

In-situ fitting of CBPM instrumental errors to improve turn-by-turn resolution

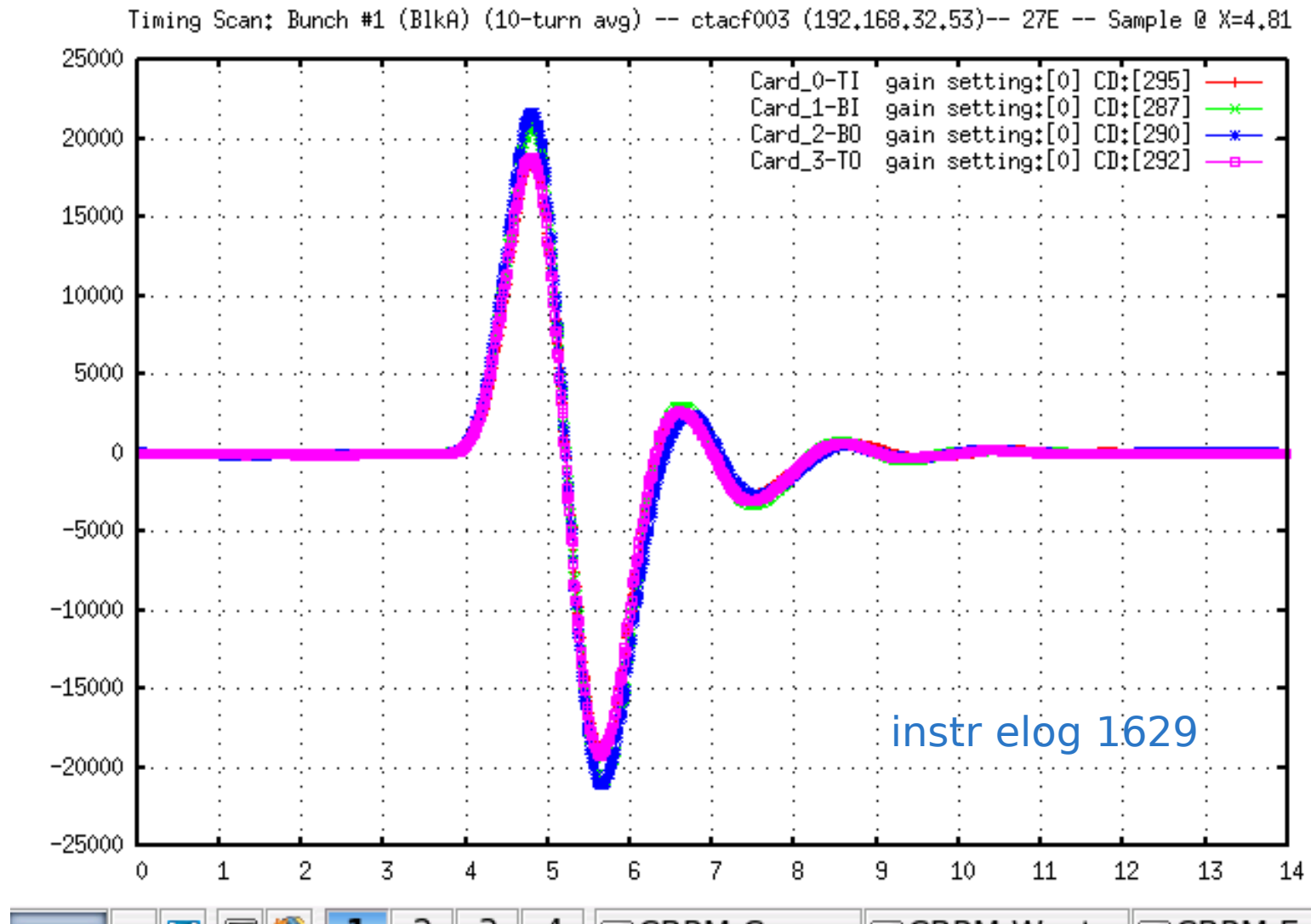
Antoine

CBPM meeting

May 7, 2021

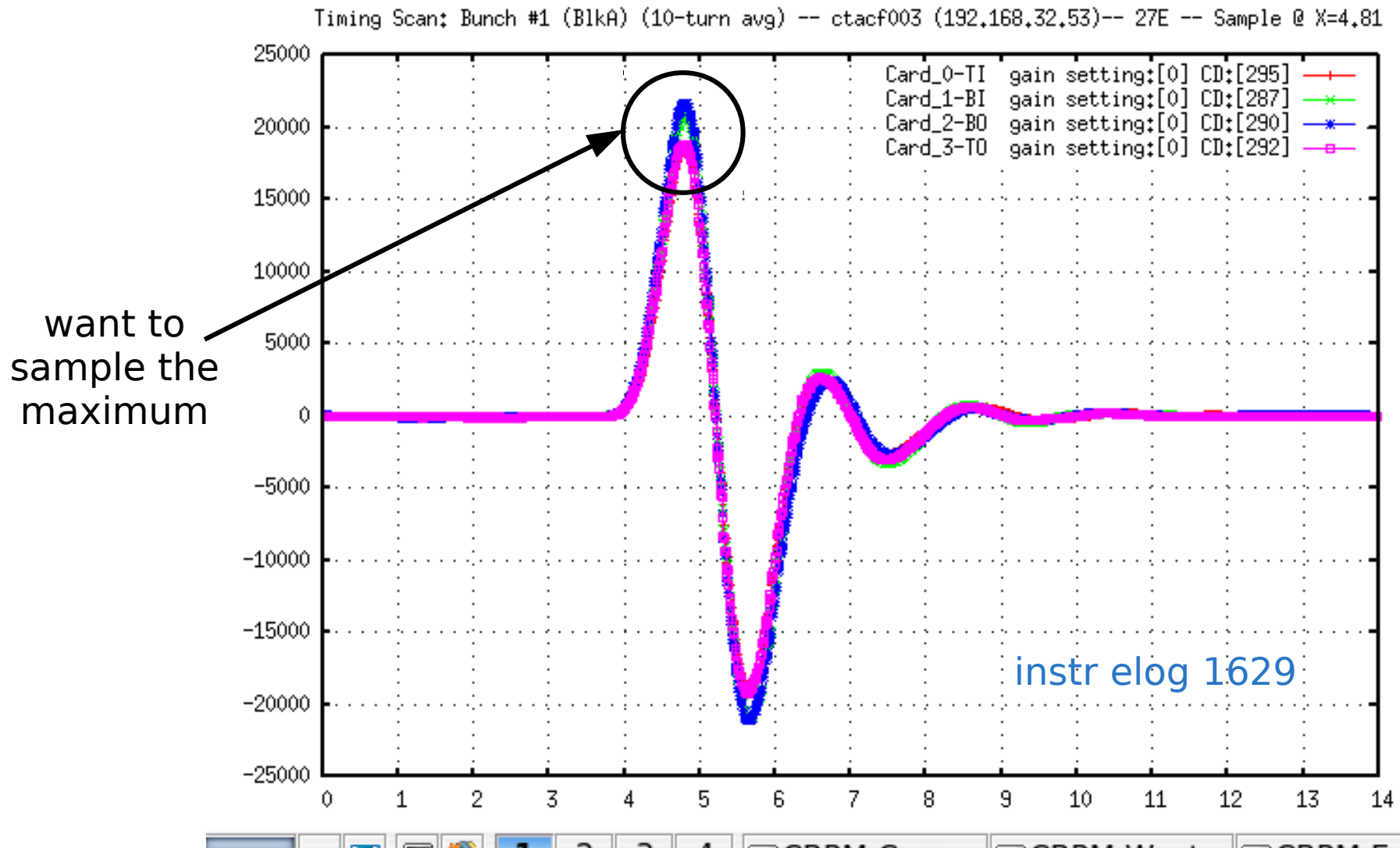
Beam position measurement

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Measurement position precision

Turn-by-turn precision is limited by various instrumental effects:

- x electronics/ambient noise
- x timing alignment (offset) and jitter
- x *maximum amplitude of the pulse (because two bullets above)*

Design		Noise [ADU]	Digitized amplitude [ADU]	Un-correlated timing jitter [ps]				Timing offset [ps]				"Old" North Arc ky = 19.8 mm	North Arc ky = 22.3 mm	South Arc ky = 10.4 mm
				inner top	inner bottom	outer bottom	outer top	inner top	inner bottom	outer bottom	outer top	Vertical precision [micron]	Vertical precision [micron]	Vertical precision [micron]
Current	Ideal	9	32,768	10	10	10	10	0	0	0	0	8.5	9.6	4.5
	Best	9	24,576	10	10	10	10	0	0	0	0	8.9	10.0	4.7
	Realistic	9	16,384	10	10	10	10	10	0	0	10	12.7	14.3	6.7
	Realistic	9	16,384	10	10	10	10	10	10	10	10	15	16.9	7.9
	Realistic	9	8,192	10	10	10	10	10	10	10	10	17.6	19.8	9.2
Future	1	5	65,536	0	0	0	0	0	0	0	0	0.8	0.9	0.4
	2	5	65,536	1	1	1	1	1	1	1	1	0.8	0.9	0.4
	3	9	65,536	0	0	0	0	0	0	0	0	1.4	1.6	0.7
	4	9	65,536	2	2	2	2	2	2	2	2	1.5	1.7	0.8
	5	9	65,536	2	2	2	2	0	0	0	0	1.4	1.6	0.7
	6	9	65,536	8	8	8	8	10	10	10	10	10.6	11.9	5.6
	7	5	32,768	1	1	1	1	1	1	1	1	1.5	1.7	0.8
	8	9	32,768	1	1	1	1	1	1	1	1	2.7	3.0	1.4
	9	9	32,768	2	2	2	2	10	10	10	10	3.6	4.1	1.9
	10	9	32,768	2	2	2	2	2	2	2	2	2.8	3.2	1.5
	11	9	32,768	5	5	5	5	5	5	5	5	4.4	5.0	2.3
	12	9	32,768	5	5	5	5	10	10	10	10	6.6	7.4	3.5
	13	9	32,768	5	5	5	5	1	1	1	1	3.4	3.8	1.8
	14	9	32,768	10	10	10	10	1	1	1	1	8.6	9.7	4.5

https://docs.google.com/spreadsheets/d/1J_CoilNyVV0tr0kwNhGepiCcPhAw7kMNpi-UiOISaxY/edit?pli=1#gid=2145145041

Non-linear position reconstruction

Without instrumental effects, one can solve:

$$b_1 - f_{b_1}(x, y) = \epsilon \rightarrow 0,$$

$$b_2 - f_{b_2}(x, y) = \epsilon \rightarrow 0,$$

$$b_3 - f_{b_3}(x, y) = \epsilon \rightarrow 0,$$

$$b_4 - f_{b_4}(x, y) = \epsilon \rightarrow 0$$

Where $f_{b_i}(x, y)$ is the Poisson look-up table map for a given button response

The system is determined (4 equations, 2 unknowns) \rightarrow can be solved no problem

With instrumental effects, first equation becomes:

$$b_1 - f_{b_1}(x, y) \times \alpha_{noise}^{b_1} \cdot \cos \left[\omega(t_j^{b_1} + t_o^{b_1}) \right] = \epsilon \rightarrow 0$$

Non-linear reconstruction

With instrumental effects, one turn correspond to the four equations:

$$b_1 - f_{b_1}(x, y) \times \alpha_{noise}^{b_1} \cdot \cos \left[\omega(t_j^{b_1} + t_o^{b_1}) \right] = \epsilon \rightarrow 0,$$

$$b_2 - f_{b_2}(x, y) \times \alpha_{noise}^{b_2} \cdot \cos \left[\omega(t_j^{b_2} + t_o^{b_2}) \right] = \epsilon \rightarrow 0,$$

$$b_3 - f_{b_3}(x, y) \times \alpha_{noise}^{b_3} \cdot \cos \left[\omega(t_j^{b_3} + t_o^{b_3}) \right] = \epsilon \rightarrow 0,$$

$$b_4 - f_{b_4}(x, y) \times \alpha_{noise}^{b_4} \cdot \cos \left[\omega(t_j^{b_4} + t_o^{b_4}) \right] = \epsilon \rightarrow 0$$

System is heavily undetermined (4 equations, 14 unknowns) → how do you solve that? There are infinite number of solutions....

Turn-by-turn behavior

With instrumental effects, back to one equation:

$$b_1 - f_{b_1}(x, y) \times \alpha_{noise}^{b_1} \cdot \cos \left[\omega(t_j^{b_1} + t_o^{b_1}) \right] = \epsilon \rightarrow 0$$

Gaussian random
turn-by-turn

fixed turn-by-turn?
depends on the
longitudinal beam
jitter

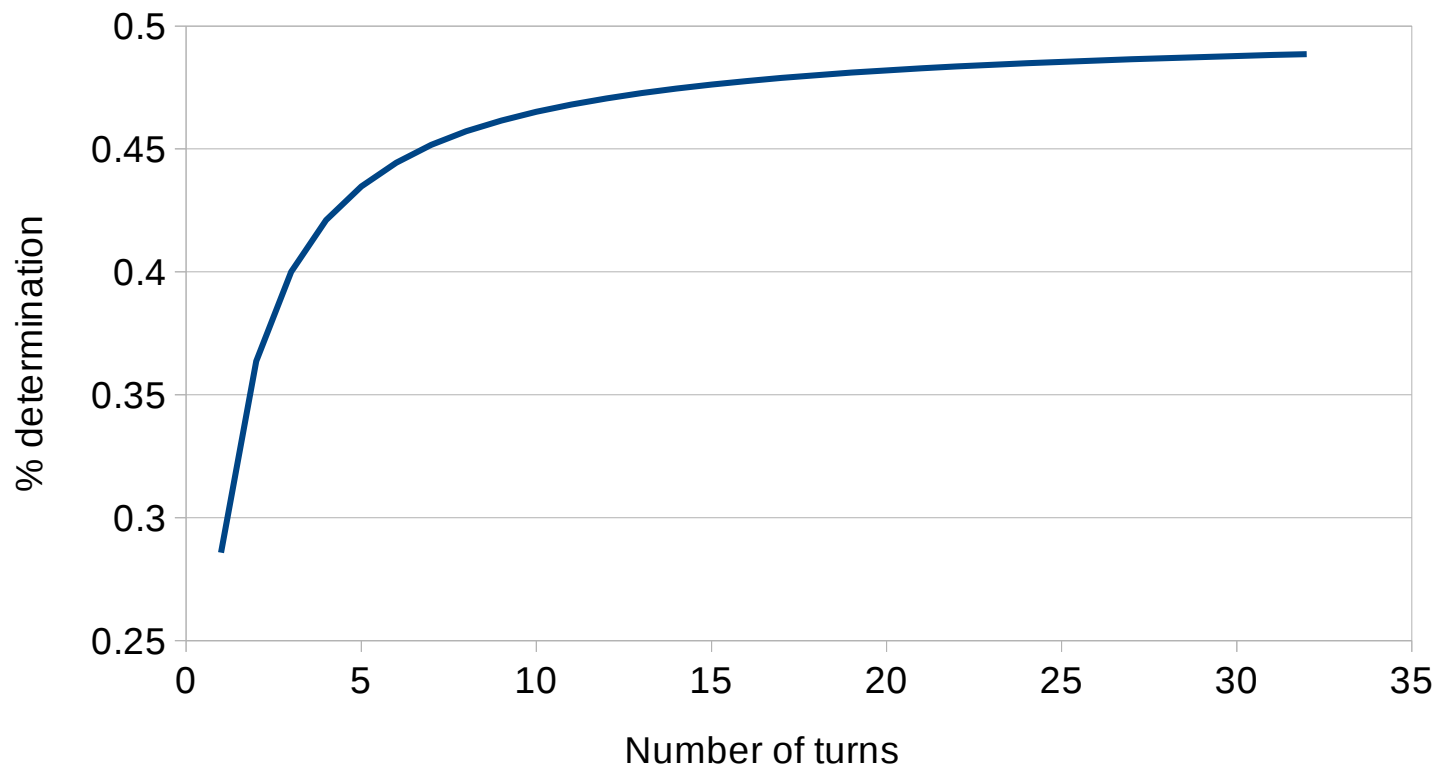
Using consecutive turns

Assuming the beam position is fixed, by solving for consecutive turns, the undetermination of the system can be reduced:

1 turn: 4 equations, 14 unknowns → 29% determined

2 turns: 8 equations, 22 unknowns → 36% determined

...



50% is the asymptotic maximum

Instead of solving the system

If we have a good model of the instrumental effects (we believe we do) → can generate simulated data varying all the effects to get a large ensemble of data representative of all the possible scenarios

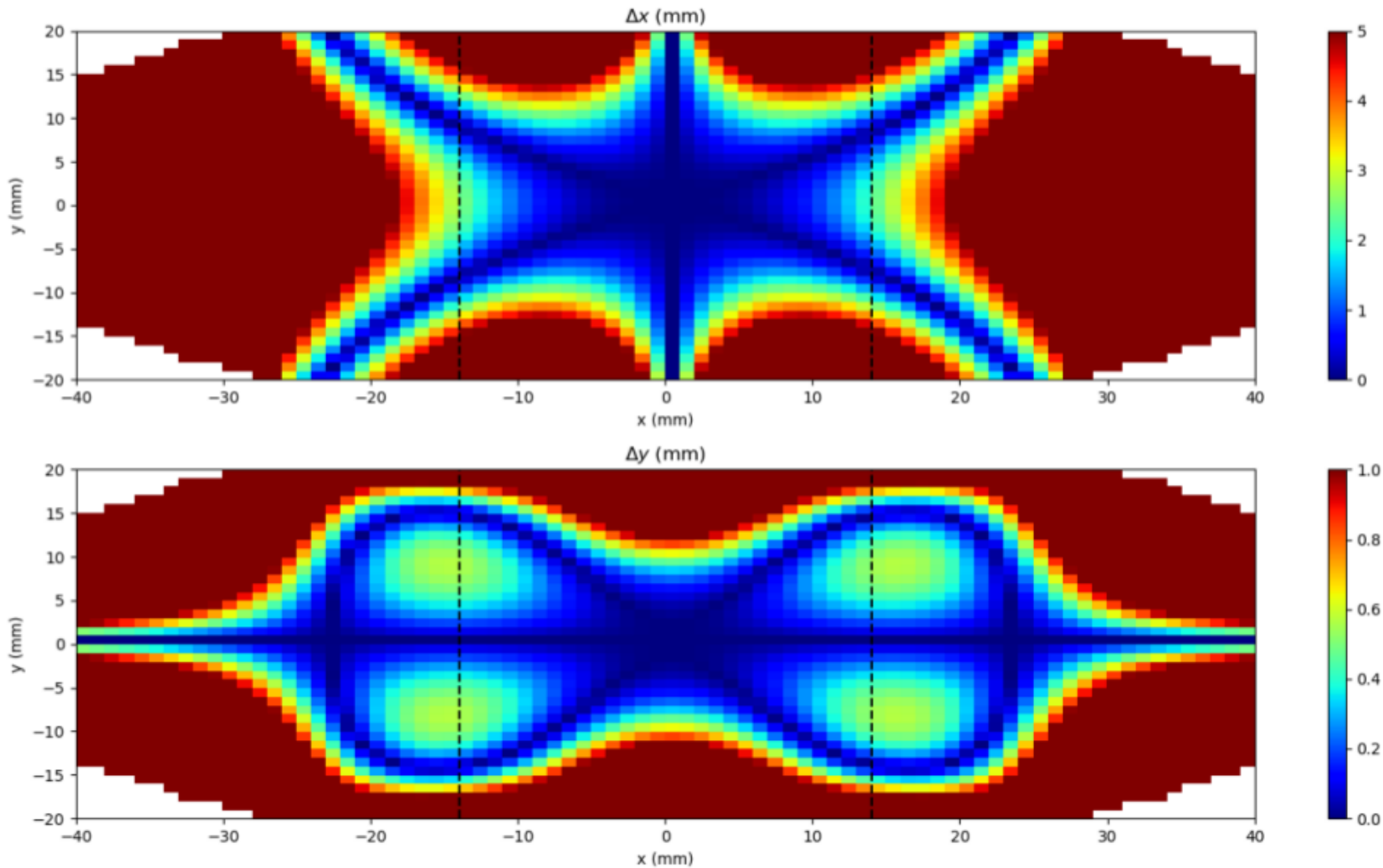
If we have a good model, and a large simulated dataset → can train a Machine Learning algorithm to reconstruct the beam position fitting for? reducing? filtering out? the instrumental effects

Note: the Machine Learning algorithm will only do as well as the model's ability to reproduce real data

When it comes to non-linear regression: artificial neural networks are a go-to solutions. I do have experience using Tensor Flow with multi-layer perceptron (MLP), convolutional neural network (Conv1D, Conv2), long short term memory network (LSTM)



x,y Deviation from Linear



|Difference| between actual (x,y) and (x,y) as computed using linear $k_{x,y}$ from $(x,y) = (0,0)$

2018.09.07

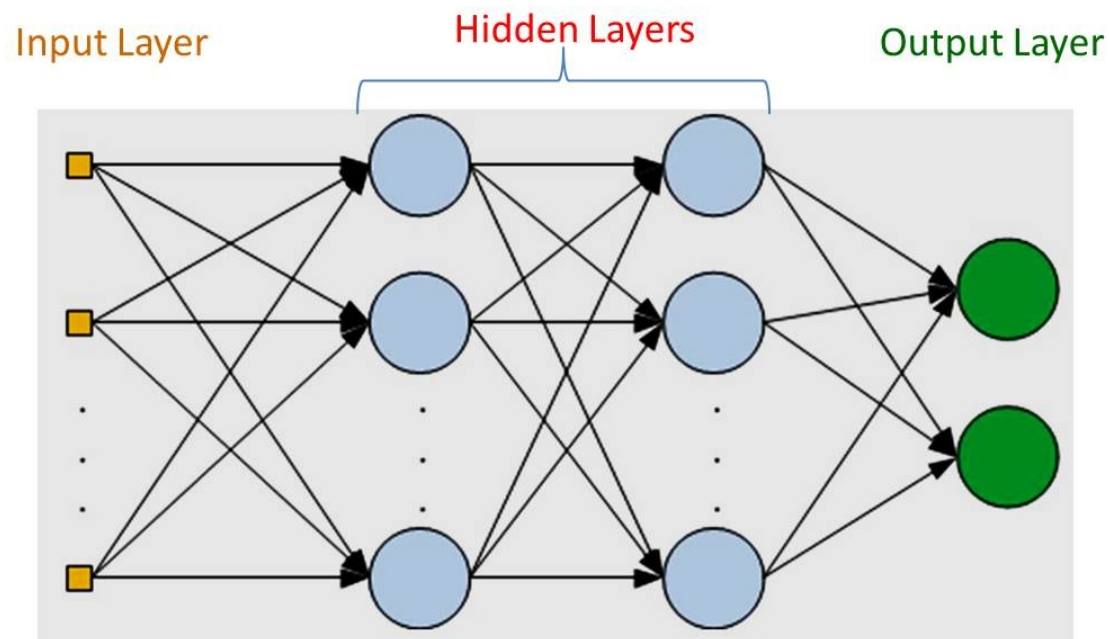
Tentative road-map

Without instrumental effect:

- x linear regime: few neurons, 1 hidden layer Perceptron (**REU student!**)
- x non-linear regime: many neurons, 2+ hidden layers Perceptron (deep learning)

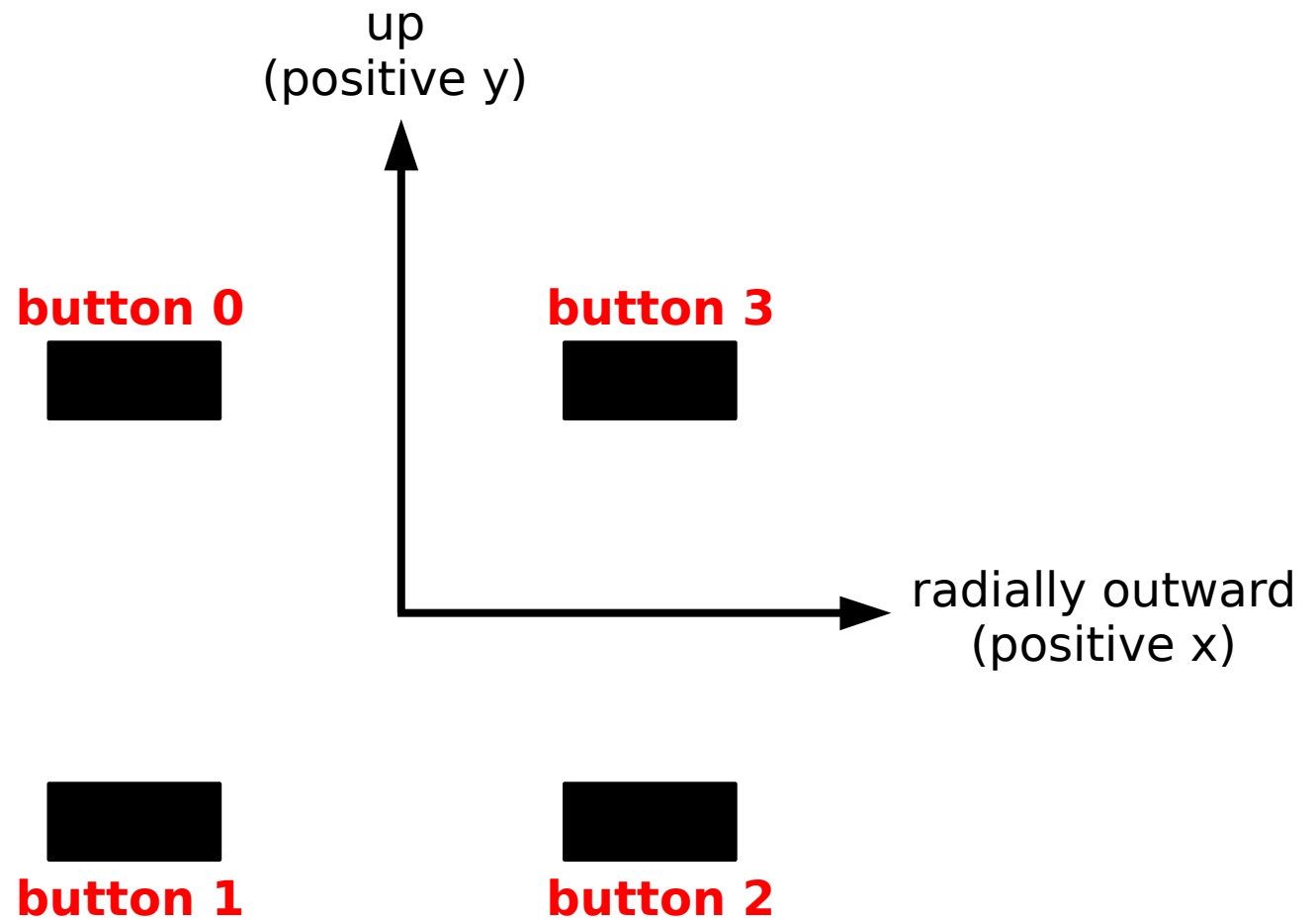
With instrumental effect (adding one a a time):

- x linear regime: many neurons, 1 hidden layer Perceptron
- x non-linear regime: many neurons, 2+ hidden layers Perceptron (deep learning)



Additional materials

CBPM convention



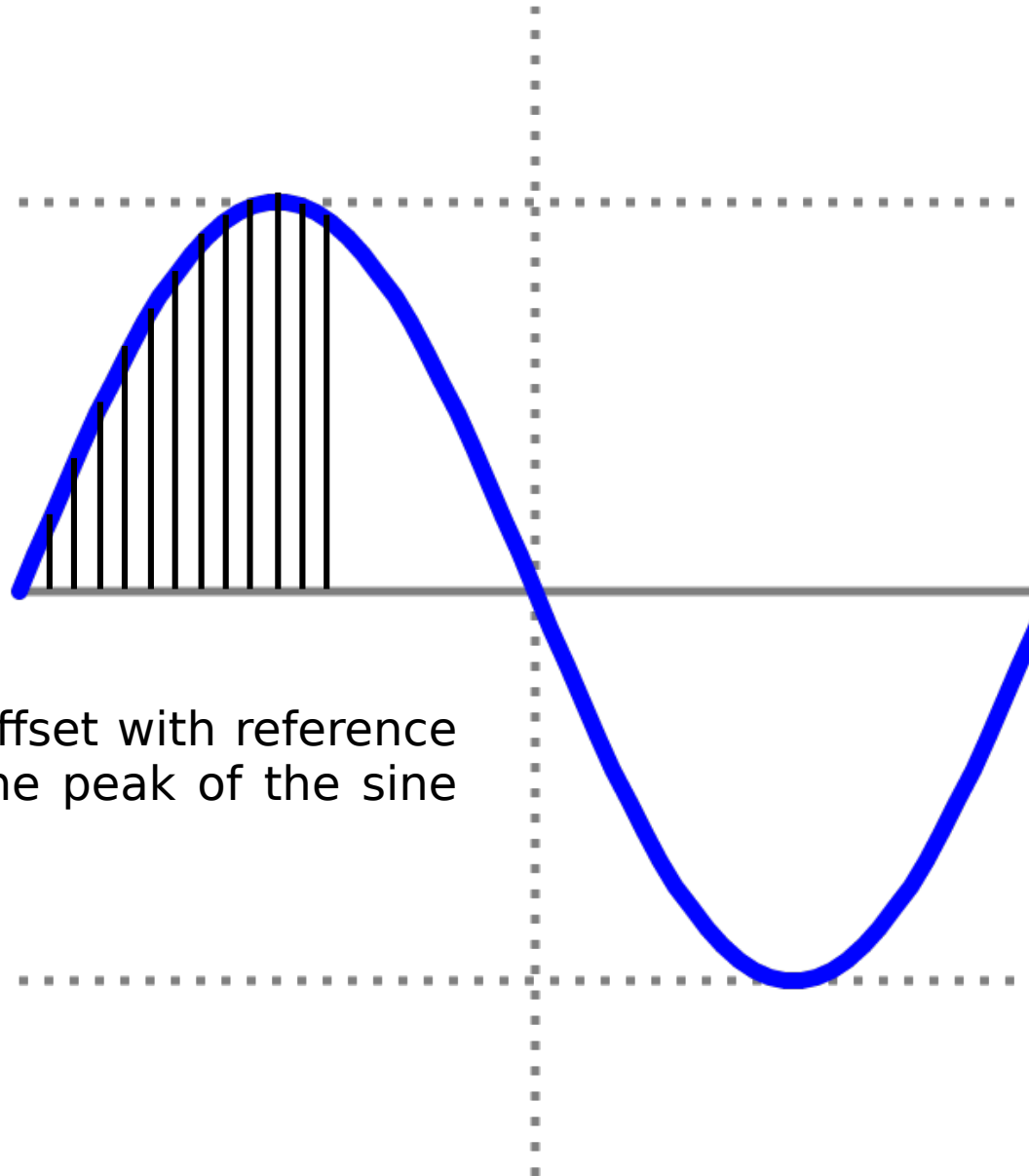
Horizontal and vertical centroids

$$y = k_y \frac{(b_0 + b_3) - (b_1 + b_2)}{b_0 + b_3 + b_1 + b_2}, \quad k_y = 19.8 \text{ mm}$$

$$x = k_x \frac{(b_2 + b_3) - (b_0 + b_1)}{b_2 + b_3 + b_0 + b_1}, \quad k_x = 25.9 \text{ mm}$$

Timing offset

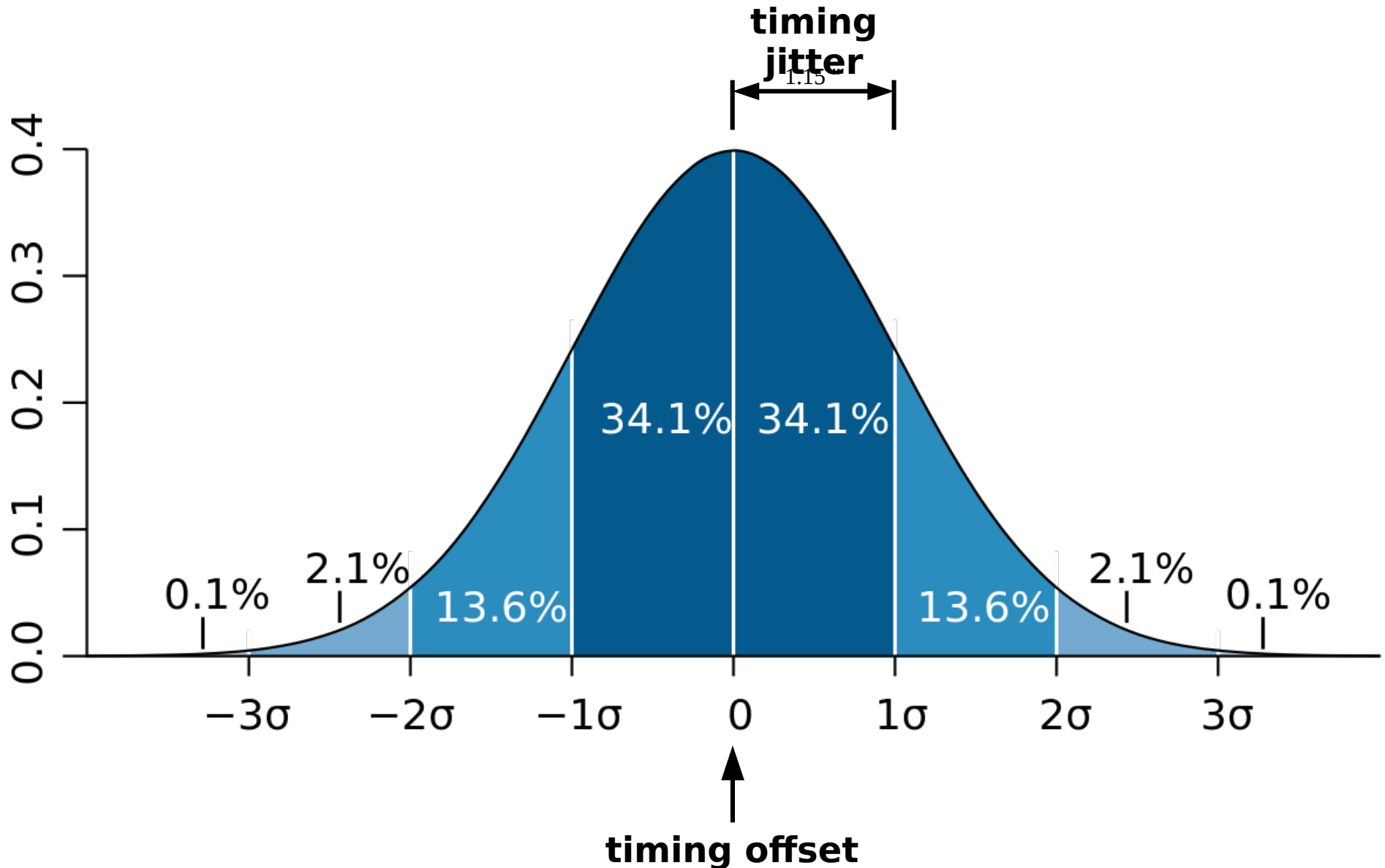
Amplitude of the sine wave set to button amplitude from previous step. Sine wave frequency set to whatever (500 MHz by default).



10 ps unit timing offset with reference corresponding to the peak of the sine wave

Timing jitter

For a given timing offset: Gaussian timing jitter with reference at the timing offset



Gain variation

Gaussian gain variation with reference at 1

