Anomaly Detection

Softnix Technology

Chakrit Phain

Agenda Day 2

- Anomaly Detection and Supervised Learning
- Neural Network & Deep Learning
- Anomaly Detection with LSTM & GRU
- Anomaly Detection with Autoencoder
- Anomaly Detection Workshop

Softnix

Anomaly Detection

Day 2

Softnix

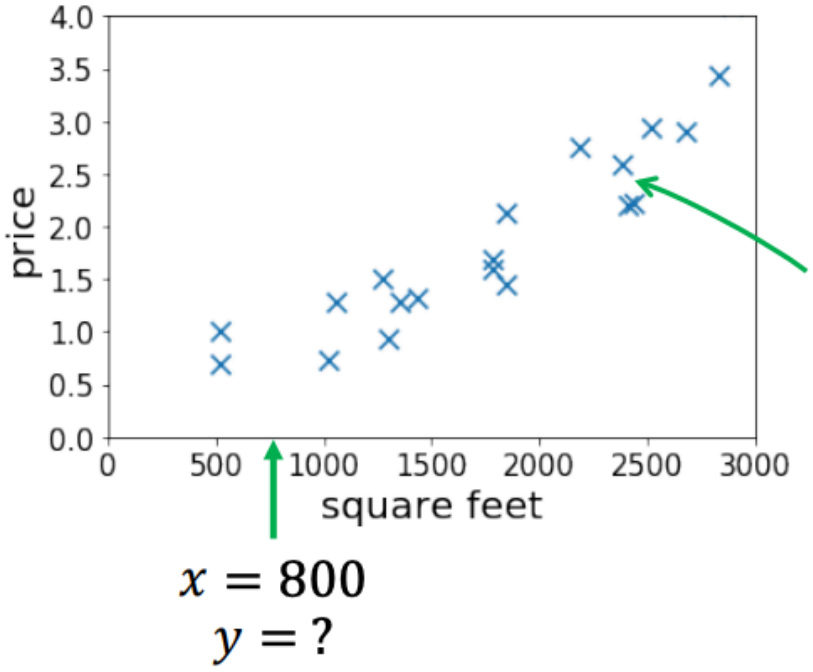
Anomaly Detection and Supervised Learning

Supervised Learning

- Given: a dataset that contains n samples

$$(x^{(1)}, y^{(1)}), \ldots (x^{(n)}, y^{(n)})$$

- Task: if a residence has x square feet, predict its price?



15th sample
$(x^{(15)}, y^{(15)})$

$x = 800$
$y = ?$

http://cs229.stanford.edu/notes2020spring/lecture1_slide.pdf

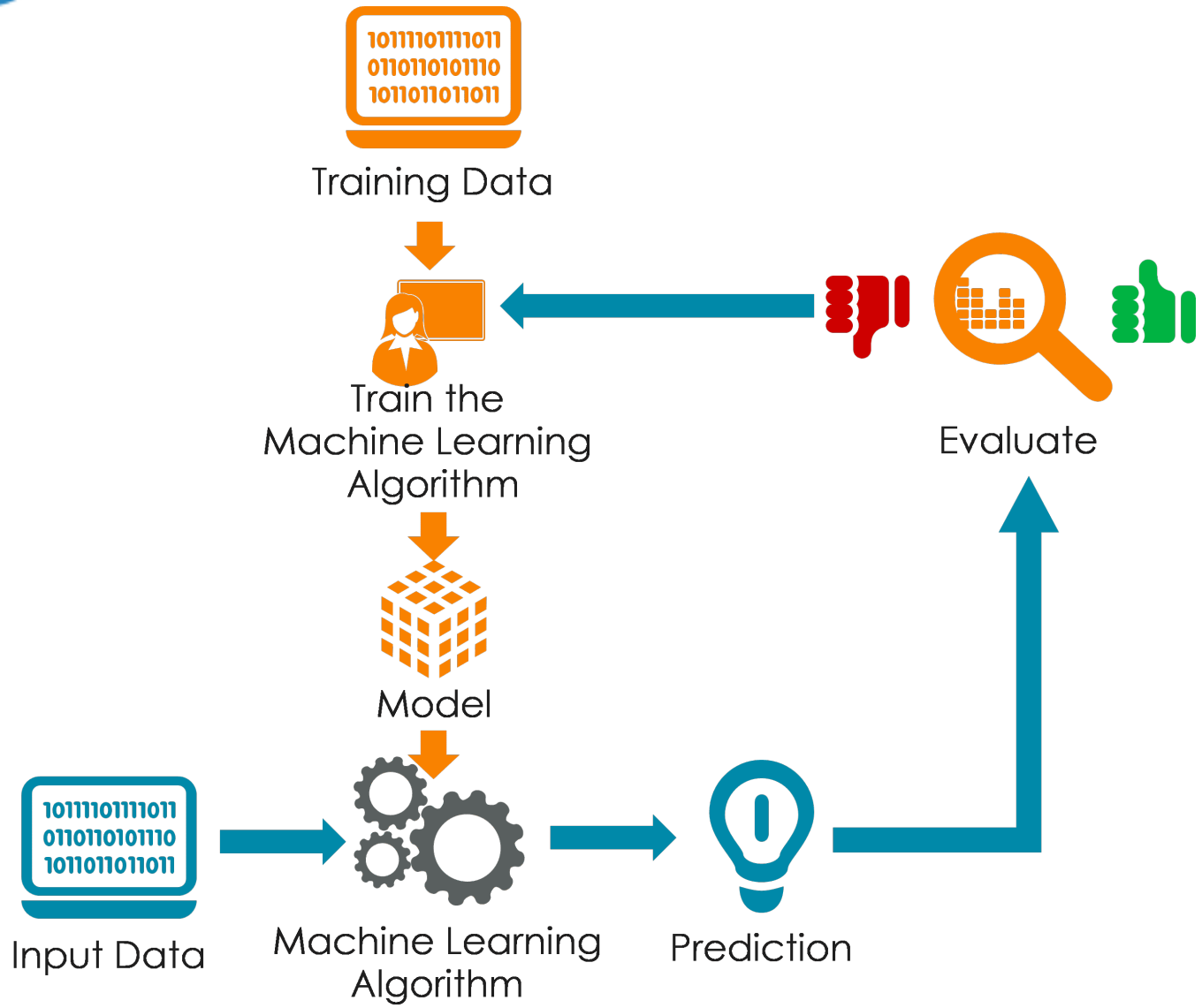
Housing Price Prediction

- $x \in \mathbb{R}^d$ for large d
- E.g.,

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ \vdots \\ \vdots \\ x_d \end{bmatrix} \begin{array}{l} \text{--- living size} \\ \text{--- lot size} \\ \text{--- \# floors} \\ \text{--- condition} \\ \text{--- zip code} \\ \vdots \end{array} \longrightarrow y \text{ --- price}$$

http://cs229.stanford.edu/notes2020spring/lecture1_slide.pdf

Supervised Learning

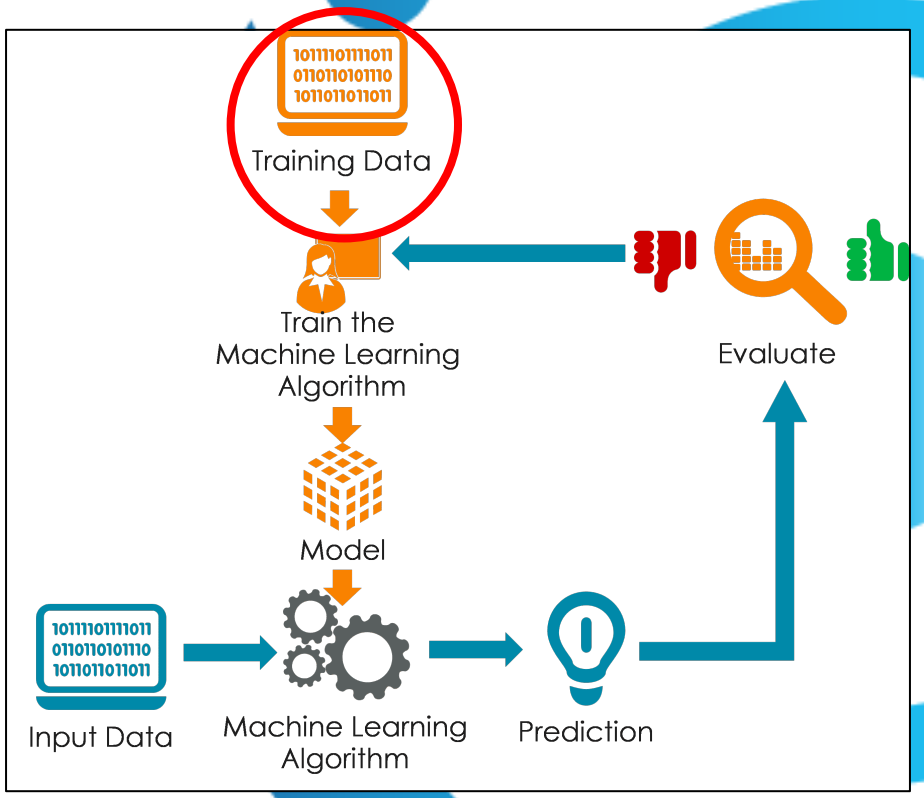


Supervised Learning

Dimension,Factor

Label

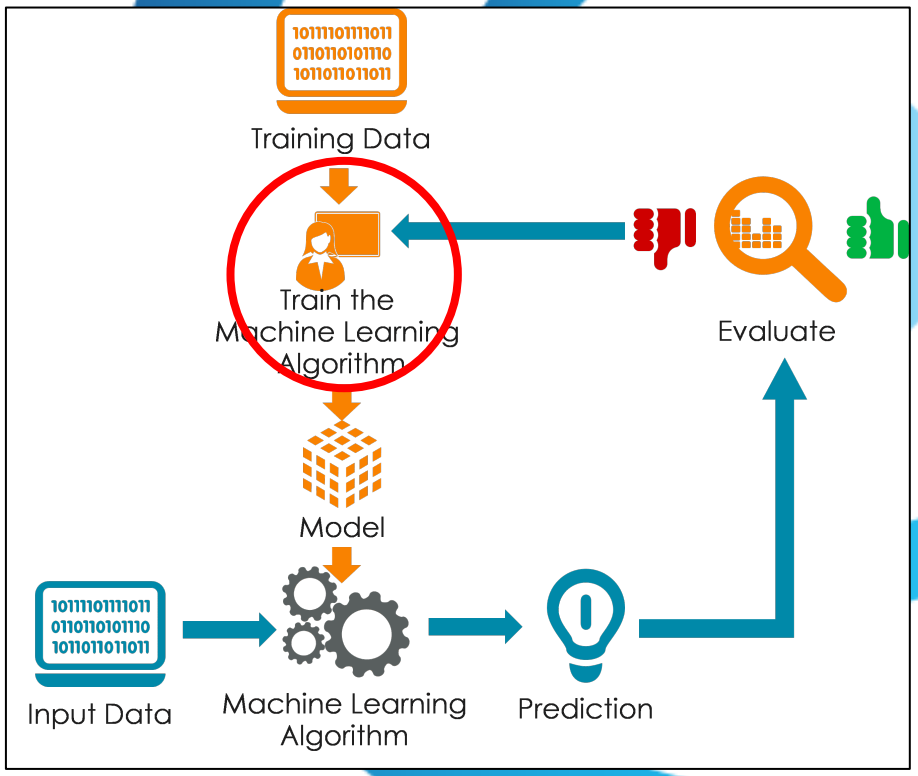
age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
57	0	1	130	236	0	0	174	0	0.0	1	1	2	0



Supervised Learning

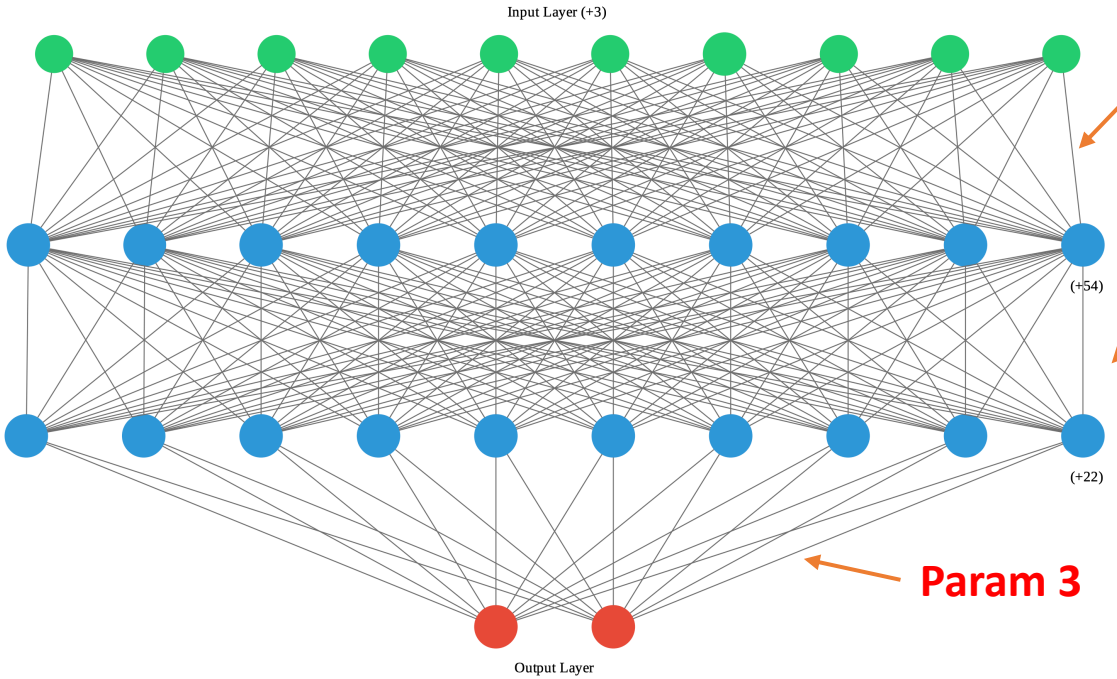
Top 10 Algorithms every Machine Learning Engineer should know

1. Naïve Bayes Classifier Algorithm
2. K Means Clustering Algorithm
3. Support Vector Machine Algorithm
4. Apriori Algorithm
5. Linear Regression Algorithm
6. Logistic Regression Algorithm
7. Decision Trees Algorithm
8. Random Forests Algorithm
9. K Nearest Neighbours Algorithm
10. Artificial Neural Networks Algorithm



Supervised Learning

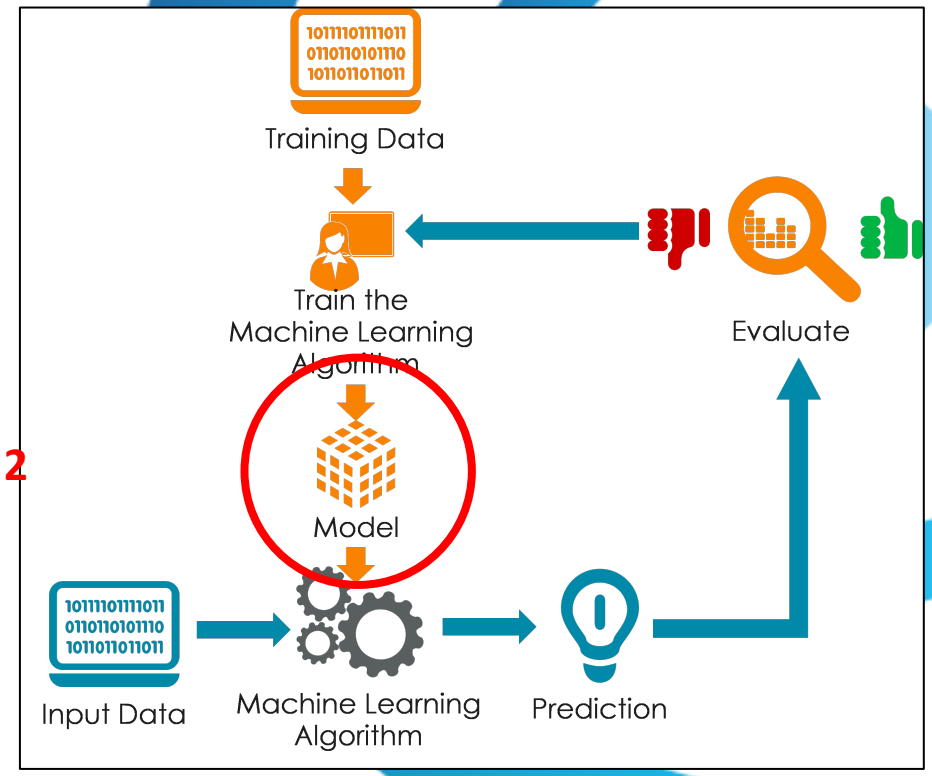
```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_20 (Dense)             (None, 64)                896
_________________________________________________________________
dense_21 (Dense)             (None, 32)                2080
_________________________________________________________________
dense_22 (Dense)             (None, 2)                 66
=================================================================
Total params: 3,042
Trainable params: 3,042
Non-trainable params: 0
_________________________________________________________________
```



Param 1

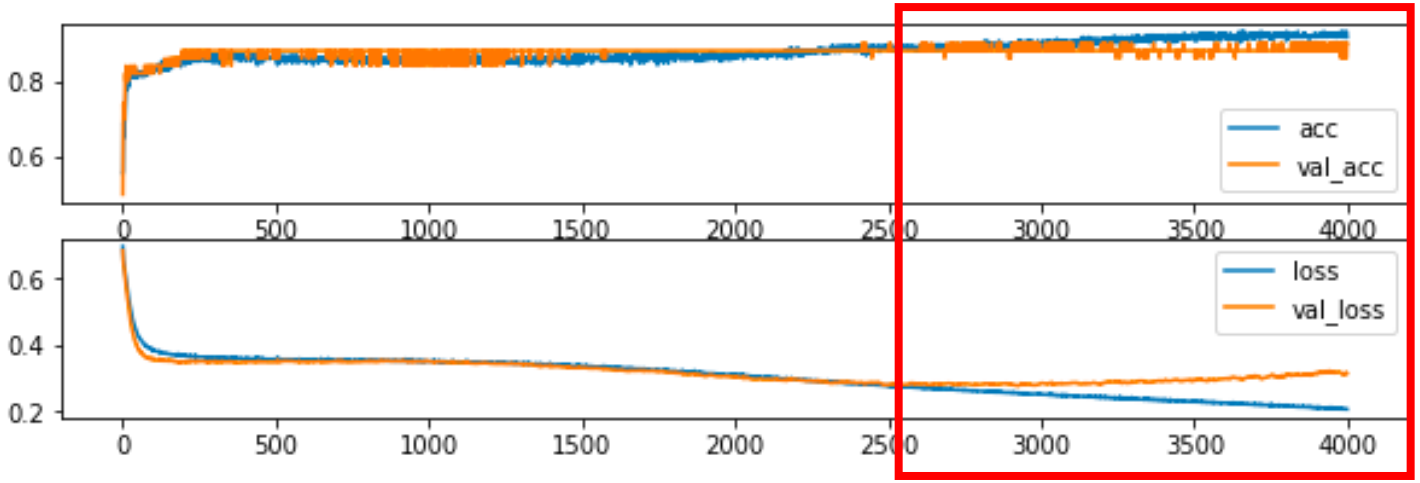
Param 2

Param 3

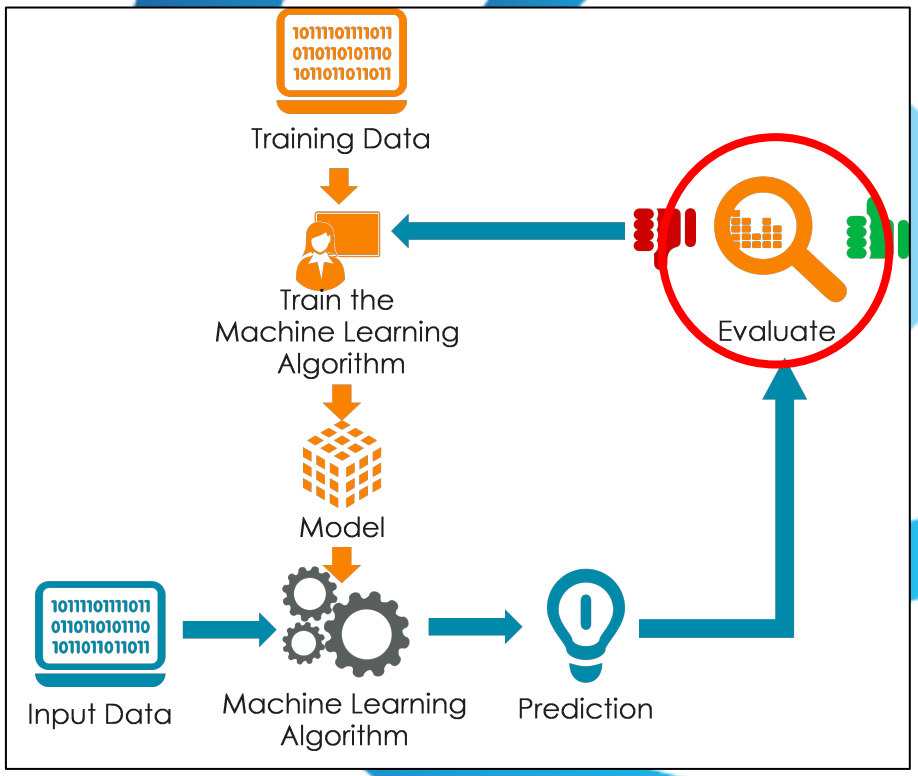


Supervised Learning

Overfit

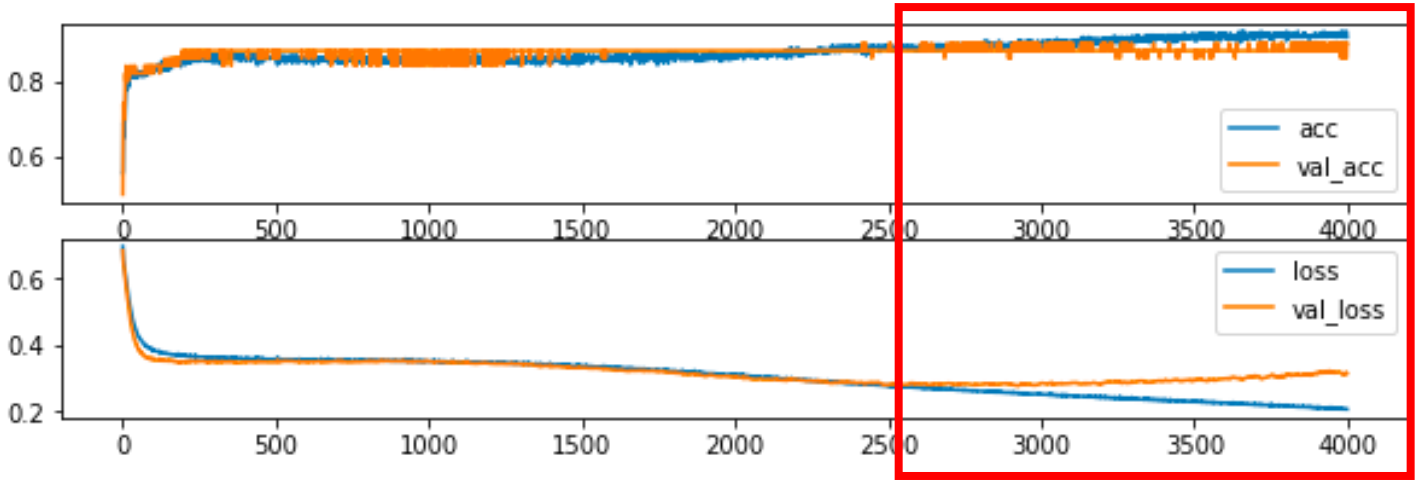


	precision	recall	f1-score	support
0	0.90	0.78	0.84	23
1	0.83	0.93	0.88	27
micro avg	0.86	0.86	0.86	50
macro avg	0.87	0.85	0.86	50
weighted avg	0.86	0.86	0.86	50
samples avg	0.86	0.86	0.86	50



Supervised Learning

Overfit



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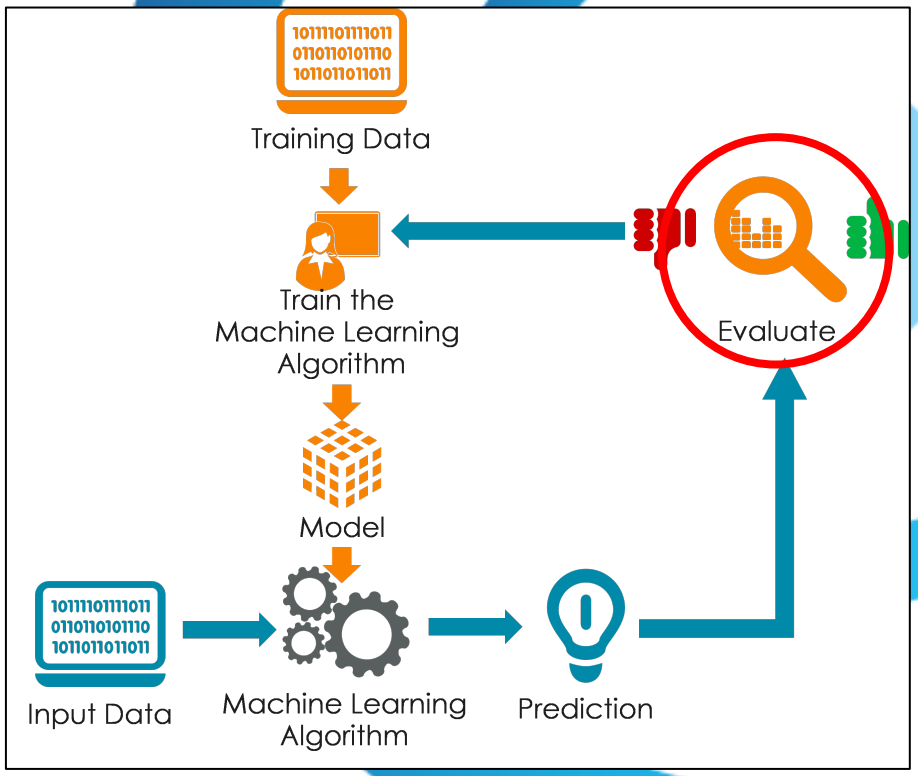

Supervised Learning

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Raw | Blame

Open in Colab

Data set https://www.kaggle.com/ronitf/heart-disease-uci?select=heart.csv

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow.keras as keras
import numpy as np
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [2]:
```
df = pd.read_csv("https://raw.githubusercontent.com/krmonline/AnomalyDetection/master/datasets_33180_43520_heart.csv")
df
```

Out[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	0

303 rows × 14 columns

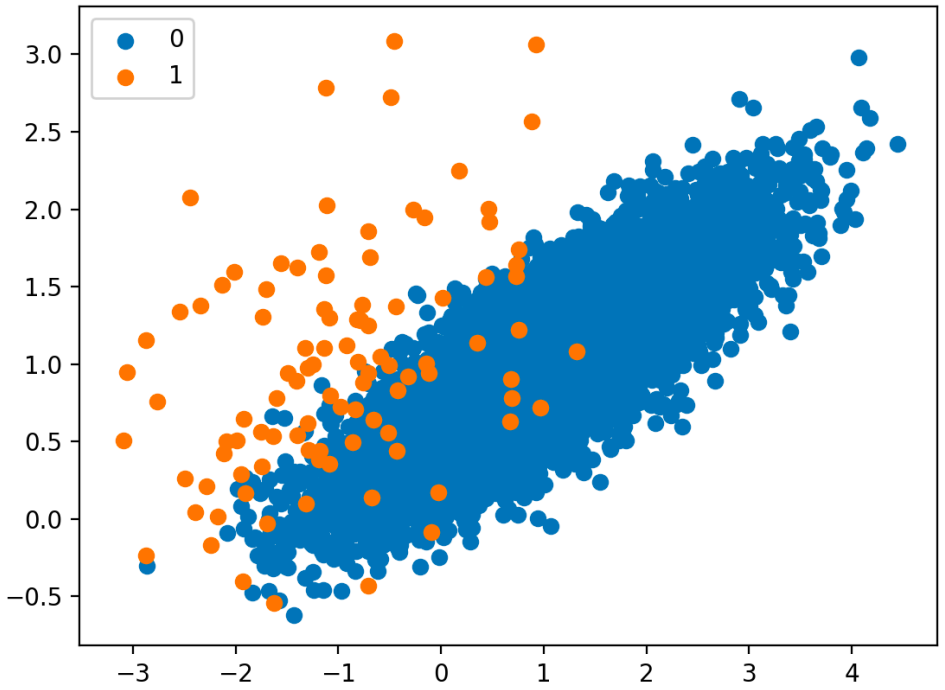
In [3]:
```
from sklearn.preprocessing import minmax_scale
```

In [4]:
```
n = minmax_scale(df)
df2 = pd.DataFrame(n)
```

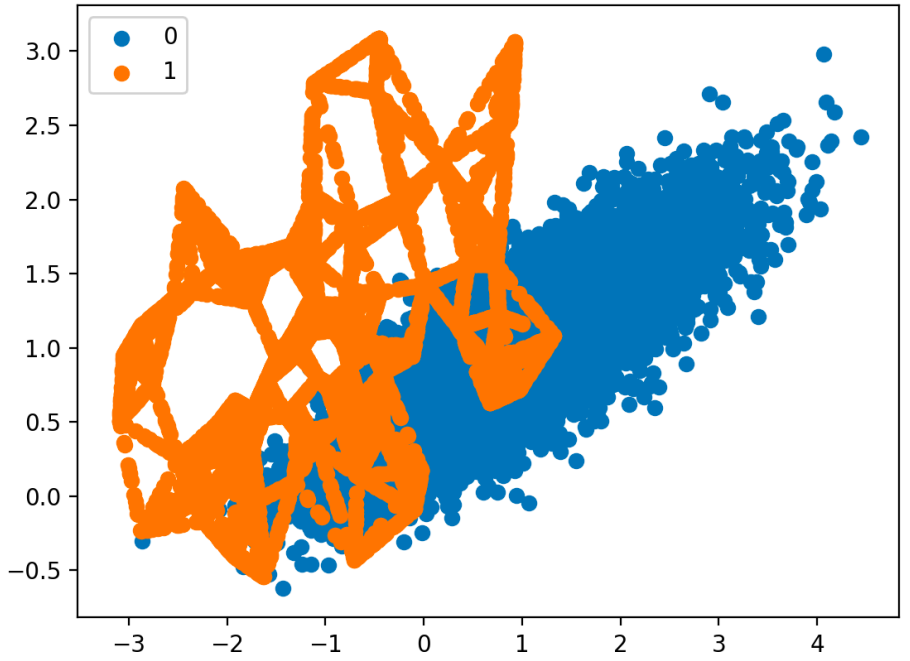
https://github.com/krmonline/AnomalyDetection/blob/master/Heart_disease_uci_Dataset.ipynb

Supervised Learning and Imbalance data

Oversampling



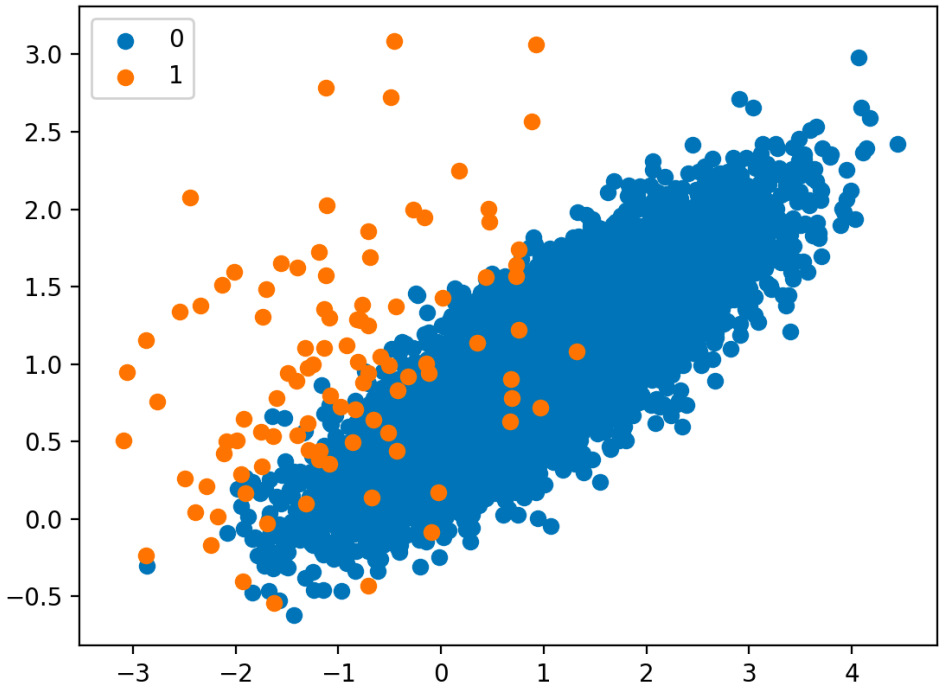
Original dataset



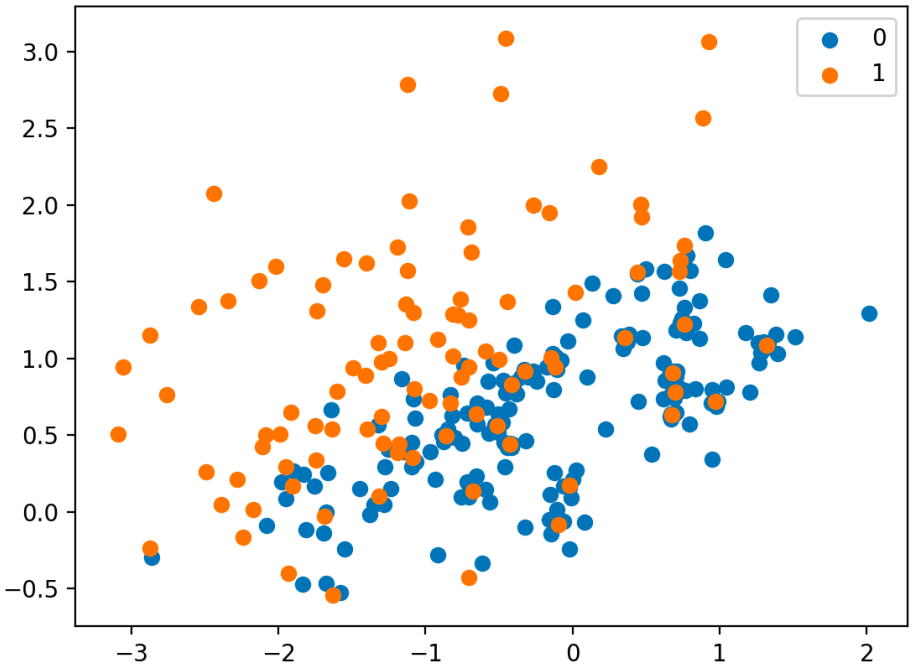
Over sampling with smote

Supervised Learning and Imbalance data

Undersampling



Original dataset



Undersampling

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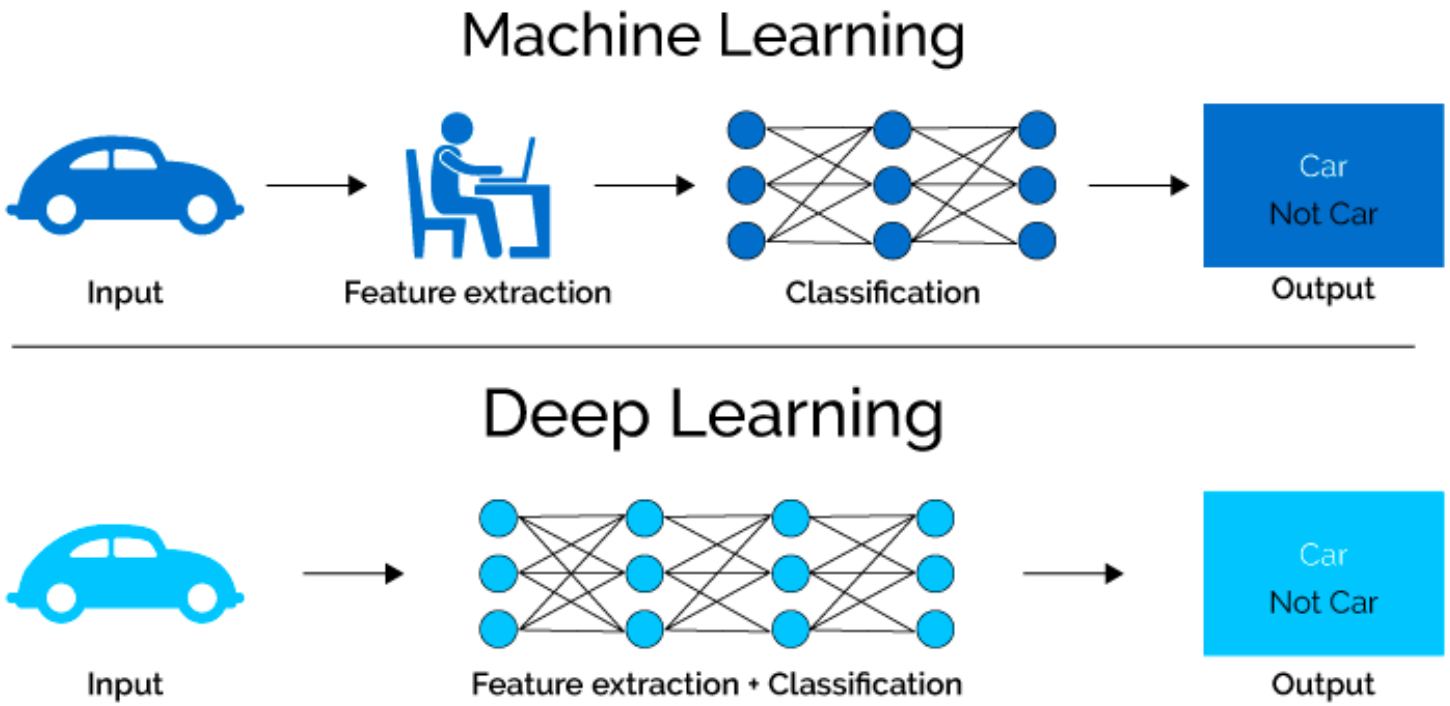
Neural Network & Deep Learning

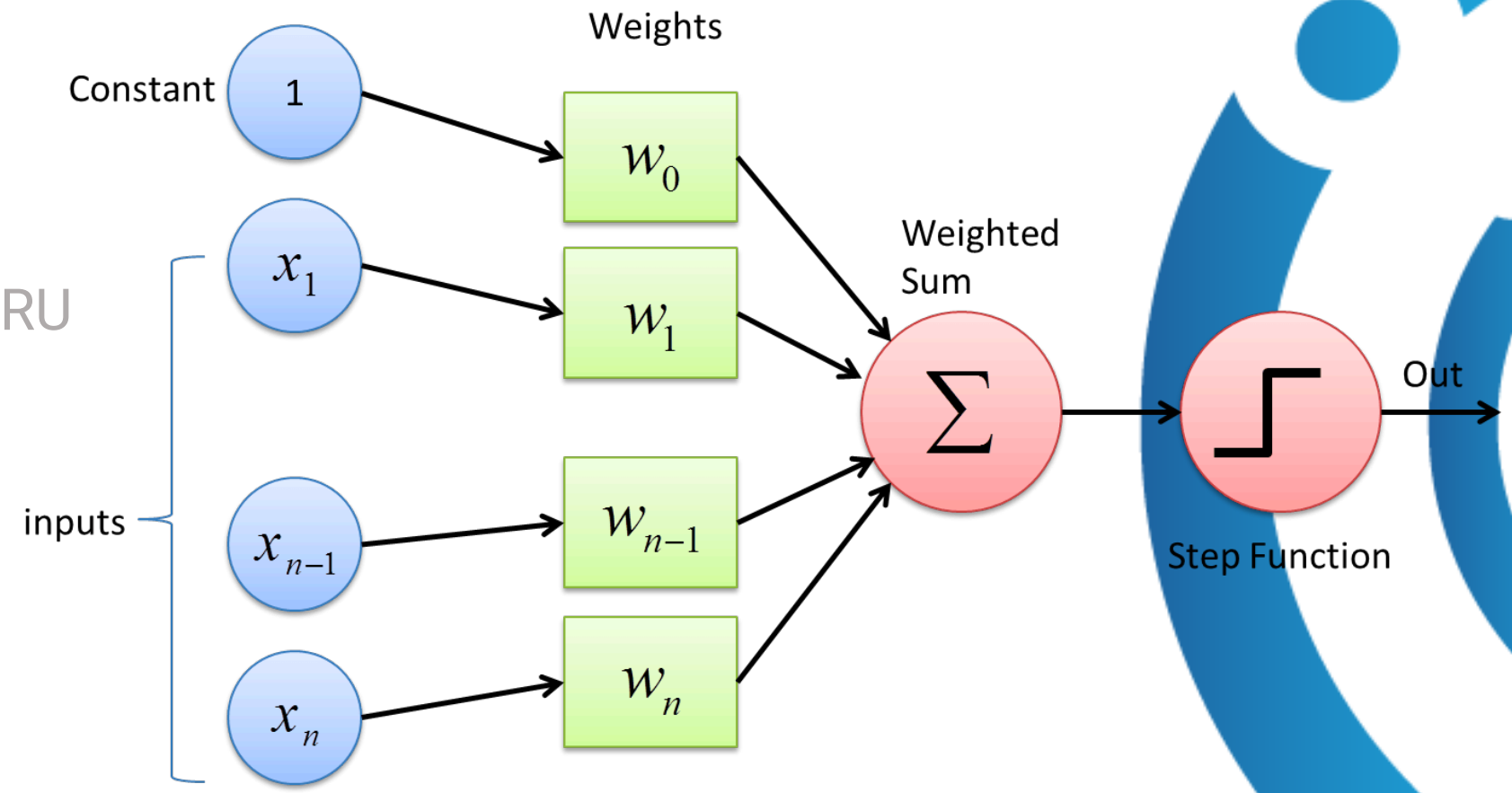
Deep Learning

- Part of machine learning field of learning representations of data. Exceptional effective at learning patterns.
- Utilizes learning algorithms that derive meaning out of data by using a hierarchy of multiple layers that mimic the neural networks of our brain.



Neural Network

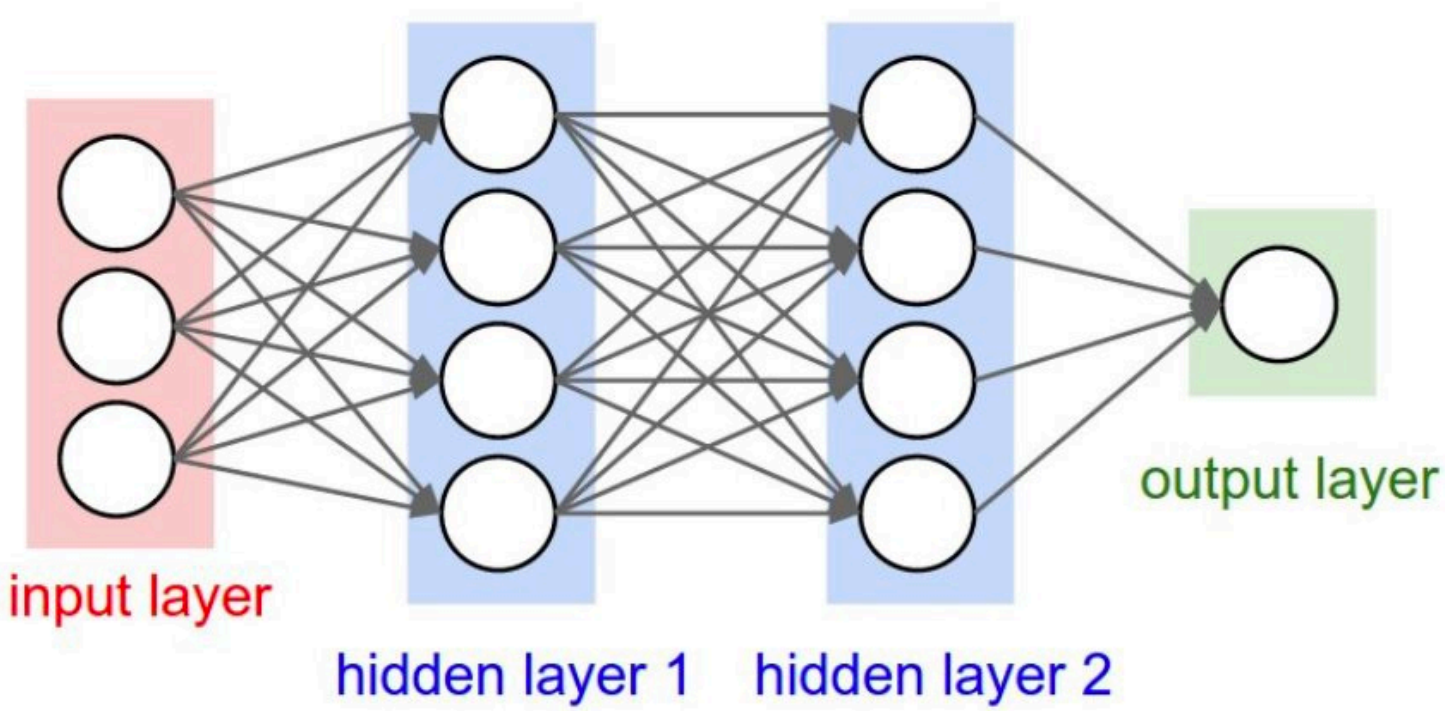
- NN
- DNN
- RNN
- LSTM & GRU



https://deepai.org/machine-learning-glossary-and-terms/perceptron

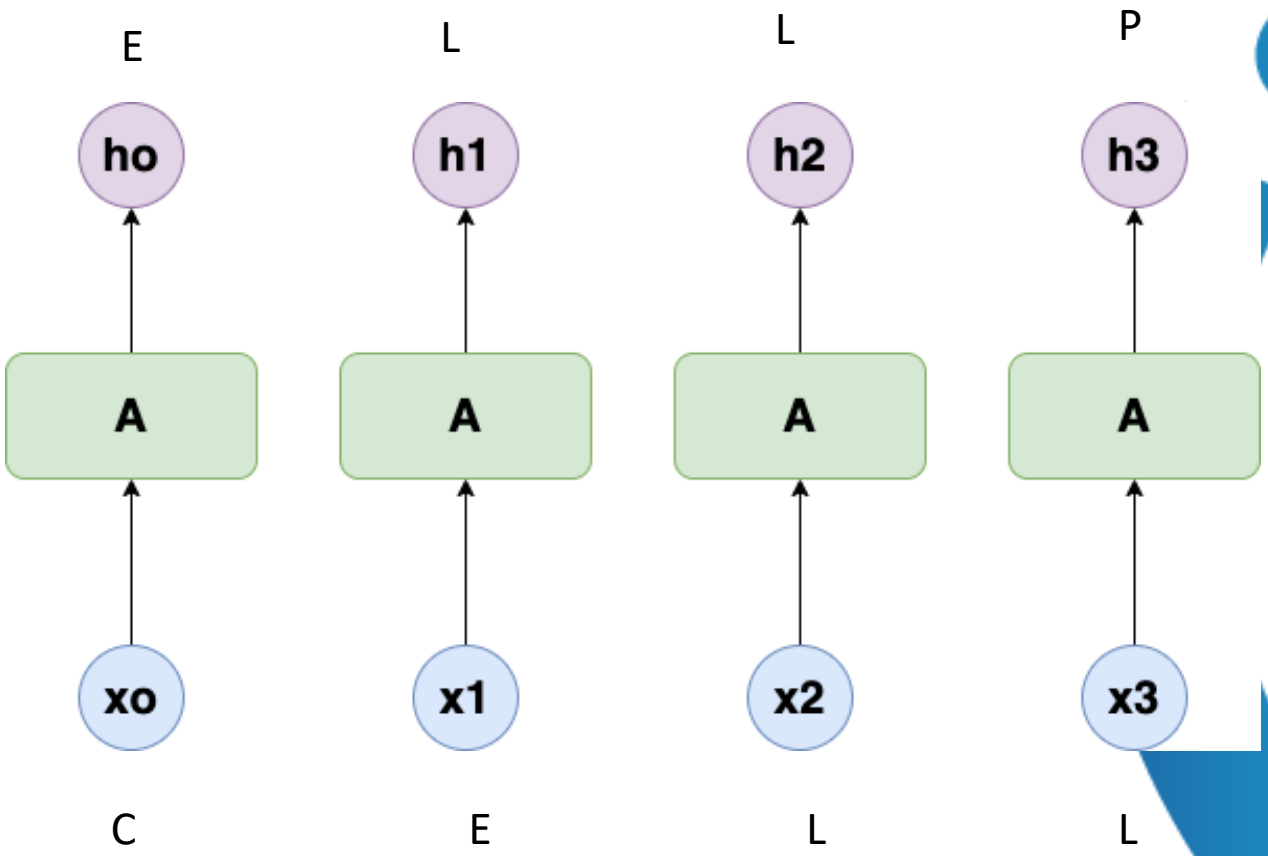
Deep Learning

- NN
- DNN
- RNN
- LSTM & GRU



Deep Learning

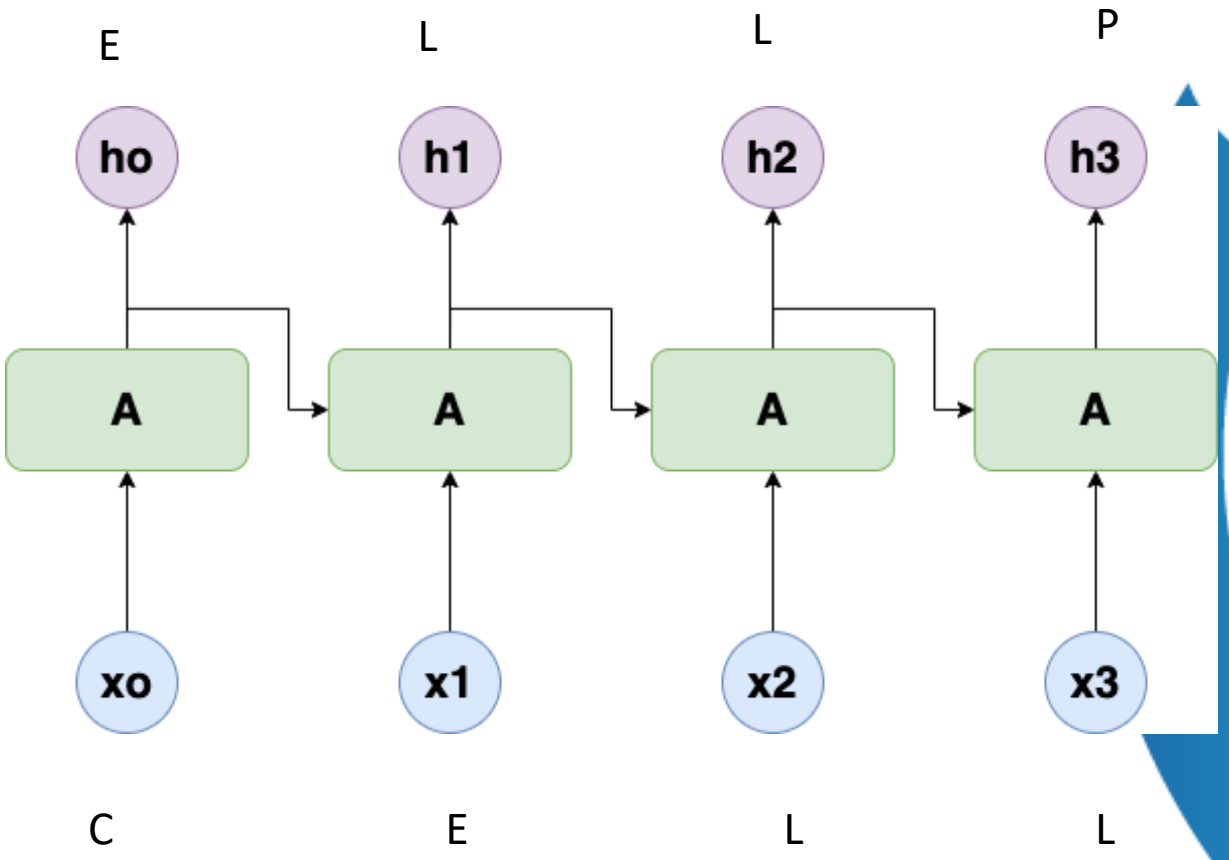
- NN
- DNN
- RNN
- LSTM & GRU



Cellphone

Deep Learning

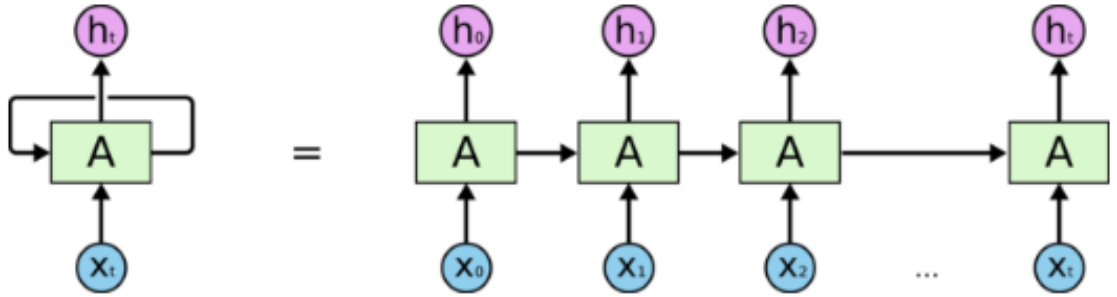
- NN
- DNN
- RNN
- LSTM & GRU



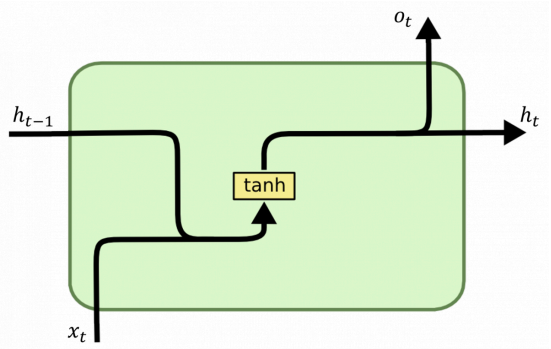
Cellphone

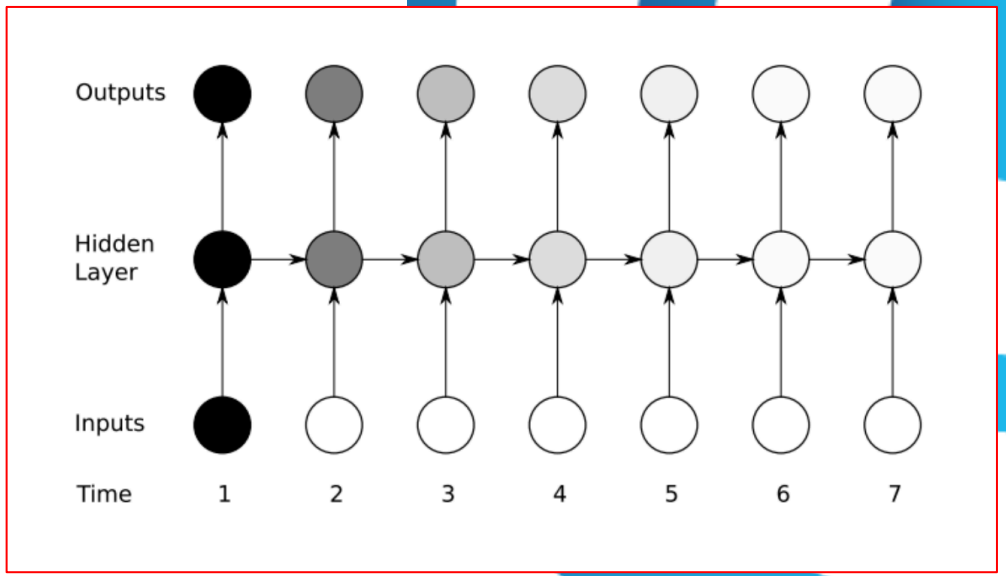
Deep Learning

- NN
- DNN
- RNN
- LSTM & GR



An unrolled recurrent neural network.



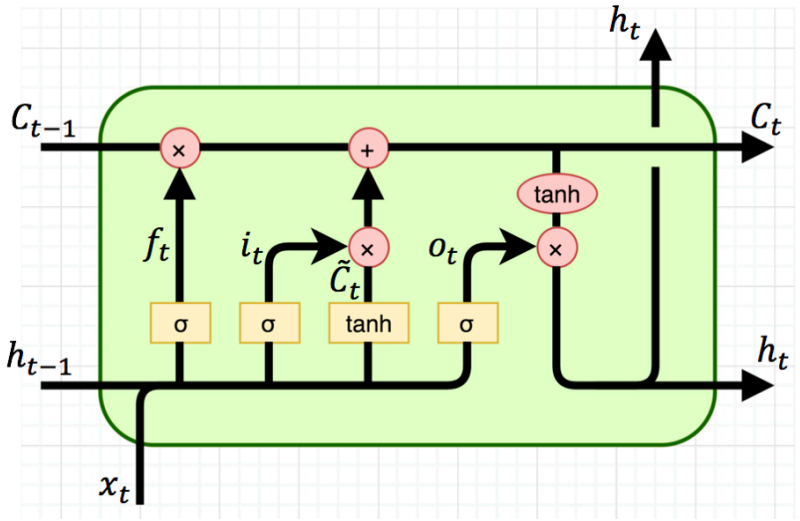


vanishing gradient

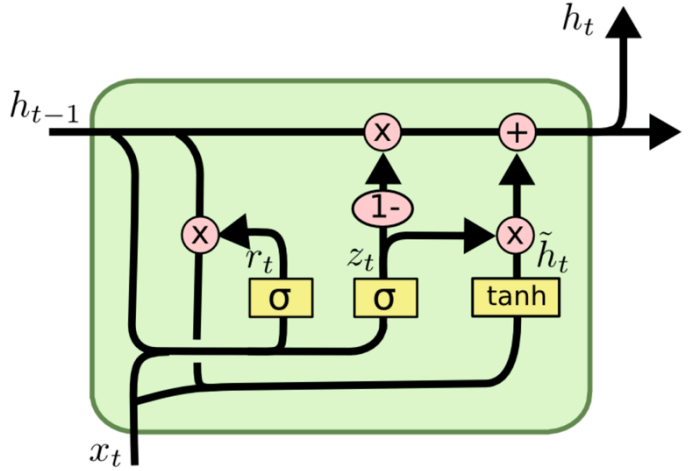
https://towardsdatascience.com/understanding-rnn-and-lstm-f7cdf6dfc14e

Deep Learning

- NN
- DNN
- RNN
- LSTM & GRU



LSTM

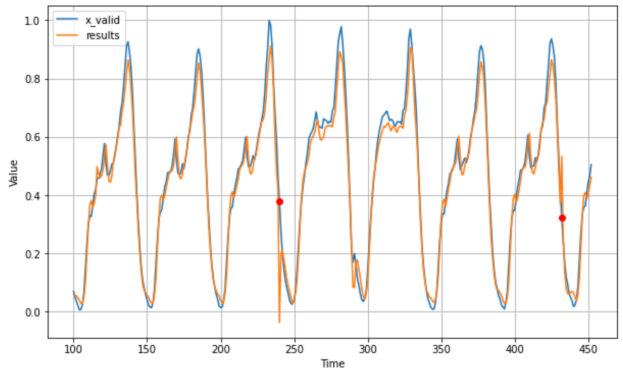


GRU

https://mc.ai/simple-rnn-vs-gru-vs-lstm-difference-lies-in-more-flexible-control/

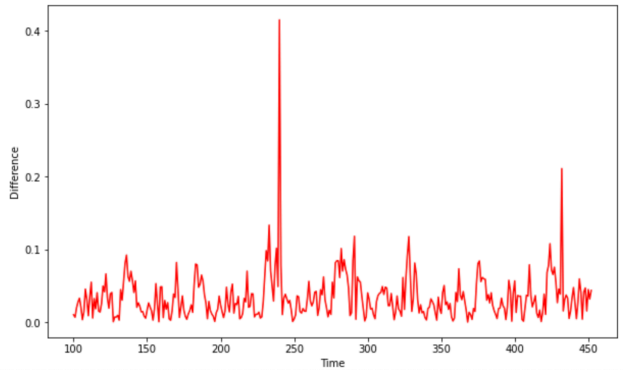
Deep Learning

```
plt.plot(time_valid[i],x_valid[i], 'ro')
```



In [184]:
```
plt.figure(figsize=(10, 6))
diff  = []
for i in range(len(x_valid)):
    diff.append(np.abs(x_valid[i] - results[i]))
plt.plot(time_valid,diff,'r-')
plt.xlabel("Time")
plt.ylabel("Difference")
```

Out[184]: Text(0, 0.5, 'Difference')



https://github.com/krmonline/AnomalyDetection/blob/master/LSTM_GRU.ipynb

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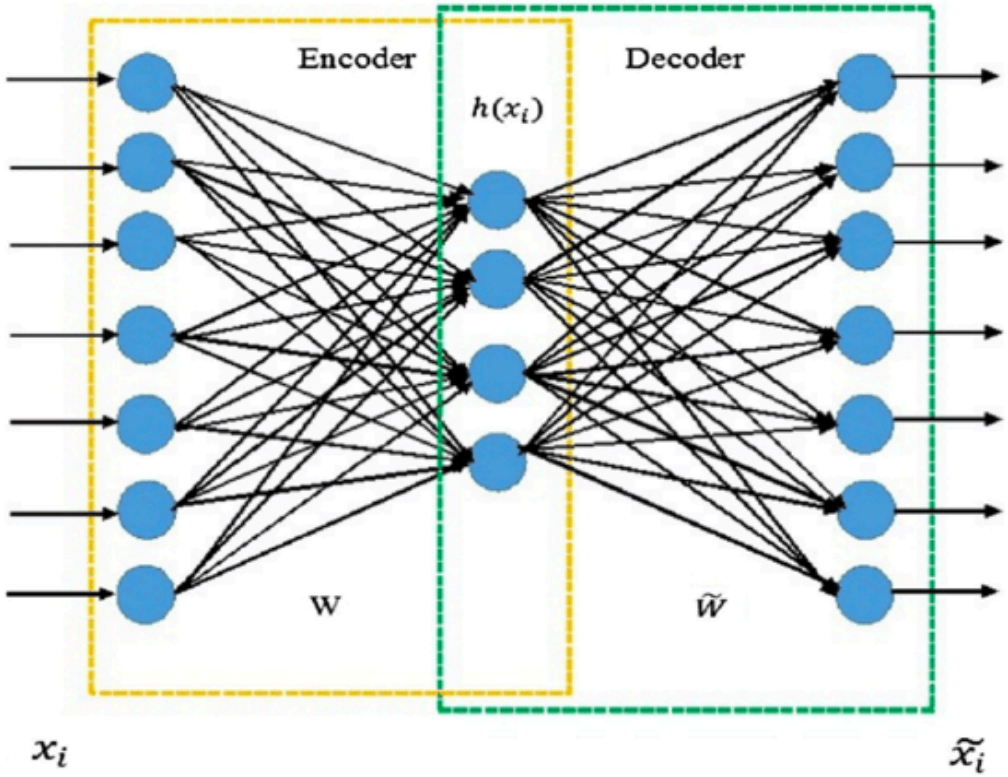
Anomaly Detection with Autoencoder

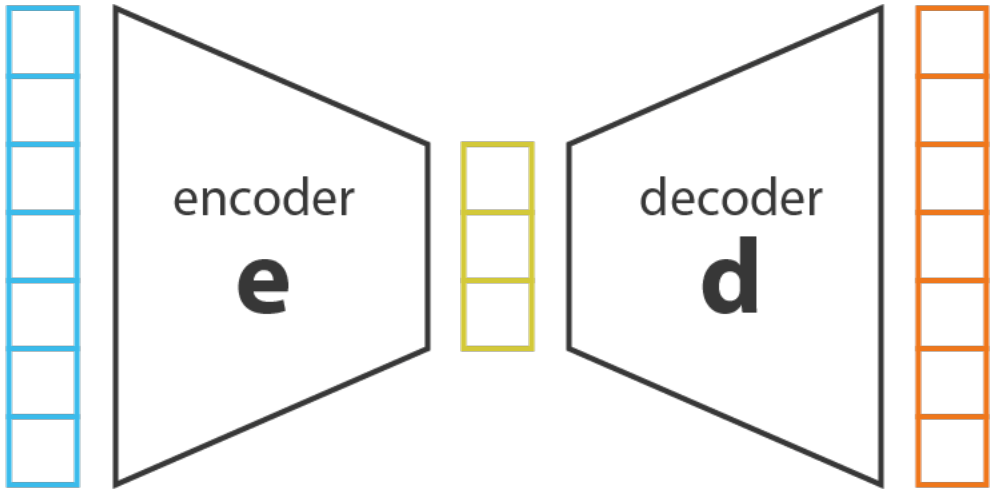
Autoencoder

Autoencoders are a specific type of feedforward neural networks where the input is the same as the output.



https://www.researchgate.net/figure/Autoencoder-architecture_fig1_318204554

การทำงานของ Autoencoder



x

initial data
in space R^n

e(x)

encoded data
in latent space R^m (with m<n)

d(e(x))

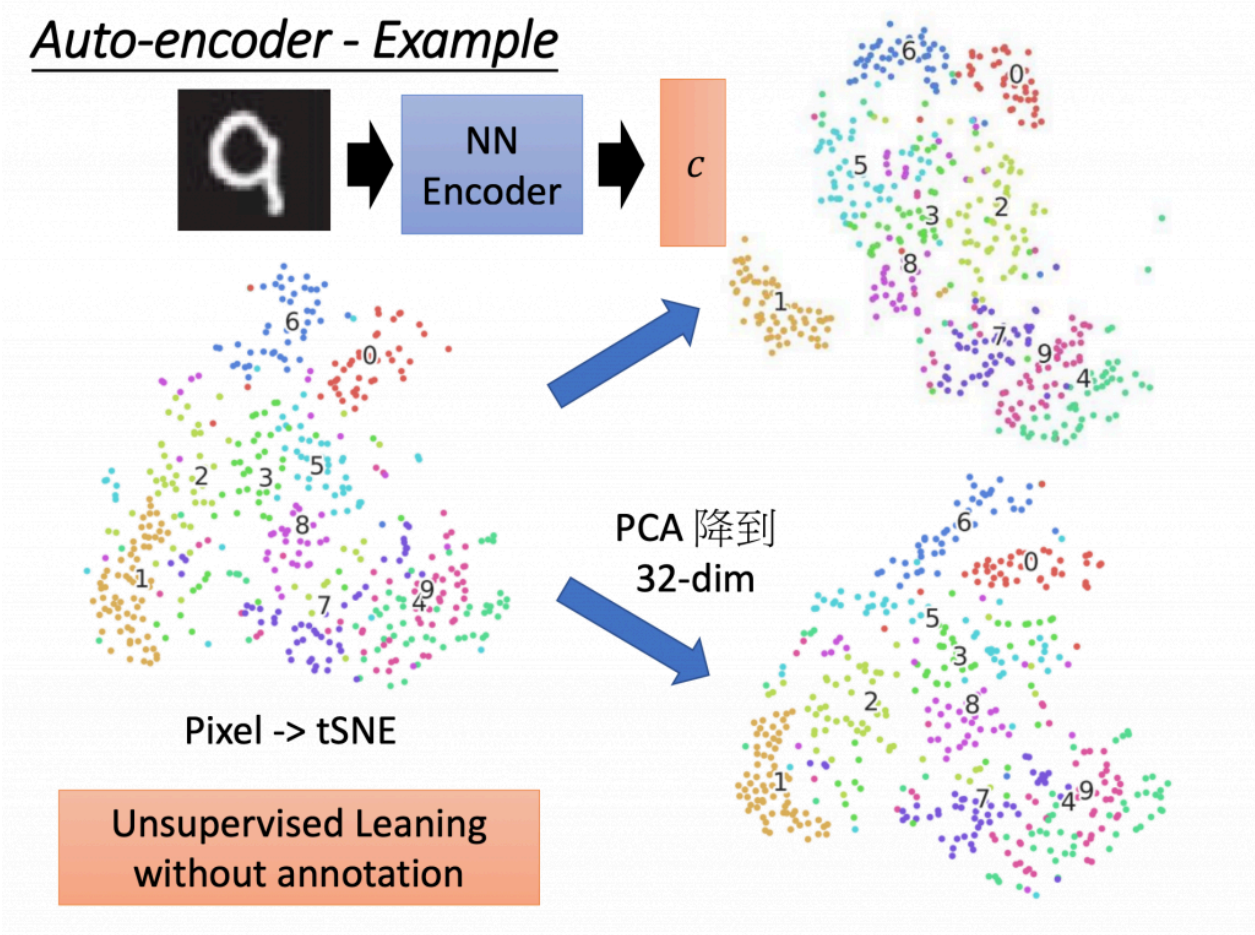
encoded-decoded data
back in the initial space R^n

$x = d(e(x))$ ➡ **lossless encoding**
no information is lost when reducing the number of dimensions

$x \neq d(e(x))$ ➡ **lossy encoding**
some information is lost when reducing the number of dimensions and can't be recovered later

https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

ความสามารถในการทำ Dimension Reduction



Anomaly detection step with Autoencoder

- First, if your dataset that should be examined for anomalies is imbalanced (which is almost always the case) you must use an autoencoder
- Train the autoencoder using the mean squared error loss function only on normal data, don't use any anomalous data instances during training
- After the training, the loss value for anomalies should be much higher than for normal data instances
- Find out a loss value threshold that best distinguishes anomalies from normal data.

https://towardsdatascience.com/anomaly-detection-with-autoencoders-in-tensorflow-2-0-a1a6c9ebf495

Autoencoder application

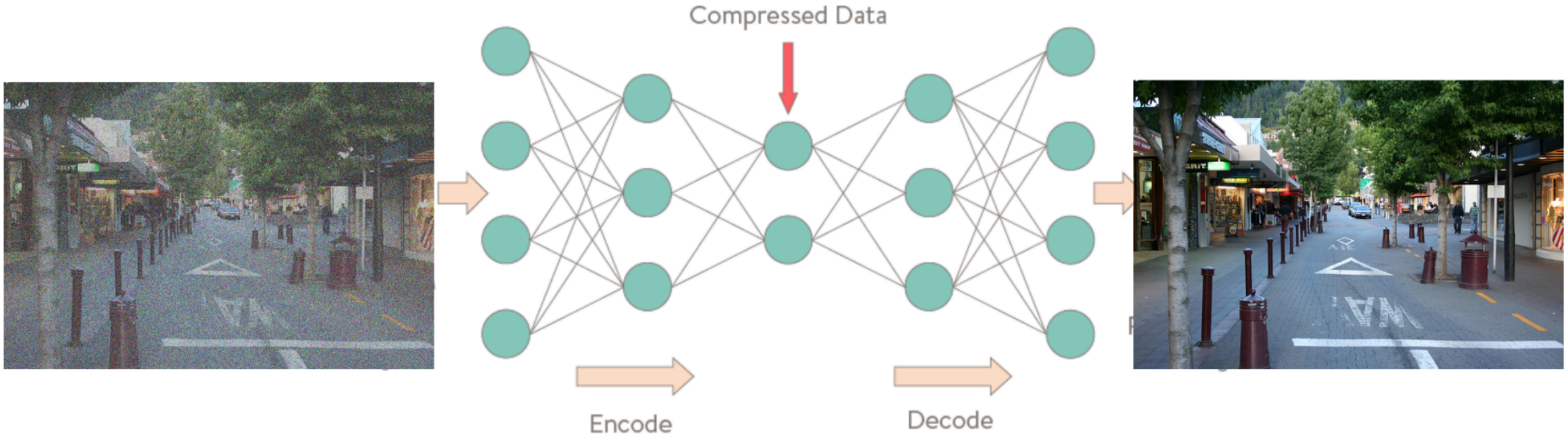


Image denoising

Autoencoder Example

master · AnomalyDetection / Autoencoder.ipynb · Go to file · ···

krmonline Created using Colaboratory — Latest commit 0fb09aa 1 hour ago — History

File display

1 contributor

341 lines (341 sloc) | 9.19 KB — Raw | Blame

Open in Colab

In [1]:
```
import  tensorflow as tf
import numpy as np
from sklearn.metrics import mean_squared_error
```

In [15]:
```
x = [0,1,2,3,4,5,6,7]
X = tf.keras.utils.to_categorical(x)
X
```

Out[15]:
```
array([[1., 0., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 0., 0., 0., 1.]], dtype=float32)
```

In [16]:
```
inputs = tf.keras.Input(shape=X.shape[1])
encoder = tf.keras.layers.Dense(3, activation='sigmoid')
decoder = tf.keras.layers.Dense(X.shape[1], activation='sigmoid')
outputs = decoder(encoder(inputs))
model = tf.keras.Model(inputs,outputs)
```

In [17]:
```
model.compile(loss=tf.keras.losses.MeanSquaredError(),
              optimizer=tf.keras.optimizers.SGD(learning_rate=3.5))
```

In [70]:
```
model.fit(X,X,epochs=2000,verbose=0)
```

Out[70]:
```
<tensorflow.python.keras.callbacks.History at 0x7f7ceff4ae10>
```

In [71]:
```
pred = model.predict(np.array([[0., 1., 0., 0., 0., 0., 0., 0.]]))
print(pred)
print(np.round(pred))
```

```
[[1.0024011e-03 8.8290018e-01 9.2455745e-04 8.0137193e-02 2.5001941e-06
```

https://github.com/krmonline/AnomalyDetection/blob/master/Autoencoder.ipynb

Autoencoder Step

Open in Colab

In [13]:
```
import numpy as np
import tensorflow as tf
#from keras.models import Sequential, Model
#from keras.layers import LSTM  ,RepeatVector ,TimeDistributed , Dense ,  GRU
#from keras.utils import plot_model
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.metrics import mean_squared_error
```

In [15]:
```
df = pd.read_csv('https://raw.githubusercontent.com/krmonline/AnomalyDetection/master/data/timeseries1.csv',names=['eps'])
len(df.eps)
series = df.eps.values
```

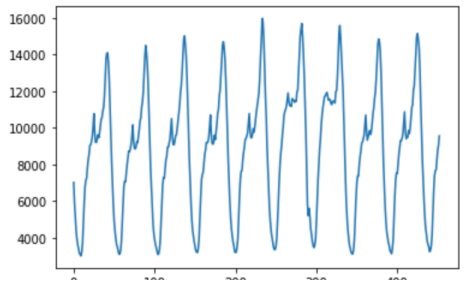
In [16]:
```
from sklearn.preprocessing import minmax_scale
```

In [64]:
```
#Prepare
def split_sequence(sequence, n_steps):
    X, y = list(), list()
    for i in range(len(sequence)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the sequence
        #print("end_ix="+str(end_ix))
        if end_ix > len(sequence)-1:
            break
        seq_x = [tmp for tmp in sequence[i:end_ix]]
        X.append(seq_x)
    return np.array(X)

seq_step  = 5
```

In [4]:
```
plt.plot(df)
```

Out[4]:
```
[<matplotlib.lines.Line2D at 0x7fa2809ac240>]
```



https://github.com/krmonline/AnomalyDetection/blob/master/LSTM_AutoEncoder.ipynb

Softnix

Workshop

Softnix

- ใช้ Technique ต่าง ๆ จากที่ได้เรียนรู้เพื่อหา Anomaly จาก File timeseries5_anomaly.csv

- ใช้ Technique ต่าง ๆ จากที่เรียนรู้ หาค่า Anomaly จาก ODDS Data Set

Softnix

Thank You