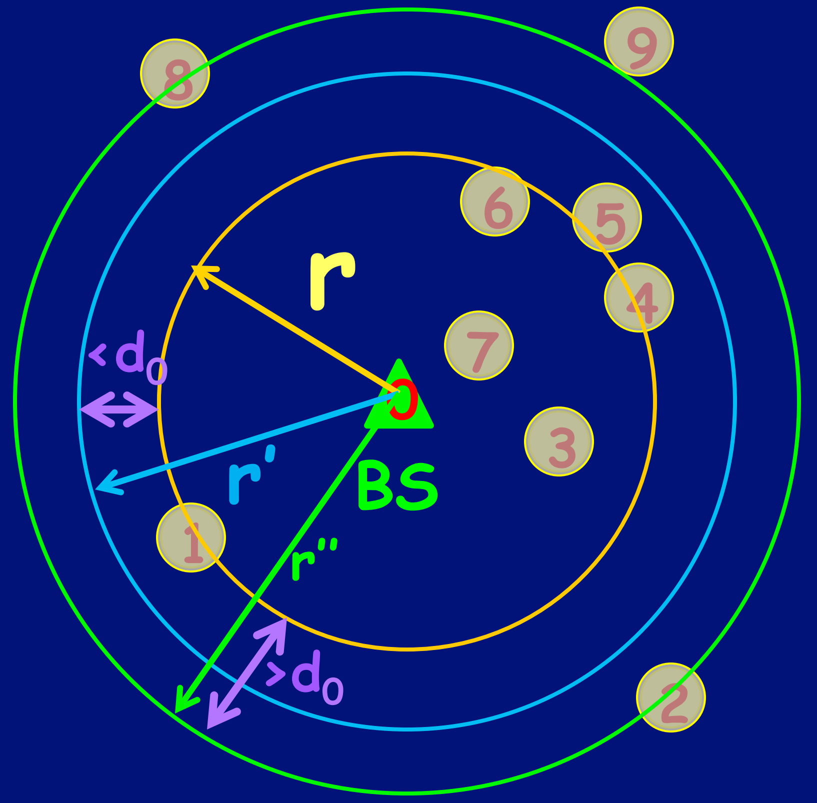
d_0: de-correlation distance

Algorithm 3: Example

$$d_0^2 = r^2 + (r')^2 - 2rr'\cos[\pi \Pr(corr)]$$

$$\cos[\pi \Pr(corr)] = \frac{r^2 + (r')^2 - d_0^2}{2rr'}$$

$$\Pr\{\text{Corr}\} = \frac{1}{\pi}\cos^{-1}\left(\frac{r^2 + (r')^2 - d_0^2}{2rr'}\right)$$



d_0: de-correlation distance

Research Challenges:
User Selection: CLUSTERING

1. Random Clustering

   CR users are randomly divided into clusters of equal size when the positions of both CR users and PUs are not available.

2. Reference-based Clustering

   CR user positions with respect to a given reference.

3. Statistical Clustering

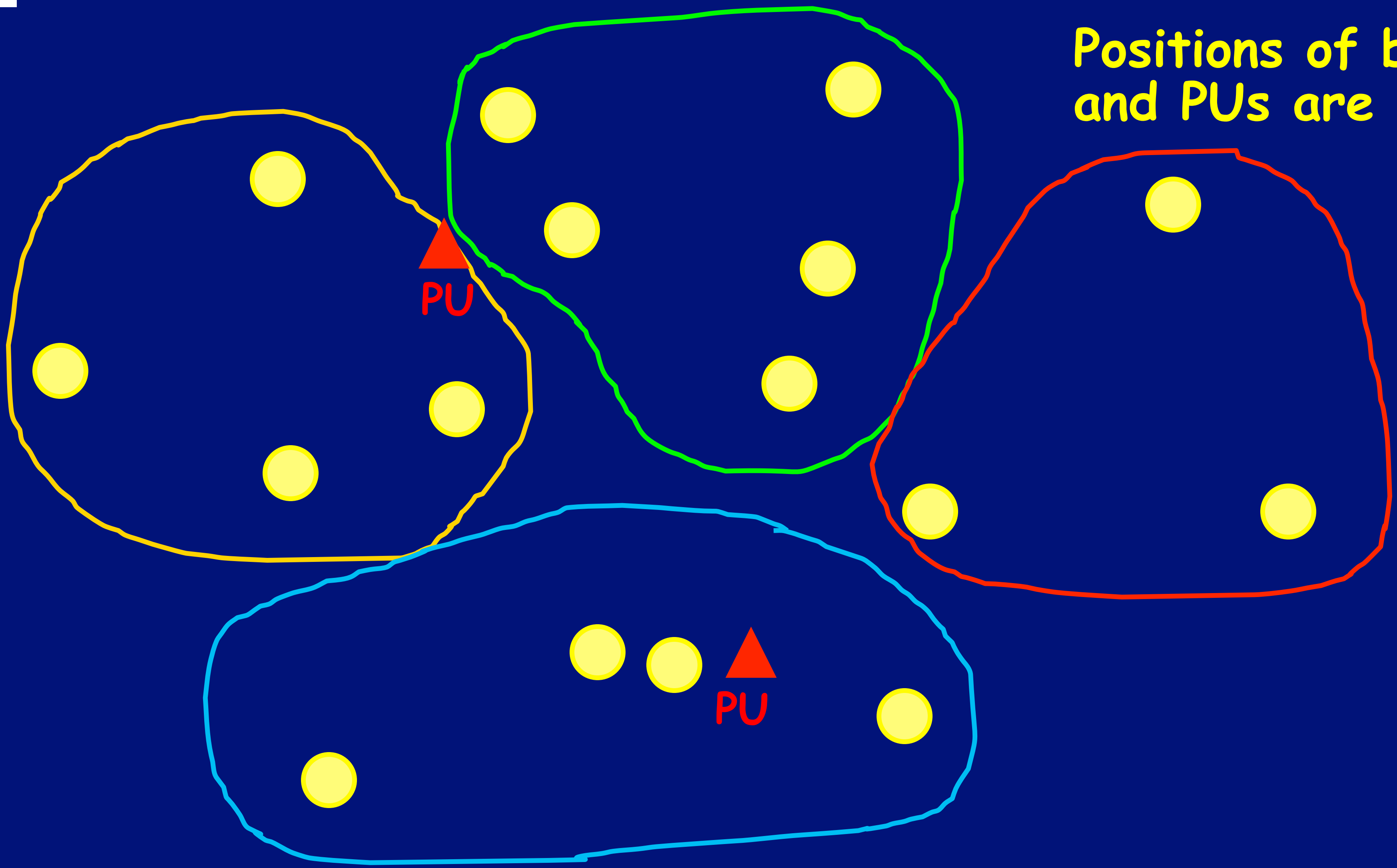
   Clusters are formed by using the statistical information and the proximities of CR users when only the positions of CR users are known.

4. Distance-based Clustering

   Only k out of K CR users closer to the PU in a cluster participate in cooperative sensing when the positions of both CR users and PUs are known.

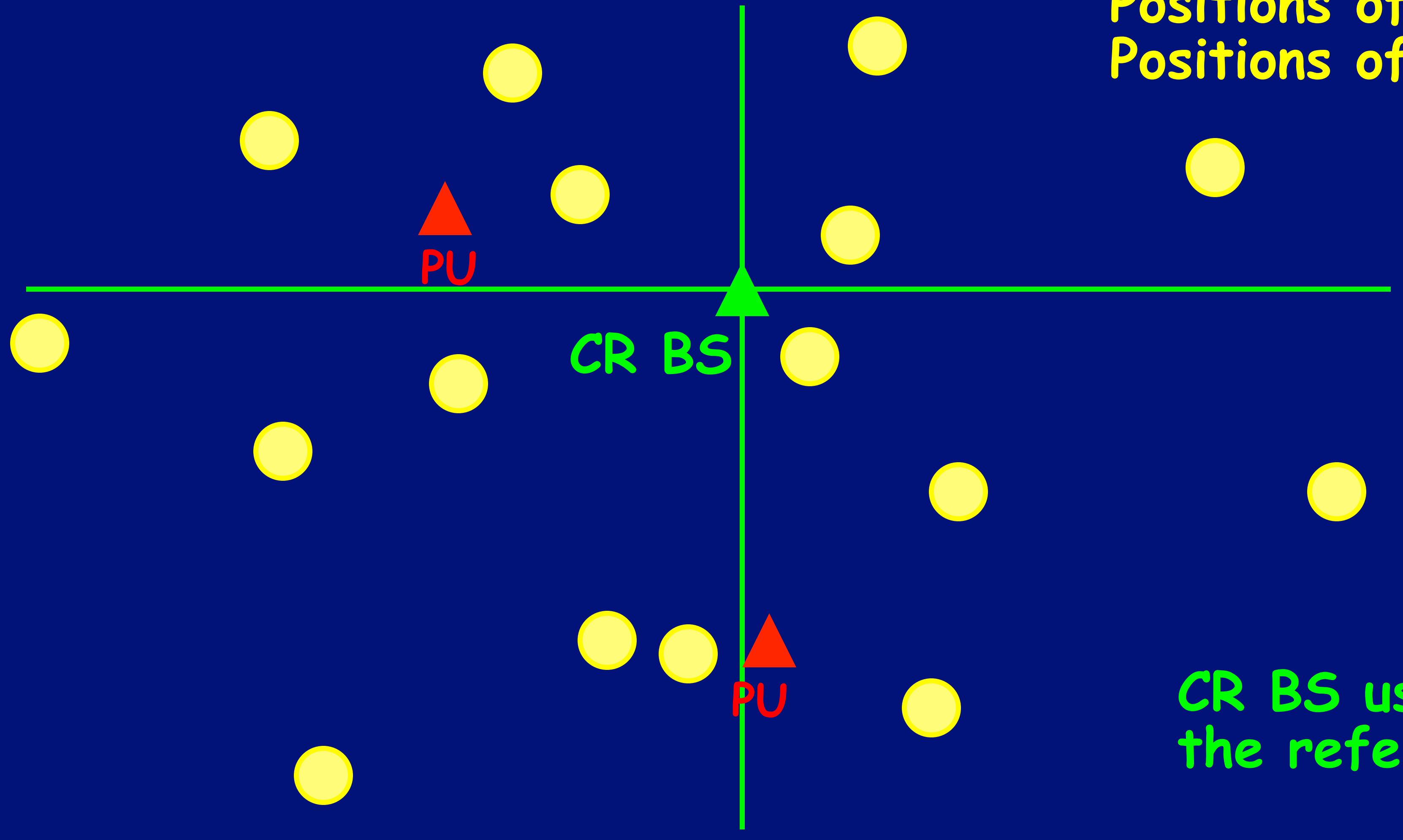
Random Clustering Example

Positions of both CRs and PUs are unknown



Reference-Based Clustering Example

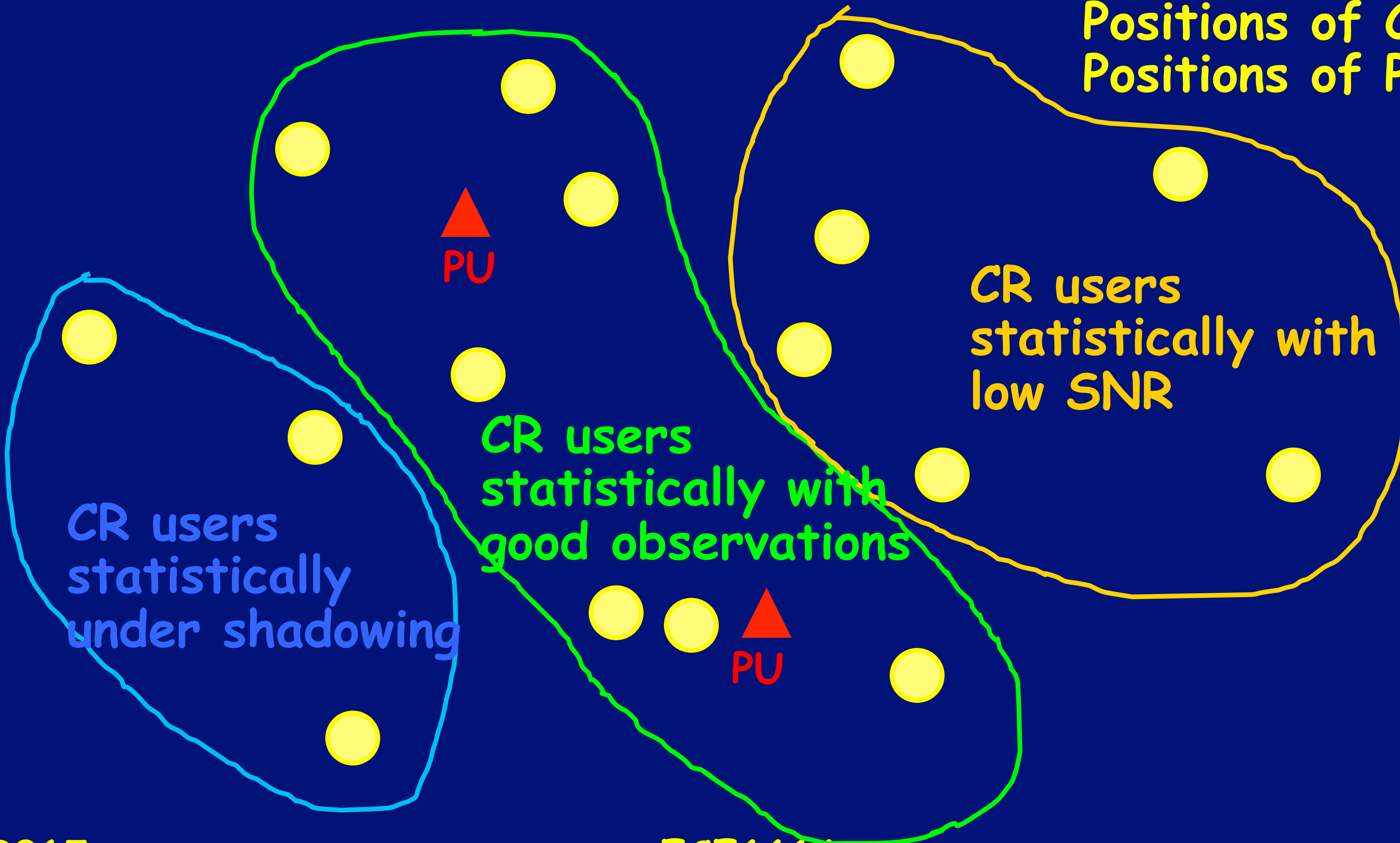
Positions of CRs known
Positions of PUs unknown



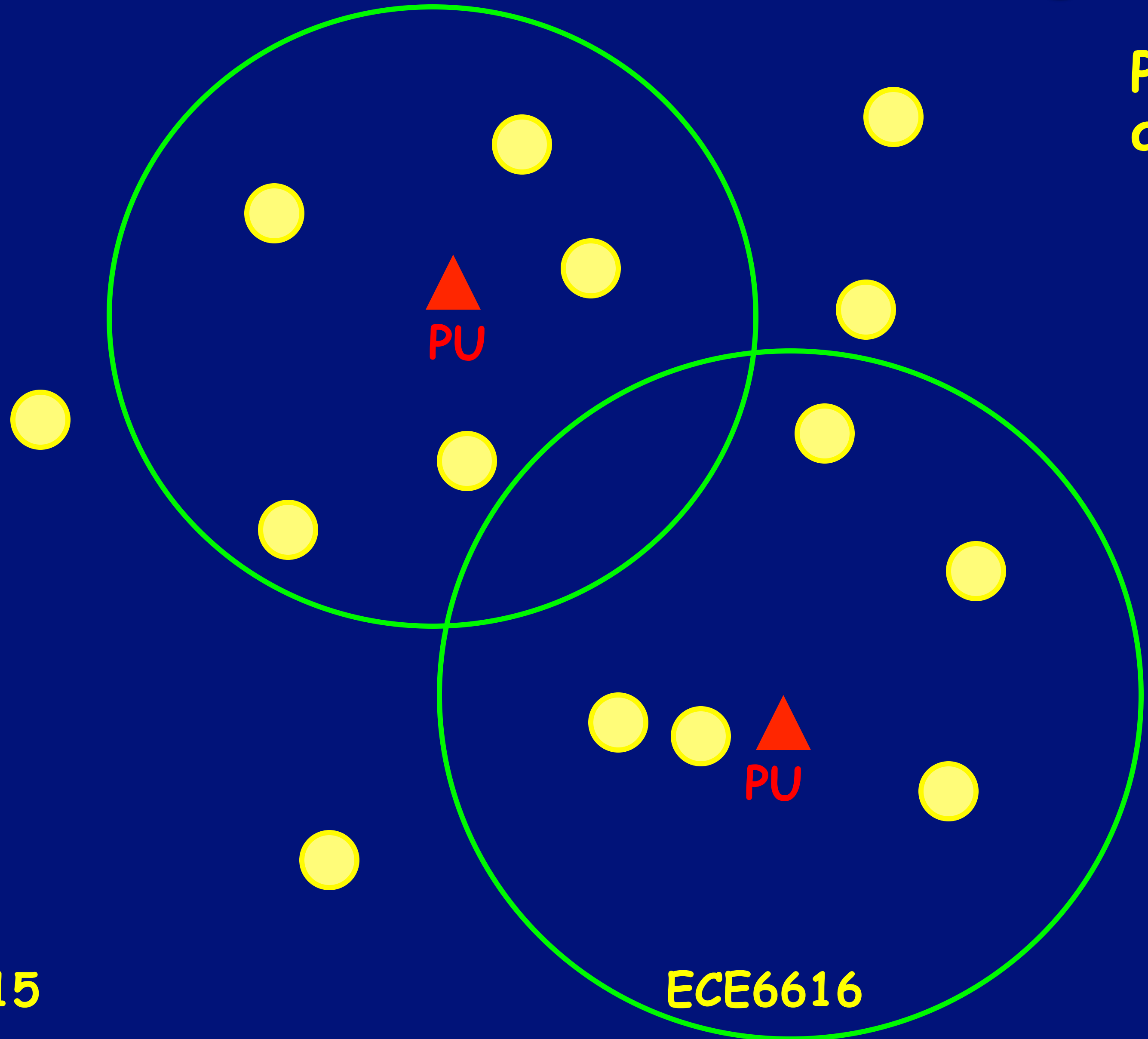
CR BS used as
the reference

Statistical-Based Clustering Example

Positions of CRs known
Positions of PUs unknown



Distance-Based Clustering Example



Positions of both CRs and PUs known

Only 5 out of N CR users closest to PUs are selected

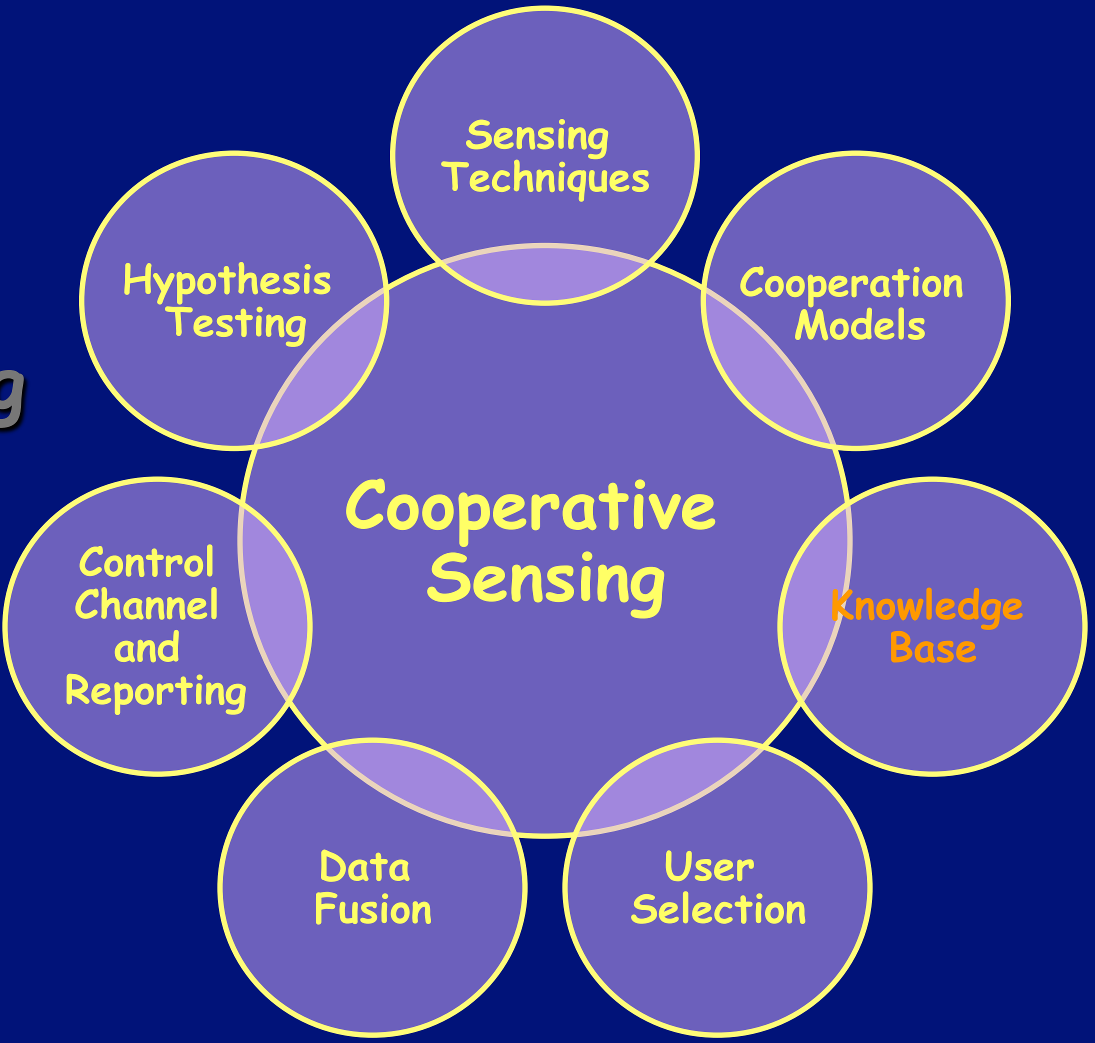
Research Challenges:
User Selection: OVERHEAD

- User selection is strongly related to:
  * Type of cooperative sensing overhead
  * Control channel bandwidth
  * Energy efficiency
  * Security issues

- Tradeoff exists between
  * Detection performance and
  * Each type of overhead

Elements of Cooperative Sensing

- Sensing Techniques
- Hypothesis Testing
- Control Channel/Reporting
- Data Fusion
- User Selection
- **Knowledge Base**
- Cooperation Models



Elements: Knowledge Base

- Performance of cooperative sensing schemes depends on the knowledge of PU characteristics;

  e.g., traffic patterns, location, and transmit power.

- PU information (e.g., in a database) help for PU detection.

- Database → Knowledge Base.

→ Important for cooperative sensing because it can help

→ assist, complement, or even replace cooperative sensing to detect PUs and identify available spectrum holes.

Elements: Knowledge Base

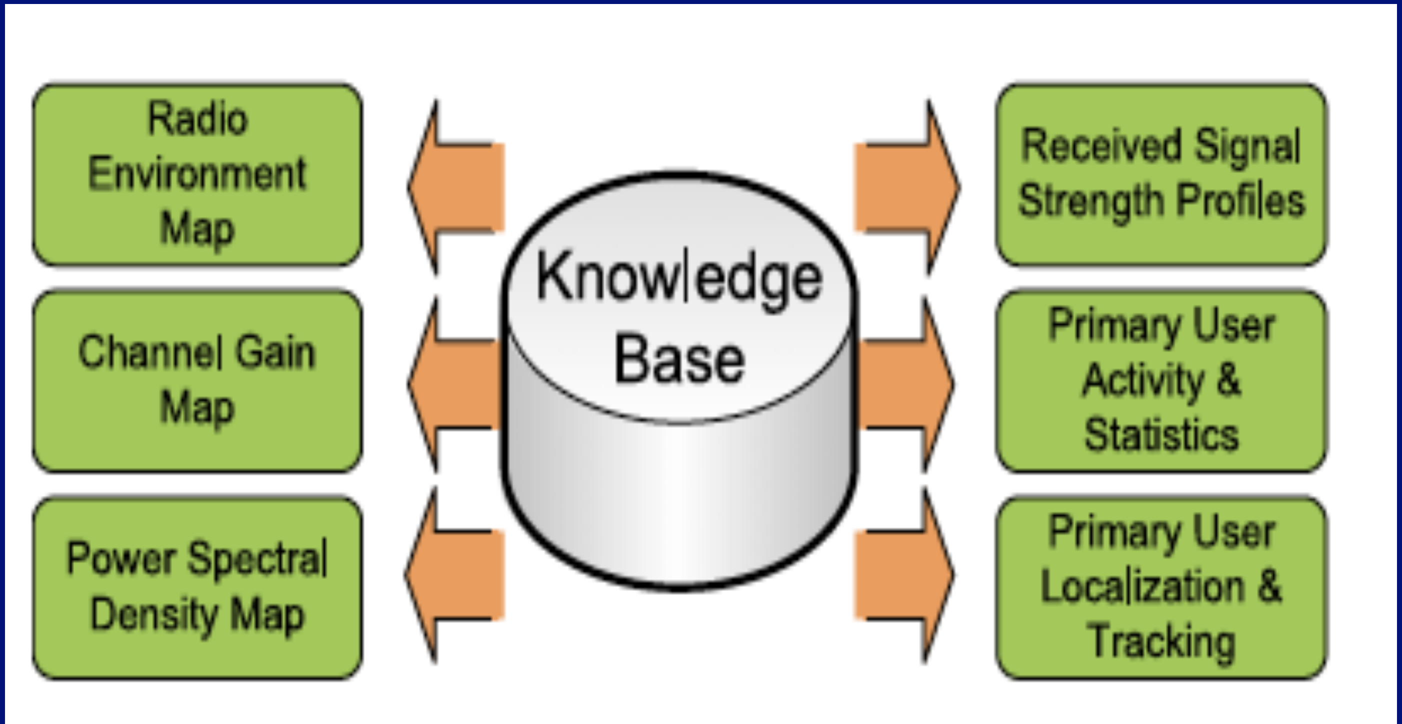
REMARKS:

- Not part of classic cooperative sensing, but has become more important recently
- Accumulated knowledge in the DB can facilitate cooperation process and help improve the sensing performance

Elements: Knowledge Base

- Knowledge to be acquired and stored in database
  - Primary User Activity
  - Location Information of PUs and CR users
  - Statistical models
    - Trust, reputation, and behavior models for CR users
  - Profiles
    - Received Signal Strength (RSS) profiles
    - CR User Profiles
  - Spectral Maps
    - Radio Environment Maps (REM)
    - Power Spectral Density (PSD) Maps
    - Channel Gain Maps

Research Challenges: Knowledge Base



Research Challenges: Knowledge Base: REM

Y. Zhao, J. Gaeddert, K.K. Bae, J.H. Reed,
"Radio Environment Map enabled situation-aware cognitive radio learning algorithms", Proc. of Software Defined Radio, 2006.

REM (Centralized Database) contains:

* locations of CR users
* available spectrum
* spectrum regulation and policies
* shadowing areas, and
* PU signal types.

REM can be accessed and utilized by each CR user to improve the detection performance in local sensing and also in cooperative sensing.

NOTE:

Large communication overhead due to a large amount of information transferred among CR users.

Research Challenges: Knowledge Base: Power Spatial Density Maps

J. Bazerque and G. Giannakis,
"Distributed Spectrum Sensing for Cognitive Radio Networks by Exploiting Sparsity",
IEEE Transactions on Signal Processing 58 (3), pp.1847-1862, 2010.

A distributed cooperative sensing scheme based on Power Spectral Density (PSD) maps for CRAHNs

CR users locally collect PSD samples and cooperatively estimate the basis expansion coefficients of the PSD map by exchanging messages with one-hop neighbors.

Consensus on the estimates is reached by using
Distributed least-absolute shrinkage and selection operator (D-Lasso) algorithm.

Research Challenges: Knowledge Base: Channel Gain Maps

S.-J. Kim, E. Dall'Anese, and G.B. Giannakis,
"Cooperative spectrum sensing for cognitive radios using Kriged Kalman filtering",
IEEE Journal of Selected Topics in Signal Processing, 2010.

Each CR user maintains **a Channel Gain Map**
(consists of path loss, shadowing, and fading components).

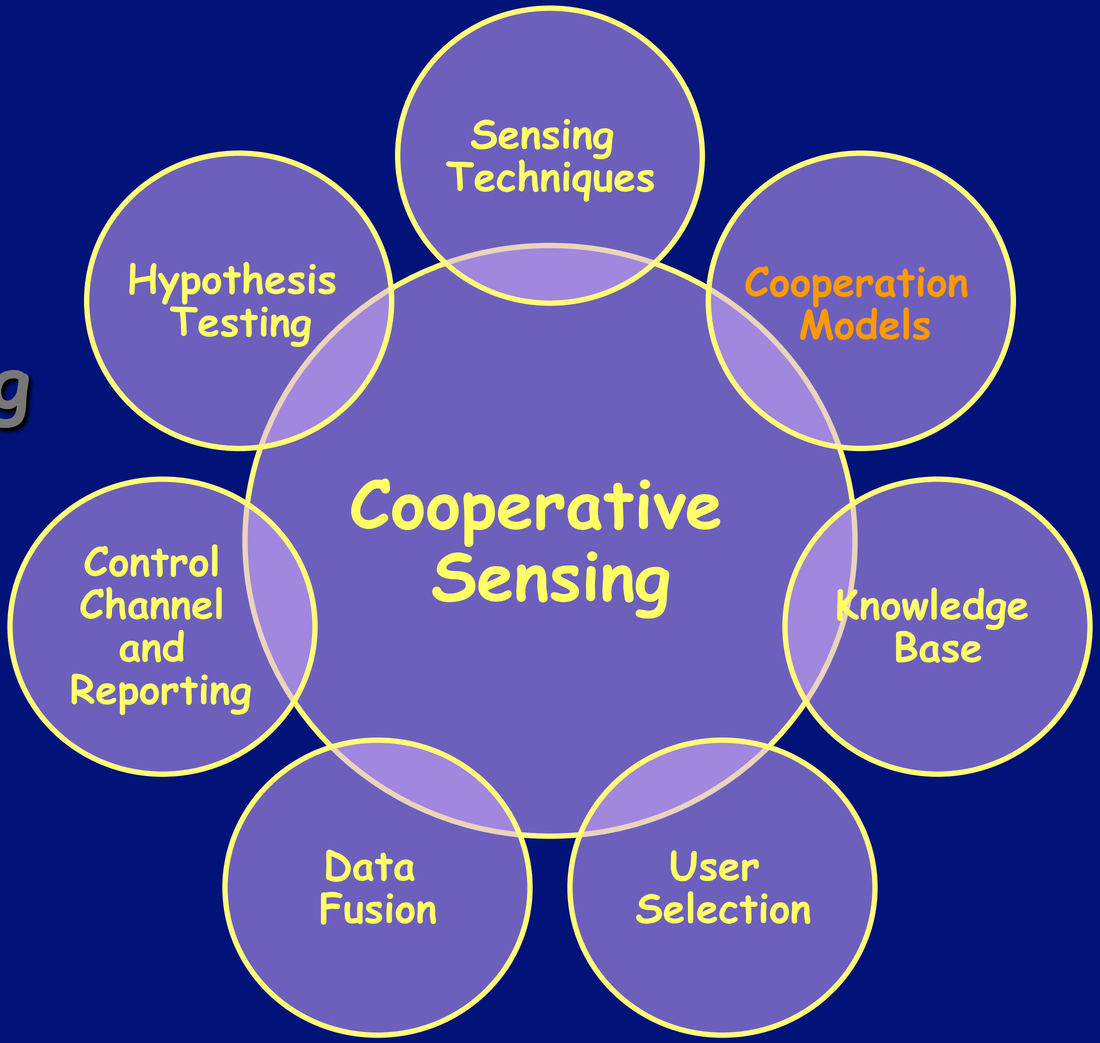
Kriged Kalman filtering is used to track shadow fading at any point in an area.

Cooperative Sensing formulated as a "sparse regression problem with time weighted non-negative Lasso to exploit the sparsity of PU locations".

Based on the established channel gain maps, a centralized algorithm and a distributed algorithm using alternating direction method of multipliers (ADMoM) are used for tracking PU locations.

Elements of Cooperative Sensing

- Sensing Techniques
- Hypothesis Testing
- Control Channel/Reporting
- Data Fusion
- User Selection
- Knowledge Base
- Cooperation Models



Elements: Cooperation Models

Question:

How do CR users cooperate to perform spectrum sensing and achieve the optimal detection performance?

Most popular approach →

Parallel Fusion (PF) model in distributed detection and data fusion.

PF models aim to achieve the detection performance by using distributed signal processing techniques to determine

* How are the observations combined and tested
* How are the decisions made.

Elements: Cooperation Models

B. Wang, K. Ray Liu, T. Clancy,
"Evolutionary cooperative spectrum sensing game: how to collaborate?"
IEEE Transactions on Communications 58 (3), pp. 890–900, 2010.

Behavior of cooperating CR users is modeled by Game Theory.

→Improve the sensing-parametric utility function by analyzing the interactions and the cooperative or non-cooperative behaviors of CR users.

NOTE:

* Parallel cooperation model emphasizes the "sensing" part

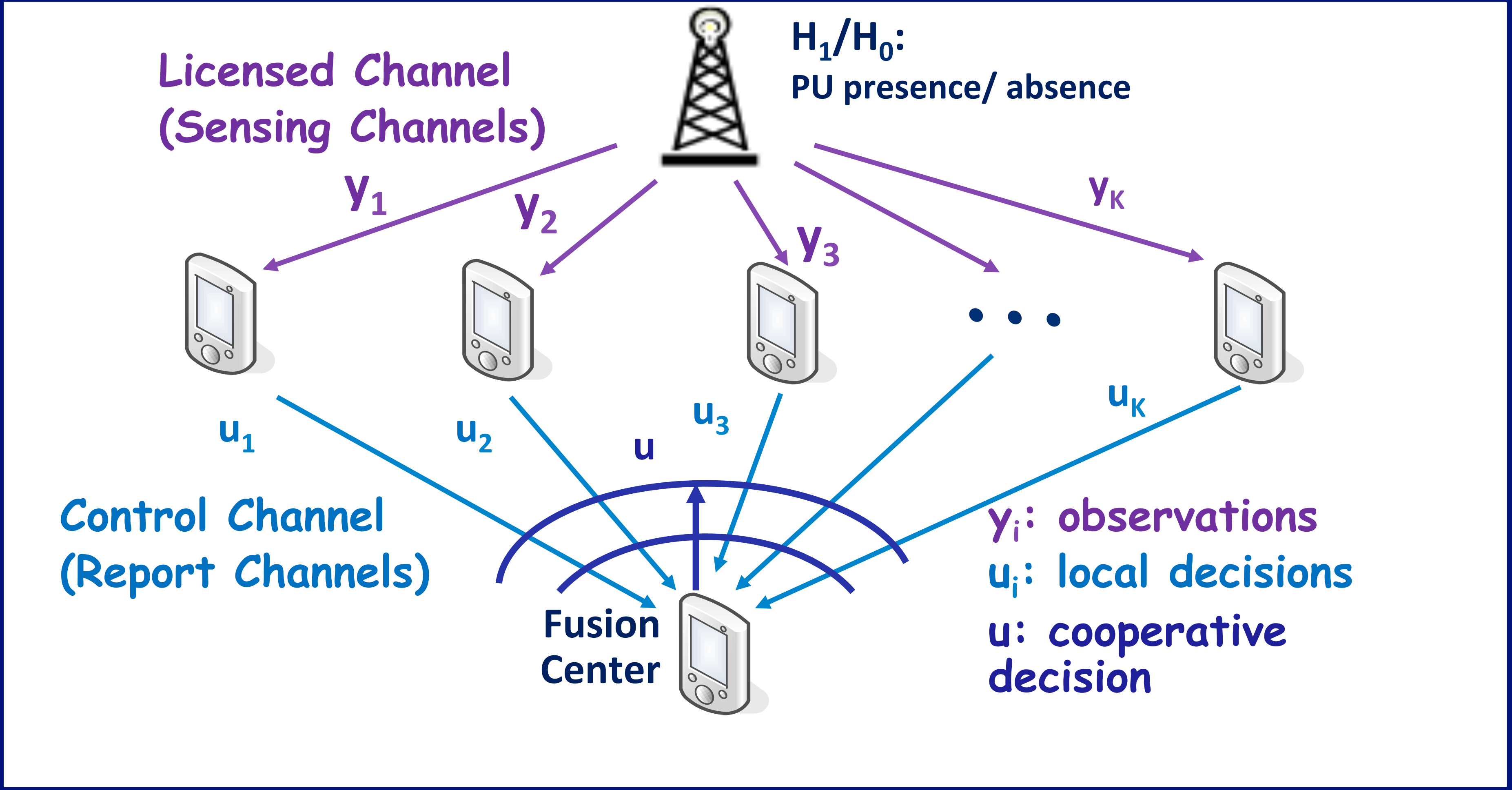
* Game Model focuses on the "cooperative" part in cooperative sensing.

Elements: Cooperation Models

P.K. Varshney, Distributed Detection and Data Fusion, Springer-Verlag, New York, 1997.

- Parallel Fusion Model
  - Most popular model originated from distributed detection and data fusion in sensor networks
  - Conventional view of cooperative sensing
  - Focus more on "sensing" part of cooperative sensing

Parallel Fusion Model



Elements:
Cooperation Models

- **Game Theoretical Model**
  - Investigate the interactions among cooperating and/or selfish CR users in cooperative sensing
  - Focus more on "cooperation" part of cooperative sensing

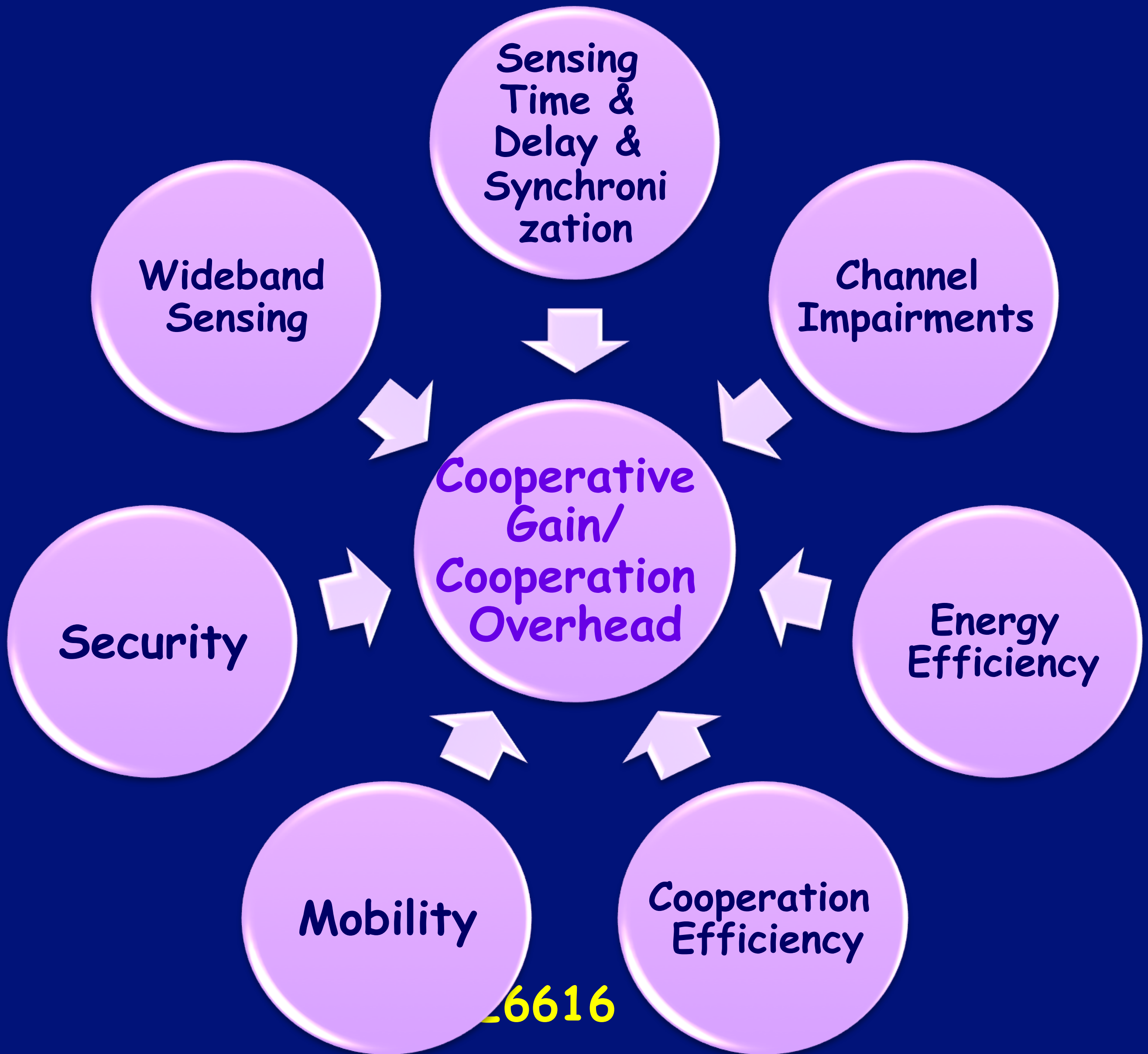
Research Challenges: Cooperation Models

- **Modeling Cooperation Overhead**
  - Most existing cooperative sensing models focus on detection performance and cooperative gain, not cooperation overhead
  - Proper modeling of cooperation overhead can reveal realistic achievable cooperative gain
  - Modeling of cooperation overhead is still an open challenge !

Research Challenges: Cooperation Models

- **Modeling Primary User Cooperation**
  - PUs could cooperate with CR users in certain applications such as military CR ad hoc networks
  - New models for cooperation between PUs and CR users in cooperative sensing are needed!!

DOMINATING FACTORS AFFECTING COOPERATIVE GAIN and COOPERATION OVERHEADS



Gain & Overhead:
Sensing Time & Delay & Synchronization

- **Sensing Time**
  - Long sensing time can improve detection performance, but can reduce transmission time and CR throughput

Gain & Overhead:
Sensing Time & Delay & Synchronization

- Reporting Delay
  - Sharing local sensing data with fusion center (FC) or other CR users incurs reporting delay
  - Incurred overhead due to cooperation

Gain & Overhead:
Sensing Time & Delay & Synchronization

- **Synchronization Issue**
  - Synchronizing CR users for cooperation or asynchronous cooperation also incurs overhead

Gain & Overhead: Energy Efficiency

- Cooperative sensing may consume more energy in all aspects
  - Sensing, reporting, data fusion, broadcast decision, etc
- Energy consumption overhead does not receive much attention yet in cooperative sensing
- Joint optimization of energy cost and other performance criteria may mitigate the overhead

Research Challenges:
Modeling Energy Consumption

- Existing methods simply model energy consumption in sensing, sleeping, and transmission/reporting as fixed values

- Many factors affect the degree of energy consumption
  - Different sensing techniques and sensing interval will consume different amount of energy
  - Energy consumption in reporting may depend on the transmit power level adapted to channel conditions

- More accurate energy model for cooperative sensing is needed

Gain & Overhead: Cooperation Efficiency

- **Sensing Scheduling**
  - Cooperation efficiency of centralized schemes is determined by

    * how often CR users cooperate with each other (sensing period) and

    * what type of sensing CR users should perform (e.g., fast sensing or fine sensing)

Gain & Overhead: Cooperation Efficiency

- **Rate of Convergence**
  - Cooperation efficiency of distributed schemes focuses on
    - * how fast CR users can reach an unanimous cooperative decision,

      i.e., convergence rate of the distributed algorithm for making a decision

Gain & Overhead: Primary User Mobility

- Large-scale PUs (e.g., TV tower and cellular BSs) are fixed

  while small-scale PU
  (e.g. wireless microphones and emergency radios) are mobile

- PU tracking facilitates the detection of mobile PUs

Research Challenges:
PU Mobility and Tracking

- Accurate PU tracking relies on efficient localization methods with location estimation

- Effective location estimation methods based on received signal strength values of PU signals remains a challenge

Research Challenges:
Impact of Mobility Parameters

- How to identify mobility parameters

  Mobility speed, direction of movement, Doppler frequency, density of CR users, moving trajectory profile, locations of CR users

that affect the detection performance and evaluate their impact on cooperative gain and cooperation overhead ?

Research Challenges: Mobility

Other Important Issues

- How to utilize spatial diversity from mobility to improve detection performance while preventing it from compromising cooperation gain?
- How cooperation can be maintained in movement?
- How much cooperation is needed?
- CR mobility along with mobile PUs makes PU tracking and detection more challenging

Gain & Overhead: Security

- **Security Risks for cooperative operations**
  - Manipulation of reporting sensing data
  - Interception of transmitting sensing data
  - Denial-of-service (DoS) attack
  - Control channel jamming attack
  - Node capture and PU emulation attacks
- **Major security concerns in cooperative sensing**
  - Byzantine failure
  - Data falsification

Conclusions

- **Cooperative Sensing**
  - Combat multipath fading and shadowing
  - Mitigate receiver uncertainty and hidden terminal problems
  - Consist of the following elements
    - Sensing techniques, hypothesis testing, control channel and reporting, data fusion, user selection, knowledge base, cooperation models

- **Cooperation Incurs Overhead!!!**
  - Sensing time and delay, channel impairments, energy efficiency, cooperation efficiency, mobility, security, wideband sensing

Conclusions

- Cooperative sensing must consider the tradeoff between achievable cooperative gain and manageable cooperation overhead
- Primary Research Challenges
  - Energy efficiency, impact of mobility, security, user selection, wideband cooperative sensing
- Active Research Areas
  - Wideband sensing with compressed sensing, security issues