A machine learning approach to improve UHF RFID gate operation

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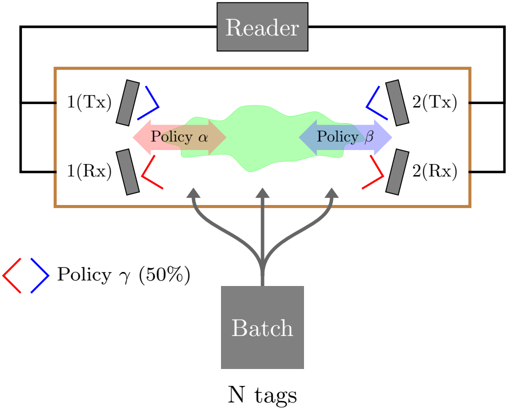
Machine learning in RFID

- **Smart processing of raw data:** discriminate tags by position or direction, characterize physical signature privacy.
- **Enhanced services:** position estimation enhancement or data stream enhancement.
- **RFID network planning.**
- **Smart gate control.**

Machine learning for smart gate control

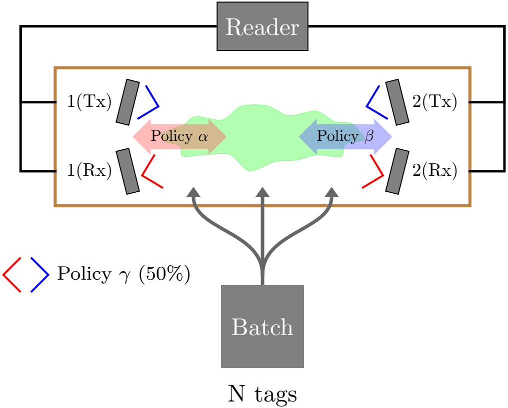
- Self-configuration of channel, power, etc.
- If conditions change dynamically, the parameters have to be adaptively tuned.
- Machine learning approaches to **adapt to previously unseen situations.**

Scenario setup



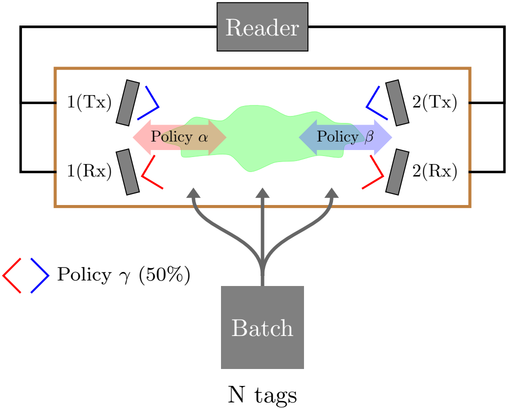
Portal has two bistatic dislocated antenna pairs, which can be configured with 3 different policies: α, β, γ.

Scenario setup (II)



Random variations (box placement, size, tag distribution, number of tags, materials) occur for **each box.**

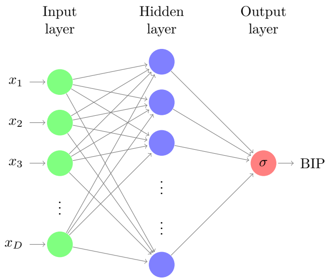
Scenario setup (III)



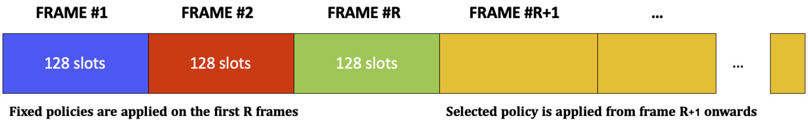
Goal is **select the best interrogation policy** for each box, i.e., the one maximizing the batch identification chances.

Predictive system

- The input features act as a **signature for the batch reading process.**
- The **policy** is also an input data.
- The output indicates **whether the batch will be totally identified.**



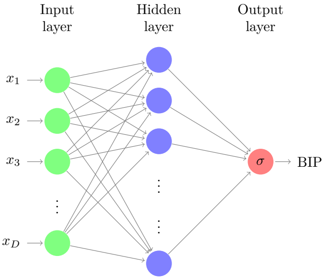
Predictive system (II). Input features



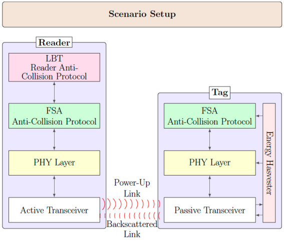
- Provide a good and homogeneous representation for each batch's interrogation characteristics.
- The first *R* frames have **always** the same configuration and the following statistics are obtained:
  - The number of tags read in the frame.
  - The average received signal strength (RSS) in slots with successful tag identification.
  - The average RSS in slots with collision.

Predictive system (III). Output usage

- For each policy the predictive system outputs the **probability of batch identification** (BIP).
- The smart gate uses the predictive system for each possible policy and selects the one with the **highest predicted BIP**, or triggers and alarm reporting a batch-reading problem if BIP is too low.



Predictive system (IV). Training dataset



Dataset has been obtained using a simulator whose main characteristics are:

- DFSA anti-collision protocol
- Detailed link budget considering distance, antenna aiming, multi-path propagation, and shadowing effects.
- Detailed physical level operation: outage, capture-effect, etc.

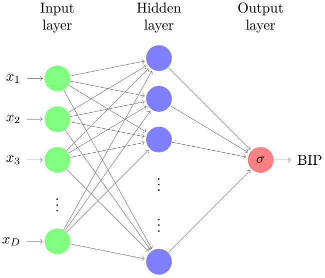
Predictive system (V). Training dataset

	tags1	prx1	prxcol1	tags2	prx2	prxcol2	tags3	prx3	prxcol3	p1	p2	p3	read	ntags	ntagsread	t	L	deltax	deltay	ratioread
0	43	463.923948	268.417880	25	12.811179	11.193044	40	33.592932	28.787916	0	1	0	0	374	198	1.61456	1.2	-0.849142	0.220086	0.529412
1	56	63.989058	41.242380	43	179.557768	110.227699	52	36.262325	35.439436	0	1	0	1	495	495	1.50685	1.2	0.231049	-0.023392	1.000000
2	4	5.854288	2.753060	10	1301.072056	382.142322	3	49.809477	20.410527	0	1	0	0	969	868	3.18503	1.2	1.457764	0.158543	0.895769
3	16	248.493288	99.043218	35	54.762808	44.114597	16	33.786838	33.286323	0	0	1	0	873	869	3.35403	1.2	-0.225589	0.187781	0.995418
4	52	48.320220	34.359324	16	303.016551	142.371279	49	44.131153	37.294393	0	0	1	0	868	646	3.77257	1.2	0.332630	0.070283	0.744240
5	47	90.033243	58.397142	49	89.993321	65.947717	45	35.260748	34.987634	1	0	0	0	647	605	2.42120	1.2	0.011847	-0.124331	0.935085
6	31	221.286109	138.350224	49	35.101189	24.886162	32	41.552065	30.799659	0	0	1	1	614	614	2.11716	1.2	-0.448501	-0.239353	1.000000
7	23	144.872846	94.478192	49	69.251143	47.159606	22	39.236560	32.259763	0	0	1	0	835	834	3.13821	1.2	-0.210190	-0.075780	0.998802
8	7	6.482436	5.559946	17	1274.195156	378.905979	10	35.709743	30.679662	1	0	0	0	779	63	4.04028	1.2	1.232831	0.126354	0.080873
9	50	49.251192	39.673925	35	191.854600	108.032985	42	35.810033	33.442442	0	0	1	0	723	680	2.99863	1.2	0.226599	0.027517	0.940526
10	45	675.619154	334.075826	7	5.689932	5.614713	48	25.517865	21.476021	0	1	0	0	331	135	1.47899	1.2	-1.176226	-0.198254	0.407855
11	51	47.468377	36.896946	41	189.271819	104.853400	50	36.795469	33.127666	1	0	0	0	537	424	2.06805	1.2	0.279484	0.242150	0.789572
12	20	164.072651	84.435992	39	72.086243	51.747810	21	47.834638	32.266159	0	1	0	0	1000	738	4.26755	1.2	-0.127273	0.136171	0.738000

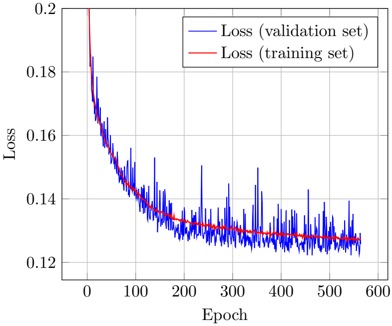
Dataset contains **120000 records** where the policy as well as the box characteristics are randomly selected.

Predictive structure

- Predictions are created with a 2-layer artificial-neural-network.
- Inputs are normalized and passed to a 20-nodes hidden layer with *tanh* activation.
- Policy is provided as input with one hot encoding.
- Output layer activation is sigmoid and the ann loss function is the binary cross-entropy.



Predictive structure (II). Training



- Network has been implemented in Keras/TF
- 20% of the training records are left out as validation
- Training used back-propagation with Adam optimizer, using 32 as batch size.
- Network training ends using early stopping mechanism using 100 epochs patience. About 600 training-eopchs are used.

Predictive structure (III). Results

Configuration	Accuracy	Precision	Recall	Fall-out
R = **1**	89.74%	89.98%	89.27%	9.80%
R = **2**	94.55%	94.30%	94.61%	5.50%
R = **3**	94.86%	94.75%	94.81%	5.10%

- R=3 achieves the best results (very close with R=2)
- Accuracy is high (95%) with low fall-out (5

Predictive structure (IV). Results

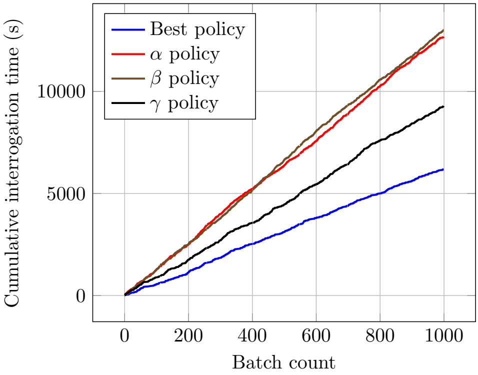
Policy	Accuracy	Precision	Recall	Fall-out
α	94.59%	92.92%	94.03%	5.02%
β	94.73%	92.44%	94.92%	5.40%
γ	95.26%	97.51%	95.24%	4.70%

- Slightly better reliability of the γ policy predictions
- Very close to the operation reliability of the other policies.

Smart versus normal gate comparison

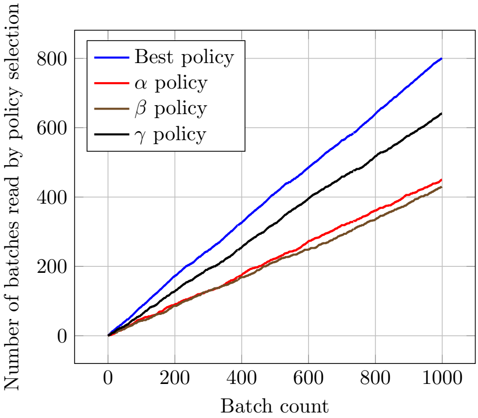
- The operation of the smart gate has been compared against a normal one.
- Normal gate uses always a predefined policy.
- The **simulator measures the cumulative time** requiered for boxes interrogation.
- **Batch interrogation time has been determined using an auxiliary ANN**.
- **Unreadable batches are relocated**, a process performed by a human operator which takes a random time between 10 and 30 s.
- After relocation it is assumed that the batch can always be read.

Smart versus normal gate comparison (II)



The performance of the best policy, which is adaptive, outperforms the best static one by 30%.

Smart versus normal gate comparison (III)



The ratio of batches which don't require relocation to complete the interrogation is 80.2% with the adaptive policy, but it drops to 64% with the best static policy.

Conclusions

- New predictive capability for RFID gates proposed.
- Based on the signature from initial reading frames, the batch identification probability is predicted.
- Results indicate a good predictive performance, suitable for online gate operations.
- This method is able to save operation time.
- Dataset and code available at `https://github.com/javiervales/smartgate`