Artificial Neural Networks and Deep Learning

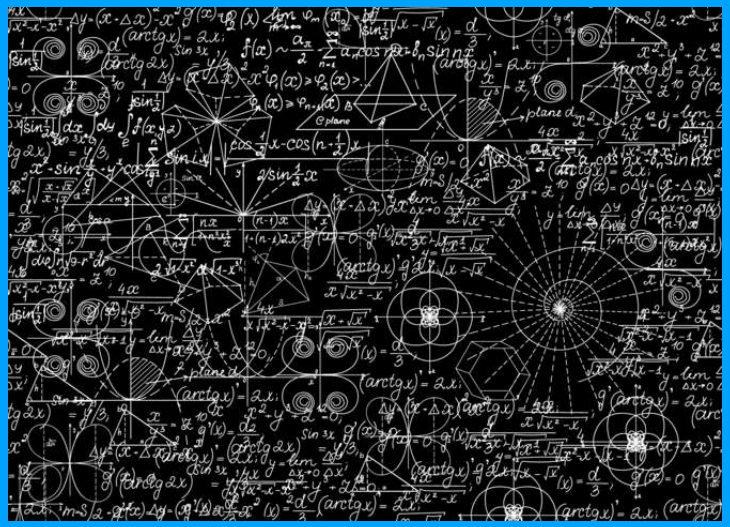
Week 3

Keras, overfitting and regularization

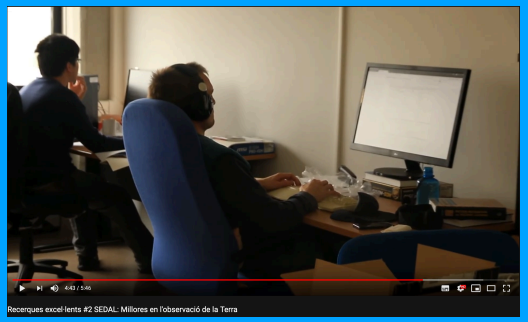

ATLANTIC
OCEAN
North Sea
Norwegian Sea
Baltic Sea
Barent
ICELAND
IRELAND
UNITED KINGDOM
DENMARK
NETHERLANDS
GERMANY
POLAND
BELARUS
RUSSIA
ESTONIA
LATVIA
LITHUANIA
FRANCE
SPAIN
ITALY
SWITZERLAND
AUSTRIA
HUNGARY
SLOVAKIA
ROMANIA
UKRAINE
SERBIA
BULGARIA
GREECE
TURKEY
Black Sea
Mediterranean Sea
Tyrrhenian Sea
Ionian Sea

AI for earth observation

Pure ML

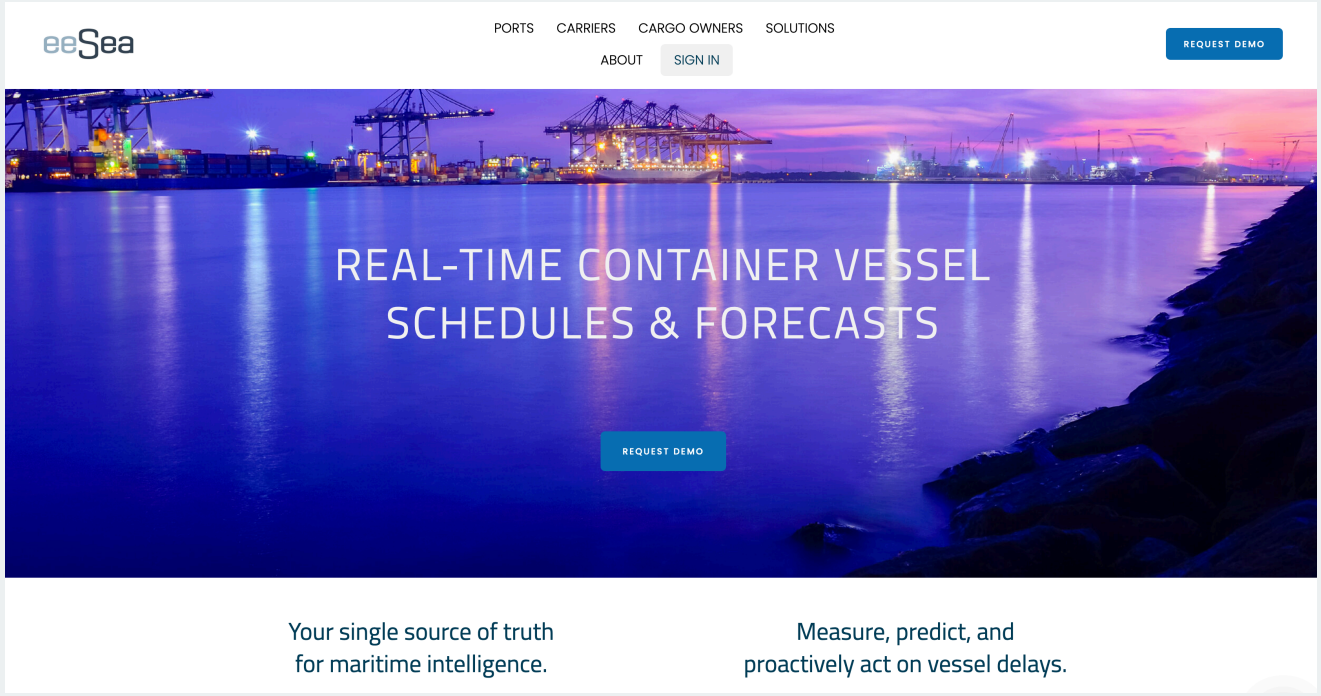


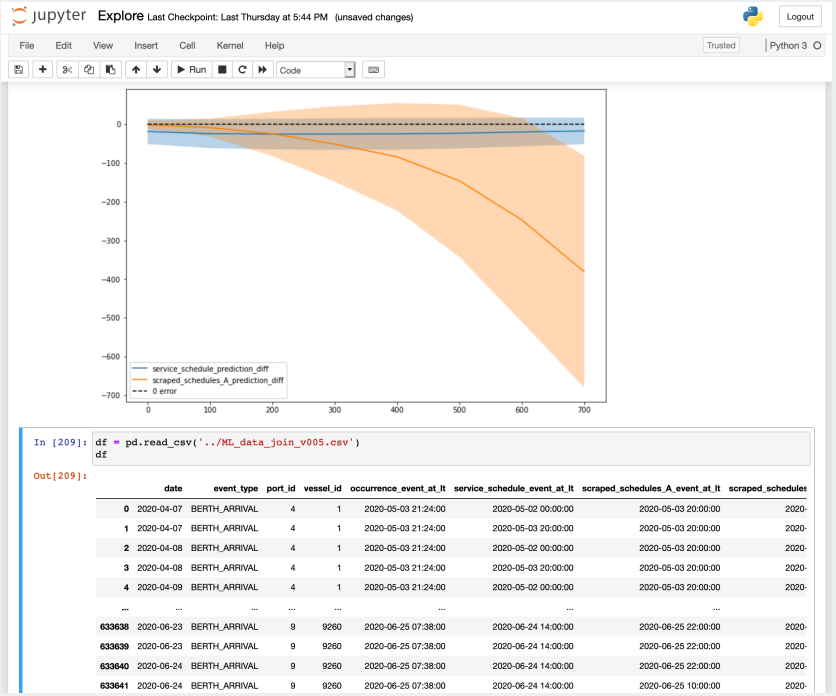
Theory versus practice



Pure earth science

Vessel forecasting





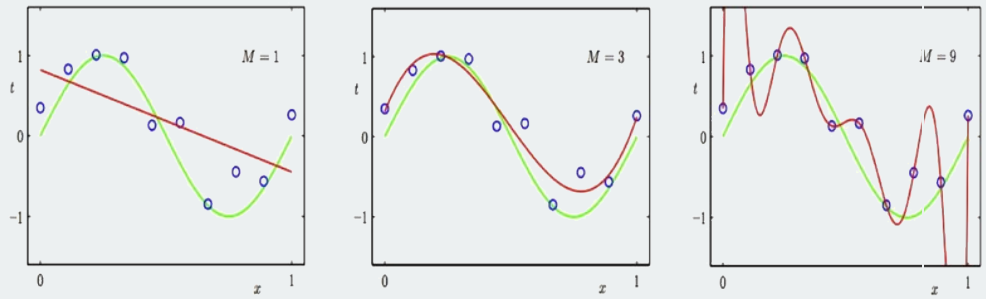
	date	event_type	port_id	vessel_id	occurrence_event_at_lt	service_schedule_event_at_lt	scraped_schedules_A_event_at_lt	scraped_schedules
0	2020-04-07	BERTH_ARRIVAL	4	1	2020-05-03 21:24:00	2020-05-02 00:00:00	2020-05-03 20:00:00	2020-
1	2020-04-07	BERTH_ARRIVAL	4	1	2020-05-03 21:24:00	2020-05-03 20:00:00	2020-05-03 20:00:00	2020-
2	2020-04-08	BERTH_ARRIVAL	4	1	2020-05-03 21:24:00	2020-05-02 00:00:00	2020-05-03 20:00:00	2020-
3	2020-04-08	BERTH_ARRIVAL	4	1	2020-05-03 21:24:00	2020-05-03 20:00:00	2020-05-03 20:00:00	2020-
4	2020-04-09	BERTH_ARRIVAL	4	1	2020-05-03 21:24:00	2020-05-02 00:00:00	2020-05-03 20:00:00	2020-
...	...	...	...	...	...	...	...	...
633638	2020-06-23	BERTH_ARRIVAL	9	9260	2020-06-25 07:38:00	2020-06-24 14:00:00	2020-06-25 22:00:00	2020-
633639	2020-06-23	BERTH_ARRIVAL	9	9260	2020-06-25 07:38:00	2020-06-24 14:00:00	2020-06-25 22:00:00	2020-
633640	2020-06-24	BERTH_ARRIVAL	9	9260	2020-06-25 07:38:00	2020-06-24 14:00:00	2020-06-25 22:00:00	2020-
633641	2020-06-24	BERTH_ARRIVAL	9	9260	2020-06-25 07:38:00	2020-06-24 14:00:00	2020-06-25 10:00:00	2020-

Regularization

Tricks to avoid overfitting

Under- and Over-fitting examples

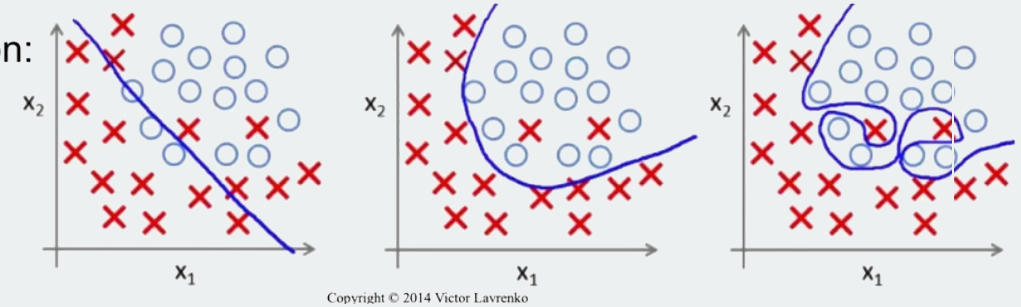
Regression:



predictor too inflexible:
cannot capture pattern

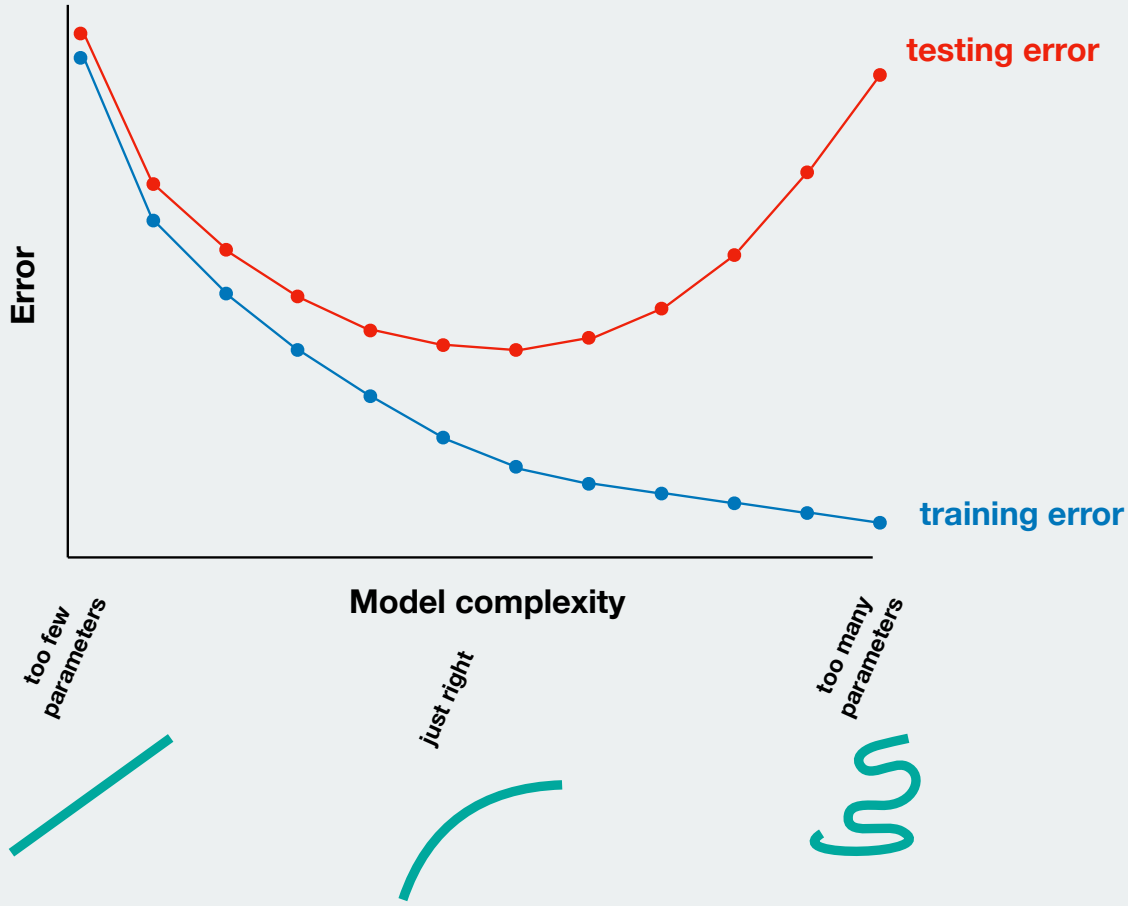
predictor too flexible:
fits noise in the data

Classification:

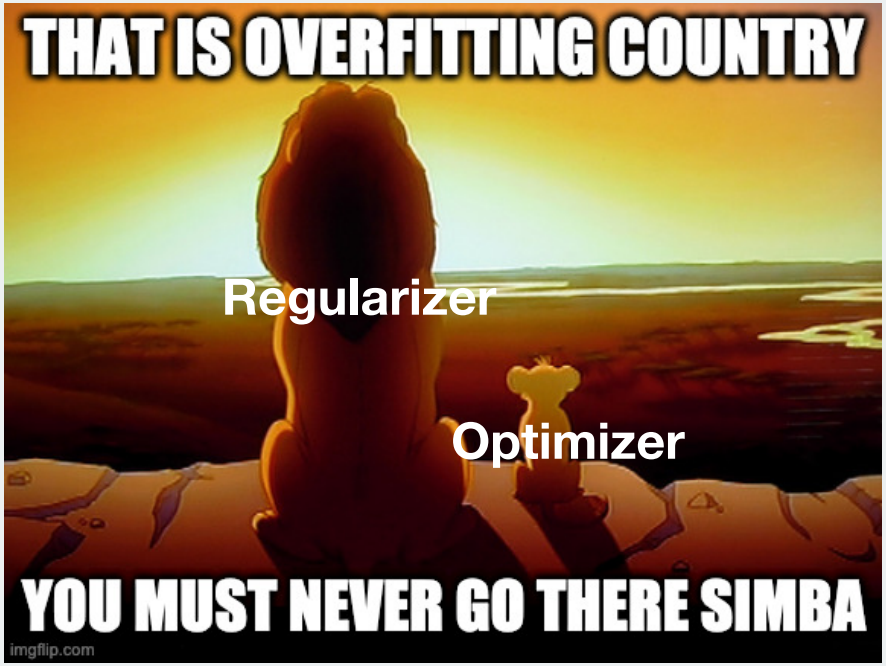


Underfitting **Overfitting**

Regularization – underfitting and overfitting



Regularization – *how* does regularization reduce overfitting?



Regularization – Different techniques

L-norm regularization: "Introduce a cost for large weights"

$$C = Loss + Regularization\ term$$

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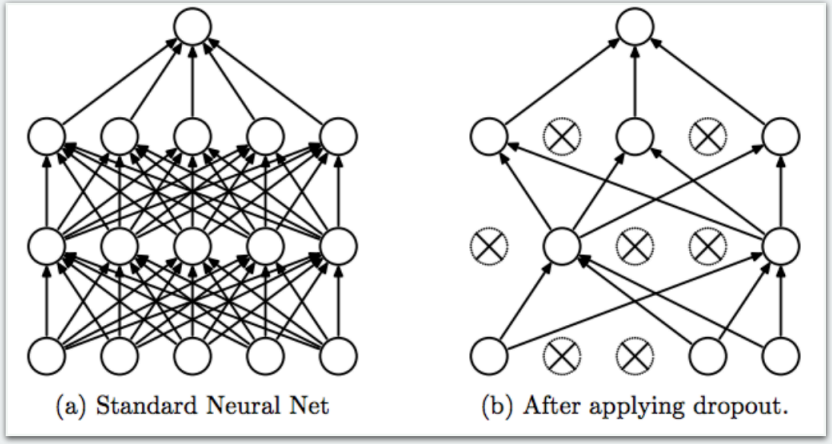
Dropout:

"In each SGD step, randomly ignore a fraction *p* of neurons"



Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting", JMLR 2014

- Can select *p* in wide range. Typical is 0.2 – 0.8, dependent on size of ANN
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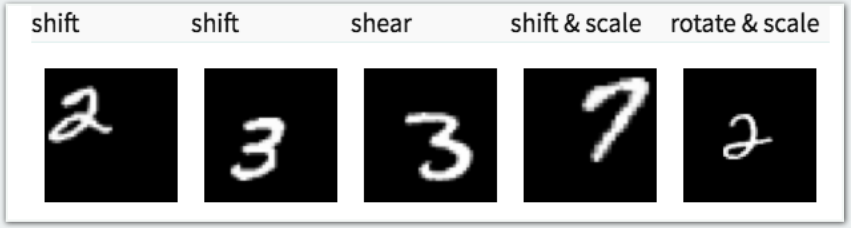
Data augmentation

"Shear, shift, scale and/or rotate input data"



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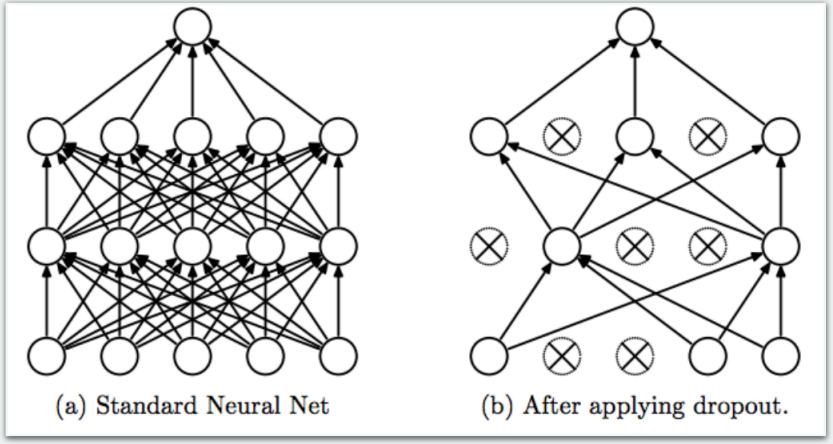

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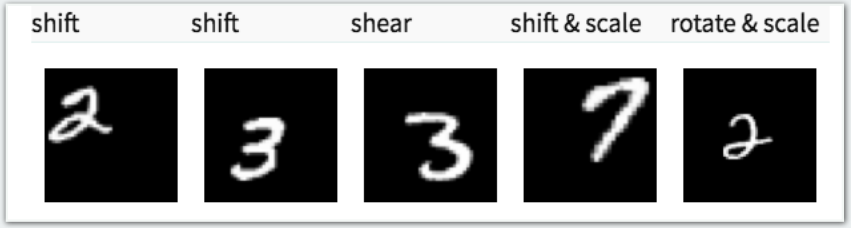
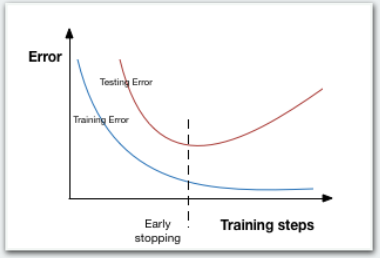


Early stopping

"Stop training when performance on validation dataset starts worsening"



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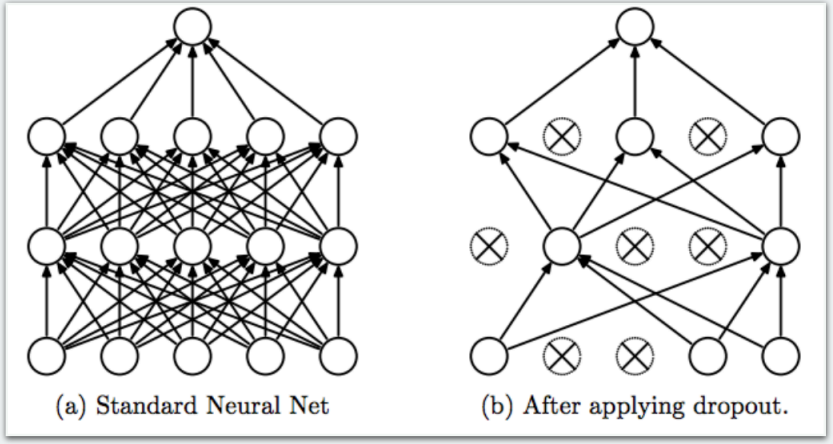

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A quick word on:

The Vanishing Gradient Problem

Vanishing gradients – A problem in *deep* neural nets

Problem:

- Gradients closer and closer to the input tend to get smaller and smaller
- Leads to smaller weight updates near input and larger weight updates near output
- Bad because layers near input take part in recognizing “simple” patterns, which are important to learning

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$

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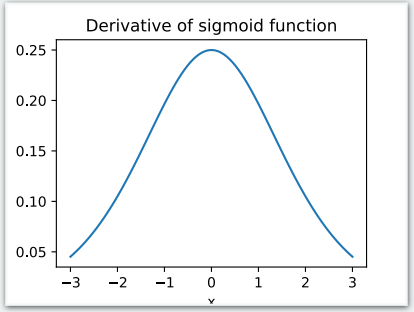

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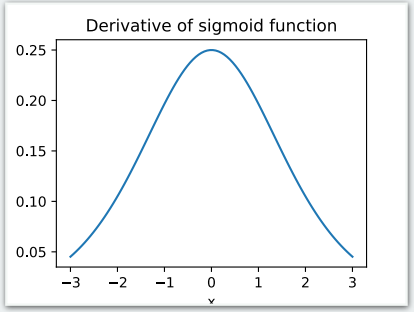
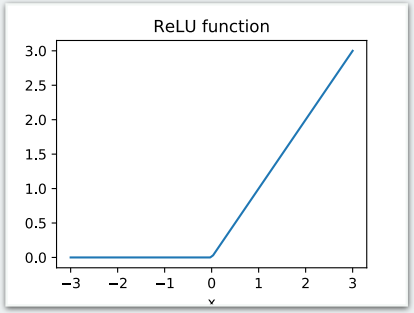
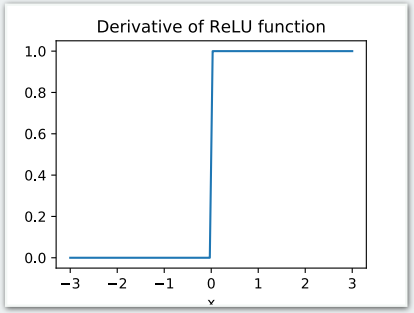


Solution:

- Use an activation function without small gradient for high values
- Candidate activation function: ReLU





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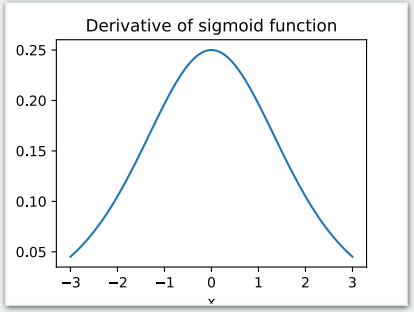

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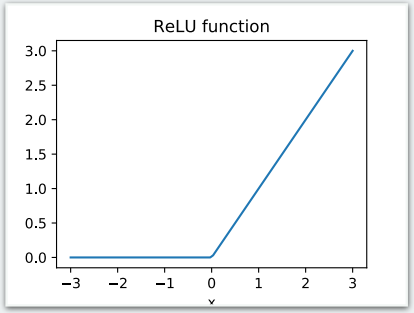
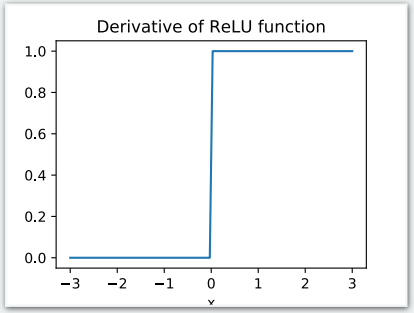
Problems with ReLU:

- Exploding gradients!





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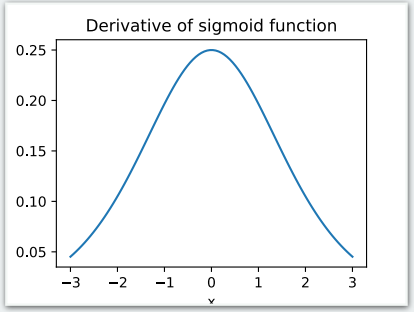

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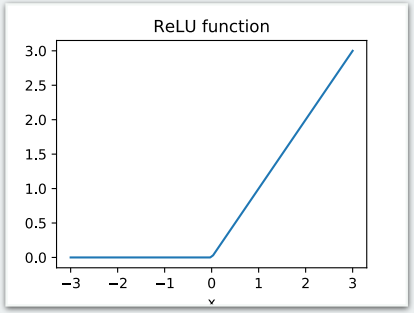

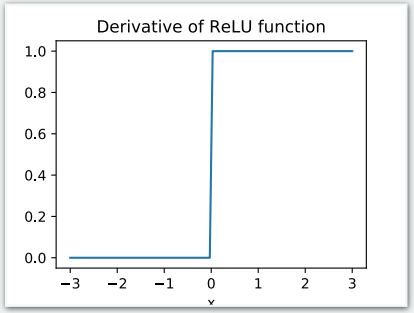

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