

Marcos Morote Balboa

An analysis of the Virgo arm cavities imperfections using Machine Learning



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Let's break the title down:



An analysis of the Virgo arm <u>cavities imperfections</u> using Machine Learning

Let's break the title down:

1) Cavities imperfections



An analysis of the Virgo arm cavities imperfections using <u>Machine Learning</u>

Let's break the title down:

- 1) Cavities imperfections
- 2) What is Machine Learning and why do we need it?



An <u>analysis</u> of the Virgo arm cavities imperfections using Machine Learning

Let's break the title down:

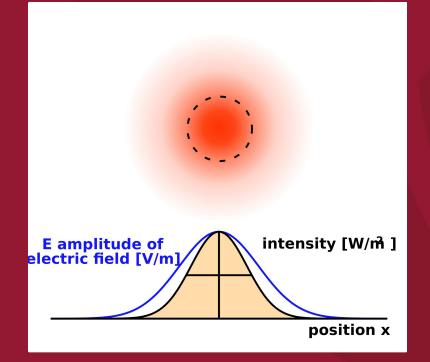
- 1) Cavities imperfections
- 2) What is Machine Learning and why do we need it?
- 3) The analysis



An analysis of the Virgo arm cavities imperfections using Machine Learning

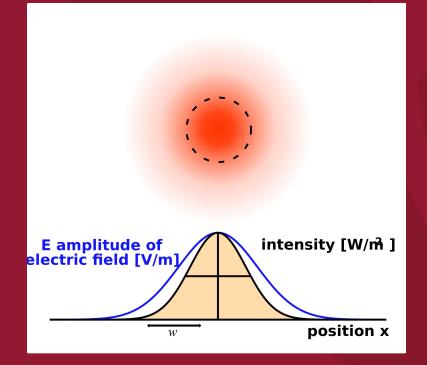
Cavities imperfections: mismatching, misalignment and astigmatism





Gaussian beam

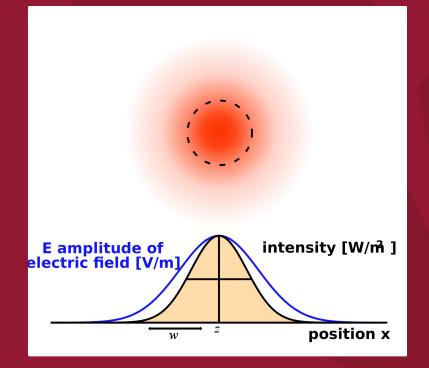




Gaussian beam

- Waist size w

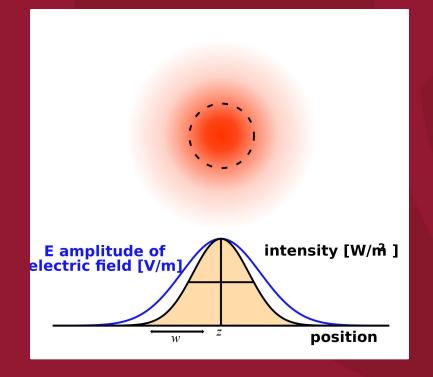




Gaussian beam

- Waist size w
- Waist position z







- Waist size w
- Waist position z

→ The cavity has the same parameters (*target*)!



If the parameters match



If the parameters match \longrightarrow the beam is *coupled* to the cavity



If the parameters match \longrightarrow the beam is *coupled* to the cavity

If the parameters **don't** match



If the parameters match \longrightarrow the beam is *coupled* to the cavity

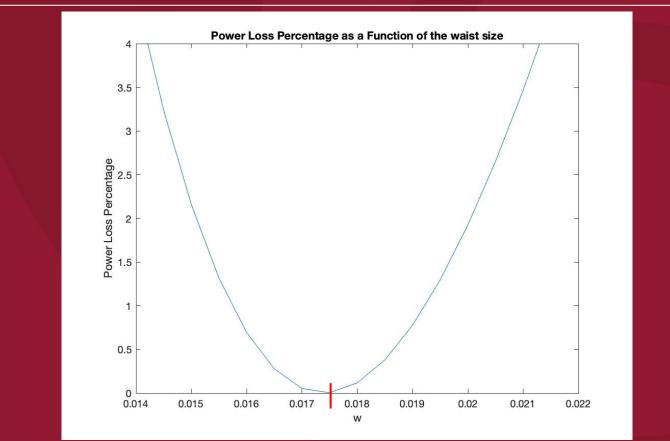
If the parameters **don't** match — *mode mismatch*



If the parameters match \longrightarrow the beam is *coupled* to the cavity

If the parameters **don't** match — *mode mismatch*

→ power loss



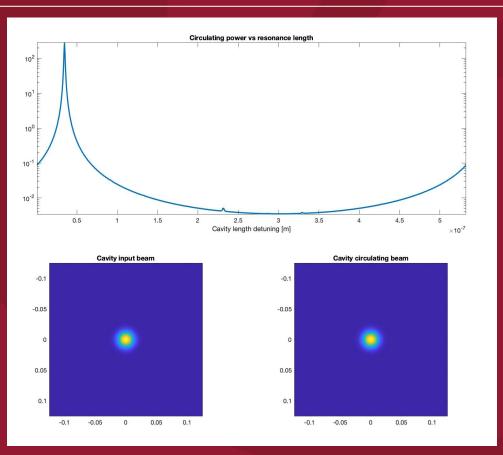






Target parameters

----- *Fundamental mode* of the cavity





Target parameters

----- *Fundamental mode* of the cavity

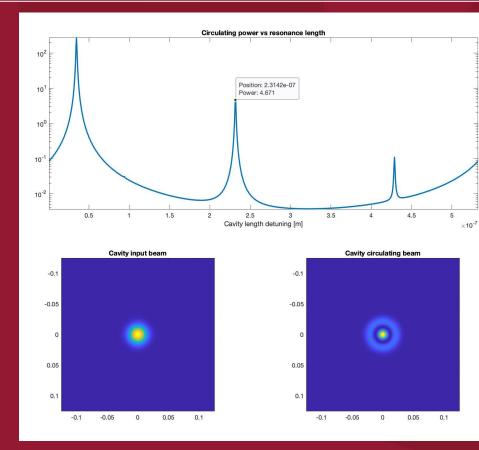
Different parameters

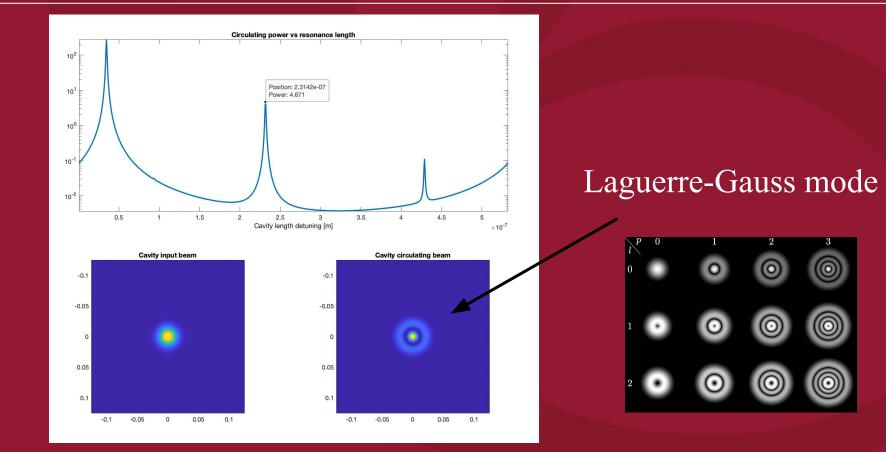


Target parameters

----- *Fundamental mode* of the cavity

→ High Order Modes (HOM)





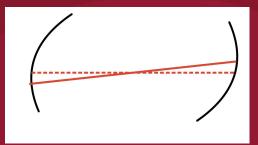




- Mirrors tilted in same direction

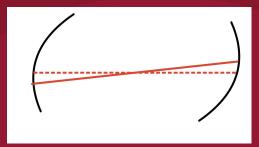


Mirrors tilted in same direction → *tilt*





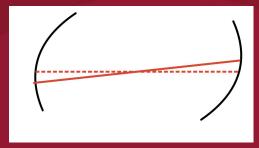
Mirrors tilted in same direction → *tilt*



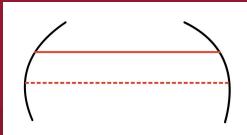
- Mirrors tilted in opposite direction



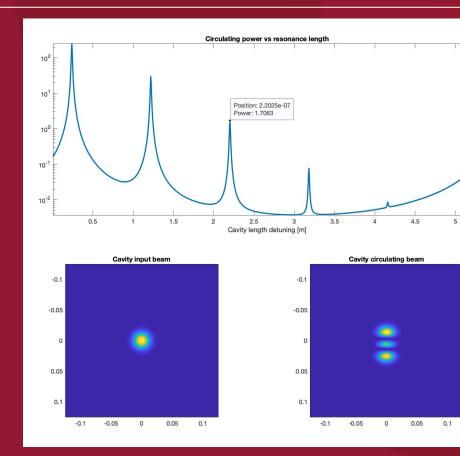
Mirrors tilted in same direction → *tilt*



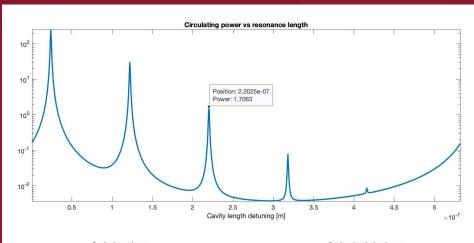
Mirrors tilted in opposite direction —> *shift*

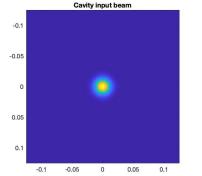


×10⁻⁷

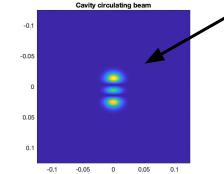






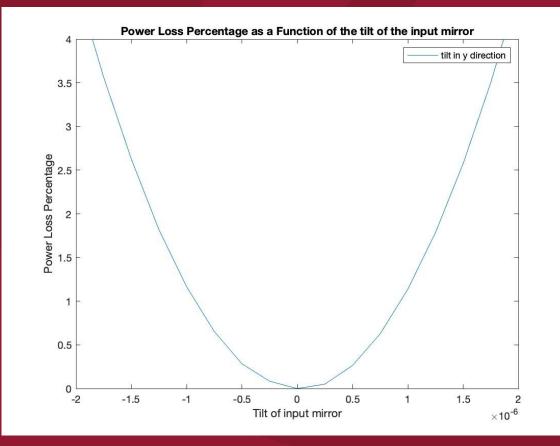


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Hermite-Gauss mode

00	10	20	30
01	**	21	31
02	12	22	33

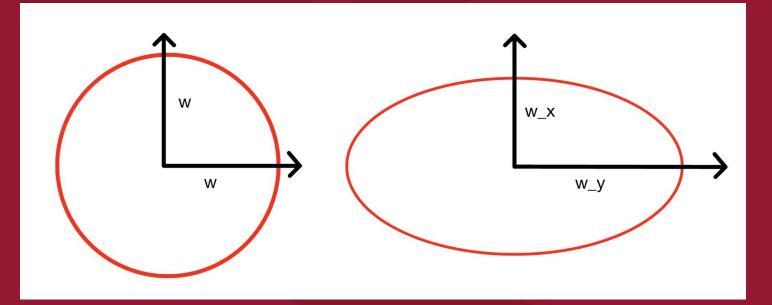


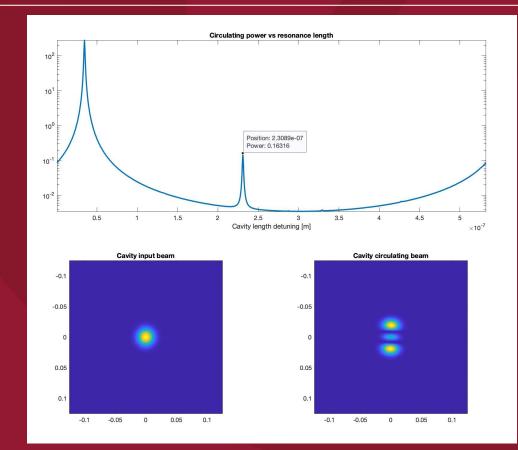


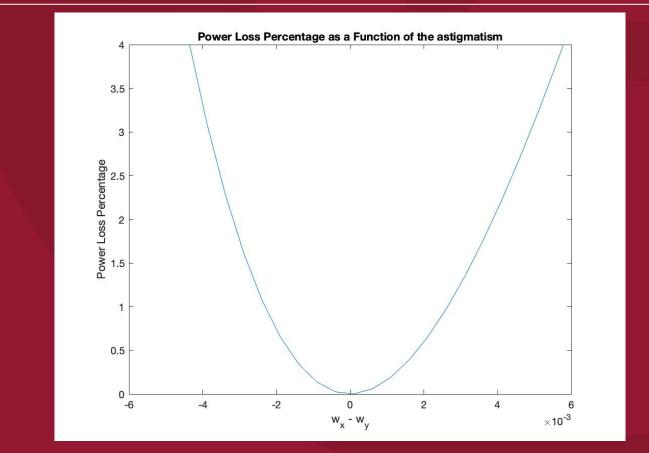
Astigmatism: asymmetric beam



Astigmatism: asymmetric beam

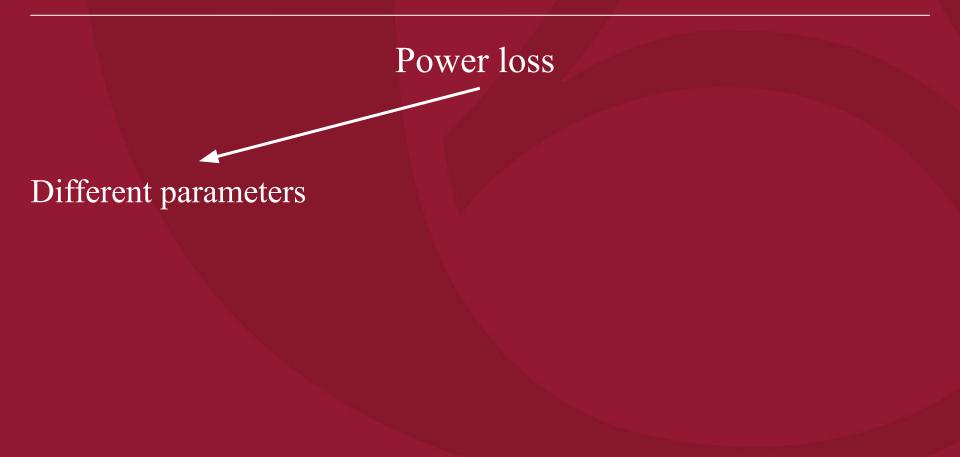


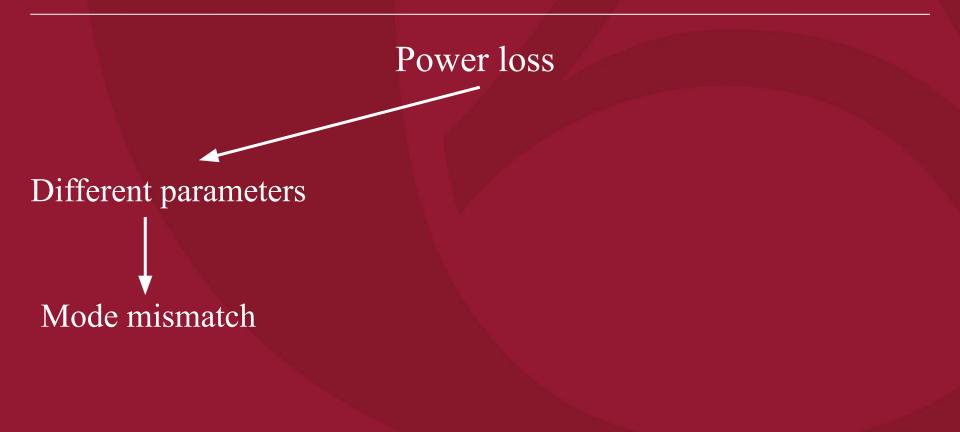


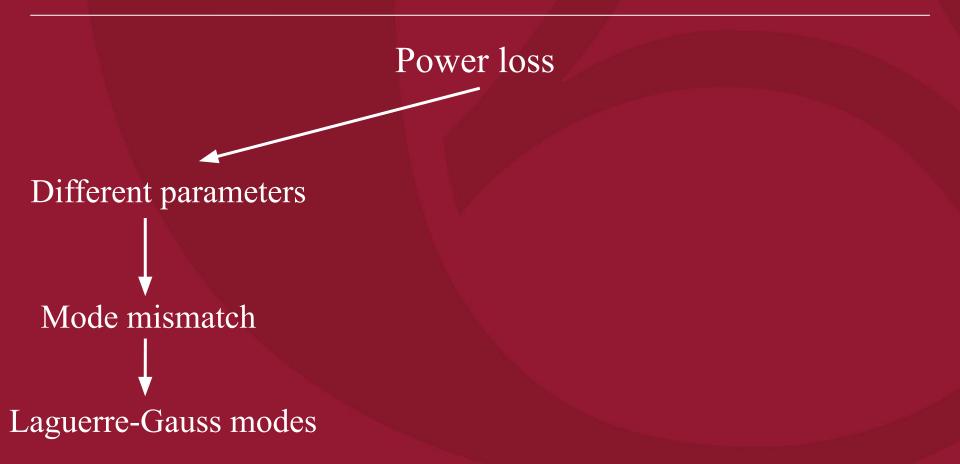


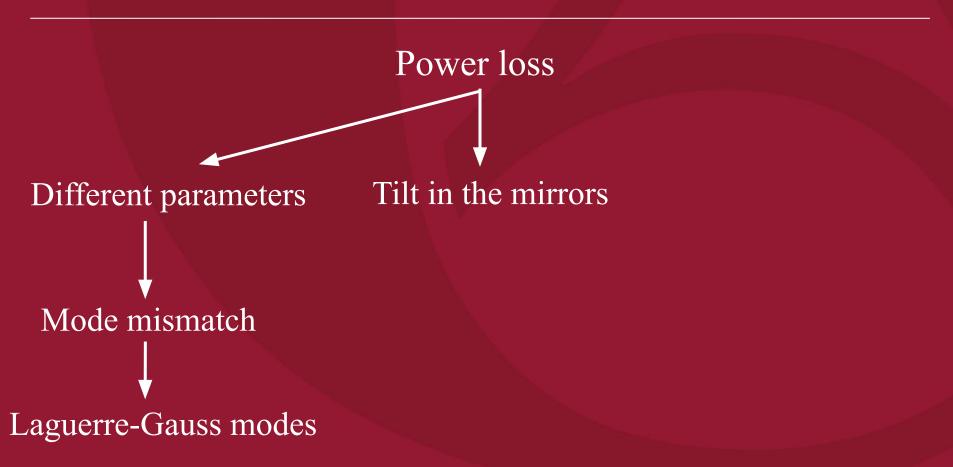


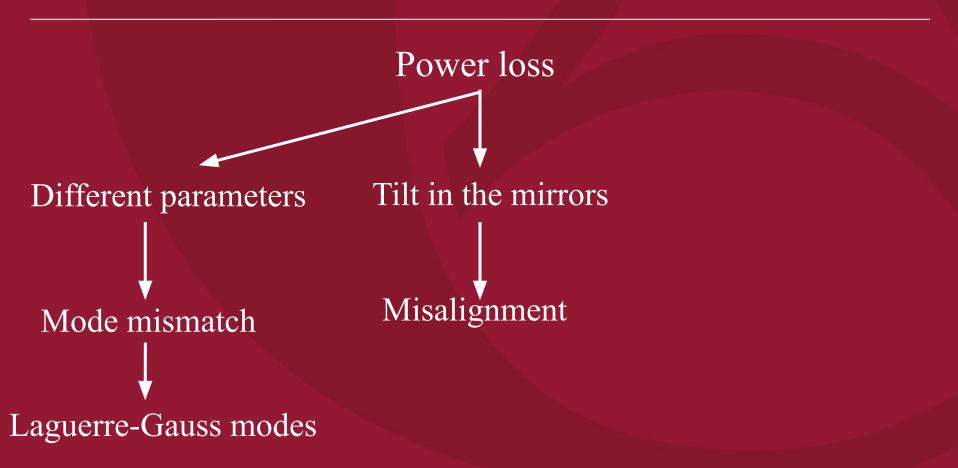


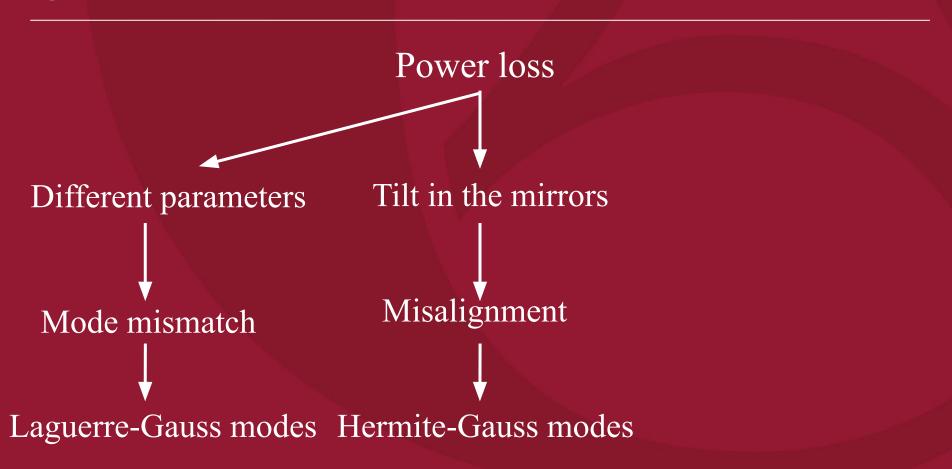


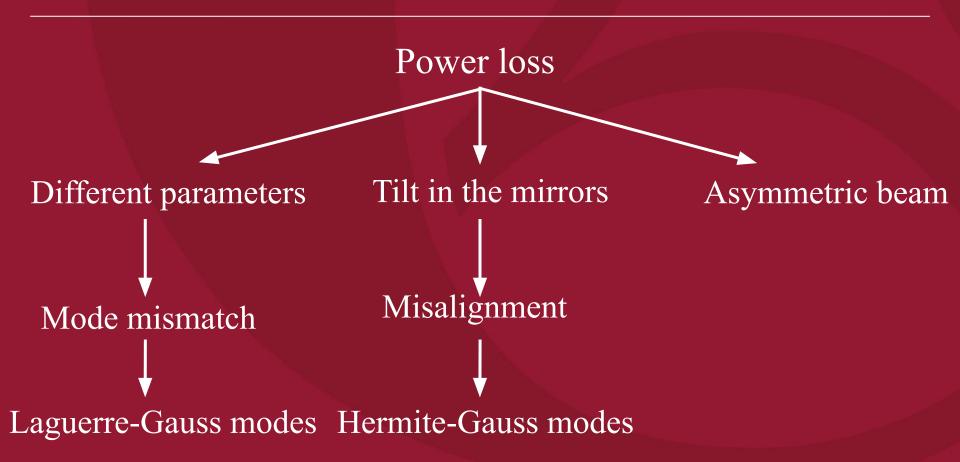


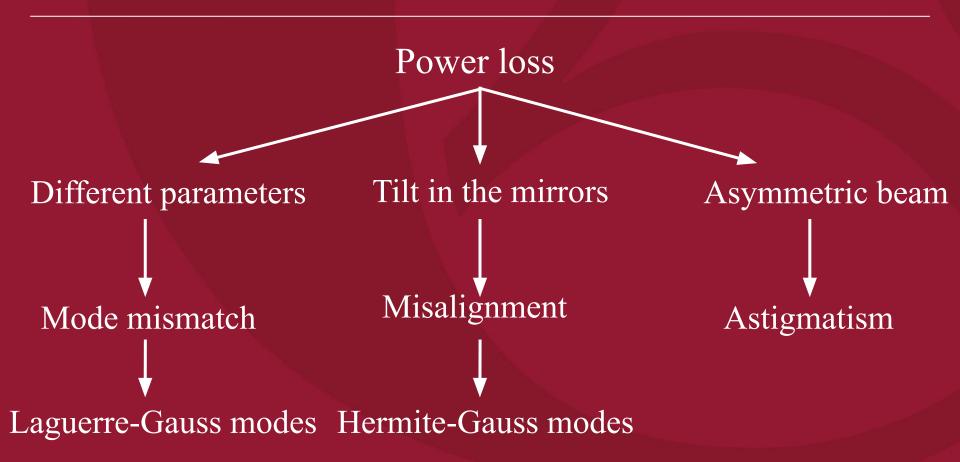


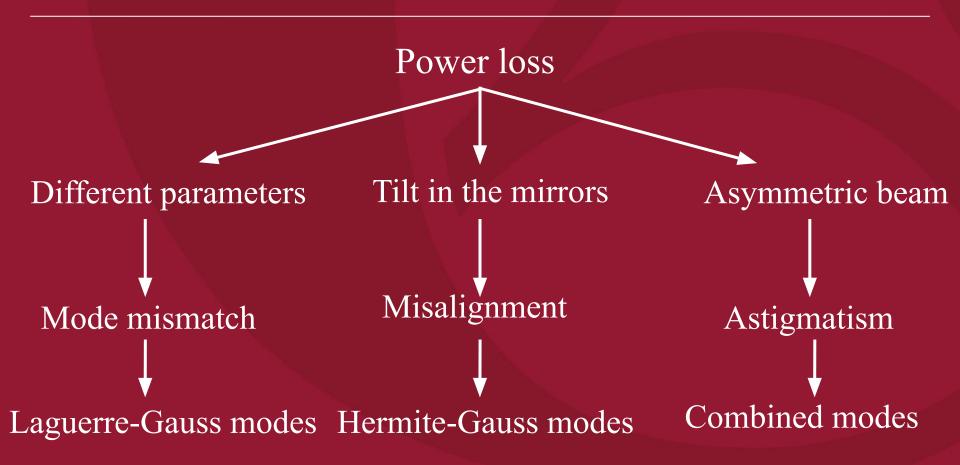






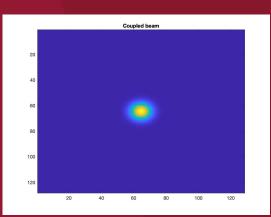


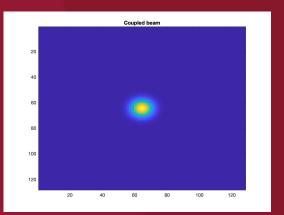


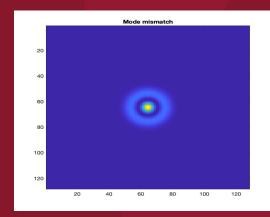


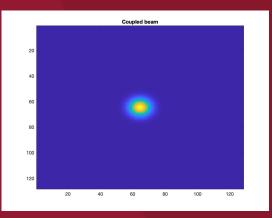


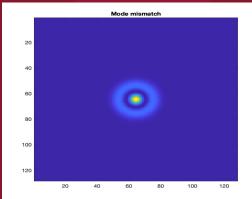


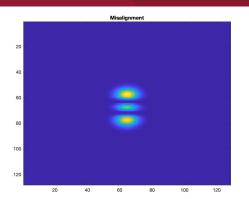




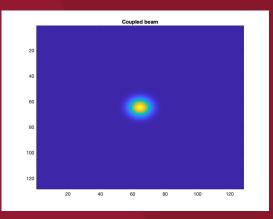


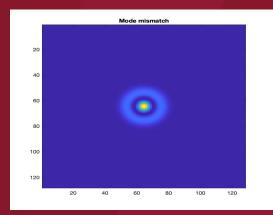


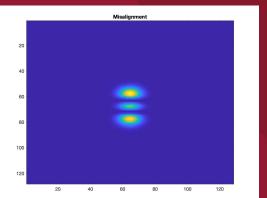


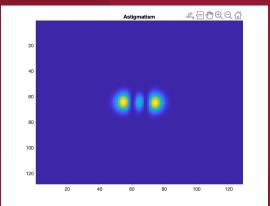


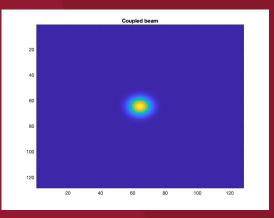




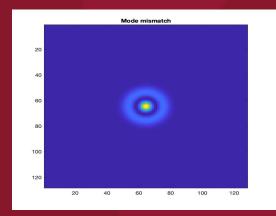




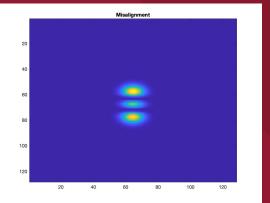


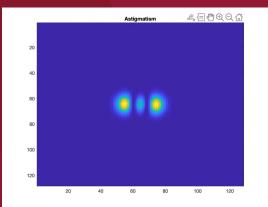


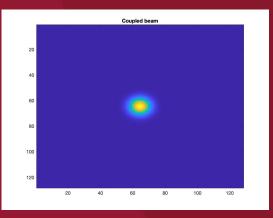
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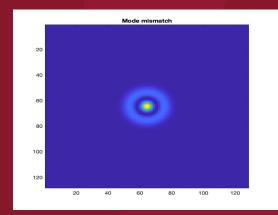
We can easily tell the difference, but not the exact contribution of each parameter





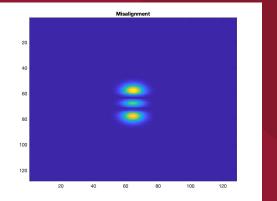


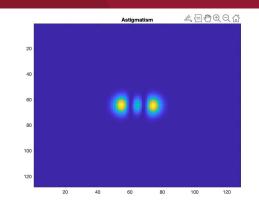
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We can easily tell the difference, but not the exact contribution of each parameter

→ How then?







2) What is Machine Learning and why do we need it?



Machine learning (ML) is a field devoted to understanding and building methods that let machines "learn".



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Machine learning algorithms build a <u>model</u> based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so.



- "Complex fit" (with too many parameters)



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- Useful for evolving systems

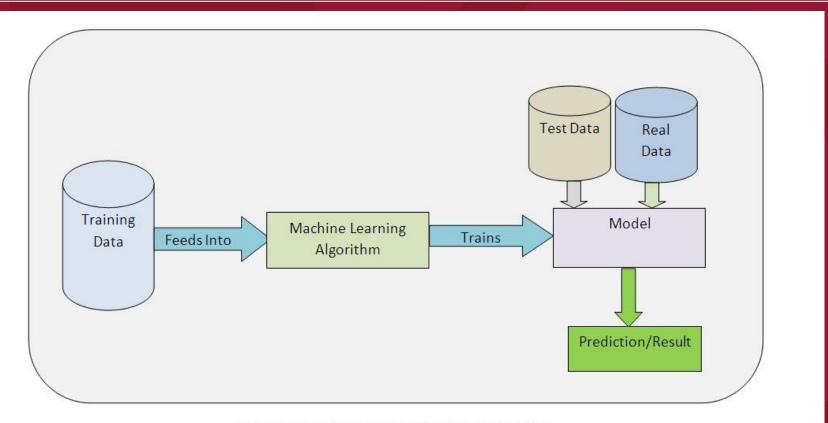


- "Complex fit" (with too many parameters)

- Useful for evolving systems

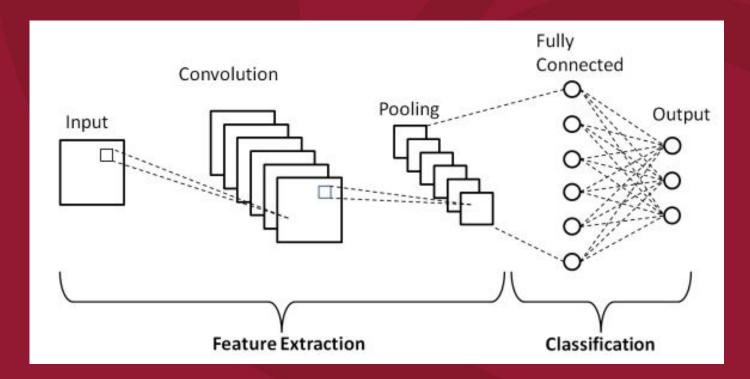
- Can handle nonlinearity

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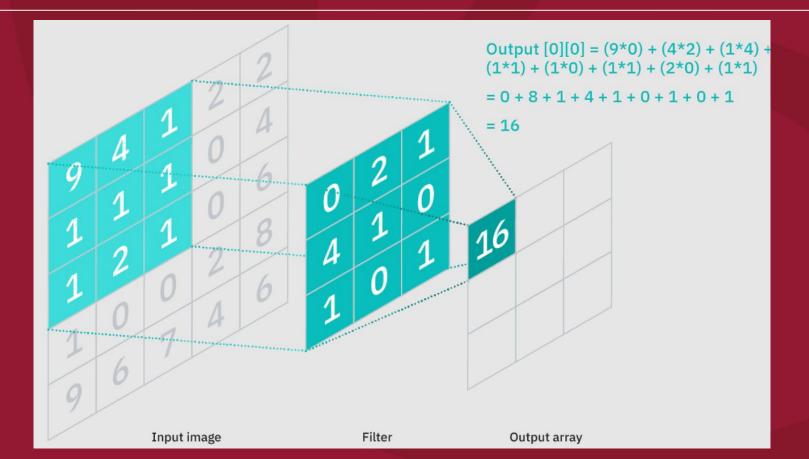


A Simple Machine Learning Pipeline Explanation

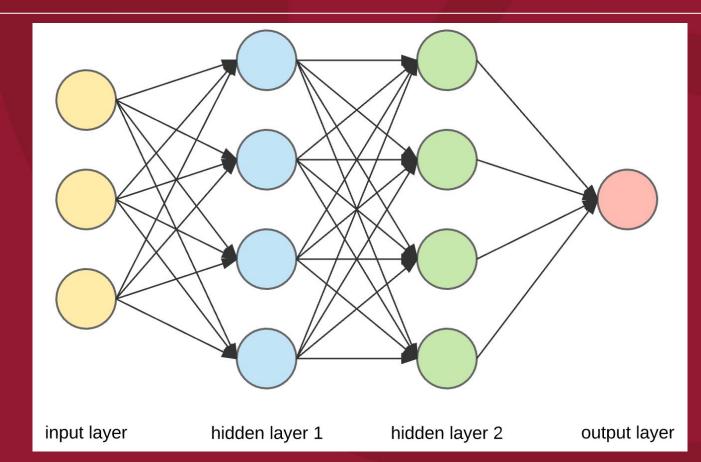
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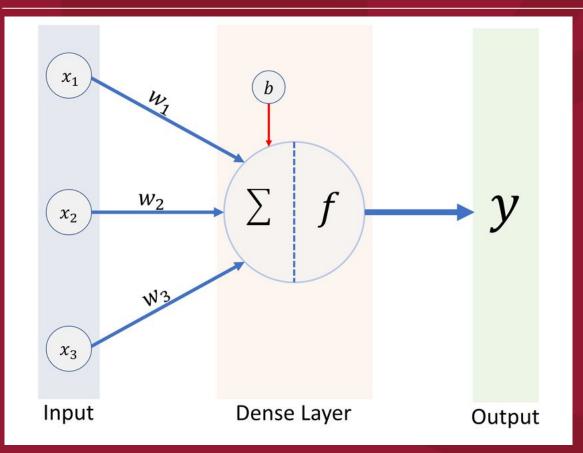
What is Machine Learning and why do we need it? 19



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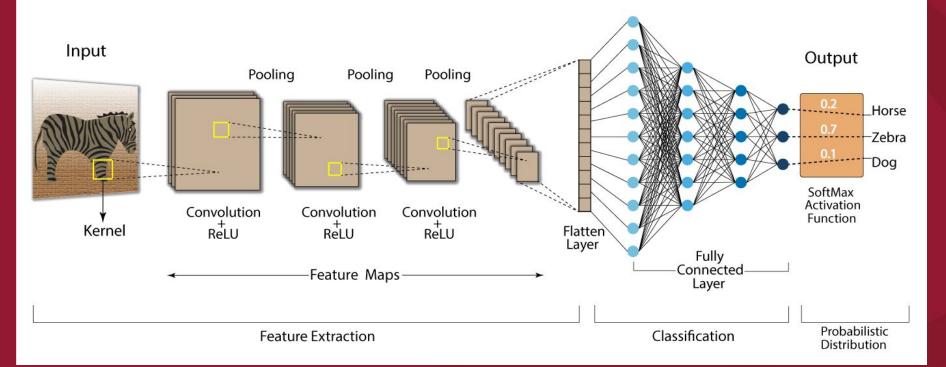
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Weighted sum + activation function













 "Machine Learning for Quantum-Enhanced Gravitational-Wave Observatories" - Chris Whittle, Ge Yang, Matthew Evans, Lisa Barsotti (05/2023)



 "Machine Learning for Quantum-Enhanced Gravitational-Wave Observatories" - Chris Whittle, Ge Yang, Matthew Evans, Lisa Barsotti (05/2023)

 "Predicting the motion of a high-Q pendulum subject to seismic perturbations using machine learning" - Nicolas Heimann, Jan Petermann, Daniel Hartwig, Roman Schnabel, Ludwig Mathey















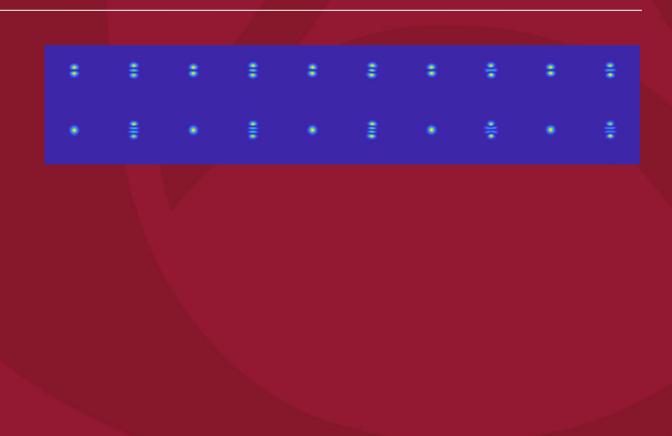




The analysis

24

Input: Cavity scan

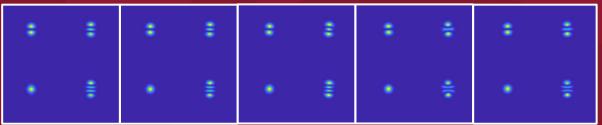




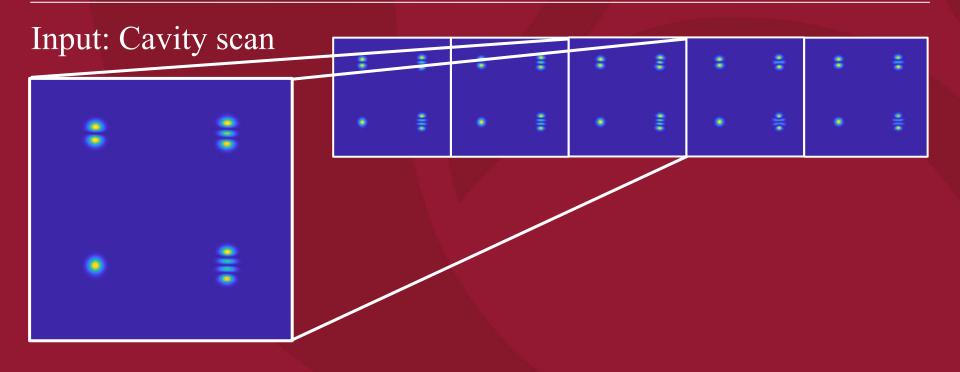
The analysis

24

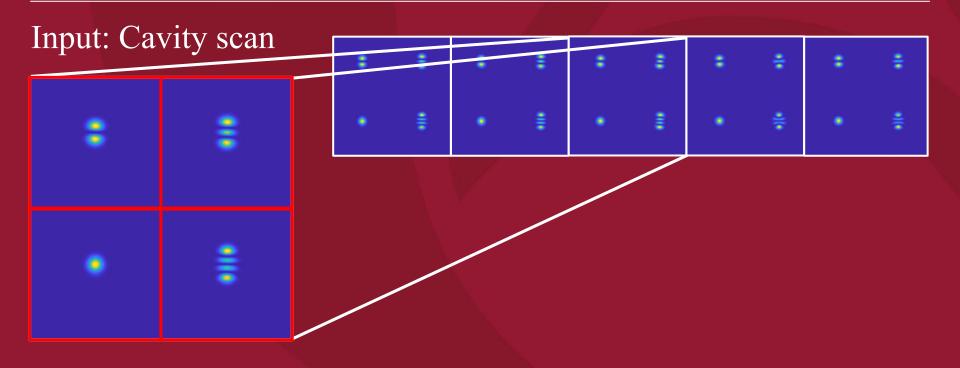
Input: Cavity scan



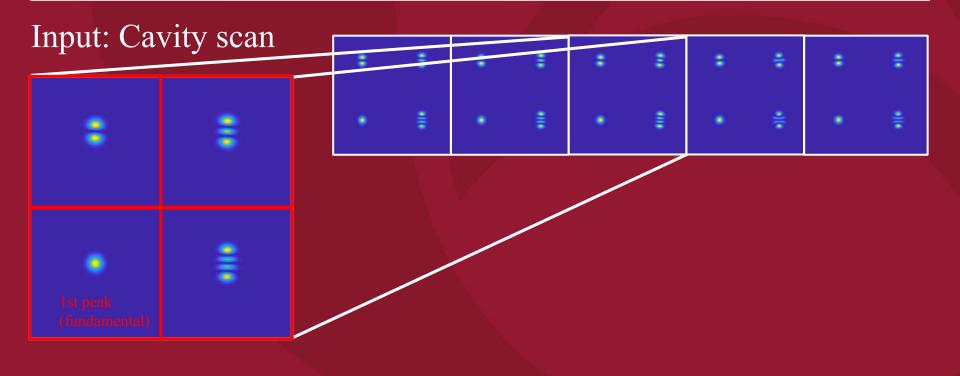




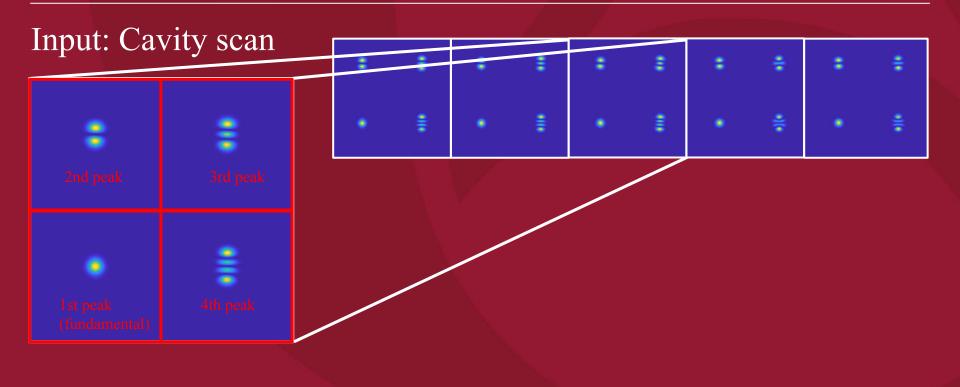




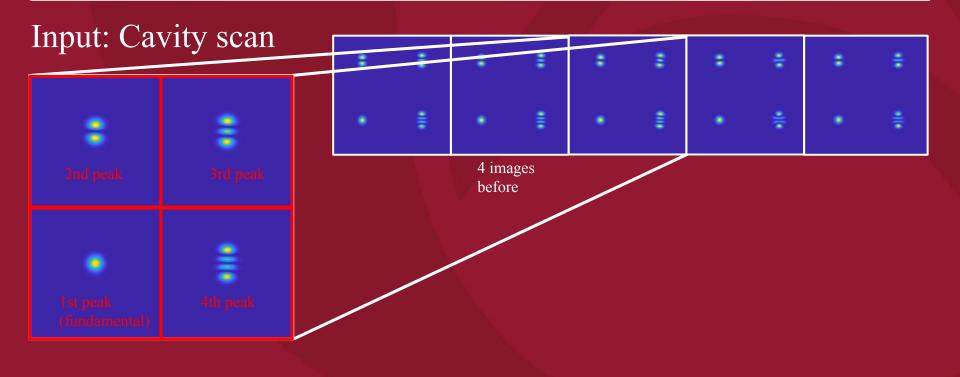




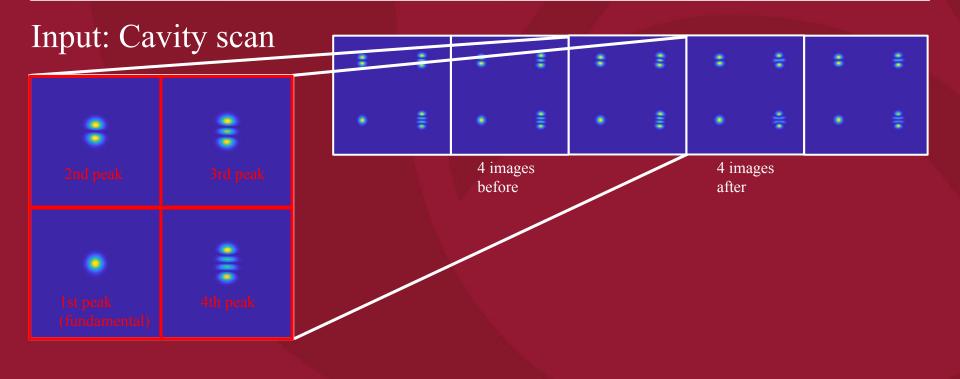




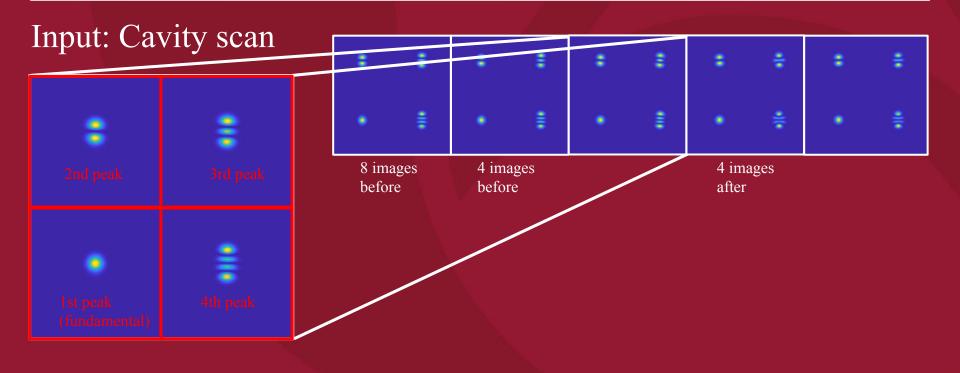




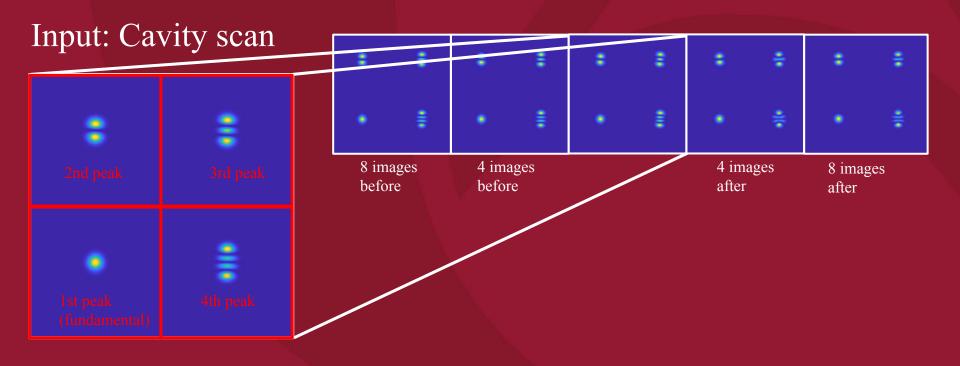




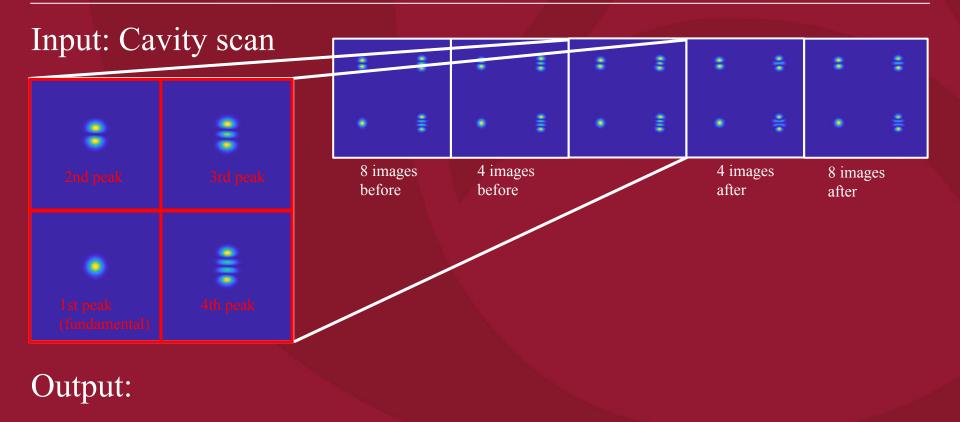






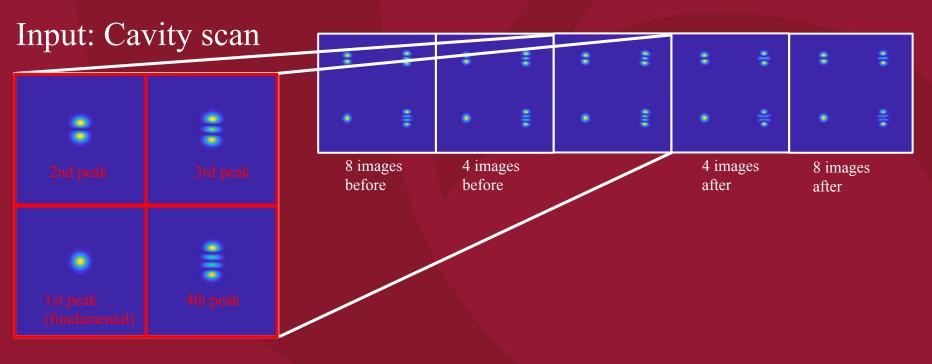








24



Output: 6 parameters



24

Input: Con	ity coon									
Input: Cav		: ;	•	:	8	÷ ÷	÷ ÷			
:	8	• #	•	•	ŧ	• ÷	• ‡			
		8 images before	4 images before			4 images after	8 images after			
	-									
	4th peak	1.021481e-05 -7.055408e-06 1.480248e-05 9.489621e-06 5.835023e-06	7.370700e-06 8.647666e-07 -2.501442e-07 8.344123e-06 4.686980e-06	1.470483e-02 2.189797e-02 2.053623e-02 1.928437e-02 2.004127e-02	2.154197e-02 2.198858e-02 1.485315e-02 1.393262e-02 1.702361e-02	1.630334e+03 8.840545e+02 1.299284e+03 1.971087e+03 1.666676e+03	7.816893e+02 2.113696e+03 2.030001e+03 2.057856e+03 8.940506e+02			
Output: 6	parameters	6.714626e-06 6.353345e-06 8.629999e-06 6.821513e-06 -1.219244e-05 8.171058e-06 1.599171e-06	-8.471469e-06 -3.300469e-06 5.366009e-06 4.631630e-06 -1.470467e-08 -4.424416e-06 -6.535669e-06	1.600343e-02 2.183487e-02 1.522350e-02 1.599565e-02 2.191734e-02 1.798709e-02 1.489804e-02	1.402331e-02 1.392165e-02 1.786926e-02 1.951602e-02 1.657414e-02 1.968400e-02 1.585560e-02	7.889807e+02 1.325980e+03 1.336735e+03 1.666078e+03 1.556308e+03 2.036754e+03 1.957863e+03	1.889214e+03 1.215013e+03 1.618946e+03 8.809679e+02 9.743404e+02 2.096454e+03 1.020829e+03			

-4.634147e-06

-4.692404e-07

2.165335e-02

1.665072e-02

1.665736e-02

2.082628e-02

9.453327e+02

1.556303e+03

1.015949e+03

1.471580e+03

1.020067e-05

3.815951e-06



Input: Cox	titu ann						
Input: Cav		: :	•	:	8	* ÷	: :
:	:	• ‡	•	•	8	• ÷	•
		8 images before	4 images before			4 images after	8 images after
	:						
	4th peak	1.021481e-05 -7.055408e-06 1.480248e-05 9.489621e-06 5.835023e-06	7.370700e-06 8.64/666e-07 -2.501442e-07 8.344123e-06 4.686980e-06	1.470483e-02 2.189797e-02 2.053623e-02 1.928437e-02 2.004127e-02	2.154197e-02 2.198858e-02 1.485315e-02 1.393262e-02 1.702361e-02	2 8.840545e+02 2 1.299284e+03 2 1.971087e+03	7.816893e+02 2.113696e+03 2.030001e+03 2.057856e+03 8.940506e+02
Output: 6	6.714626e-06 6.353345e-06 8.629999e-06 6.821513e-06 -1.219244e-05 8.171058e-06	-8.471469e-06 -3.300469e-06 5.366009e-06 4.631630e-06 -1.470467e-08 -4.424416e-06	1.600343e-02 2.183487e-02 1.522350e-02 1.599565e-02 2.191734e-02 1.798709e-02	1.402331e-02 1.392165e-02 1.786926e-02 1.951602e-02 1.657414e-02 1.968400e-02	2 1.325980e+03 2 1.336735e+03 2 1.666078e+03 2 1.556308e+03	1.889214e+03 1.215013e+03 1.618946e+03 8.809679e+02 9.743404e+02 2.096454e+03	

-4.424416e-06

-6.535669e-06

-4.634147e-06

-4.692404e-07

1.489804e-02

2.165335e-02

1.665072e-02

1.968400e-02

1.585560e-02

1.665736e-02

2.082628e-02

2.036754e+03

1.957863e+03

9.453327e+02

1.556303e+03

8.171058e-06

1.599171e-06

1.020067e-05

3.815951e-06

24

1.020829e+03

1.015949e+03

1.471580e+03



Power Loss Percentage

The analysis

imes10⁻⁶

Power Loss Percentage as a Function of the tilts input mirror end mirror data1 3.5 0 data2 3 2.5 2 1.5 1 0.5 0 -3 -2 -1 0 2 1 3

Tilt of input mirror

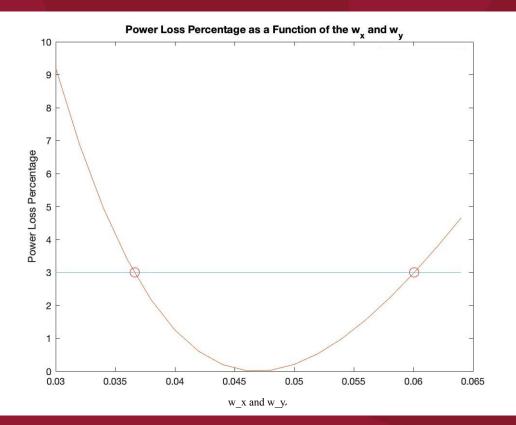
Intersection points for input mirror: (-1.6025e-06, 3) (1.6182e-06, 3)

25

Intersection points for end mirror: (-9.0485e-07, 3) (9.0784e-07, 3)



26



Intersection points for w_x: (0.036643, 3) (0.060077, 3)

Intersection points for w_y: (0.036643, 3) (0.060077, 3)



3.5

3

1

0.5

0 500

1000

1500

R_x and R_y

The analysis

Power Loss Percentage as a Function of the R_x and R_y input mirror end mirror C data1 data2

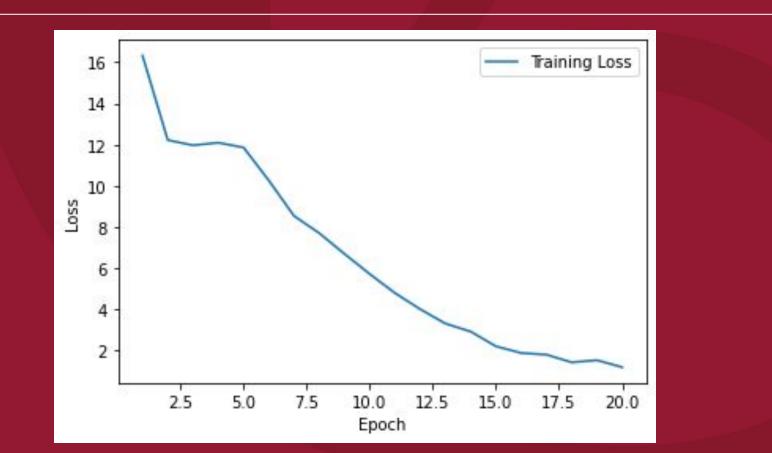
2000

2500

Intersection points for R_x: (636.2939, 3) (2208.2487, 3) 27

Intersection points for R_y: (632.8729, 3) (2158.5623, 3)













Variable number of inputs (number of peaks)





29

Variable number of inputs (number of peaks)







Variable number of inputs (number of peaks)

Truncation

Loss of data





Variable number of inputs (number of peaks)



Padding

29

Loss of data





Variable number of inputs (number of peaks)

Truncation

Loss of data

Padding

29

Extra worthless data



Next steps

30

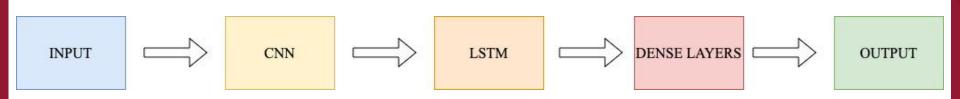
Long Short-Term Memory Convolutional Neural Network (LSTM CNN)





30

Long Short-Term Memory Convolutional Neural Network (LSTM CNN)





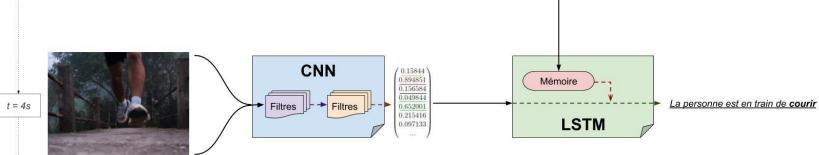
t = 0s

t = 2s



31

CNN 0.46007 Mémoire 0.232315 0.154224 La personne est immobile Filtres -Filtres 0.053963 0.199242 LSTM 0.705248 CNN $\begin{pmatrix} 0.78454 \\ 0.154156 \\ \hline 0.981210 \end{pmatrix}$ Mémoire 0.181139 La personne semble marcher Filtres Filtres ----0.004184 0.008749 LSTM 0.416271





Thank you for listening!