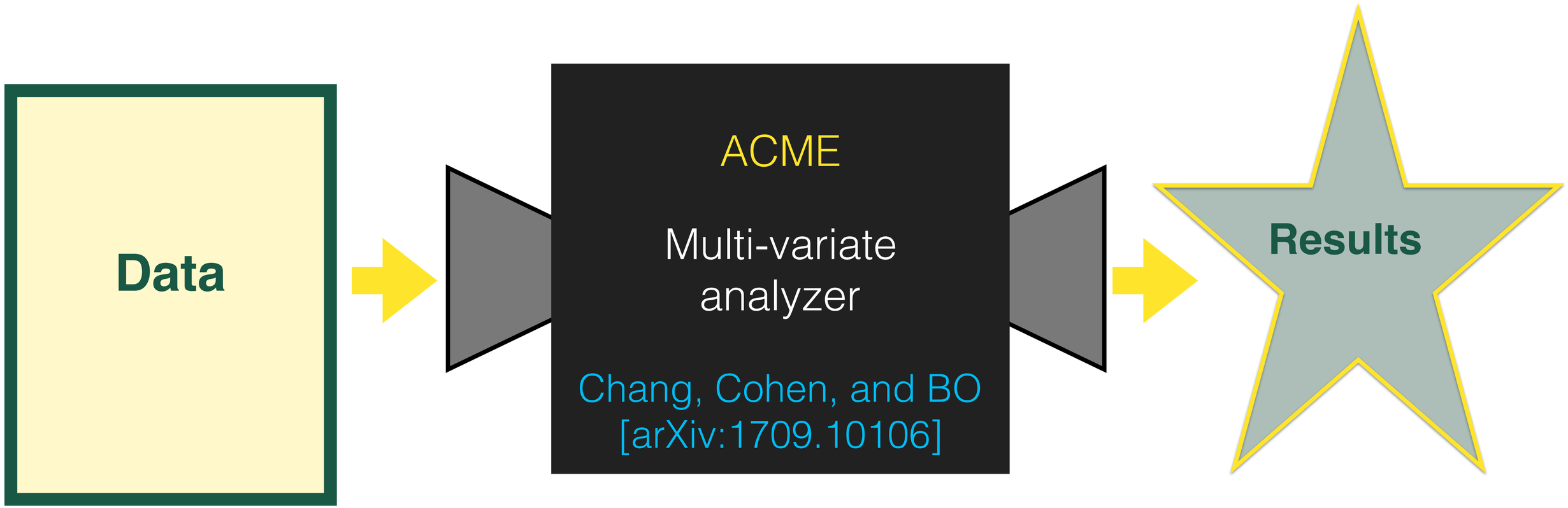
"Planing" to expose what the machine is learning



Bryan Ostdiek
Machine Learning for Jet Physics Workshop
Lawrence Berkeley National Laboratory
December 13, 2017

Review: Linear Regression

How to fit data

1. Plot the data
2. Define the function
   - $f(x, \vec{a}) = a_0 + a_1 x$
3. Choose how to know what fits best
   - a.k.a. *Loss Function*
   - MSE: $L(x, y, \vec{a}) = \frac{1}{N} \sum_{i=1}^{N} \left(f(x_i, \vec{a}) - y_i \right)^2$
5. Find the minimum error (loss) (cost)
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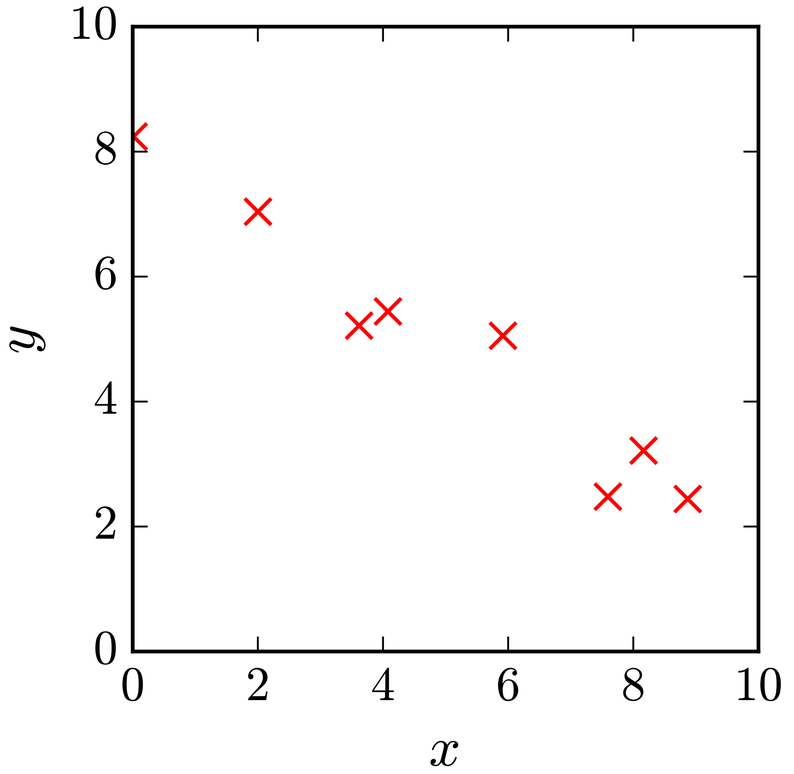

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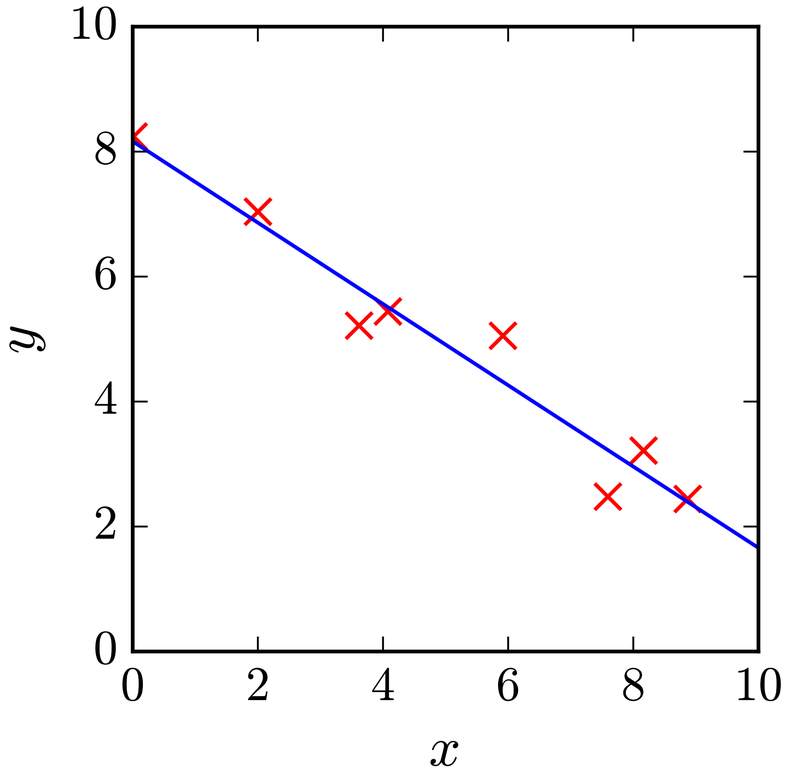

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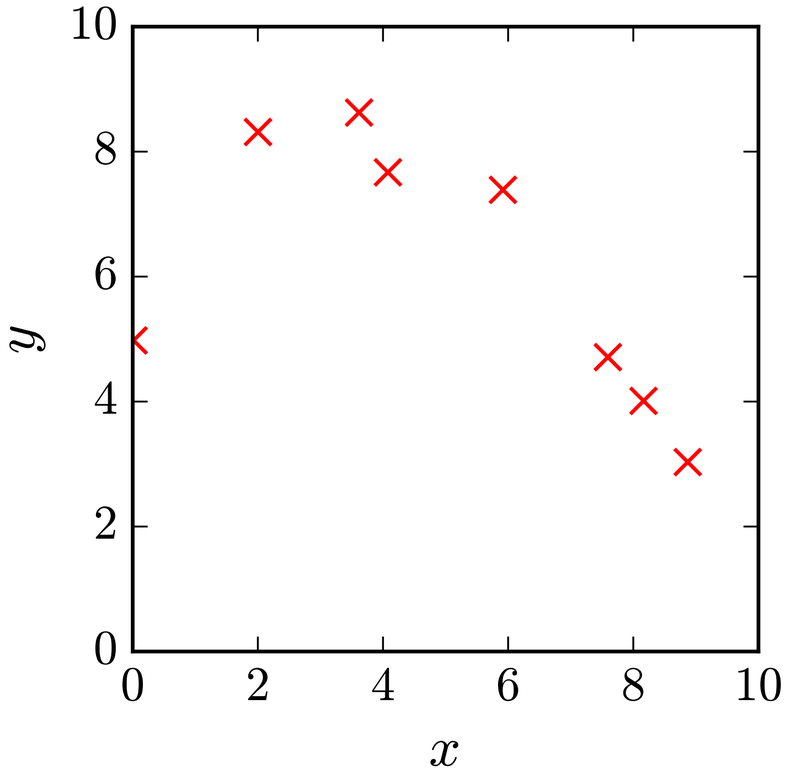

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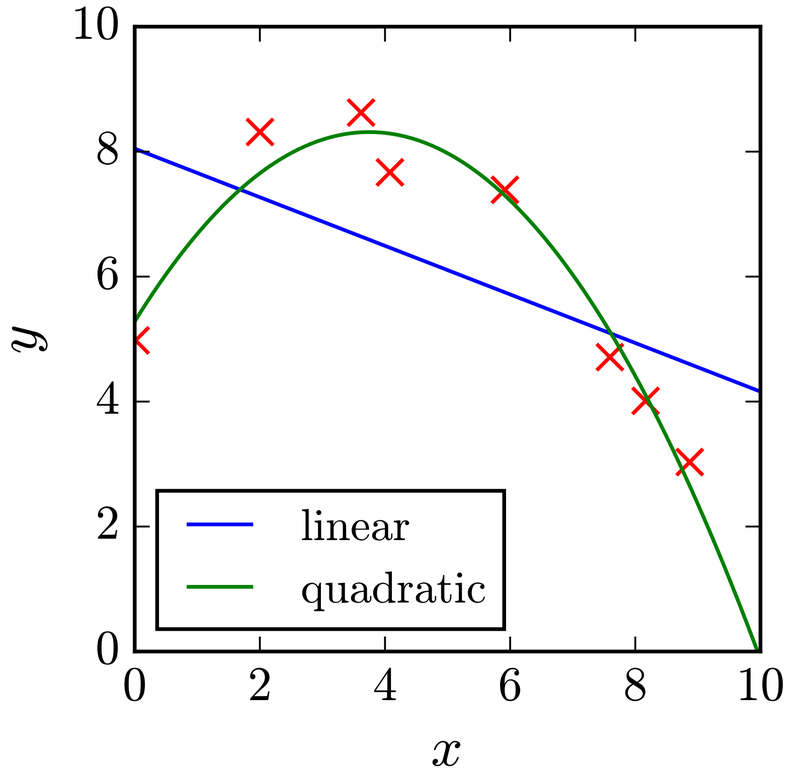

Is that good enough?
How many parameters can we add?

Review: Linear Regression

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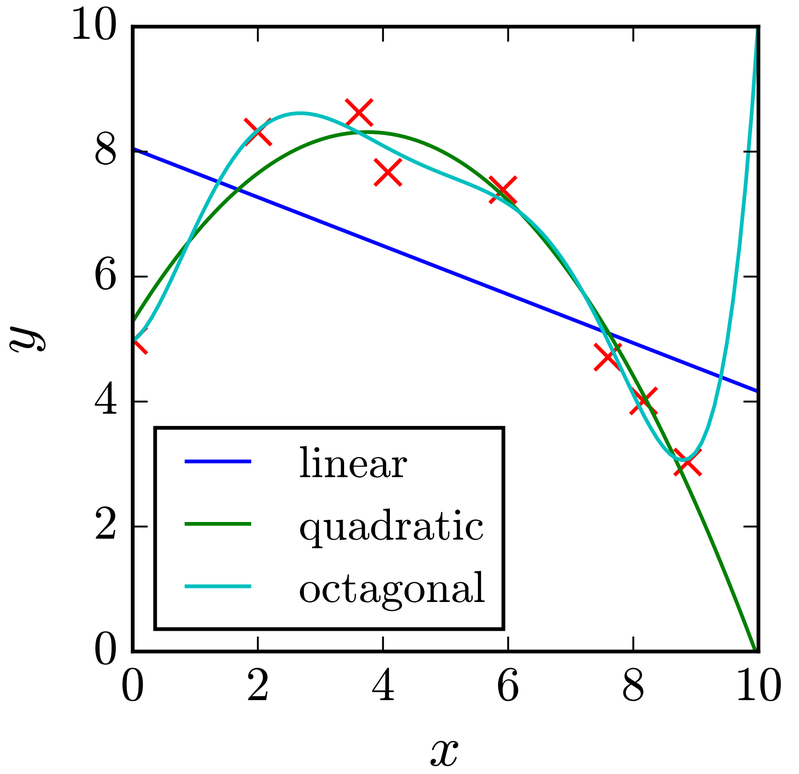

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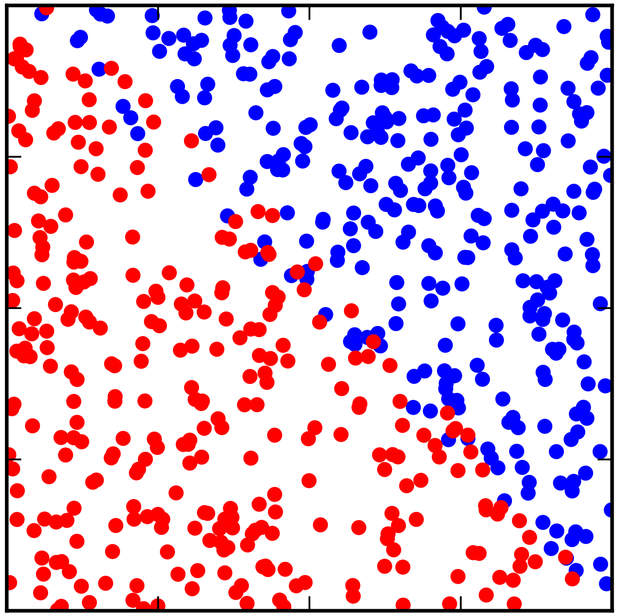
What is the machine learning?

Logistic regression similar, but intuition is off/different



Chang, Cohen, and BO [arXiv:1709.10106]

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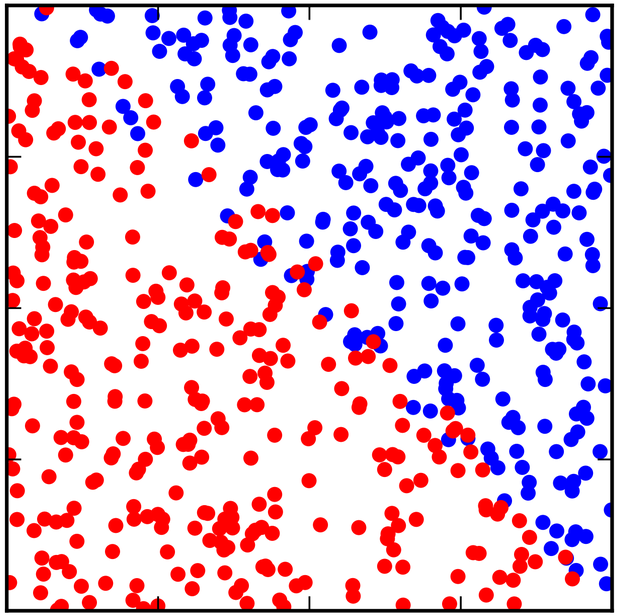

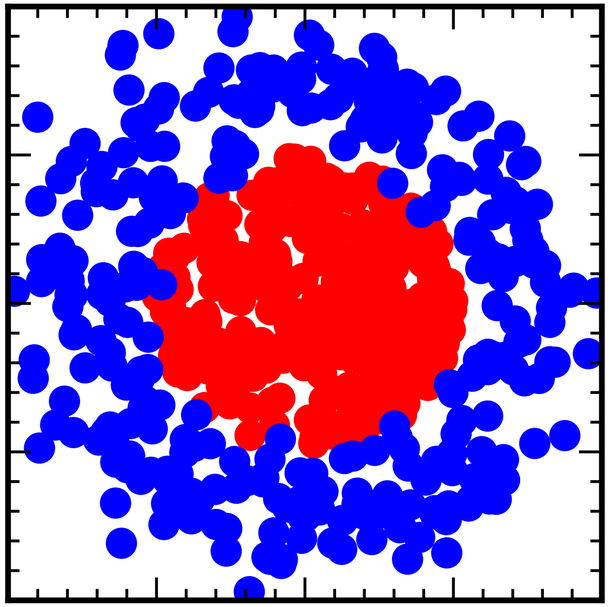

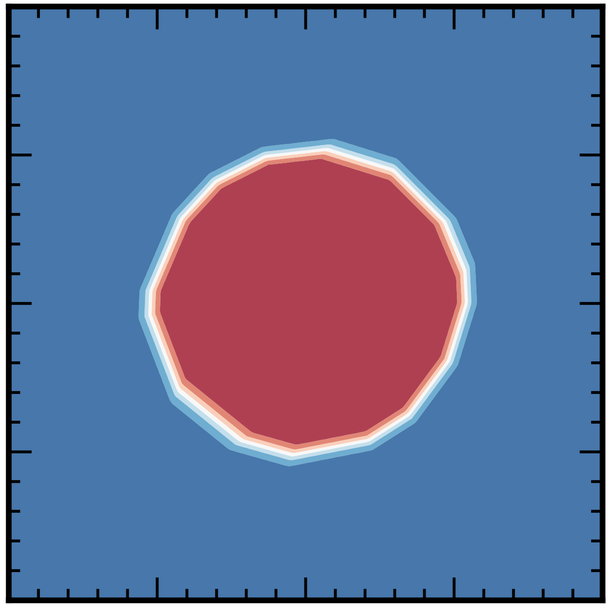

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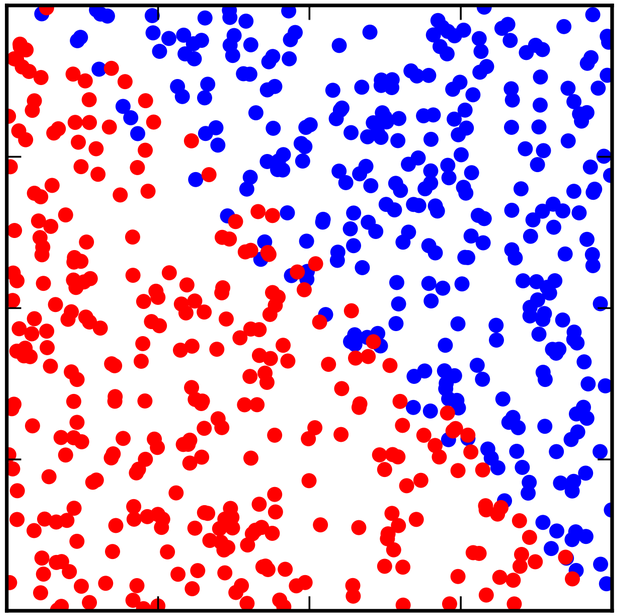

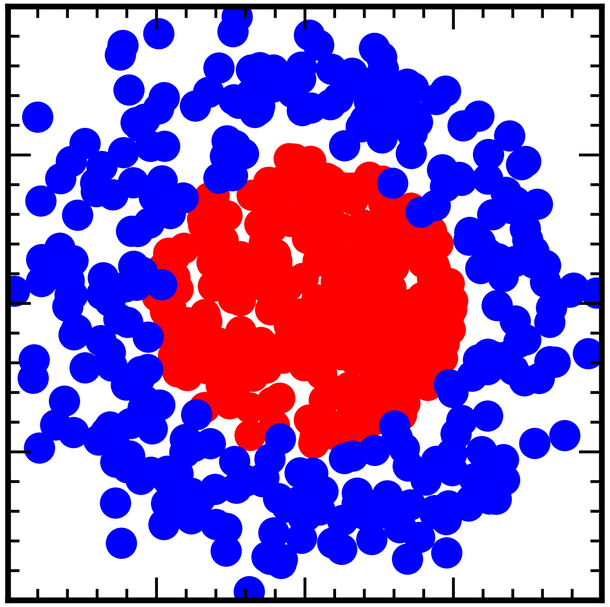

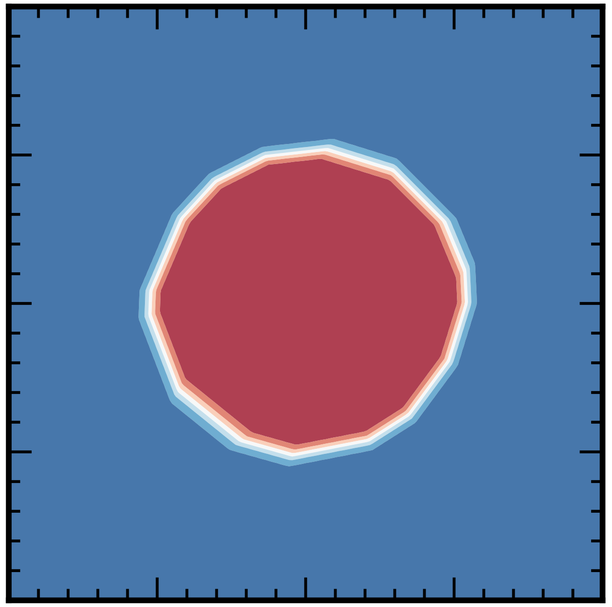

It has learned generically where events are in “any” parameter space. Wrong question to ask.

Chang, Cohen, and BO [arXiv:1709.10106]

What is the machine learning?

Can we find what information the machine is learning?

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Planing

See also de Oliveria, Kagan, Nachman, Schwartzman [arXiv:1511.05190]

(a) Train machine on low level data
(b) Compute low level AUC
(c) Choose a variable: compute (planing) weights
(d) Train machine on weighed (planed) data
(e) Compute planed AUC
(f) Compare: looking for significant performance drop

Removing information from training samples

Similar to what experiments do with different p_T samples

What is the machine learning?

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Planing

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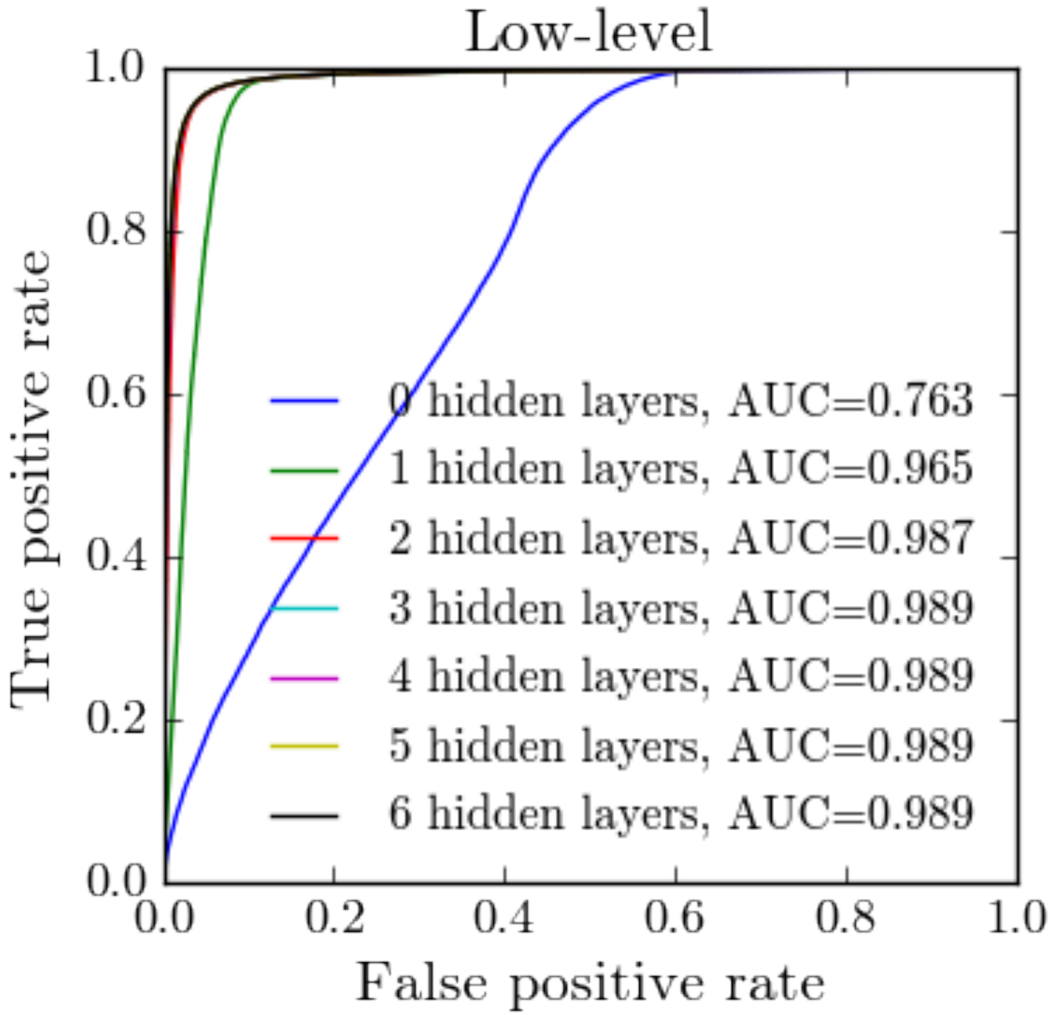
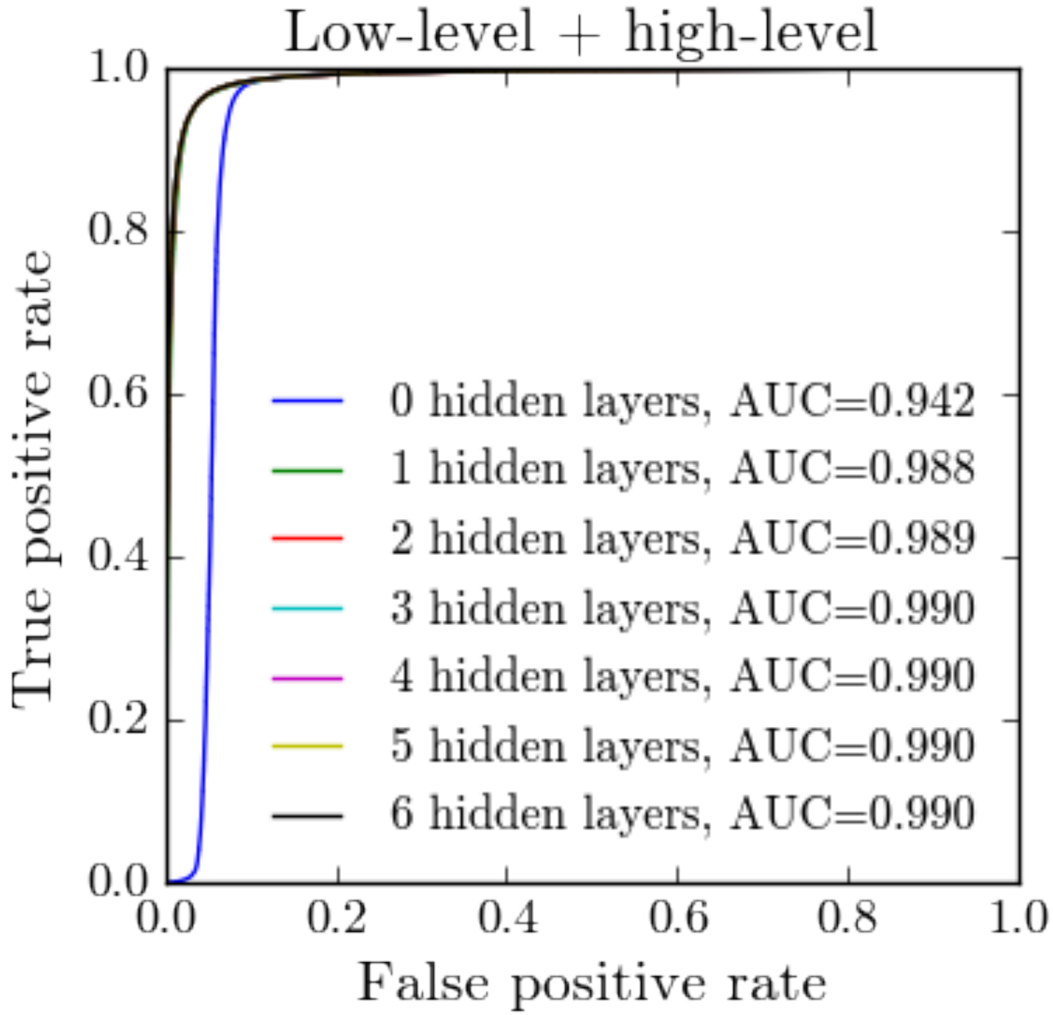
Saturation

Used in Baldi, Sadowski, Whiteson [arXiv:1402.4735 and 1410.3469]; Baldi, Bauer, Eng, Sadowski, Whiteson [arXiv:1603.09349]; Guest, Collado, Baldi, Hsu, Urban, Whiteson [arXiv:1607.08633]; Datta, Larkoski [arXiv:1704.08249]; Aguilar-Saavedra, Collins, Mishra [arXiv:1709.01087]

(a) Train network on low level data
(b) Compute low level AUC
(c) Add high level variable
(d) Train new machine using low + high level info
(e) Compute AUC
(f) No performance gain implies information has been learned

Using saturation to pick the network





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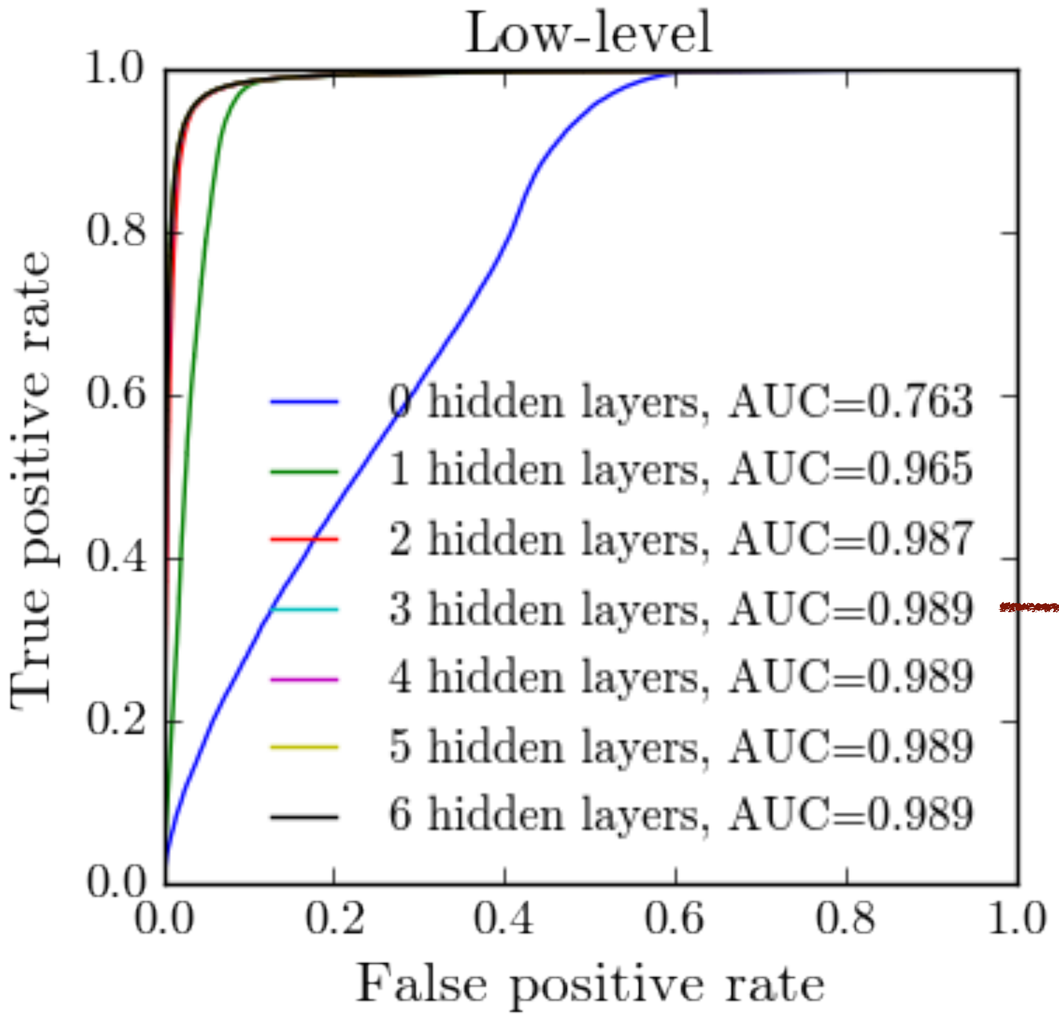
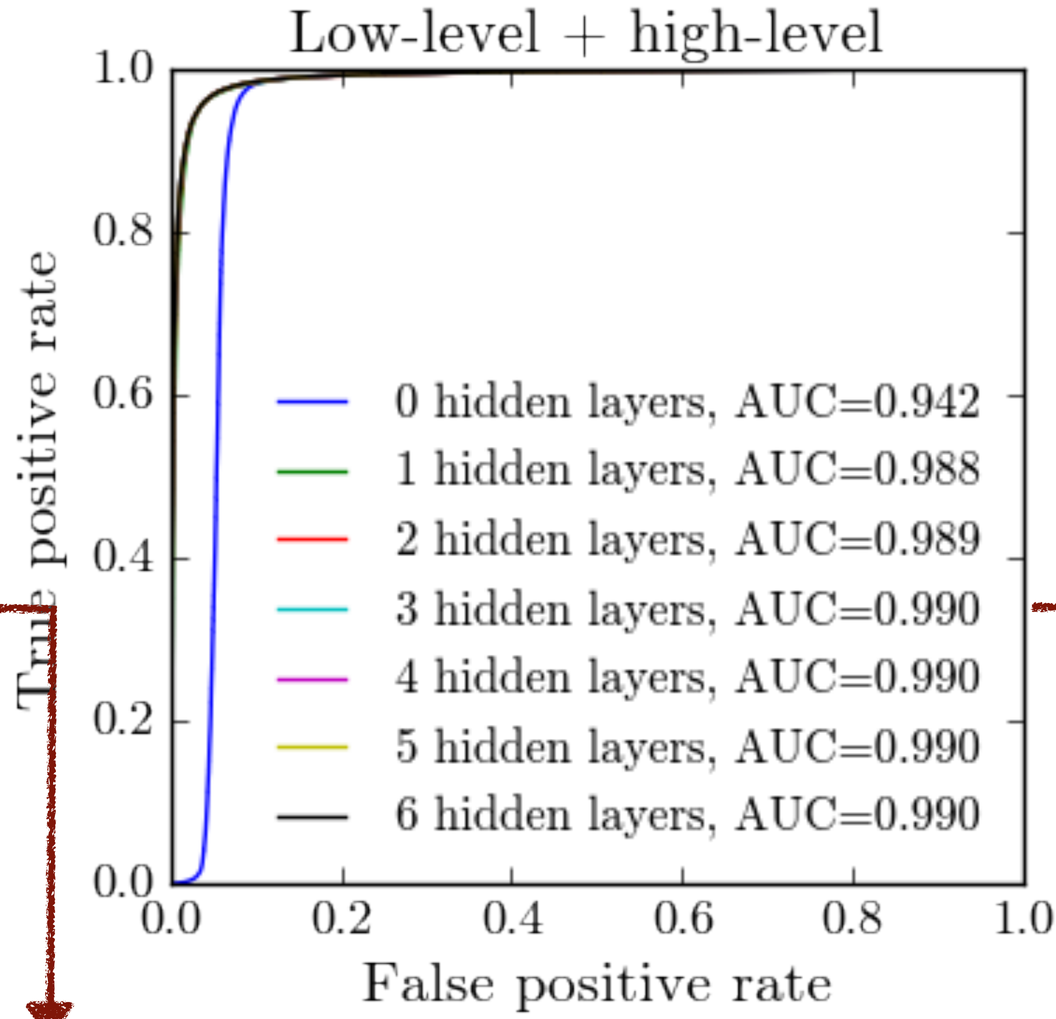
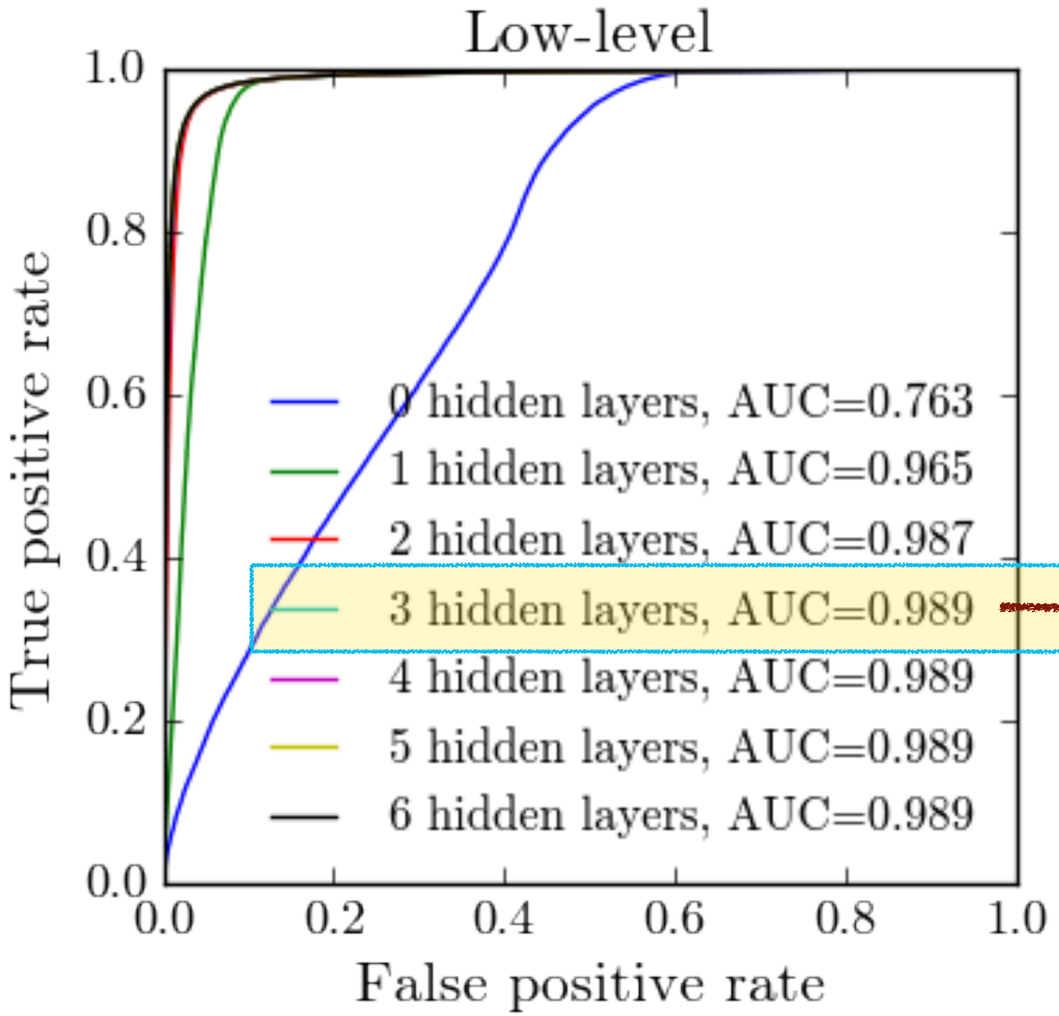
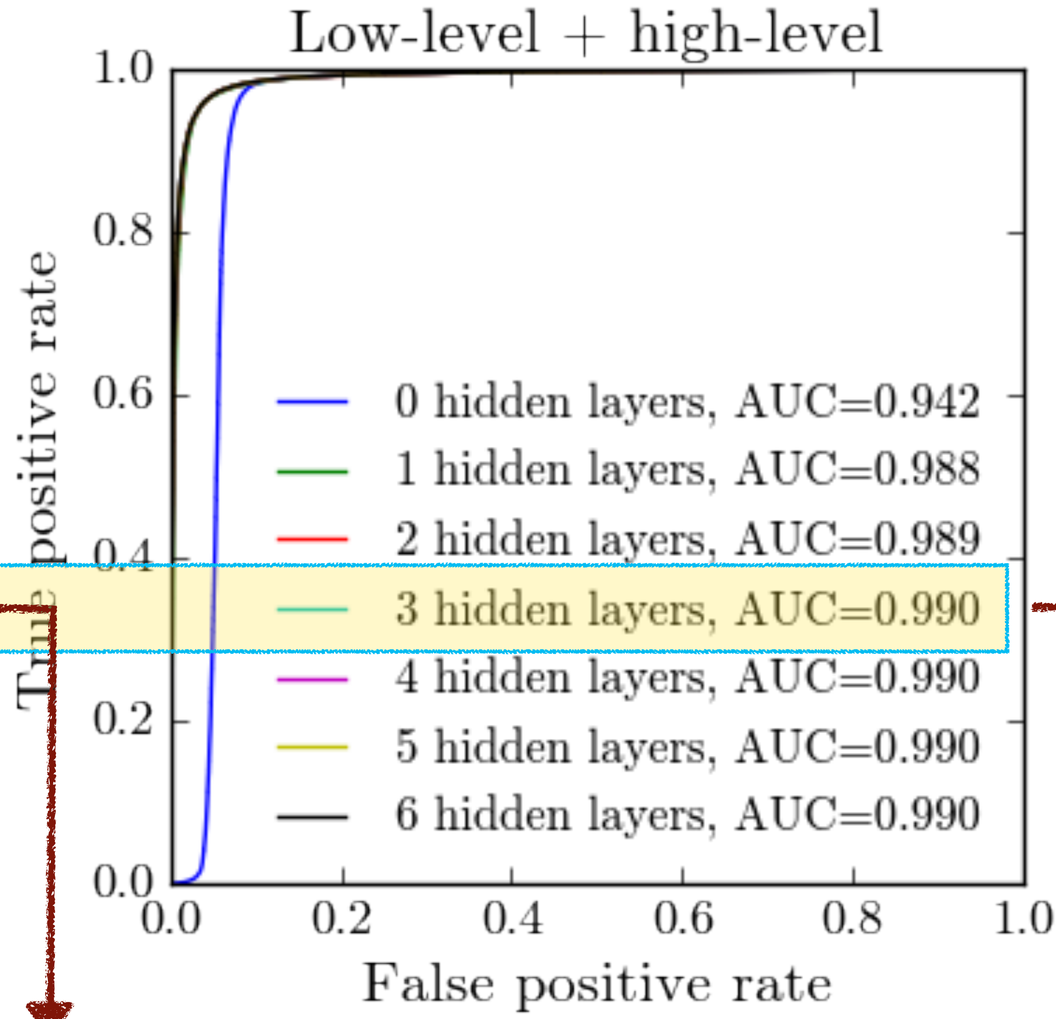




Minimal improvement

Using saturation to pick the network





high-level not adding much

Minimal improvement

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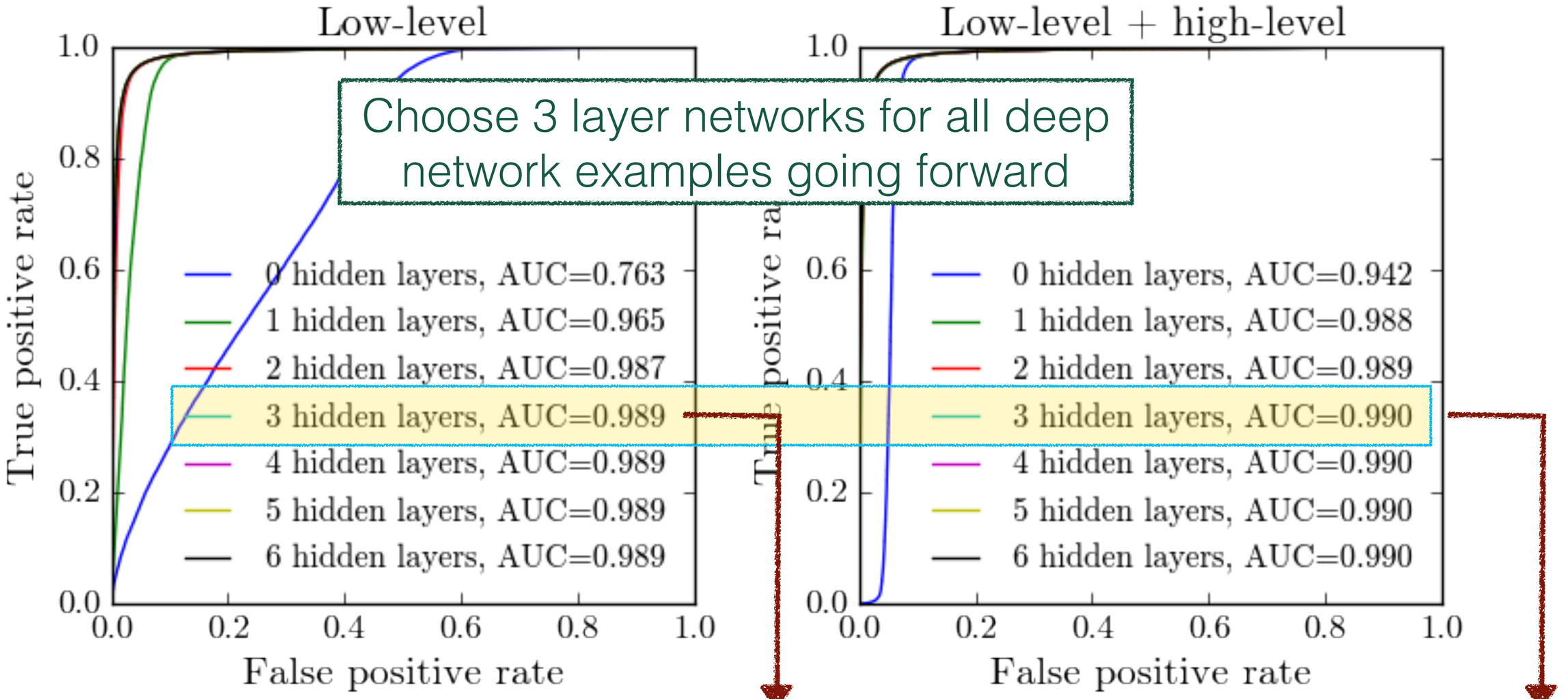
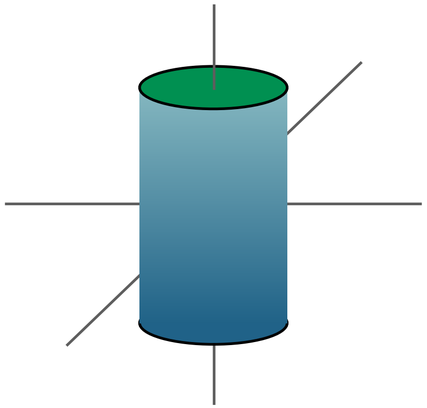


Choose 3 layer networks for all deep network examples going forward

high-level not adding much

Minimal improvement

Example with a toy model

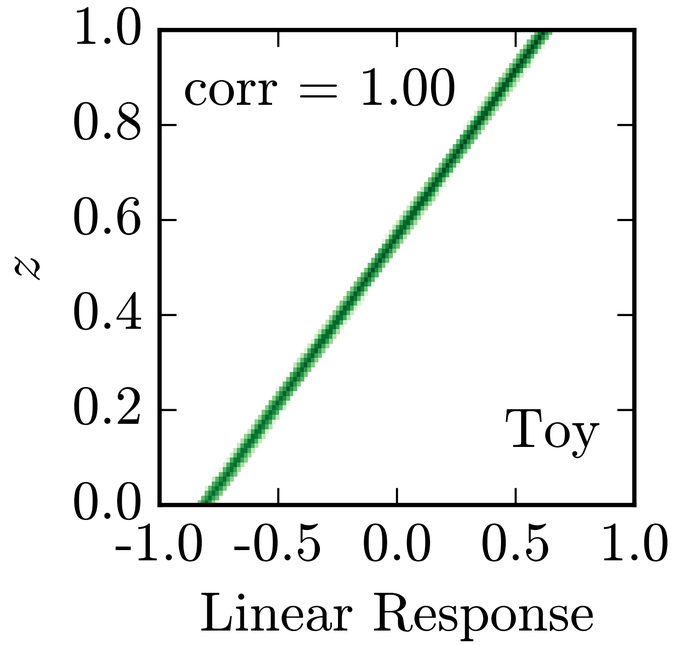


Signal Distribution: $f(\vec{x}) = [\Theta(r_0 - r) + C_r] \cdot [z \cdot B_z + C_z]$

Background Distribution: Uniform

Results

(x, y, z)	r	Planed	Linear AUC	Deep AUC
✓	✘	✘	0.61275(01)	0.81243(45)
✓	✓	✘	0.79672(01)	0.81388(23)
✓	✘	r	0.61030(01)	0.61026(02)
✓	✘	(r, z)	0.5081(16)	0.49998(03)



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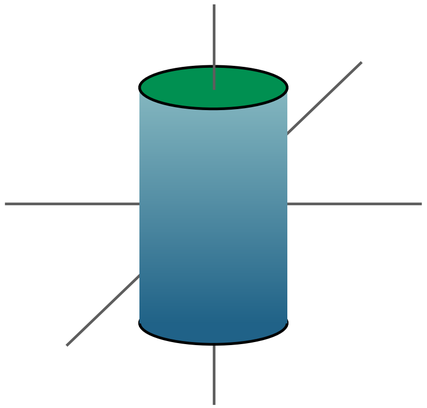

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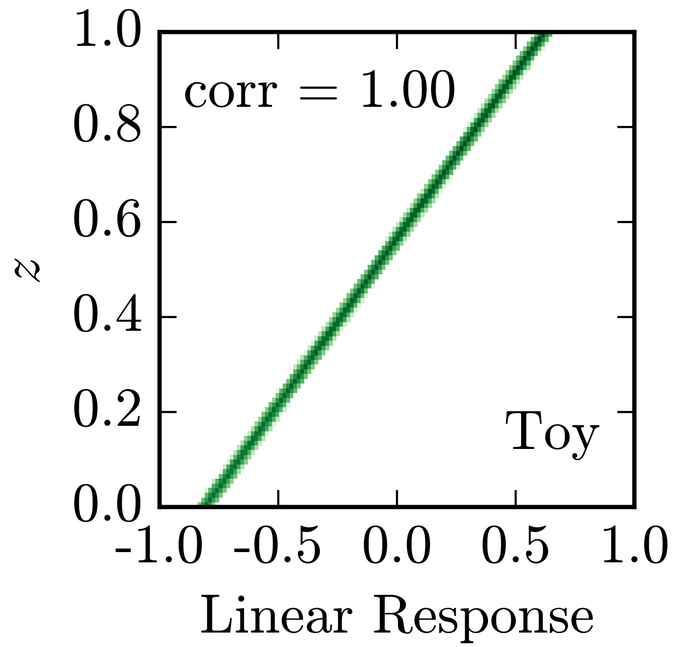

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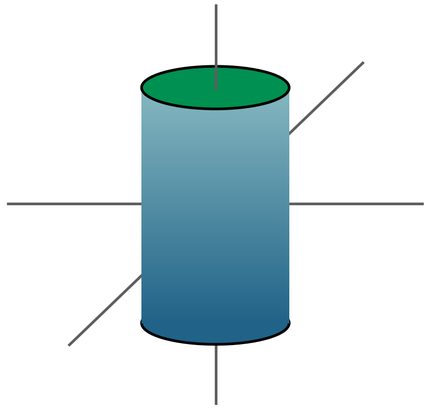

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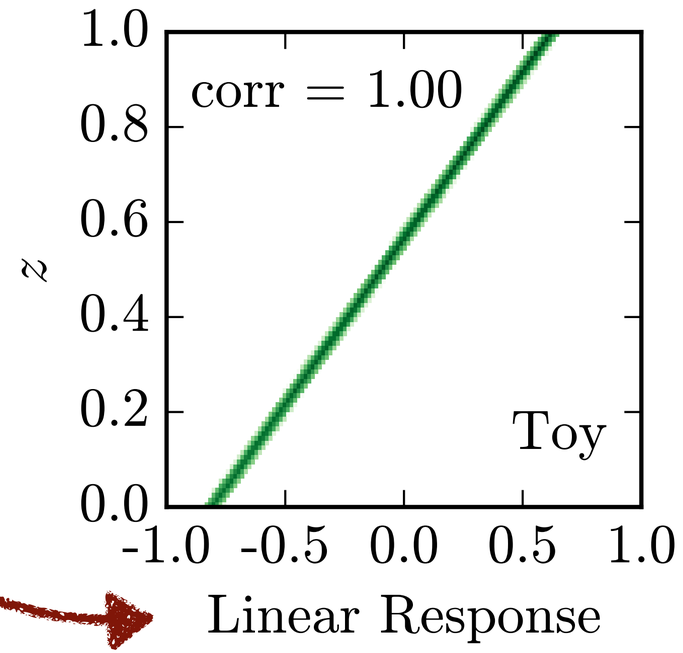

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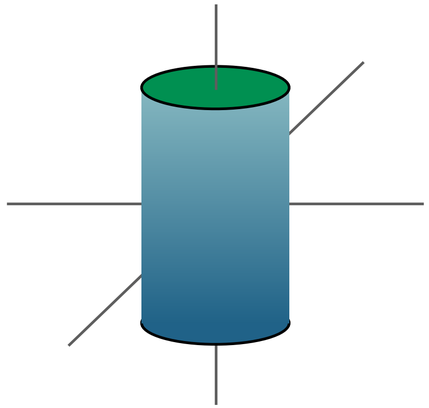

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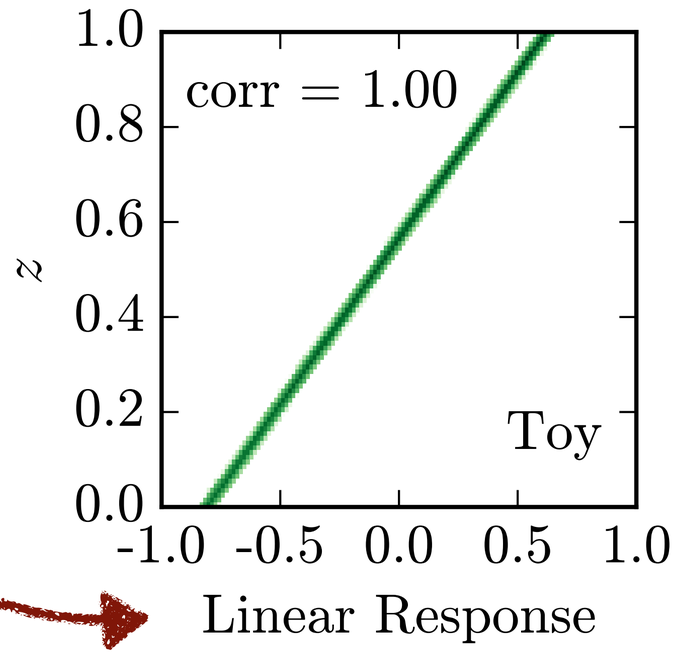
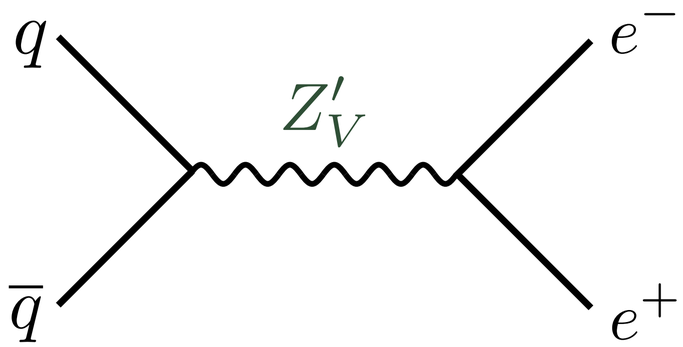
No discrimination left



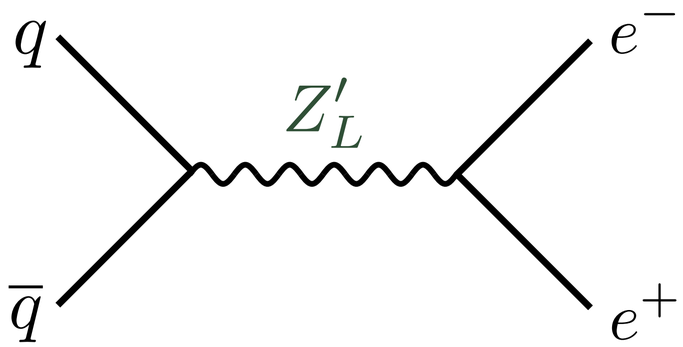
BSM Models

$$\mathcal{L} \supset Z'_\mu \sum_f Q_f \left(g_L \bar{f} \gamma^\mu P_L f + g_R \bar{f} \gamma^\mu P_R f \right)$$



Vector couplings

$$g_L = g_R$$



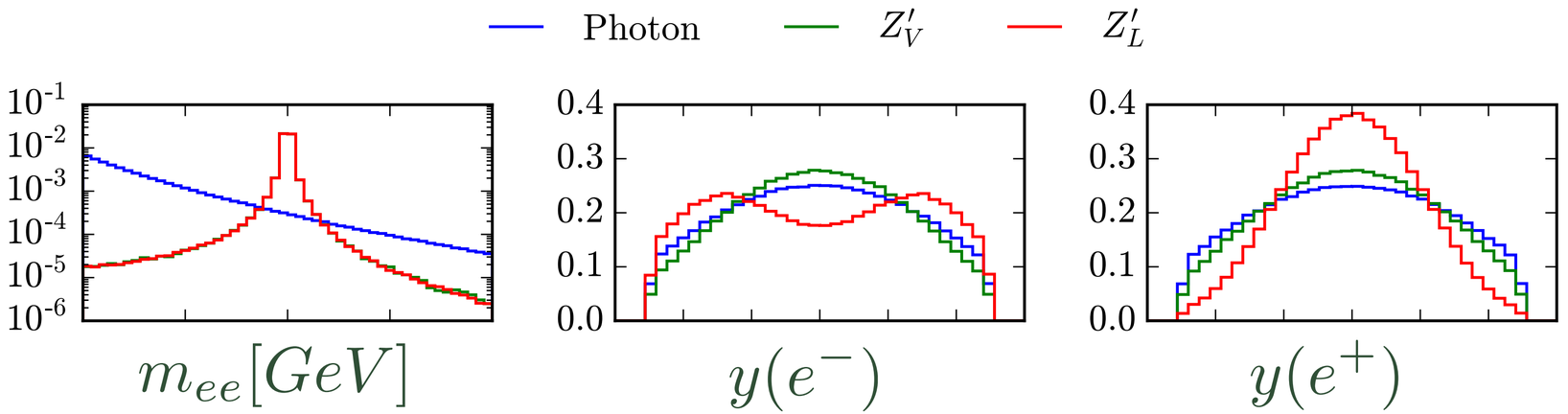
Left-handed couplings

$$g_R = 0$$

What is the machine learning?

How much information is there to learn in a given distribution?

Original distributions



Planed distributions

$(E, \vec{p})$	m	Planed	Linear AUC	Deep AUC
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✓	✓	✘	0.938967(01)	0.989007(03)
✓	✘	m	0.50550(29)	0.4942(48)

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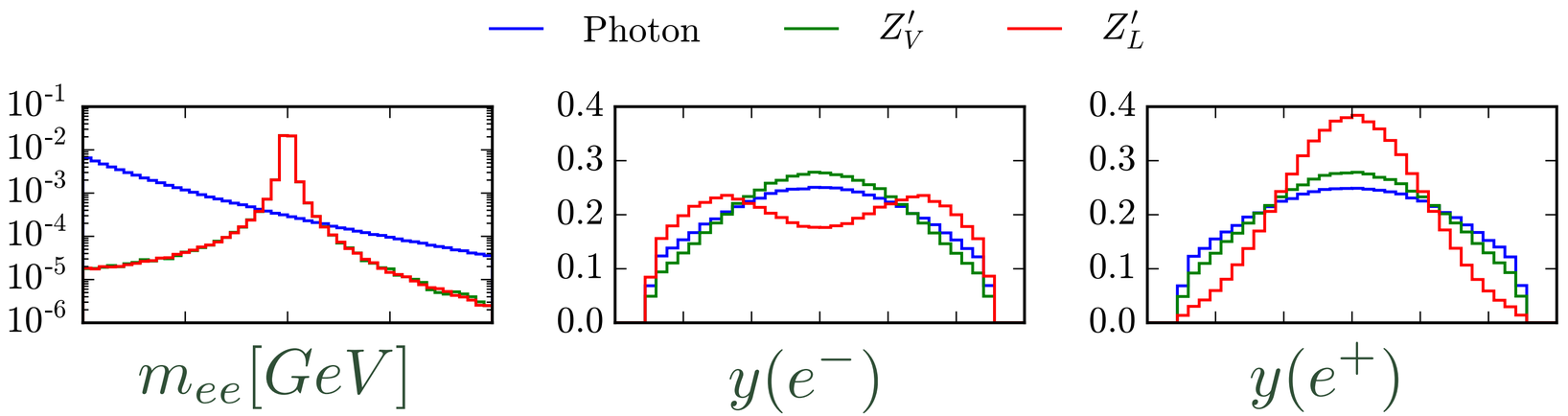

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Something more than m_{ee}?

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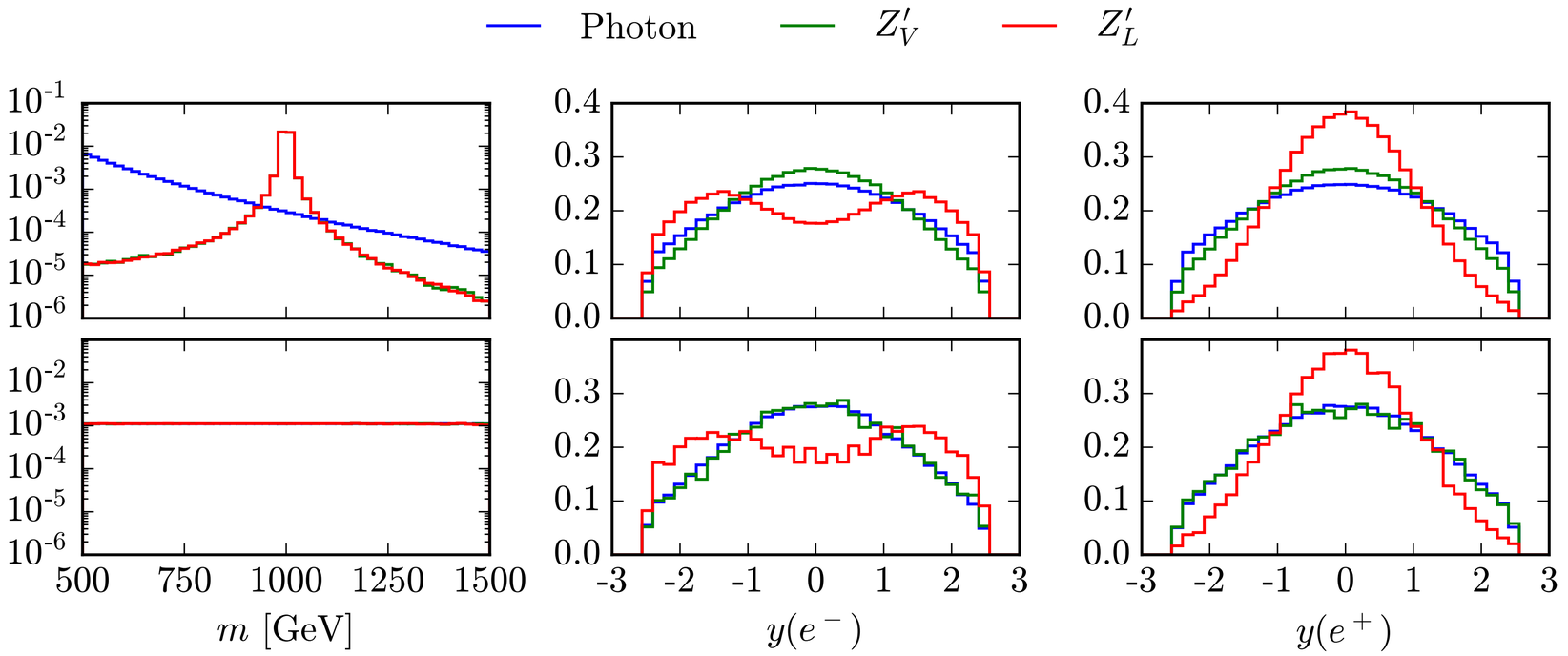

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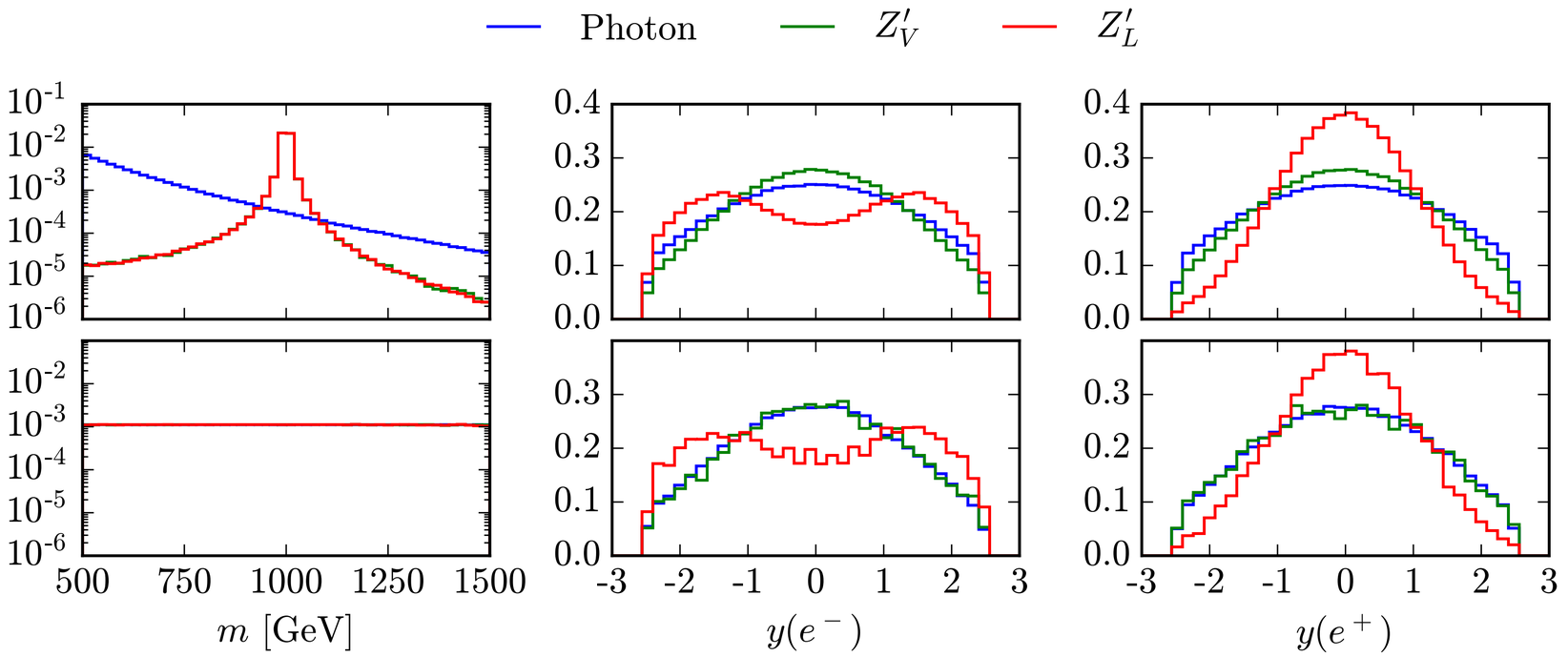

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✓	✘	m	0.50550(29)	0.4942(48)

Something more than m_{ee}?

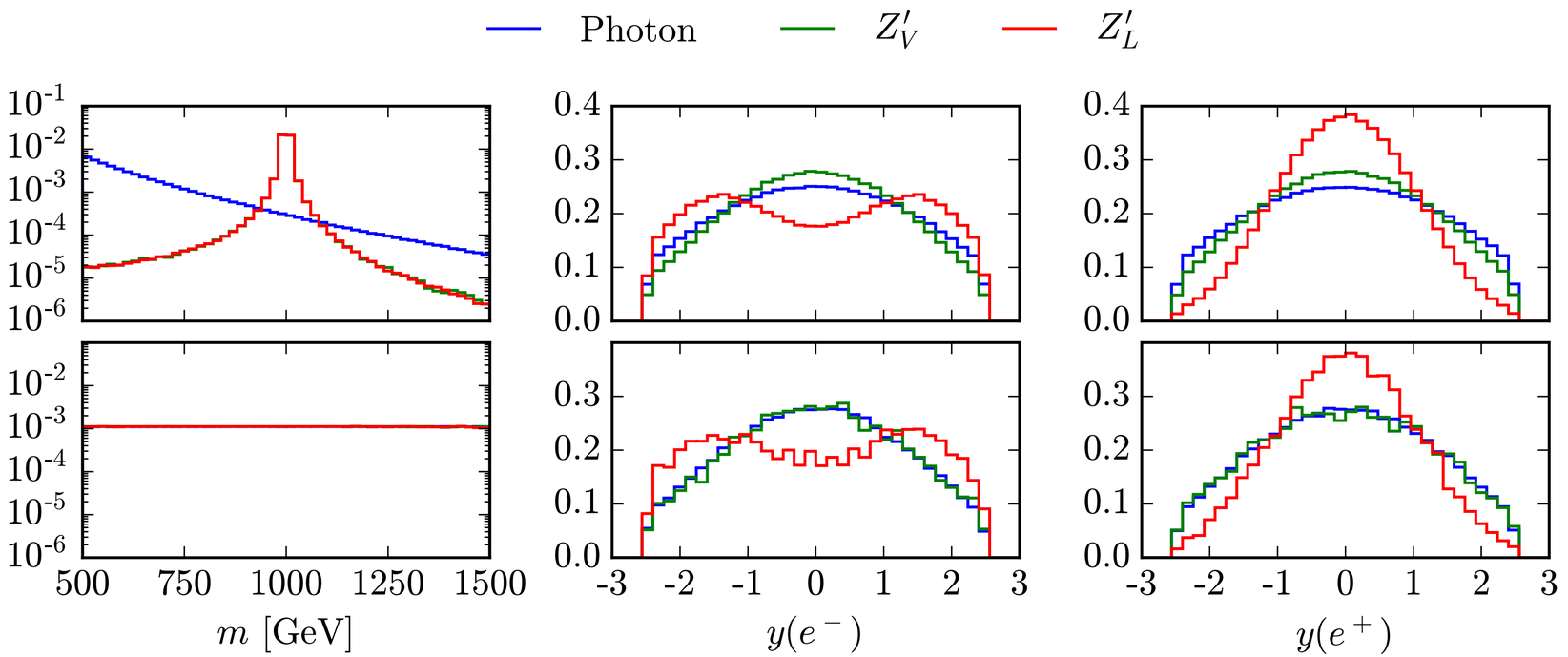
NO!

What is the machine learning?

How much information is there to learn in a given distribution?

Original distributions

Planed distributions



$(E,\vec{p})$	m	Planed	Linear AUC	Deep AUC
✓	✘	✘	0.746221(01)	0.988510(98)
✓	✓	✘	0.938967(01)	0.989007(03)
✓	✘	m	0.50550(29)	0.4942(48)

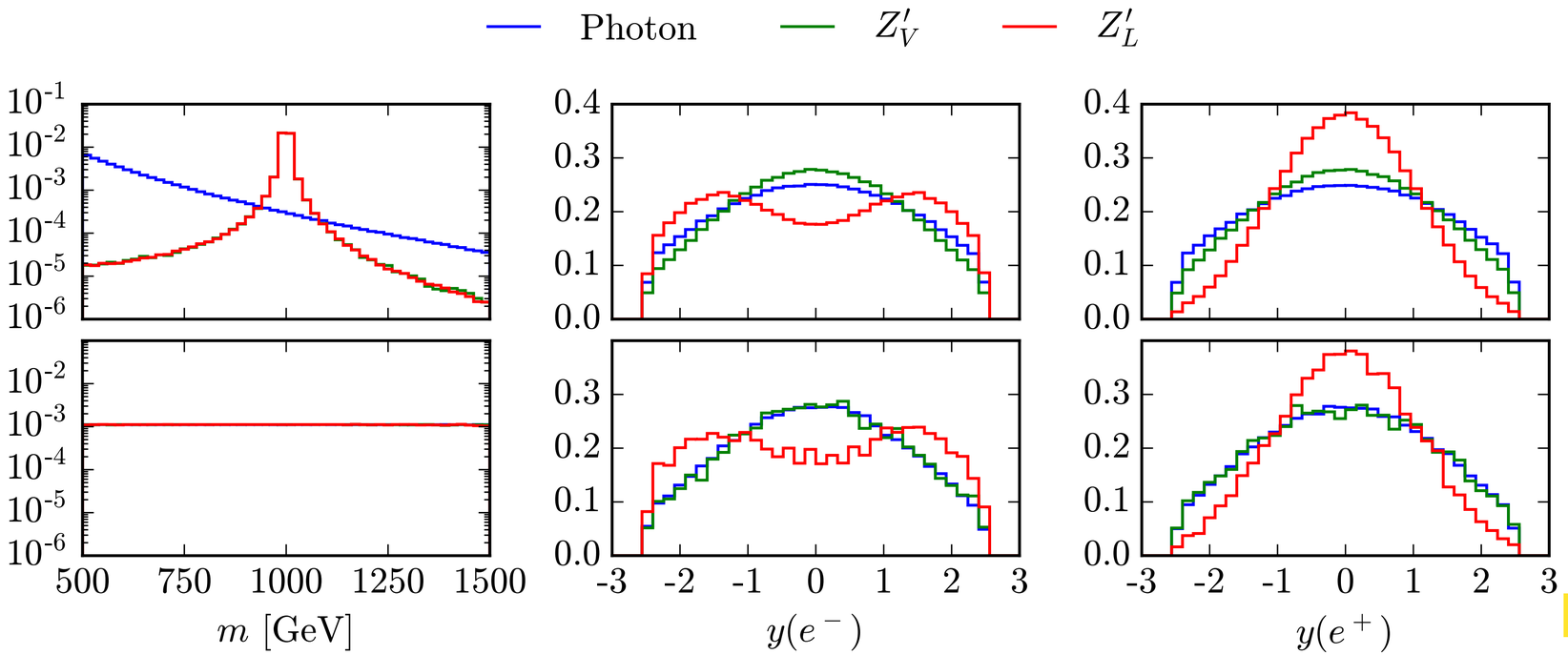
$(E,\vec{p})$	m	Planed	Linear AUC	Deep AUC
✓	✘	✘	0.763280(05)	0.989353(59)
✓	✓	✘	0.942004(02)	0.989826(10)
✓	✘	m	0.626648(28)	0.6258(24)
✓	✘	$(m, \Delta\lvert y\rvert)$	0.52421(15)	0.5320(25)

What is the machine learning?

How much information is there to learn in a given distribution?

Original distributions

Planed distributions



More Information

$(E,\vec{p})$	m	Planed	Linear AUC	Deep AUC
✓	✘	✘	0.746221(01)	0.988510(98)
✓	✓	✘	0.938967(01)	0.989007(03)
✓	✘	m	0.50550(29)	0.4942(48)

Linear

$(E,\vec{p})$	m	Planed	Linear AUC	Deep AUC
✓	✘	✘	0.763280(05)	0.989353(59)
✓	✓	✘	0.942004(02)	0.989826(10)
✓	✘	m	0.626648(28)	0.6258(24)
✓	✘	$(m, \Delta\lvert y\rvert)$	0.52421(15)	0.5320(25)

What is the machine learning?

$(E,\vec{p})$	m	Planed	Linear AUC	Deep AUC
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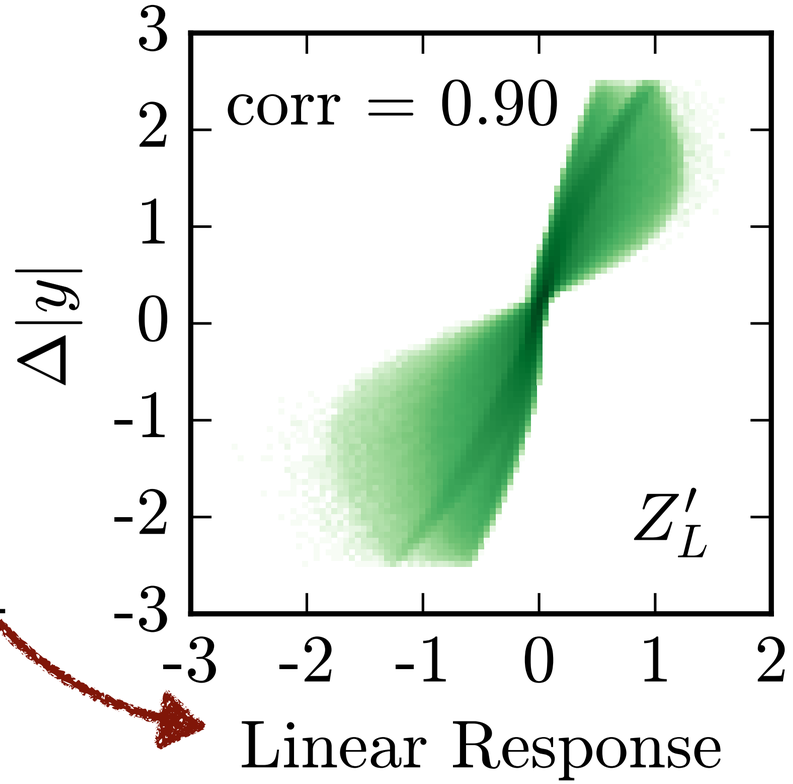

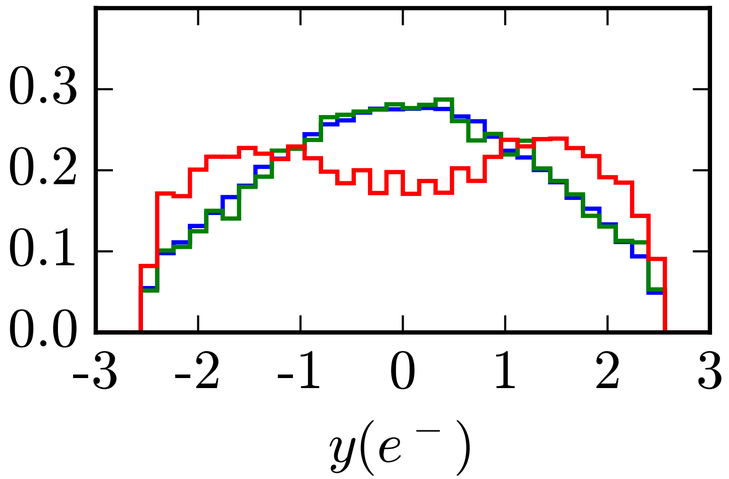

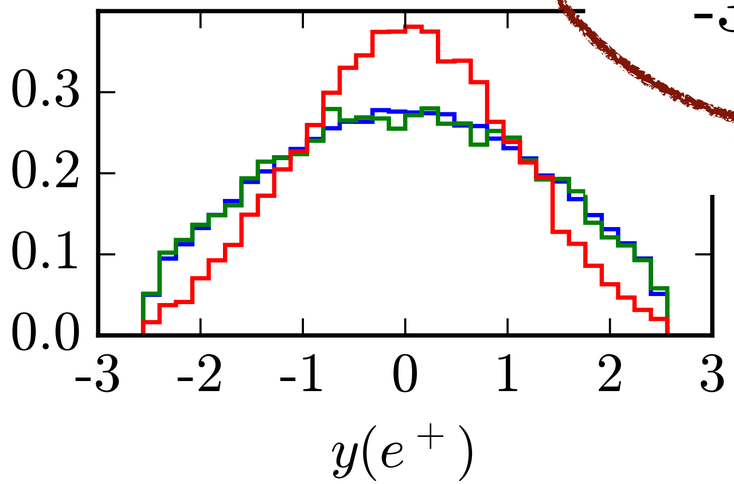

What is the machine learning?

$(E, \vec{p})$	m	Planed	Linear AUC	Deep AUC
✓	✘	✘	0.763280(05)	0.989353(59)
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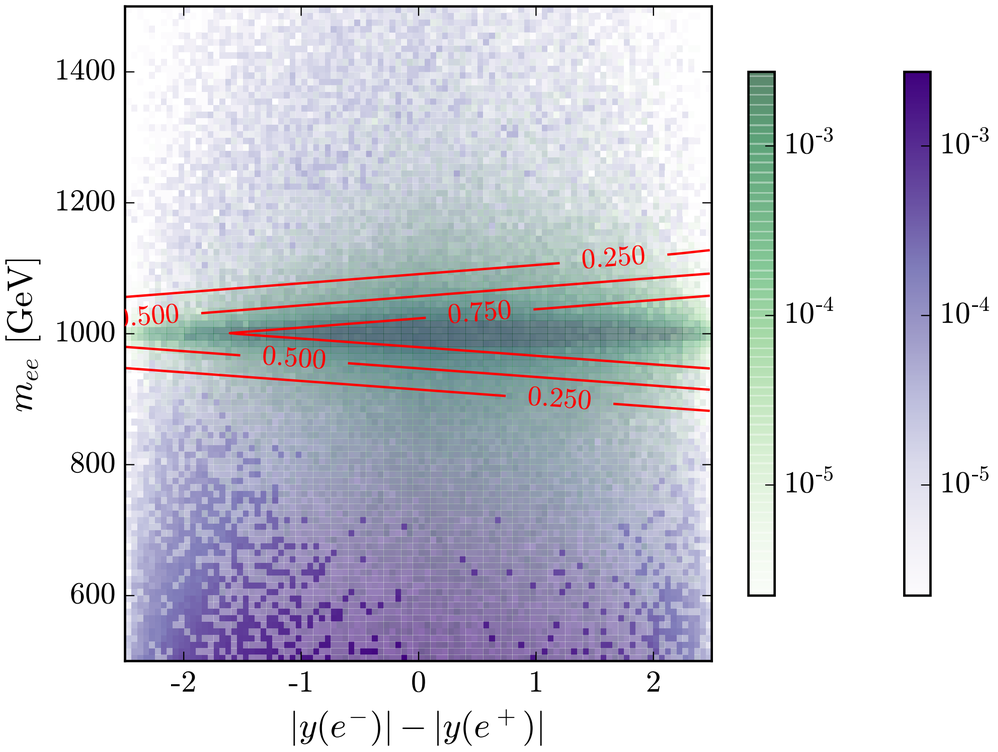

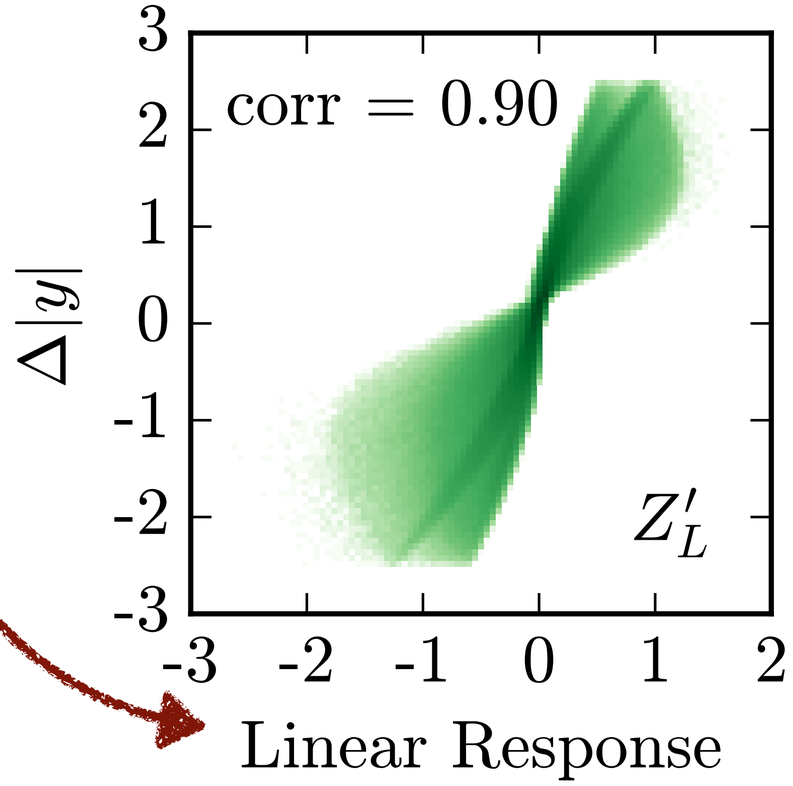

Using only mass: AUC = 0.939, ACC = 0.937

Using both: AUC = 0.989, ACC = 0.958

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Conclusion

- Iteratively remove information to see what the machine needs to learn
- Process allows for simple way to see if discriminating power is linear or not

Future Directions

- Apply to more realistic setting
- What if best variables are unknown?
- What if many iterations are needed?