

AI-ASSISTED DISCOVERY OF PHYSICS LAWS

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$$x = x_0 + v_0 t + \frac{1}{2} a t^2$$

$$S = \frac{(v^2 - v_0^2)}{2a}$$

$$\Delta U = A + Q$$

$$F = \frac{GMm}{R^2}$$

$$P = \rho gh$$

$$Q = \lambda m$$

$$N = N_0 2^{-t/T}$$

$$A = FS \cos \alpha$$

$$P = \frac{F}{S}$$

$$\Delta d = \frac{(2k+1)\lambda}{2}$$

$$X = X_{\max} \cdot \cos \omega t$$

$$\phi = \frac{P}{P_0 \cdot 100\%}$$

$$v_2 = \frac{(v_1 + v)}{1 + v_1 v / c^2}$$

$$Ft = \Delta p$$

$$F = mg$$

$$t = \frac{t_1}{\sqrt{1 - v^2/c^2}}$$

$$\lambda = vT$$

$$T = 2\pi \sqrt{LC}$$

$$E = \frac{kq}{R^2}$$

$$Z = \sqrt{(X_C - X_L)^2 + R^2}$$

$$E = \frac{mv^2}{2}$$

$$P = IU$$

$$\eta = \frac{(Q_1 - Q_2)}{Q_1}$$

$$E = 2\pi k\sigma$$

$$F = \rho gV$$

$$P = m(g+a)$$

$$\frac{V}{T} = \text{const}$$

$$\rho = \frac{m}{V}$$

$$P = mc = \frac{h}{\lambda} = \frac{E}{c}$$

$$T = \frac{2\pi\sqrt{l}}{g}$$

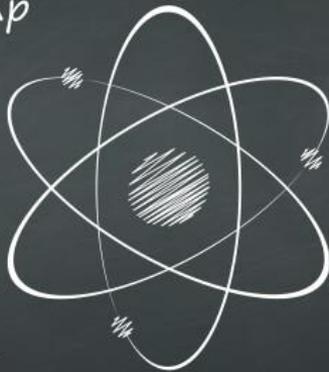
$$F = \frac{kq_1 q_2}{R_2}$$

$$F_y = -kx$$

$$d \cdot \sin \phi = k \lambda$$

$$v = v_0 + at$$

$$E = mc^2$$



$$y = ?$$

x_0	x_1	x_2	x_3	y
3.1427	2.7183	1.4142	0.5772	7.5641
-4.0039	0.1234	2.3026	3.9999	6.8839
8.1812	-1.6180	3.3333	-2.7182	-12.3129
0.0001	5.5555	0.7071	1.0001	4.1784
1.6180	-3.1415	3.1415	2.3026	3.1112
2.2222	1.0101	4.4444	-1.1111	-4.2621

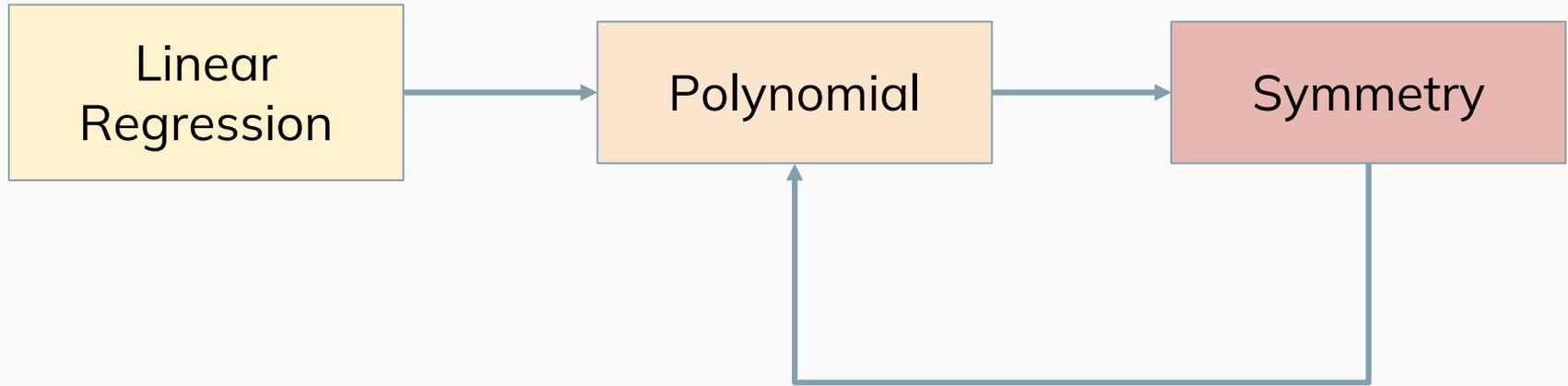
$$x_f = x_0 + v_0 t + \frac{1}{2} a t^2$$

x_0	v_0	t	a	x_f
3.1427	2.7183	1.4142	0.5772	7.5641
-4.0039	0.1234	2.3026	3.9999	6.8839
8.1812	-1.6180	3.3333	-2.7182	-12.3129
0.0001	5.5555	0.7071	1.0001	4.1784
1.6180	-3.1415	3.1415	2.3026	3.1112
2.2222	1.0101	4.4444	-1.1111	-4.2621

Let's Solve a New Mystery

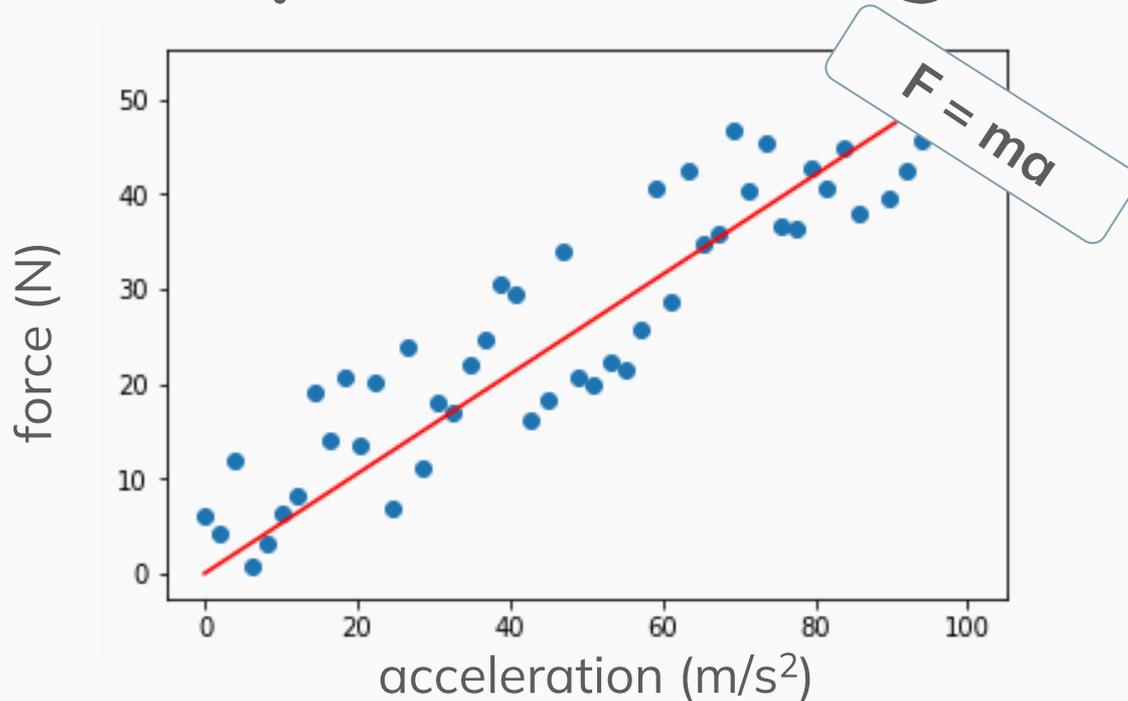
x_0	x_1	x_2	x_3	y
14	23	28	14	-448
17	30	11	16	589
15	19	11	14	739
16	14	17	14	172
20	23	16	20	584
11	11	21	18	55
28	18	30	18	352

Intro: Flow of Our Algorithm



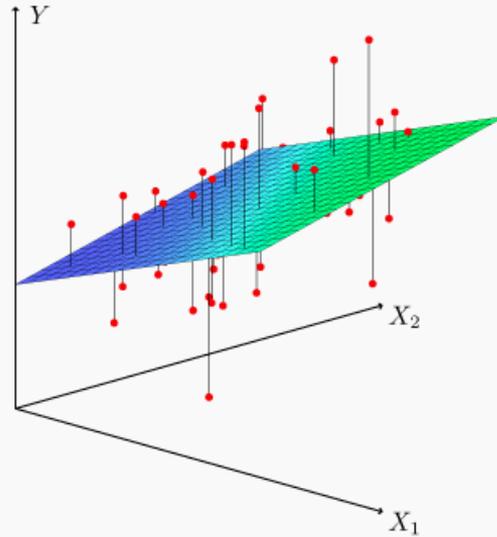
Inspiration from “AI Feynman” by Udrescu and Tegmark (2020)

First Step: Linear Regression



But how do we do this with multiple independent variables?

First Step: Linear Regression



$$y = \beta_0 + \beta_1 X_1 + \dots + \beta_n X_n$$

Let's Try It On This!

x_0	x_1	x_2	x_3	y
14	23	28	14	-448
17	30	11	16	589
15	19	11	14	739
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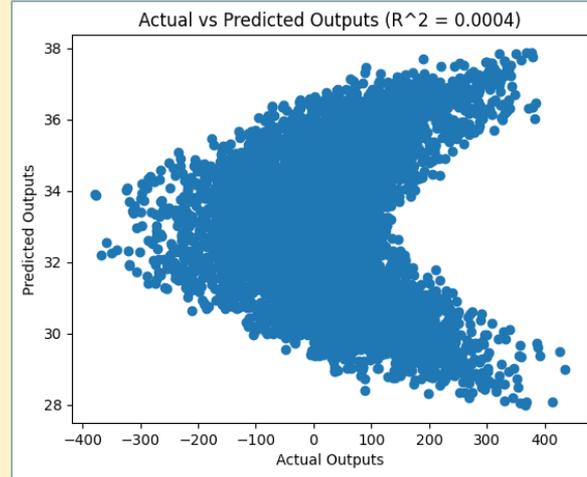
Testing Linear on the Mystery

Method

LINEAR REGRESSION

Output

Predicted Value



Actual Value

Testing Linear on the Mystery

Method	Output
LINEAR REGRESSION	

Why could this have failed?
Maybe it's a polynomial!

Second Step: Polynomial Regression

$$\text{Ex: } y_f = y_0 - 4.9t^2$$

y_0	t	y_f
1	2	-18.6
3	4	-75.4
5	6	-171.4
7	8	-306.6

y_0	y_0^2	t	t^2	y_f
1	1	2	4	-18.6
3	9	4	16	-75.4
5	25	6	36	-171.4
7	49	8	64	-306.6

Linear
Regression

Let's Try It On This!

x_0	x_1	x_2	x_3	y
14	23	28	14	-448
17	30	11	16	589
15	19	11	14	739
16	14	17	14	172
20	23	16	20	584
11	11	21	18	55
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Testing Polynomial on the Mystery

Method

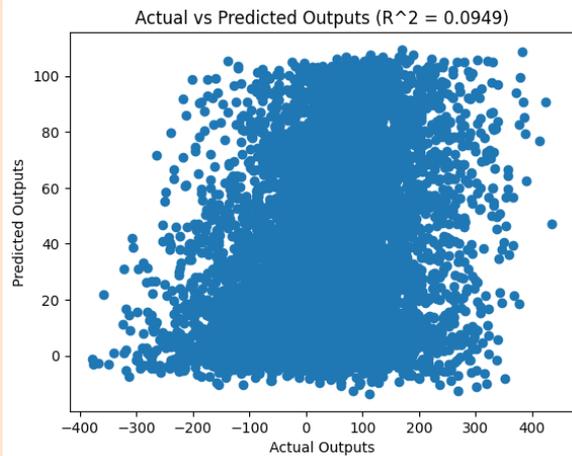
Output

LINEAR REGRESSION



POLYNOMIAL
REGRESSION

Predicted value



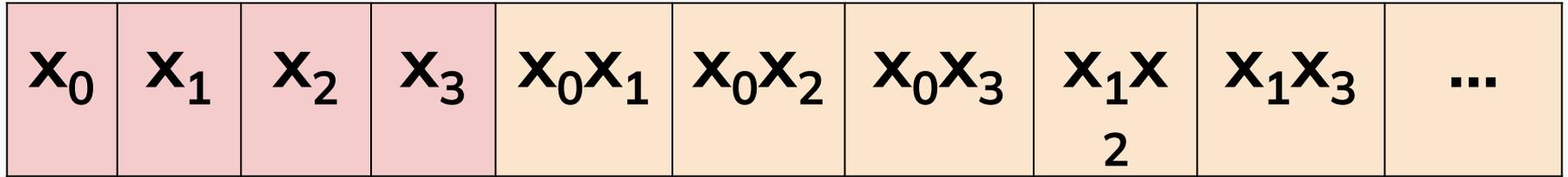
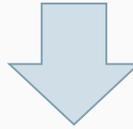
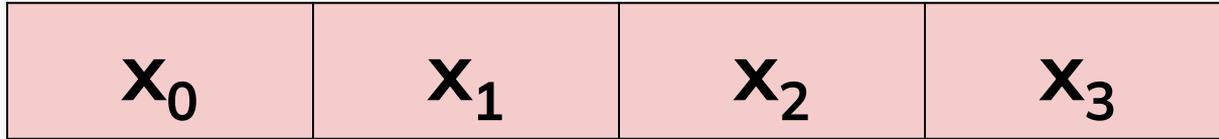
Testing Polynomial on the Mystery

Method	Output
LINEAR REGRESSION	✗
POLYNOMIAL REGRESSION	✗

Why could this have failed?

$$\text{Ex: } y = (x_0 - x_1)(x_2 - x_3) \longrightarrow x_0x_2 - x_1x_2 - x_0x_3 + x_1x_3$$

We could try...



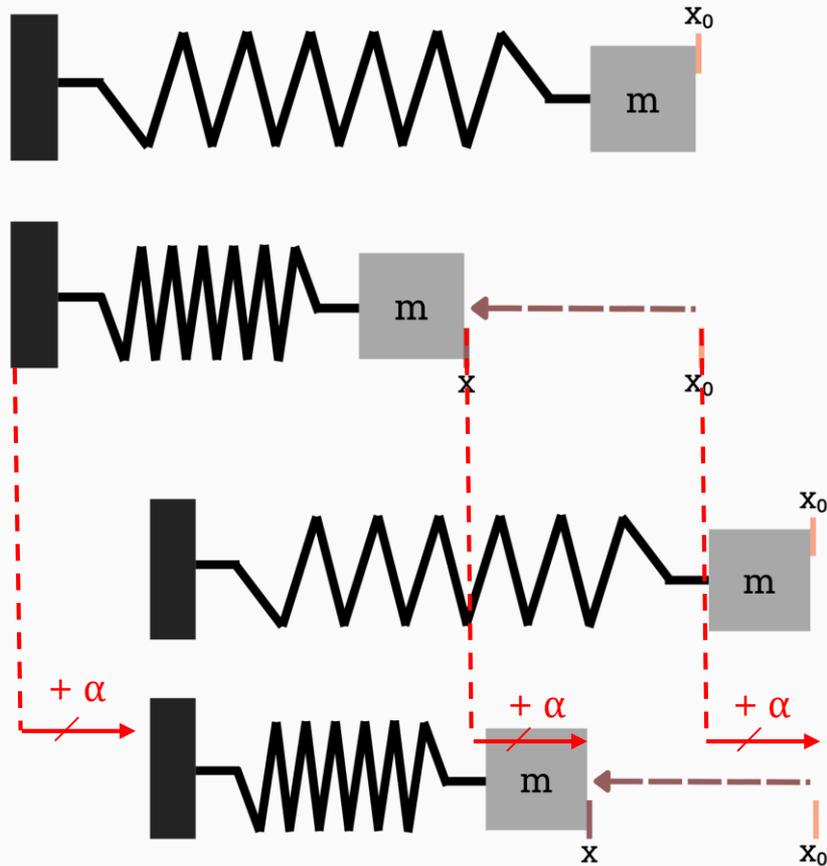
Issue: Too many combinations

$$\text{Ex: } x_0x_1^2, x_0x_1^3, x_0x_1x_2^2$$

Third Step: Symmetries

$$U_e = \frac{1}{2}k(x_0 - x)^2$$

Translational
symmetry



$$U_e = \frac{1}{2}k(x_0 - x)^2$$

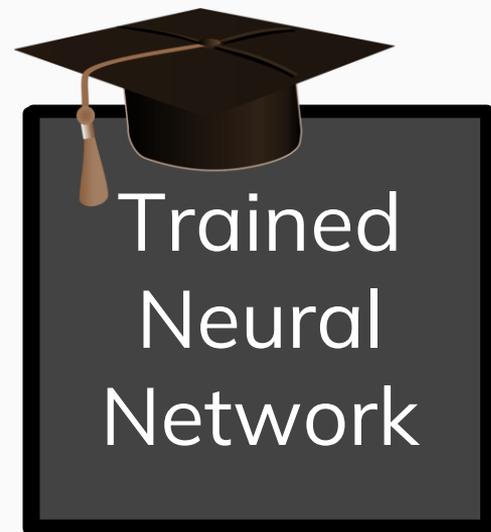
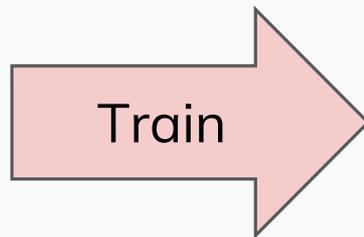
$$U_e = \frac{1}{2}k[(x_0 + \cancel{\alpha}) - (x + \cancel{\alpha})]^2 \quad \Rightarrow \quad U_e = \frac{1}{2}k(x_0 - x)^2$$

Individual values do not matter,
but their difference does

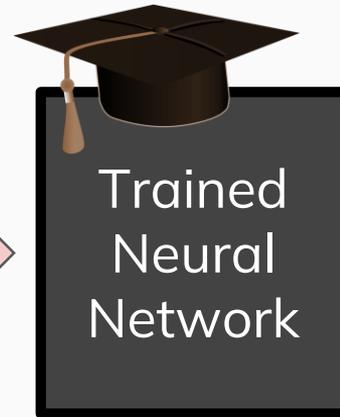
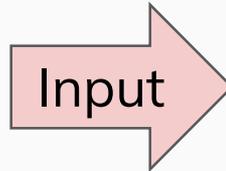


Finding Symmetries Using Neural Network

x_0	x	k	U_e
5	2	0.5	4.5
6	3	2	18
4	2	1	4
0	-4	3	48

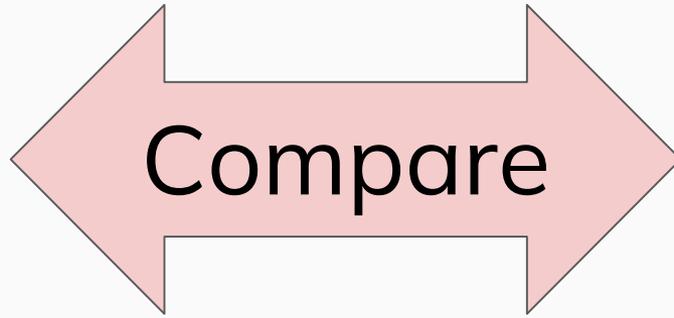


$x_0 + \alpha$	$x + \alpha$	k
$5 + \alpha$	$2 + \alpha$	0.5
$6 + \alpha$	$3 + \alpha$	2
$4 + \alpha$	$2 + \alpha$	1
$0 + \alpha$	$-4 + \alpha$	3



U_e (predicted)
4.7
18.4
3.5
45.2

U_e (predicted)
4.7
18.4
3.5
45.2



Close enough!

U_e (original)
4.5
18
4
48

x_0	x	k	U_e
5	2	0.5	4.5
6	3	2	18
4	2	1	4
0	-4	3	48

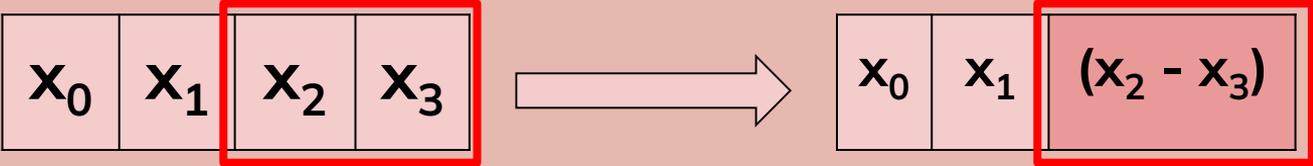
Reduce

$(x_0 - x)$	k	U_e
3	0.5	4.5
3	2	18
2	1	4
4	3	48

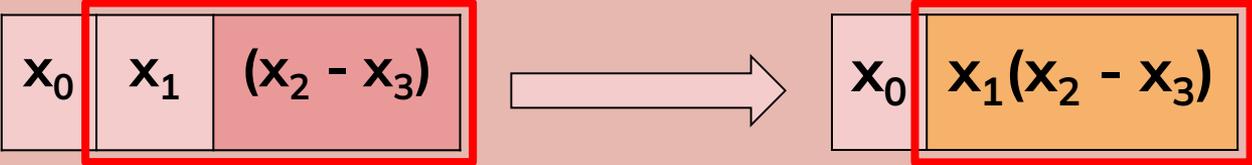
Let's Try It On This!

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Testing Symmetries on the Mystery

Method	Output
LINEAR REG.	✗
POLYNOMIAL REG. #1	✗
<p data-bbox="297 756 877 794">SYMMETRY SEARCHING</p>  <p data-bbox="280 857 759 1010">The diagram illustrates the symmetry searching process. On the left, a row of four boxes contains the variables x_0, x_1, x_2, and x_3. A red rectangular box highlights the x_2 and x_3 boxes. A large white arrow with a black outline points from this group to the right. On the right, a row of three boxes contains x_0, x_1, and $(x_2 - x_3)$. A red rectangular box highlights the $(x_2 - x_3)$ box.</p>	

Testing Symmetries on the Mystery

Method	Output
LINEAR REG.	✗
POLYNOMIAL REG. #1	✗
<p data-bbox="297 756 877 794">SYMMETRY SEARCHING</p>  <p data-bbox="285 858 761 1009">x_0 x_1 $(x_2 - x_3)$</p> <p data-bbox="1116 844 1537 1009">x_0 $x_1(x_2 - x_3)$</p>	

Testing Symmetries on the Mystery

Method	Output		
LINEAR REG.	✗		
POLYNOMIAL REG. #1	✗		
SYMMETRY SEARCHING	<table border="1"><tr><td data-bbox="1205 583 1282 672">x_0</td><td data-bbox="1282 583 1561 672">$x_1(x_2 - x_3)$</td></tr></table>	x_0	$x_1(x_2 - x_3)$
x_0	$x_1(x_2 - x_3)$		
POLYNOMIAL REG. #2 <div data-bbox="471 896 1108 1005" style="border: 2px solid black; padding: 10px; margin: 10px auto; width: fit-content;">$v_f^2 = v_0^2 + 2a(x - x_0)$</div>	<div data-bbox="1174 707 1586 1016"><p>Predicted value</p><p>Actual value</p></div>		

Bonus Features

Cross Terms

Include products of different variables

$$\text{Ex: } U_g = m \times g \times h$$

x_0	x_1	x_0x_1	x_0^2	x_1^2
2	3	6	4	9
3	5	15	9	25
4	1	4	16	1
5	2	10	25	4

$$y_f = y_0 - 4.9t^2$$

$$U_e = \frac{1}{2}k(x_0 - x)^2$$

$$v^2 = v_0^2 + 2a(x - x_0)$$

$$I = I_0 e^{-Lt/R}$$

$$x = x_{\max} \cos(\omega t + \phi)$$

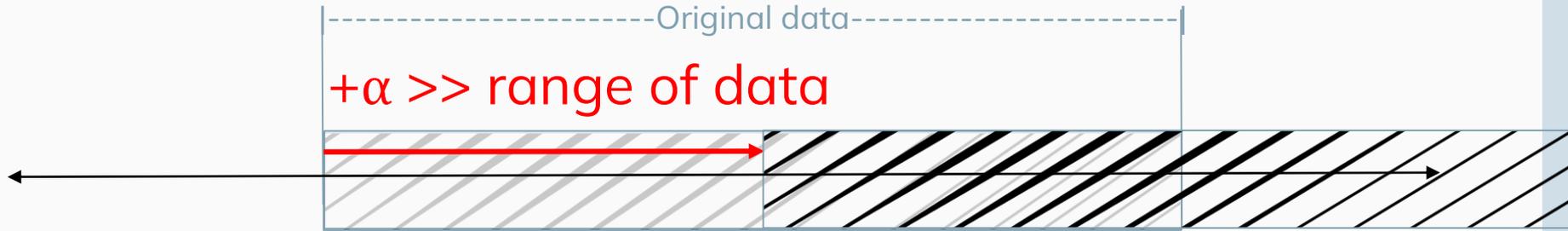
Functional Features

Apply a set of functions to all independent variables

x_0	$\sin(x_0)$	$\exp(x_0)$
$\pi/2$	1	$e^{\pi/2}$
π	0	e^π
$3\pi/2$	-1	$e^{3\pi/2}$

Practical Considerations

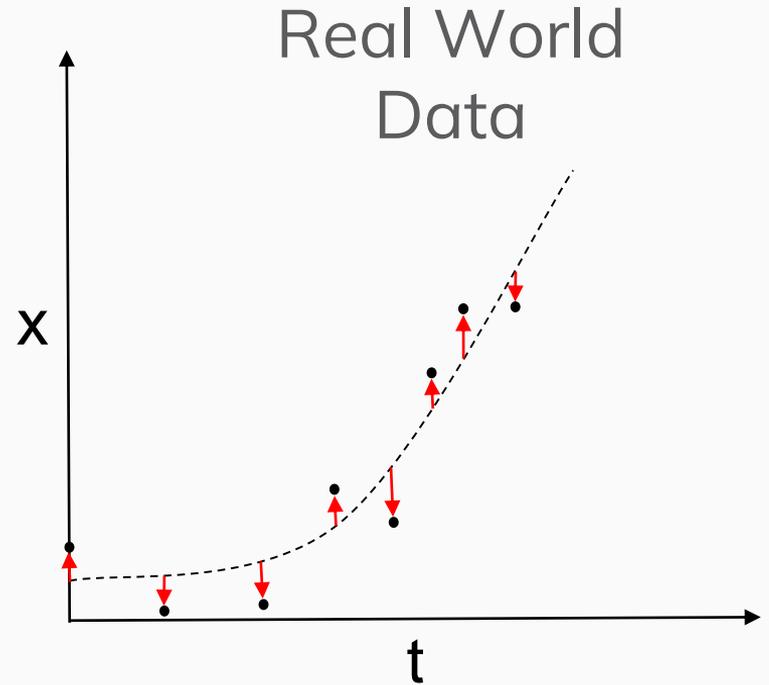
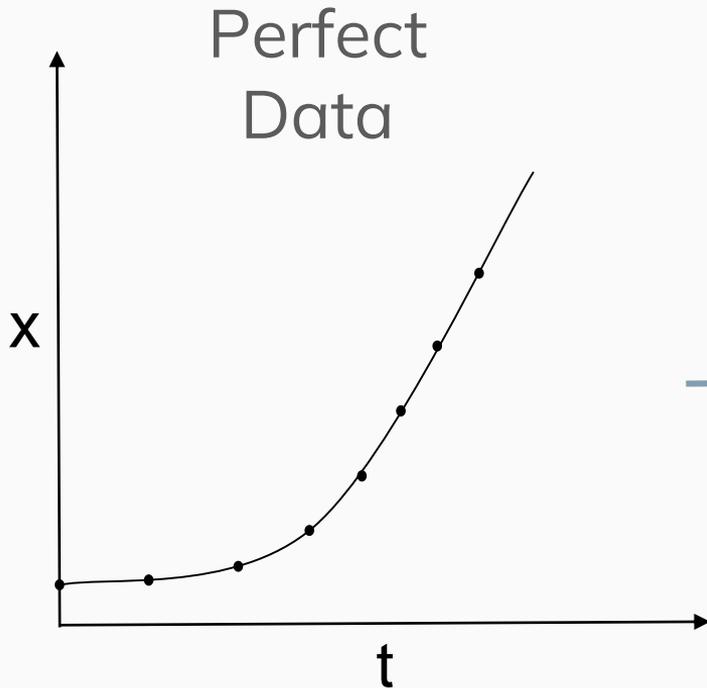
Neural Networks Aren't Perfect



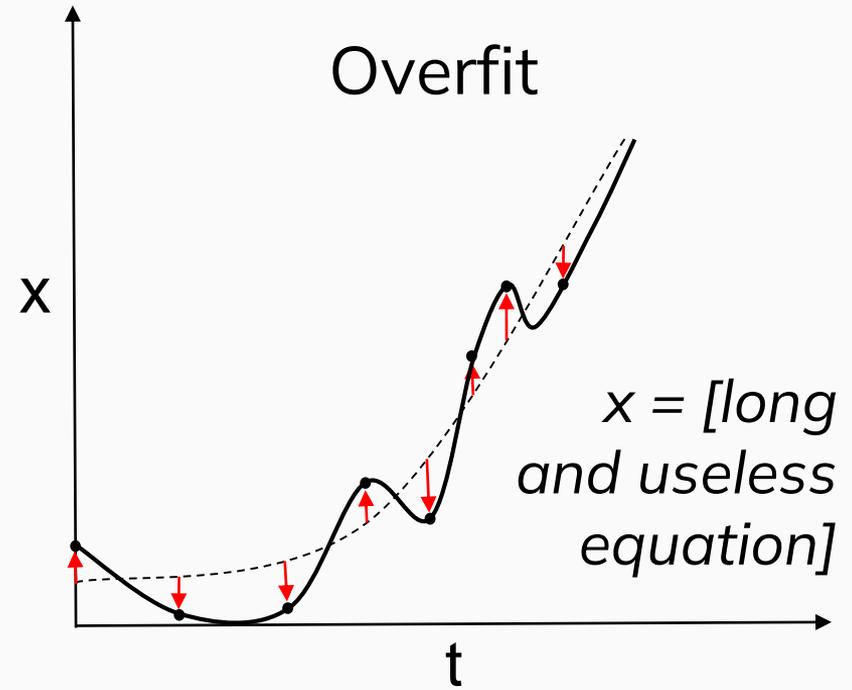
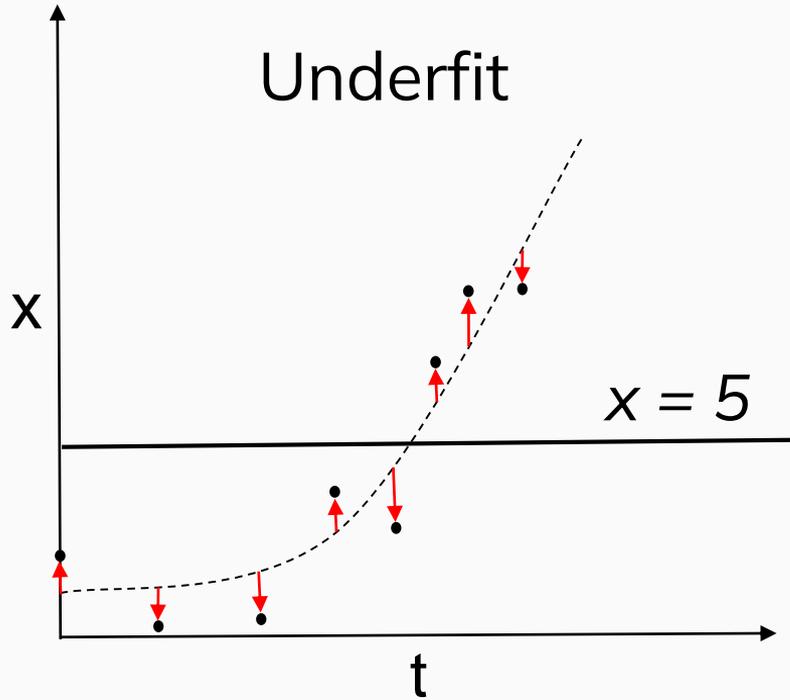
Our Approach?
Adaptive Transformation Deltas

Real Data is Noisy

$$x = x_0 + v_0 t + \frac{1}{2} a t^2$$



$$x = x_0 + v_0 t + \frac{1}{2} a t^2$$



Conclusion

- Replicated and expanded on parts of “AI Feynman” from scratch
- Developed a single workflow for **discovering mystery functions**
- AI has potential to advance science
- Embedding **symmetries** is important
- The algorithm may be expanded to deal with more types of functions and noise in the future

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