Set-Theoretic Learning for Detection in Cell-Less C-RAN Systems

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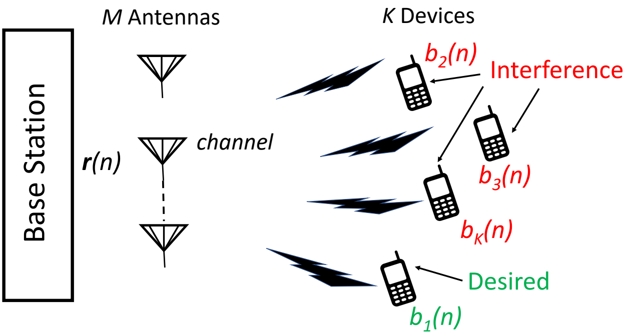
Outline

Background: Multiuser Uplink with a Single BS



Detection by Training

Train f^1 such that $(\forall n \in \mathbb{Z}_{\geq 0})\ f^1(\mathbf{r}(n)) \approx b_1(n)$

[Awan2018] D.A.Awan, R.L.G Cavalcante, M.Yukawa, S.Stanczak "*Detection for 5G-NOMA: An Online Adaptive Machine Learning Approach*": in Proceedings of ICC, Kansas City, USA 2018.

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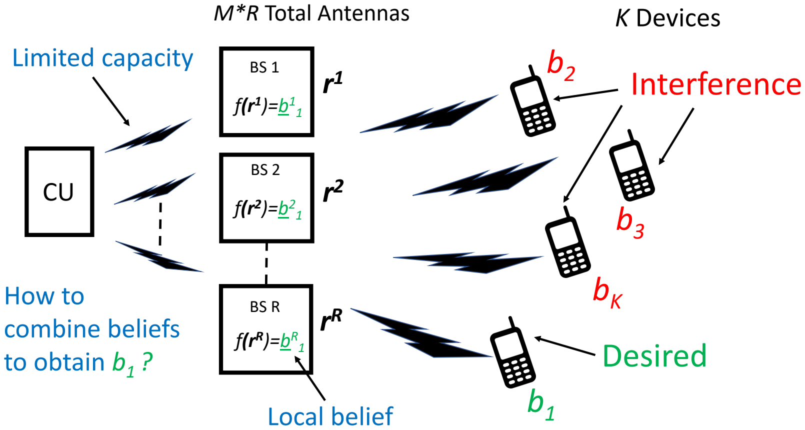
1. Background: Multi-User Detection
2. Detect & Forward CRAN
3. Contribution
4. Simulations
5. Questions

Detect & Forward with Multiple BSs



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Objective: Reliable Detection at CU

Learn likelihood functions[a] $\varphi_l(+1, \mathbf{r}^l)$, $\varphi_l(-1, \mathbf{r}^l)$ at each BS $l \in \overline{1, R}$ independently

[a] modulation is BPSK; n is omitted

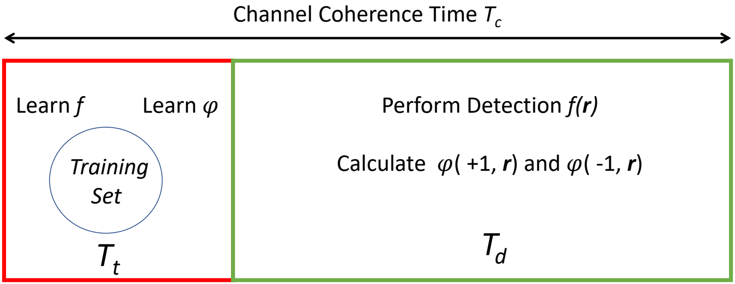
- At the CU

$$\hat{b} = \text{sgn}\left(\sum_{l=1}^{R} \log \frac{\varphi_l(+1, \mathbf{r}^l)}{\varphi_l(-1, \mathbf{r}^l)} \right); \tag{1}$$

sgn$(x) = +1$ if $x \geq 0$, otherwise sgn$(x) = -1$.

- **Future Work**: How to perform (1) at the CU? Approaches include consensus, optimal quantization etc.

Background: Learning Framework at each BS



Training set can be used to learn both f *and* φ

- **Main Idea**: Represent available information about $\varphi_{\mathbf{X}}$[1] by closed convex sets $C_1, C_2, \cdots, C_Q$.
- **Learning Algorithm**: Projection Onto Convex Sets (POCS) to obtain $\varphi_{\mathbf{X}} \in \bigcap_{q \in \overline{1,Q}} C_q$.

Prior Information for $C_1, C_2, \cdots, C_Q$.

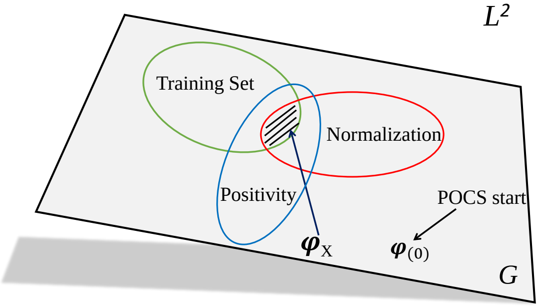
- **Training Data**: After training f extract $\mathcal{D}_{\mathbf{X}} := \{f(\mathbf{r}(n)) | b(n) = +1, n \in \overline{0, T_{\mathrm{t}} - 1}\}$.
- **Normalization**: $\int_{\mathbb{S}} \varphi_{\mathbf{X}}(x) dx = 1$; $\mathbb{S}$ is the support.
- **Positivity**: $\varphi_{\mathbf{X}}(x) \geq 0$.

One could think of other closed convex sets, e.g. mean of $\varphi_{\mathbf{X}}$

[1] $\mathbf{X}$ is the random variable associated with the filter response; we consider $b(n) = +1$

POCS in Finite Dimensional Gaussian Hilbert Space

- **Sample Set**: $\mathcal{D}_{\mathbf{X}} := \{x_1, x_2, \dots, x_N\}$
- **Assume**: $\varphi_{\mathbf{X}} \in G := \{\varphi \in L^2 | \varphi = \sum_{i=1}^{N} w_i \kappa(\cdot, x_i), (\forall i \in \overline{1,N}) w_i \in \mathbb{R}\}$
- **Gaussian Space**: If κ is the Gaussian kernel, G is a (finite-dimensional) Hilbert subspace of L^2.



Why G? Simple projections & $\varphi_{\mathbf{X}}(x)$ is well-defined & Approximation power

Projections and suitable POCS Algorithm

Projections $\mathbf{P}_{C_1}, \mathbf{P}_{C_2}, \ldots, \mathbf{P}_{C_Q}$

- **Training Samples**: Projection on a half space $\rightarrow$ has a closed form
- **Normalization**: Projection on a hyperplane $\rightarrow$ has a closed form
- **Positivity**: Projection on a closed-convex cone $\rightarrow$ we show that it's a quadratic program (QP)

Parallel POCS to deal with $\bigcap_{q \in \overline{1,Q}} C_q = \emptyset$

- Minimize : $\phi(\varphi) := \sum_{q=1}^{Q} \beta_q \|\varphi - \mathbf{P}_{C_q}(\varphi)\|_G^2$ $\rightarrow$ weighted sum of distances from each C_q

$$\varphi_{(n+1)} = \sum_{q=1}^{Q} \beta_q \mathbf{P}_{C_q}(\varphi_{(n)}) \quad \left(\sum_{q=1}^{Q} \beta_q = 1, \varphi_{(0)} \in G \right)$$

- Converges to a $\varphi^* \in \operatorname{argmin} \phi(\varphi) \in G \subset L^2$.

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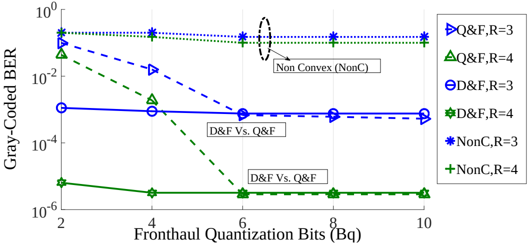
Comparison with other methods

- Graphs: Quantize & Forward (**Q&F**), Detect & Forward (**D&F**), Non-convex method (**NonC**) [Traganitis2017]
- Detection Peformance with **increasing fronthaul capacity** and **number of BSs**

Parameter	Symbol	Value
Number of BS Antennas	M	3
Cluster Size	K	6
Device SNR	SNR	randomly from $\{-3\,\text{dB}, -2\,\text{dB}, \cdots, 9\,\text{dB}, 10\,\text{dB}\}$
Modulation	$b(t)$	QAM $[\pm 1 \pm i1]$
Training Block Size	T_t	100



[Traganitis2017] P. Traganitis, A. Pags-Zamora, and G. B. Giannakis "*Learning from unequally reliable blind ensembles of classifiers*": in Proceedings of GlobalSip, Montreal, Canada, Nov 2017.

Outline

Outline For Questions

- CRAN Setting
- Detect and Forward
- Learning Framework
- Projection Onto Convex Sets
- Algorithm
- Results