## Title of the these

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January 3, 2020



- 1. Introduction

- 1. IoT Devices
- 2. IoT Applications
- 3. IoT Wireless Communications

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#### 1. IoT Devices

- IoT Applications
- IoT Wireless Communica

#### Massive IoT devices

Higher Categories

IoT devices are useless without a good communication capability



Figure 1. IoT devices [1].

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- 1. IoT Devices
- 2. IoT Applications
- IoT Wireless Communications

# Applications diversification

Each application has its own communication requirements

Challenges/Applications	Grids	EHealth	Transport	Cities	Building
Resources constraints	X	/	X	-	X
Mobility	X	-	/	/	X
Heterogeneity	-	-	-	/	X
Scalability	<b>✓</b>	-	/	/	-
QoS constraints	-	-	/	/	/
Data management	-	Х	/	/	-
Lack of Standardization	-	-	-	-	/
Amount of attacks	X	Х	/	/	/
Safety	-	1	/	-	<b>√</b>

Table 1. Main IoT challenges [2] [3]



Figure 2. IoT Applications.

# IoT platforms

#### IoT platforms is a chain of communication process

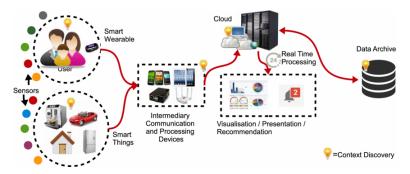


Figure 3. IoT platform.



Figure 4. IoT challenges.

# Applications diversification

Requirements

Use Case	Packet rate [pkt/day]	Min success rate [Ps,min]	Payload Size [Byte]
Wearables	10	90	
Smoke Detectors	2	90	
Smart Grid	10	90	10-20
White Goods	3	90	
Waste Management	24	90	
VIP/Pet Tracking	48	90	
Smart Bicycle	192	90	
Animal Tracking	100	90	
Environmental Monitoring	5	90	
Asset Tracking	100	90	50
Smart Parking	60	90	
Alarms/Actuators	5	90	
Home Automation	5	90	
Machinery Control	100	90	
Water/Gas Metering	8	90	
Environmental Data Collection	24	90	
Medical Assisted Living	8	90	
Micro-generation	2	90	
Safety Monitoring	2	90	100-200
Propane Tank Monitoring	2	90	
Stationary Monitoring	4	90	
Urban Lighting	5	90	
Vending Machines Payment	100	90	
Vending Machines General	1	90	1K

Table 2. Application requirements for the use cases of interest [4] [3] [5]

- 1. Introduction

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- 1. LoRa

## IoT wireless communication

Wireless communication performance need to be evaluated to match applications requirements

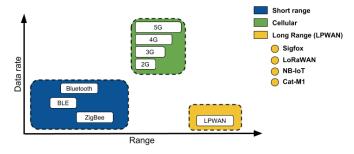


Figure 5. Short range, Cellular and Long range networks.

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## Wireless communication

Exp: LPWAN in a new technology that satisfy IoT applications requirements

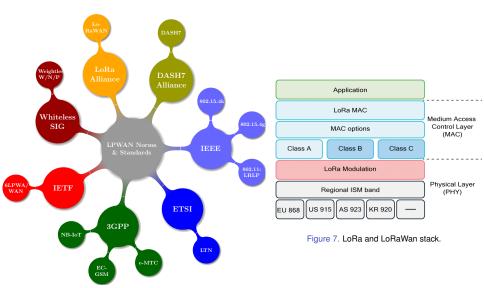


Figure 6. Wireless communication diversity.

#### LoRa modulation

Physical layer [6]

$$LoRa = \frac{2^{SF}}{BW} \left( (NP + 4.25) + \left( SW + \max \left( \left\lceil \frac{8PS - 4SF + 28 + 16CRC - 20IH}{4(SF - 2DE)} \right\rceil (CR + 4), 0 \right) \right) \right)$$
(1)

$$\mathbf{GFSK} = \frac{8}{DR}(NP + SW + PL + 2CRC) \tag{2}$$

#### Where:

- NP = 8, if LoRa . 5, if GFSK
- SW = 8, if LoRa . 3, if GFSK
- CRC = 0 if downlink packet. 1 if uplink packet
- → IH = 0 if header. 1 if no header present.
- DE = 1 if data rate optimization. 0 if not
- Pavload size (PS) = PHY Pavload bytes
- $\Rightarrow$  Spreading Factor (*SF*) = 7. 8. 9. 10. 11. 12
- Bandwidth (BW) = 125kHz, 250kHz, where BW is the bandwidth
- Coding Rate (CR) = Indicates the Coding Rate

# LoRa parameters selection

How to select the optimal configuration

- Parameters
  - → BW
  - → SF
  - → CR
  - → Transmission Power (Ptx)
  - → PS

- Metrics
  - → Signal Noise Rate (SNR)
  - → Data Rate (DR)
  - → Air Time (AT)
  - → PS<sub>max</sub>
  - → Receiver Sensitivity (S<sub>IX</sub>)

Setting	Values	Rewards	Costs
BW	7.8 <b>→</b> 500 <i>kHz</i>	DR	$S_{rx}$ , Range
SF	2 <sup>6</sup> • 2 <sup>12</sup>	$S_{rx}$ , Range	DR, SNR, PS <sub>max</sub> , P <sup>tx</sup>
CR	4/5 ➡ 4/8	Resilience	$PS_{max}, P^{tx}, AT$
P <sup>tx</sup>	-4 <b>⇒</b> 20 <i>dBm</i>	SNR	P <sup>tx</sup>
PS	59 <b>→</b> 230 <i>B</i>	PS	$P^{tx}$ , AT

Table 3. LoRa parameters selection [7]

Layer	Maximize (Reward)	Minimize (Cost)
Application	Sec security	Service Cost (SC)
Network	Range	Jitter ( <i>Jit</i> )
	Packet delivery ratio (PDR)	Traffic congestion (TC)
	PS	Round-Trip Delay ( <i>RTD</i> )
	DR	Packet Error Rate (PER)
		Time Complexity (Otime)
		Space Complexity (O <sub>space</sub> )
Radio	Mobility (Mob)	Bit Error Rate (BER)
	Symbol Rate (SR)	P <sup>tx</sup>
	Bit Rate (BR)	Co-channel Interference (CCI)
	Sensitivity (Sen)	Duty cycle (DC)
	Received Signal Strength Indication (RSSI)	Time on Air (ToA)
	Signal-to-interference & noise ratio (SINR) SNR	Path loss (PL)
	Signal-to-Interference Ratio (SIR)	

Table 4. Network selection inputs and classification of parameters [8] [9]

$$SNR_{[dB]} = 20.log(\frac{S}{N})$$

$$RSSI = Tx_{power} \cdot \frac{Rayleigh_{power}}{PL}$$

$$SR_{[sps]} = \frac{BW}{2SF}$$

$$(5)$$

$$BR_{[bps]} = SF * \frac{\frac{4}{4+CR}}{\frac{2SF}{2SF}}$$

$$(6)$$

$$PL = |RSSI| + SNR + P_{TX} + G_{RX}$$

$$Sen_{[dBm]} = -174 + 10 \log_{10} BW + NF + SNR$$

$$PER_{[pps]} = 1 - (1 - BER)^{n_{bits}}$$
8 1 \( \text{N} \) \( \text{16} \) \( 20 \) \( \text{SINR}(\frac{1}{2} - 1) \)

$$BER_{[\mathbf{bps}]} = \frac{8}{15} \cdot \frac{1}{16} \cdot \sum k = 216 - 1^{k} \left(\frac{16}{k}\right) e^{20.S/NR(\frac{1}{k} - 1)}$$
(10)

$$ToA_{s} = \frac{2^{SF}}{BW_{[Hz]}} \tag{11}$$

$$PER_{[pps]} = 1 - (1 - BER)^{n_{bits}}$$
 (12)

(13)

(7)

(8)

(9)

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (p_i - r_i)^2$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (p_i - r_i)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |p_i - r_i|$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\_Score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{precision} + \text{recall}}$$

$$TPR = \frac{TP}{TP + FN}$$

$$(10)$$

$$TPR = \frac{TP}{TP + FN}$$

$$TPR = \frac{FP}{TP + TN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$FPR = \frac{10 \log_2 P_i}{n} \text{ where } P_i = \frac{n - rank_i}{n - 1}$$

$$Serendipity = \frac{1}{n} \sum_{i \in L} \max(P_{user} - P_U, 0) \times rel_i$$

$$(24)$$

# LoRa Frame

Prea	nble	Sync msg	PHY Header	PHDR-CRC						
Modulation	length	Sync msg	PHY Header	PHDR-CRC		MAC Header				
Modulation	length	Sync msg	PHY Header	PHDR-CRC	МТуре	RFU	Major			
Modulation	length	Sync msg	PHY Header	PHDR-CRC	МТуре	RFU	Major	Dev A	Address	
Modulation	length	Sync msg	PHY Header	PHDR-CRC	МТуре	RFU	Major	NwkID	NwkAddr	ADR
0	1	2	3	4	5	6	7	8	9	10
PHY Payload								CF	RC	
	MAC Payload							MIC	CRC Type	Polynomial
				Frame Payload	MIC	CRC Type	Polynomial			
	FCtrl			FCnt	FOpts	FPort	Frame Payload	MIC	CRC Type	Polynomial
ADRACKReq	ACK	FPending /RFU	FOptsLen	FCnt	FOpts	FPort	Frame Payload	MIC	CRC Type	Polynomial
11	12	13	14	15	16	17	18	19	20	21

#### LoRa Frame

- Modulation :
  - → Lora: 8 Symbols, 0x34 (Sync Word)
  - → FSK: 5 Bytes, 0xC194C1 (Sync Word)
- Lenath:
- Sync msg:
- PHY Header : It contains:
  - → The Payload length (Bytes)
    - → The Code rate
  - → Optional 16bit CRC for payload
- → Phy Header : CRC It contains CRC of Physical Layer Header
- MType: is the message type (uplink or a downlink)
  - → whether or not it is a confirmed message (regst ack)
    - → 000 Join Request
    - → 001 Join Accept
    - → 010 Unconfirmed Data Up.
    - → 011 Unconfirmed Data Down
    - → 100 Confirmed Data Up
    - → 101 Confirmed Data Down
    - → 110 RFU
    - → 111 Proprietary
- RFU: Reserved for Future Use
- - Major: is the LoRaWAN version; currently, only a value of zero is valid → 00 LoRaWAN R1

    - → 01-11 RFU
- NwkID: the short address of the device (Network ID): 31th to 25th
- NwkAddr: the short address of the device (Network Address): 24th to
- ADR: Network server will change the data rate through appropriate MAC commands
  - → 1 To change the data rate
  - → 0 No change

- ADRACKReg: (Adaptive Data Rate ACK Request); if network doesn't respont in 'ADR-ACK-DELAY' time, end-device switch to next lower data rate.
  - → 1 if (ADR-ACK-CNT) >= (ADR-ACK-Limit)
  - → 0 otherwise
- ACK: (Message Acknowledgement): If end-device is the sender then gateway will send the ACK in next receive window else if gateway is the sender then end-device will send the ACK in next transmission.
  - 1 if confirmed data message
  - → 0 otherwise
- → FPending! /RFU ↑: (Only in downlink), if gateway has more data pending to be send then it asks end-device to open another receive window ASAP
  - → 1 to ask for more receive windows.
  - → 0 otherwise
- → FOptsLen: is the length of the FOpts field in bytes ă 0000 to 1111
- FCnt: 2 type of frame counters
  - → FCntUp: counter for uplink data frame, MAX-FCNT-GAP
  - → FCntDown: counter for downlink data frame, MAX-FCNY-GAP
- FOpts: is used to piggyback MAC commands on a data message
- FPort: a multiplexing port field → 0 the payload contains only MAC commands

  - → 1 to 223 Application Specific
  - → 224 & 225 RFU
- FRMPayload: (Frame Payload) Encrypted (AES, 128 key length) Data
- MIC: is a cryptographic message integrity code
  - → computed over the fields MHDR, FHDR, FPort and the encrypted FRMPayload.
- CRC : (only in uplink).
  - → CCITT x<sup>16</sup> + x<sup>12</sup> + x<sup>5</sup> + 1
  - $\rightarrow$  IBM  $x^{16} + x^{15} + x^5 + 1$

1.1			

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1. A Relay and Mobility Scheme

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1. A Relay and Mobility Scheme

# A Relay and Mobility Scheme for QoS Improvement in IoT

Related work<sup>1</sup>

- Only application requirements.
  - → Environment conditions, operator rules, User preferences.
- Only one (simple) normalization function for all parameters.
  - → Use Fuzzy logic with different rules for normalization.
- Only one objective function to fits all requirements.
  - Use Genetic algorithms with 3 objective functions.
- Only one application.
  - Use 3 applications with different requirements

<sup>1</sup>A. A. Simiscuka and G. Muntean, A Relay and Mobility Scheme for QoS Improvement in IoT Communications in 2018 IEEE International Conference on Communications Workshops (ICC Workshops), 00002. IEEE, May 2018, pp. 1–6.

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- 1. MCDM
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#### 1. MCDM

- 2. Genetic Algorithm
- Fuzzy Logic

Background

- Configuration parameters:
  - → SF
  - → CR
  - $\rightarrow P^{tx}$
  - → BW
    - → PS
- Configuration metrics:
  - → DR
  - → PDR
  - → RTD
  - → ToA

Metric 1 Metric 2 Metric M Configuration 1  $q_{11}$ **q**<sub>12</sub>  $q_{1M}$ Configuration 2  $q_{21}$  $q_{22}$  $q_{2M}$ Qn, m =Configuration N  $q_{N1}$  $q_{N2}$  $q_{NM}$ 

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- 1 MCDM
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- Fuzzy Logic

# Genetic Algorithm Background [11]

**Definition:** stopping criteria, population size P, and mutation probability  $p_m$  **Generate** randomly the initial configurations

repeat:

. . . for each configuration do

. . . . Train a model & compute configuration's fitness

. . . **end** . . . **for** each reproduction 1 ... P/2 do

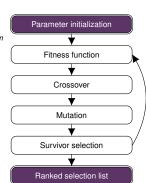
. . . . . Select: 2 configurations based on fitness

. . . . . Crossover: Produce 2 child configurations

. . . . . . Mutate: child configurations with  $p_m$ 

. . . end

until stopping criterion is met



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# **Fuzzy Logic**

Assign a degree of membership between 0 and 1

- We have a temperature value (16°), and we want to represent this value with 3 weighted vales.
  - → 0% hot
  - → 0.4% warm
  - → 0.6 % cold

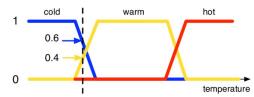


Figure 8. Temperature example.

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# Selection framework

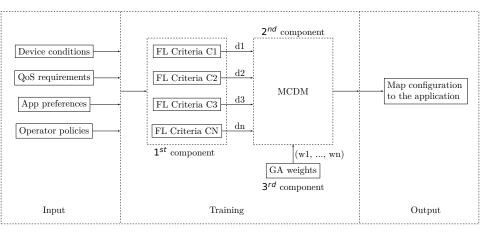


Figure 9. The proposed scheme for LoRa transmission parameters selection based on GA, FL and MCDM..

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# Experimentation

Experimentation

#### Inputs:

- Data structure
  - \* Voice, Images and Text transmission.
- → Environment conditions
  - \* Rural/Urban
  - \* Static/Mobile
  - \* Temperature
  - \* Interference/Noise
- → QoS metrics:
  - \* User layer: Cost
  - \* Network metrics: DR, Payload length.
- \* Radio metrics: Receiver sensitivity, SNR, DR, Air time,
- → MAC configuration (SF, CR, BW, Tx)
- Outputs:
- $\rightarrow$  (SF<sub>i</sub>, CR<sub>i</sub>, BW<sub>k</sub>, Tx<sub>l</sub>) optimal

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## Results

#### Comparison

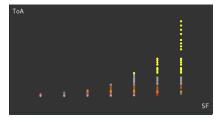


Figure 10. Impact of SF on ToA.

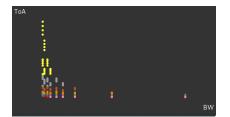


Figure 11. Impact of BW on ToA.

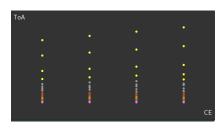


Figure 12. Impact of CR on ToA.

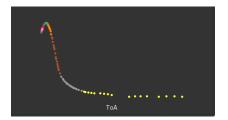


Figure 13. ToA distribution.

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# Multi criteria decision making

Layer	Maximize (Reward)	Minimize (Cost)
Application	Sec security	SC
Network	Range	Jit
	PDR	TC
	PS .	RTD
	DR	PER
		O <sub>time</sub>
		O <sub>space</sub>
Radio	Mob	BER
	SR	P <sup>tx</sup>
	BR	CCI
	Sen	DC
	RSSI	ToA
	SINR	PL
	SNR	
	SIR	

Table 5. Network selection inputs and classification of parameters [8] [9]

# Multi criteria decision making

$$SNR_{[dB]} = 20.log(\frac{S}{N})$$

$$RSSI = Tx_{power} \cdot \frac{Rayleigh_{power}}{PL}$$

$$SR_{[sps]} = \frac{BW}{2SF}$$

$$BR_{[bps]} = SF * \frac{\frac{4}{4+CR}}{\frac{2SF}{BW}}$$
(33)
(34)

$$PL = |RSSI| + SNR + P_{TX} + G_{RX}$$

$$Sen_{\text{fdBm1}} = -174 + 10\log_{10}BW + NF + SNR$$
(38)

$$Sen_{[dBm]} = -174 + 10\log_{10}BW + NF + SNR$$

$$PER_{[pps]} = 1 - (1 - BER)^{n_{bits}}$$
(38)

$$BER_{[bps]} = \frac{8}{15} \cdot \frac{1}{16} \cdot \sum_{k=1}^{\infty} k = 216 - 1^{k} \left(\frac{16}{k}\right) e^{20.SINR(\frac{1}{k} - 1)}$$
(40)

$$ToA_{s} = \frac{2^{SF}}{BW_{[Hz]}} \tag{41}$$

$$PER_{[pps]} = 1 - (1 - BER)^{n_{bits}}$$
 (42)

(43)

# Multi criteria decision making

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (p_i - r_i)^2$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (p_i - r_i)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |p_i - r_i|$$

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F1\_Score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{precision} + \text{recall}}$$

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$ROC = (TPR, FPR)$$

$$(52)$$

$$Novelty = \sum_{i=1}^{n} \frac{\log_2 P_i}{p} \text{ where } P_i = \frac{n - rank_i}{n - 1}$$

$$(53)$$

(54)

Serendipity =  $\frac{1}{n} \sum_{i \in n} \max(P_{user} - P_U, 0) \times rel_i$ 

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# Problem statement

Introduction





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... (step 1)
Methods

... (step 2)
Methods

... (step 3)
Methods

... (step 4)
Methods

# Results

Comparison



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Figure 15. .

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# Results

Comparison



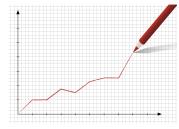


Figure 16. .

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# Discussion





Figure 17. .

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# Problem statement

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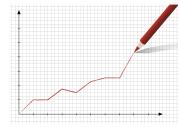


Figure 18. .

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# Game theory

Related work

```
Players: K = \{1, ..., K\}
```

- **Strategies:**  $S = S_1 \times ... \times S_K$ 
  - $\rightarrow$   $S_k$  is the strategy set of the  $k^{th}$  player.
- Rewards:  $u_k: S \longrightarrow R_+$  and is denoted by  $r_k(s_k, s_{-k})$ 
  - $\Rightarrow s_{-k} = (s_1, \dots, s_{k-1}, s_{k+1}, \dots, s_K) \in S_1 \times \dots \times S_{k-1} \times S_{k+1} \times \dots \times S_K$

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# Multi-Armed-Bandit Algorithm

Related work

```
For each step t=1,\ldots,T

Arms: \mathbf{K}=1,\ldots,\mathbf{K}

Reward: X_t^k with \mu_t^k=\mathbf{E}\left[X_t^k\right]

Bernoulli rewards: x_{k_t}\sim B(\mu_{k_t,t})

Best reward: X_t^* with \mu_t^*=\max \mu_t^k, \mathbf{k}\in\mathbf{K}

The reward k_t is revealed x_{k_t}\in[0,1]

Minimize the pseudo regret:

R(T)=\sum_{t=1}^T \mu_t^*-\mathbb{E}\left[\sum_{t=1}^T x_{k_t}\right]

where

* \mu_t^*=\max_k \mu_{k,t}
```

# **Bandit Algorithm**

### Related work

- Growing number of Thompson Sampling f i.t:
  - i denotes the starting time
  - t the current time.
- Let P(f i,t) be the probability at time t of the Thompson sampling starting at time i.
  - Initialization:  $\mathbb{P}(f_{1,1}) = 1, t = 1, 2$  $\rightarrow \forall k \in K \alpha_{k,f_1}, \leftarrow \alpha_0, \beta_{k,f_1}, \leftarrow \beta_0$
  - Decision process: at each time t:
    - $\rightarrow \forall i < t, \forall k : \theta_{k,f_{i,t}} \sim \text{Beta}\left(\alpha_{k,f_{i,t}}, \beta_{k,f_{i,t}}\right)$
    - → Play (Bayesian Aggregation): \*  $k_t = \arg\max_k \sum_{i < t} \mathbb{P}(f_{i,t}) \theta_{k,f_{i,t}}$
  - Instantaneous gain update:

$$\forall i < t \mathbb{P}\left(x_{t} | f_{i,t}\right) = \begin{cases} \frac{\alpha_{k, l_{i,t}}}{\beta_{k, l_{i,t}} + \alpha_{k, l_{i,t}}} & \text{if } x_{k_{t}} = 1\\ \frac{\beta_{k, l_{i,t}} + \alpha_{k, l_{i,t}}}{\beta_{k, l_{i,t}} + \alpha_{k, l_{i,t}}} & \text{if } x_{k_{t}} = 0 \end{cases}$$

(63)

(64)

Arm hyperparameters update:

$$\forall i < t \begin{cases} \alpha_{k, f_{i,t}} = \alpha_{k, f_{i,t}} + 1 & \text{if } x_{k_t} = 1 \\ \beta_{k, f_{i,t}} = \beta_{k, f_{i,t}} + 1 & \text{if } x_{k_t} = 0 \end{cases}$$

- Distribution of experts update:
  - $\rightarrow \forall i < t, \mathbb{P}(f_{i,t}) \propto (1-\rho) \cdot \mathbb{P}(X_t | f_{i,t-1}) \cdot \mathbb{P}(f_{i,t-1})$ 
    - $\rightarrow f_{t,t}: \mathbb{P}(f_{t,t}) \propto \rho \sum_{i=1}^{t-1} \mathbb{P}(x_t | f_{i,t-1}) \cdot \mathbb{P}(f_{i,t-1})$  $\rightarrow \alpha_{k,f_{t,t}} = \alpha_0, \beta_{k,f_{t,t}} = \beta_0$

# **Bandit Algorithm**

Related work

### THOMPSON SAMPLING (TS)

```
⇒ success counter: \alpha_k = \#(x_{k_t} = 1) + \alpha_0

⇒ failure counter: \beta_k = \#(x_{k_t} = 0) + \beta_0

⇒ At each t:

* \theta_k \sim \text{Beta}(\alpha_k, \beta_k)

* k_t = \text{arg max}_k \theta_k

\begin{cases} \alpha_k = \alpha_k + 1 & \text{if } x_{k_t} = 1 \\ \beta_k = \beta_k + 1 & \text{if } x_{k_t} = 0 \end{cases}
```

### **■ SWITCHING ENVIRONMENT**

$$\mu_{k,t} = \begin{cases} \mu_{k,t-1} & \text{probability } 1 - \rho \\ \mu_{new} \sim U(0,1) & \text{probability } \rho \end{cases}$$

(65)

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Related work

# Reward State Action Action

Figure 19. qlearning.

- $Q(s_{t+1}, a_t) = Q(s_t, a_t) + \gamma (R(s_t, a_t) Q(s_t, a_t))$ 
  - $Q(s_{t+1}, a_t) = \text{new Q-Value}$
  - $Q(s_t, a_t) = \text{old Q-Value}$
  - $\gamma$  = learning constant
  - $\Rightarrow$   $R(s_t, a_t)$  = immediate reward received after executing action a in state s at time t

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### Marcov chain

Related work

$$V(s,\pi) = \mathbb{E}_{s}^{\pi} \left( \sum_{k=0}^{\inf} \gamma^{k} \cdot r(s_{k}, a_{k}) \right), s \in \mathbb{S}$$

$$r(s_{k}, a_{k}) = G_{k} \cdot PRR(a_{k})$$
(66)

$$\pi^* = \arg\max_{\pi} V(s, \pi) \tag{68}$$

$$PRR = (1 - BER)^{L}$$

$$BER = 10^{\alpha} e^{\beta SNR} \tag{70}$$

(69)

### Marcov chain

Related work

### Learning iterative steps:

- **Choose** action  $a_k(t) \sim \pi_k(t)$
- **Observe** game outcome  $a_k(t)$ 
  - $\Rightarrow u_k(a_k(t), a_{\underline{k}}(t))$
- **Improve**  $\pi_k(t+1)$

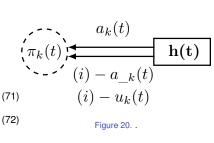
Thus, we can expect that  $\forall k \in K$ 

$$\pi_{k(t)} \xrightarrow{t \longrightarrow \infty} \pi_k^*$$

$$U_k(\pi_k(t), \pi_{\underline{k}}(t)) \xrightarrow{t \longrightarrow \infty} U_k(\pi_k^*, \pi_{\underline{k}}^*)$$

Where:

$$\pi^* = (\pi_1^*, ..., \pi_k^*)$$
 is the NE strategy profile



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## Results

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Figure 22. .

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Figure 23. .

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Introduction



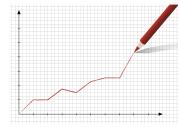


Figure 24. .

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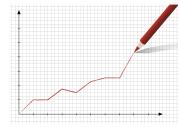


Figure 25. .

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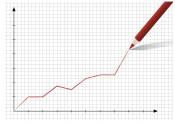


Figure 26. .

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Figure 27. .

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Introduction



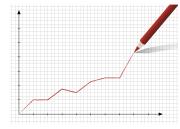


Figure 28. .

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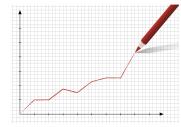


Figure 29. .

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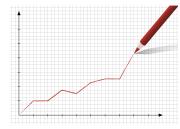


Figure 30. .

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Introduction



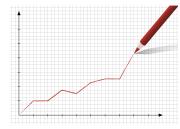


Figure 32. .

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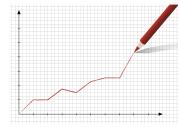


Figure 33. .

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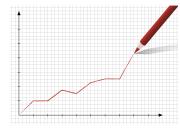
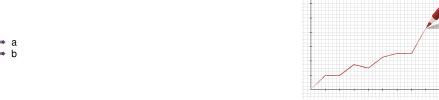


Figure 34. .

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# Conclusion

Our main goal was

- .
- •

Our main contribution was

- ....
- .

Our main results was

- .
- .

# **Future Challenges**

Conclusion

Our future goal was

- ···
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