LECTURE 8. RNN

(Recurrent Neural Network)

MANU 465

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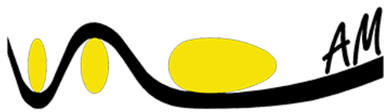

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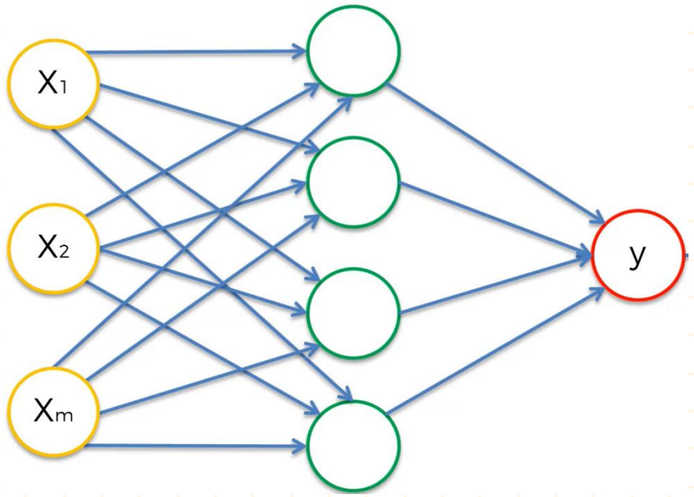
Deep Learning Algorithms & Theirs Applications

- **ANN----------→** for Regression & Classification
- **CNN----------→** for Computer Vision
- **RNN----------→** for Time Series Analysis

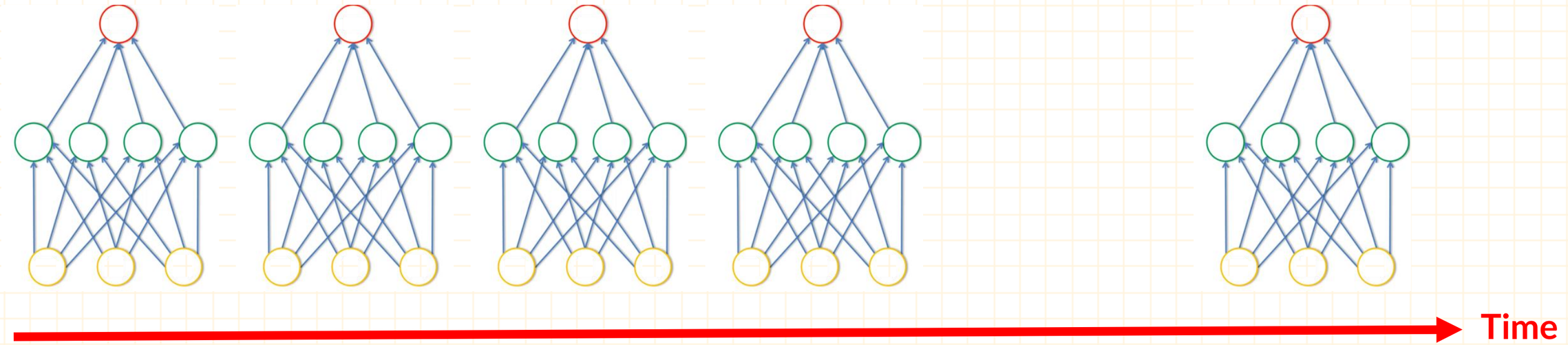
- **Self-Organizing Maps----------→** for Feature Detection
- **Boltzmann Machines----------→** for Recommendation Systems
- **AutoEncoder----------→** for Recommendation Systems

Recurrent Neural Network (RNN)

ANN

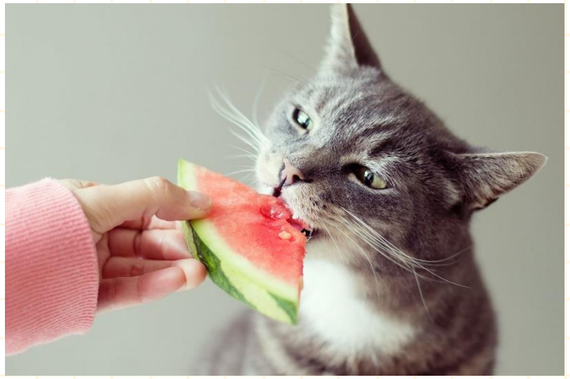


RNN



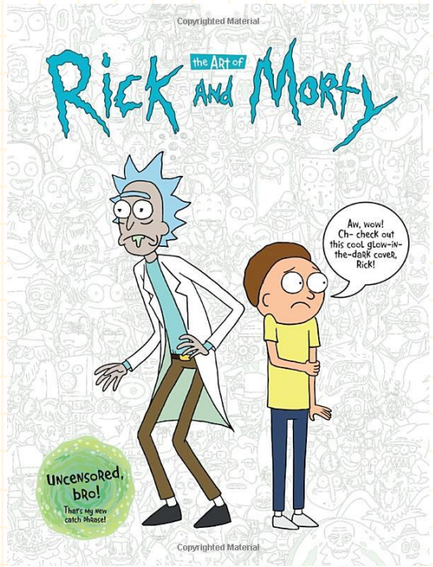
RNN Applications

- One-to-Many,

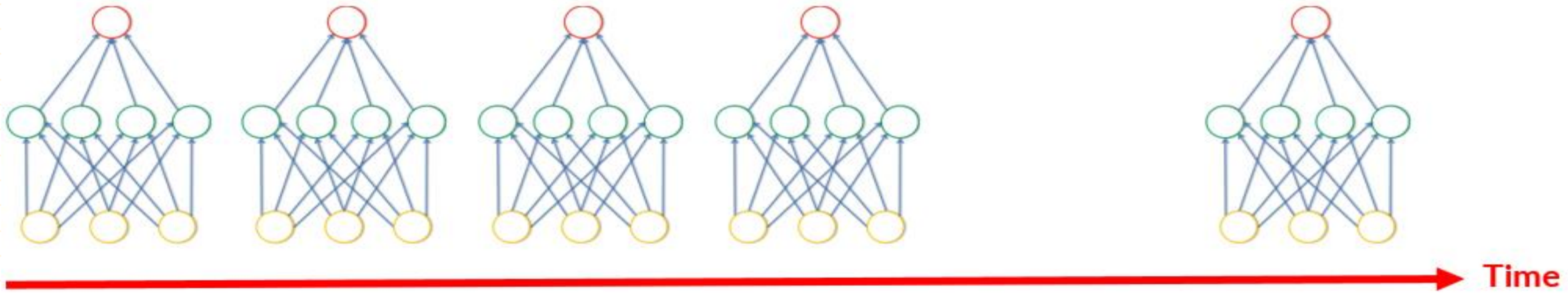


- Many-to-One,

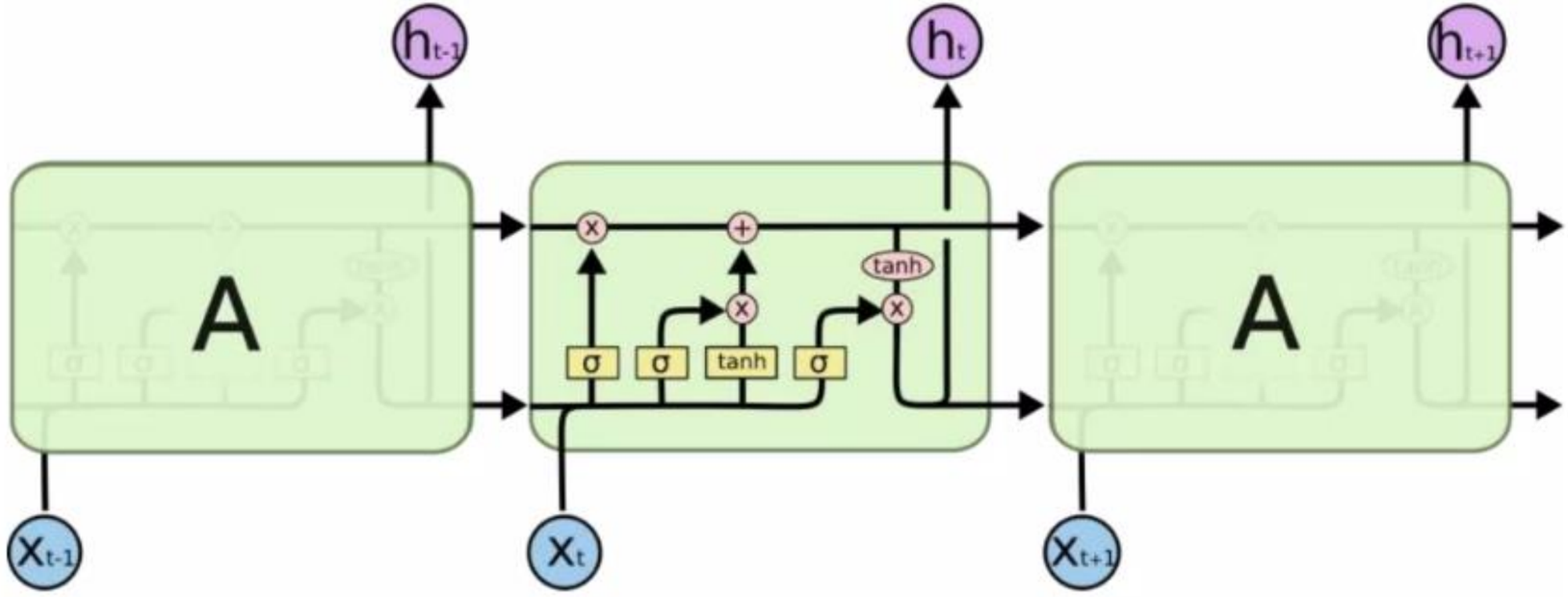
- Many-to-Many



The Issue with ANN in Solving Time Series Problems: Vanishing Gradient



The Solution: Long-Short Term Memory (LSTM)



Example) Stock Market Trend Prediction (Code & Data on Canvas)

Implement in Python:

Step 1. Scaling

Note: For Feature Scaling in RNN Models, the recommendation is Normalization, and Not Standardization.

$$x_{Standard} = \frac{x - \bar{x}}{StD(x)} \qquad x_{Normal} = \frac{x - min}{max - min}$$

```
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler()
training_set_scaled = sc.fit_transform(training_set)
```

Step 2. Creating a data Structure with Timesteps

```
TimeGroup=60    # In this example, we decide to have every 60 data points (roughly 3 month) in one group, before updatating to the next time section
LengthofData=len(training_set)
X_train = []
y_train = []
for i in range(TimeGroup, LengthofData):
    X_train.append(training_set_scaled[i- TimeGroup:i, 0])
    y_train.append(training_set_scaled[i, 0])
X_train =np.array(X_train)
y_train =np.array(y_train)
```

Step 3. Reshaping

The structure which is expected by RNN is always (# of rows, # of columns, # of indicators).

Here, we have only one indicator, which is Stock Price; you may have examples with more than 1 indicators, for example the Stock price, and the number of exchanges, etc.

```
#X_train.shape[0]  or  len(X_train[:,0])  # gives you the number of rows
#X_train.shape[1] or len(X_train[0,:])    # gives you the number of columns
```

```
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
```

Step 4. Building the RNN

```
Initiating the Model----------------------------------------------------------------
regressor = Sequential()
First layer ------------------------------------------------------------------------------------------
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.shape[1], 1)))
regressor.add(Dropout(0.2))
Second Layer -----------------------------------------------------------------------------------------
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
Third layer ------------------------------------------------------------------------------
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
Last Layer ------------------------------------------------
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))
Output-----------------------------------------
regressor.add(Dense(units = 1))
Complile---------------------------------------------
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
Fit & Run --------------------------------------------------
regressor.fit(X_train, y_train, epochs = 100, batch_size = 32)
```

Step 5. Prediction

```
dataset_total = pd.concat((dataset_train['Price'], dataset_test['price']), axis = 0)
inputs = dataset_total[len(dataset_total) - len(dataset_test) - 60:].values      # recall, we chose TimeGroup=60
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
X_test = []
for i in range(60, 80):    # 80=60+ the length of the dqta which we want to predict "len(dataset_test)"
    X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
```

Please see the full code on Canvas/Concepts/07 RNN----------

Note: Tutorial 7. LSTM (Mon, Nov 7th) is an important Tutorial where you can learn more details on this topic.

Assignment 7 (the last one)is also a good practice on this topic.