

# **CS231A CA Session**

## **PSet4 Review**

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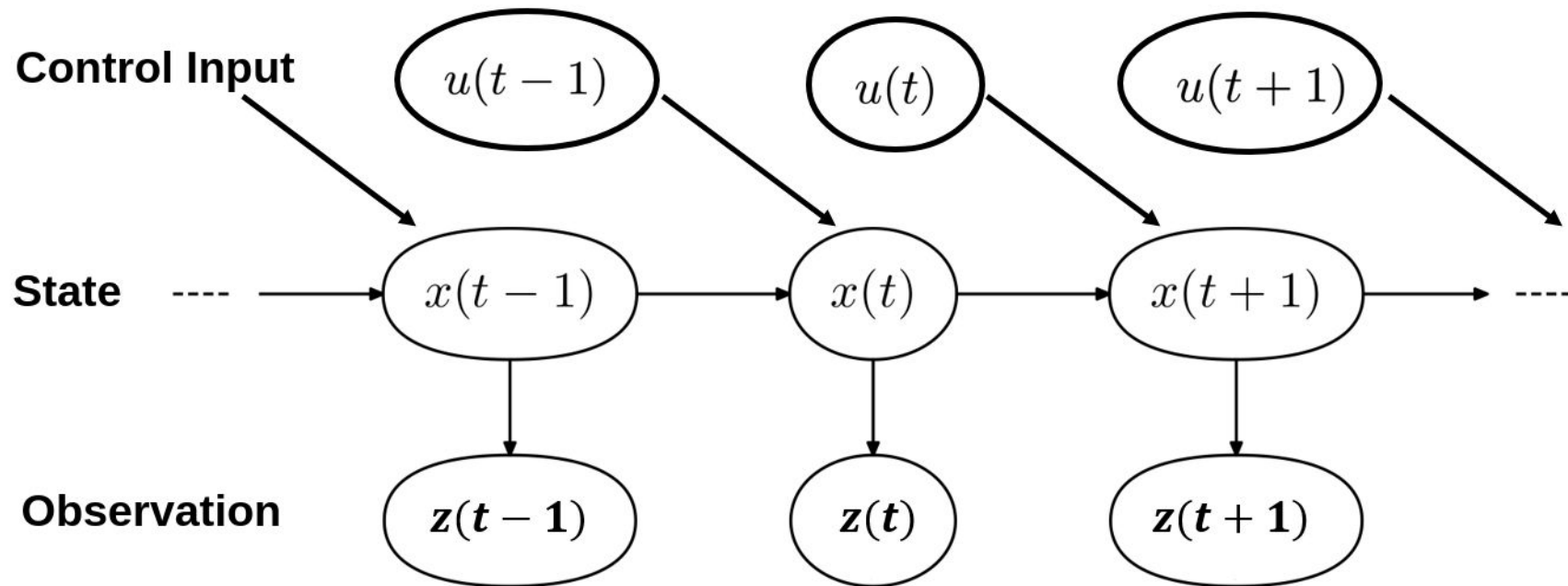
# Outline

- Extended Kalman Filter
- A brief Introduction to Tensorflow

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# Dynamical System



# Kalman Filter

An algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe.

[Source: Wikipedia](#)

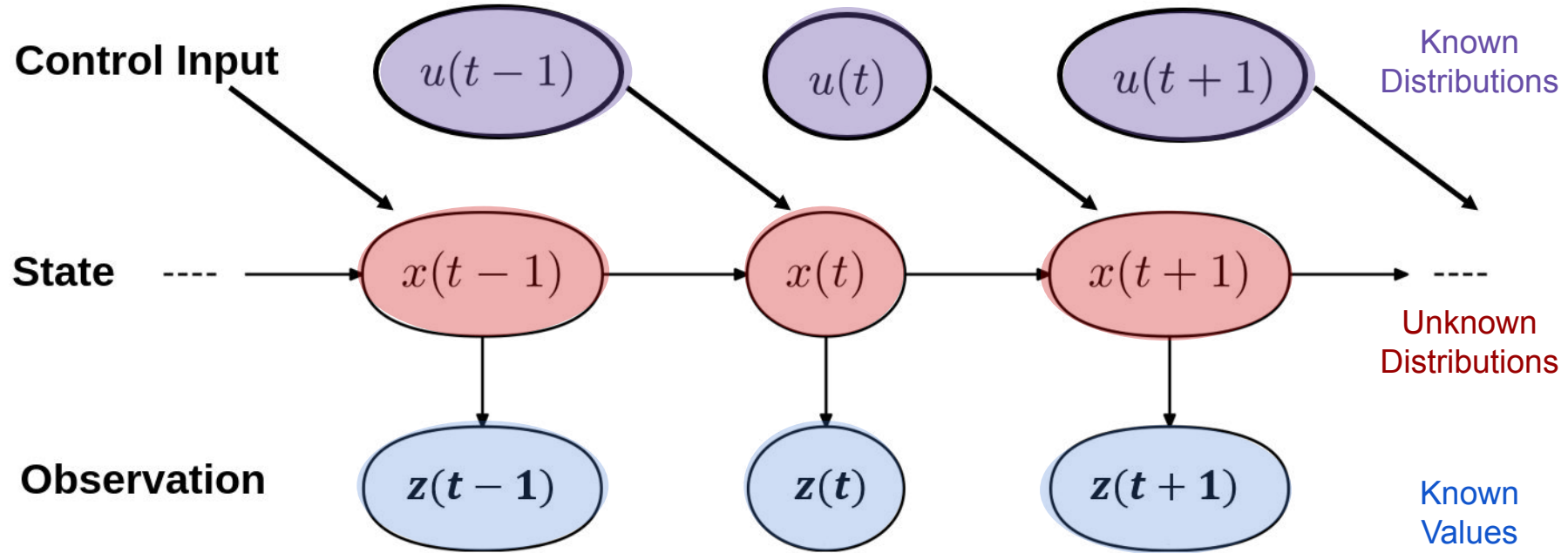
# Kalman Filter

An algorithm that uses a series of **measurements observed over time**, containing **statistical noise** and other inaccuracies, and produces **estimates of unknown variables** that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe.

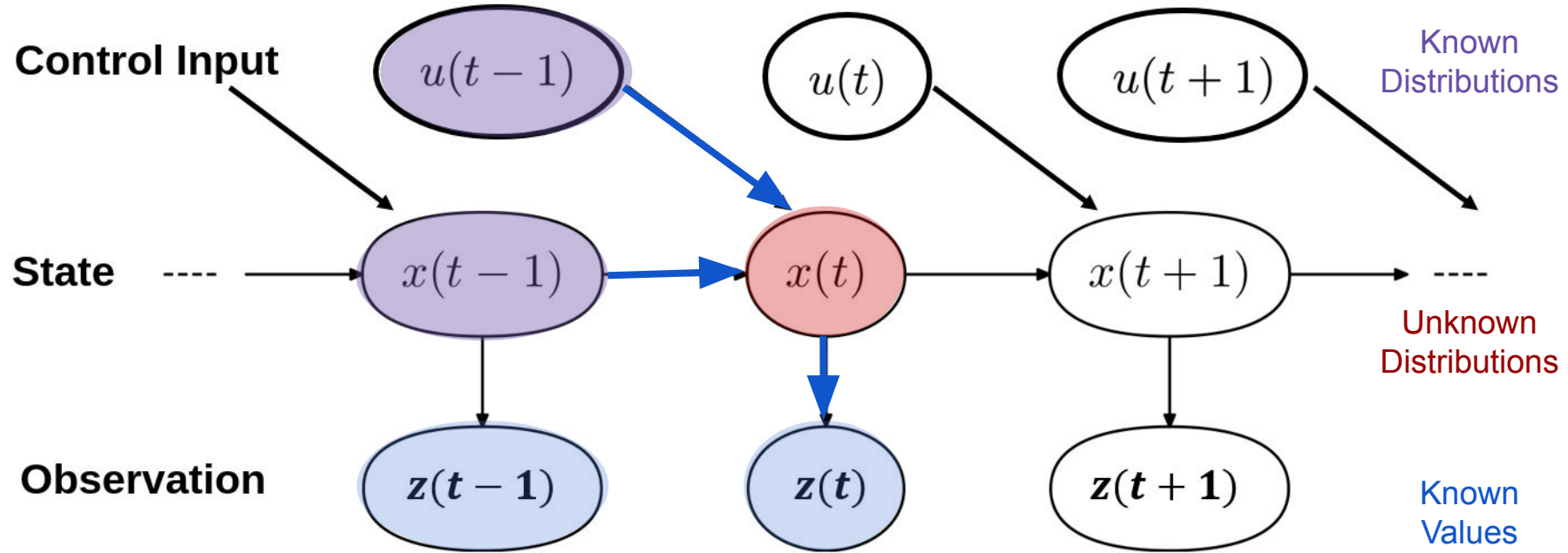
[Source: Wikipedia](#)

To make it even more illustrative ->

# What does Kalman Filter do?

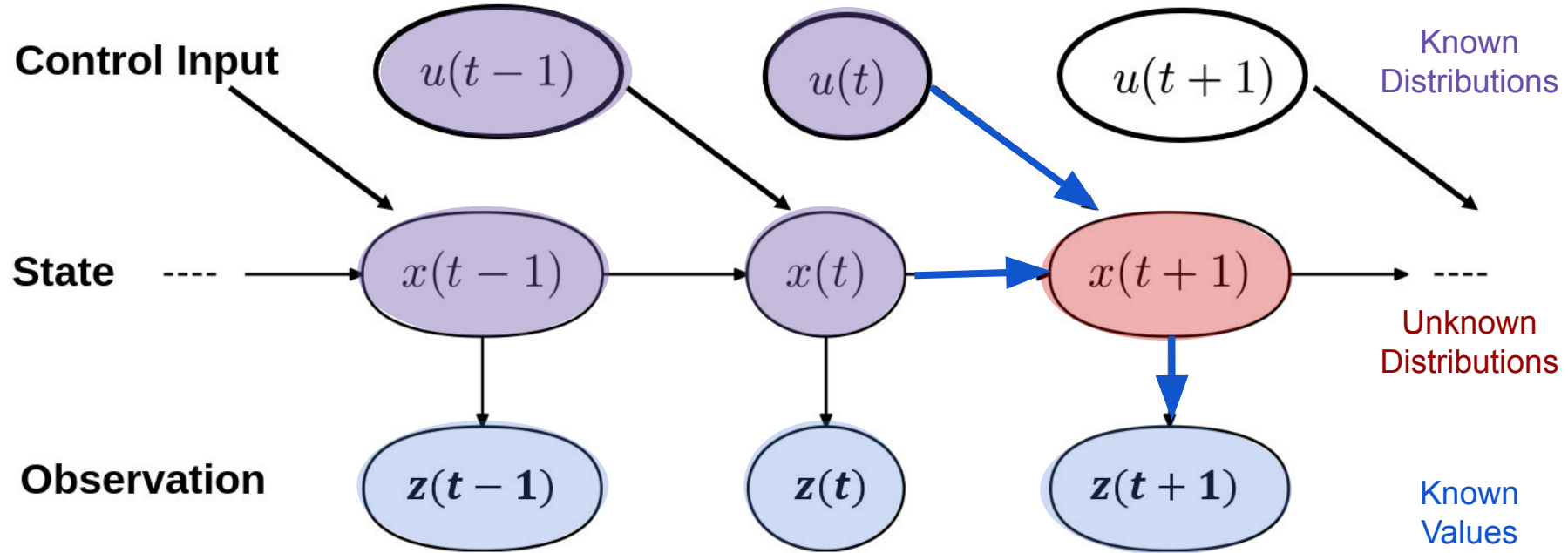


# What does Kalman Filter do?





# What does Kalman Filter do?



# Extended Kalman Filter

- Extended Kalman filter (EKF) is heuristic for nonlinear filtering problem.
- Often works well (when tuned properly), but sometimes not.
- Widely used in practice.

Based on

- Linearizing dynamics and output functions at current estimate.
- Propagating an approximation of the conditional expectation and covariance.

[Source: EE363](#)

# Extended Kalman Filter

- Extended Kalman filter (EKF) is heuristic for **nonlinear** filtering problem.
- Often works well (when tuned properly), but sometimes not.
- **Widely used in practice.**

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- **Linearizing dynamics** and output functions at current estimate.
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[Source: EE363](#)

# Implementing Extended Kalman Filter

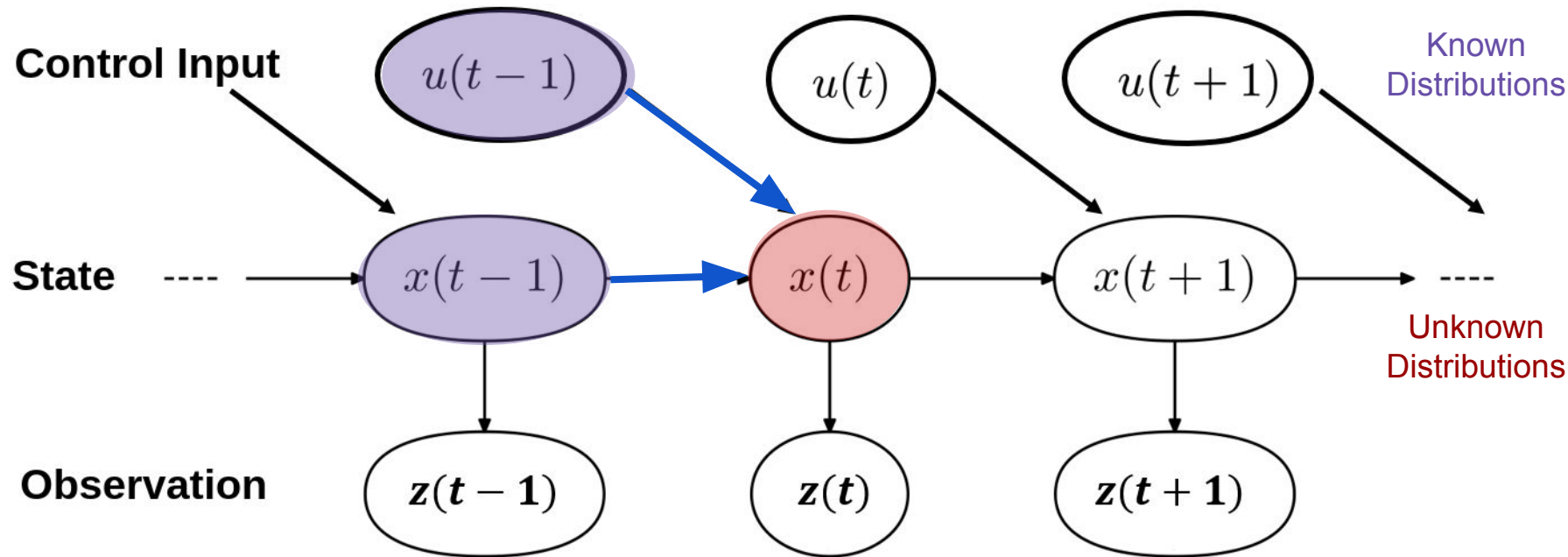
- Define the state, the control, and the noise
- Derive the system and the observation
- Compute the current Jacobian matrix (*linearizing dynamics*)
- Compute the distribution of the current state
- Iterate this process across time

# Define the State

$$x_t = \begin{bmatrix} p_t^x \\ p_t^y \\ p_t^z \\ v_t^x \\ v_t^y \\ v_t^z \end{bmatrix}$$

State: 6-dimensional vector (position, velocity)

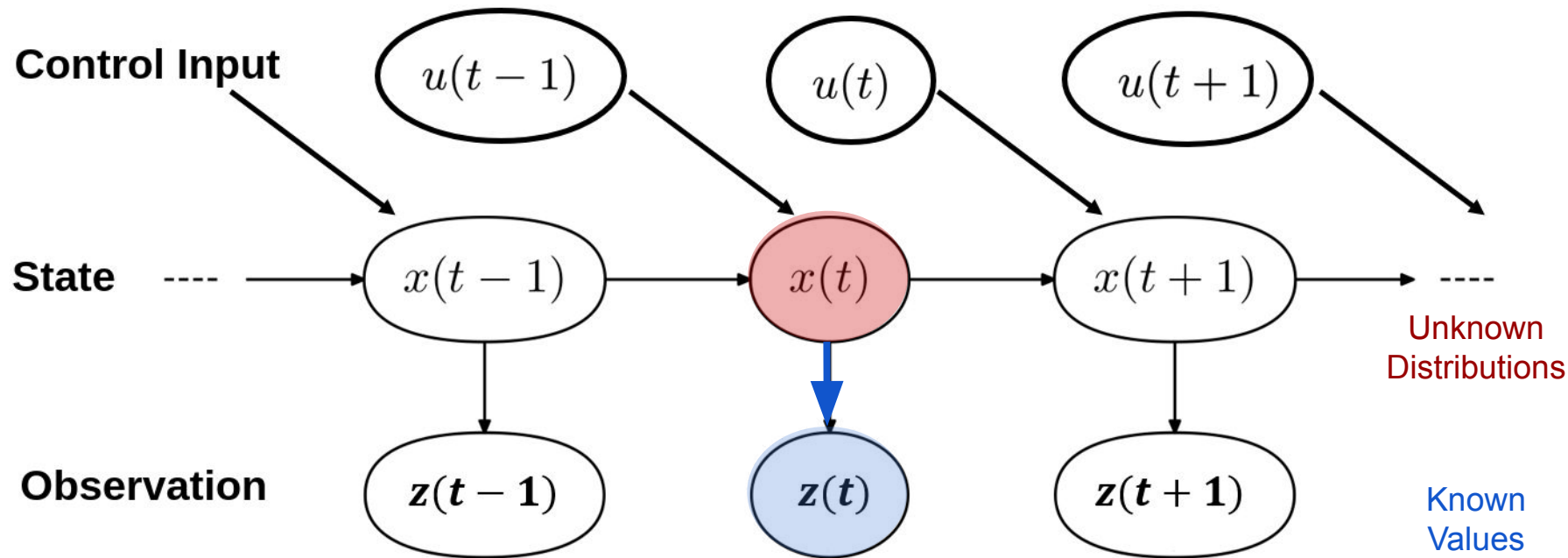
# Define the System Matrix



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$$x_t = \begin{bmatrix} p_t^x \\ p_t^y \\ p_t^z \\ v_t^x \\ v_t^y \\ v_t^z \end{bmatrix}$$
$$x_{t+1} = Ax_t + \epsilon_t$$

# Define the Observation





# Define the Observation

$$z_t = h(x_t) + v_t$$

Observation in Q1: 2-dimensional vector (pixel location)

Observation in Q2: 3-dimensional vector (pixel location, disparity)

$h(x_t)$  can be derived using the camera model we learned from previous lectures.

# Computing the Jacobian

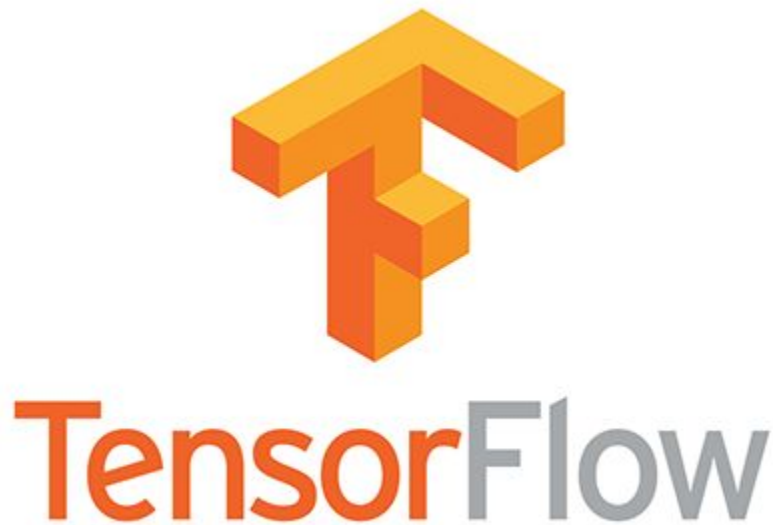
$$\mathbf{J} = \begin{bmatrix} \frac{\partial \mathbf{f}}{\partial x_1} & \cdots & \frac{\partial \mathbf{f}}{\partial x_n} \end{bmatrix} = \begin{bmatrix} \nabla^T f_1 \\ \vdots \\ \nabla^T f_m \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}$$

[Source: Wikipedia](#)

# Outline

- Extended Kalman Filter
- **A brief Introduction to Tensorflow**

# Tensorflow v.s. PyTorch



# Tensorflow

```
input = tf.placeholder(shape=[None, 480, 640, 3], dtype=tf.float32)
label = tf.placeholder(shape=[None, 3], dtype = tf.float32)
predict = make_model(input)
loss, optimizer = make_optimizer(predict, label)
saver = tf.train.Saver()

batch_size = 16
num_epochs = 15

sess=tf.Session()
sess.run(tf.global_variables_initializer())
train_losses = []
test_losses = []
for i in tqdm(range(num_epochs), desc='Training'):
    train_index = np.random.permutation(label_train.shape[0])
    current = 0

    losses = []
    while current < label_train.shape[0]:
        batch_image_train = image_train[train_index[current:min(current+batch_size, label_train.shape[0])]]
        batch_label_train = label_train[train_index[current:min(current+batch_size, label_train.shape[0])]]
        loss_val, _ = sess.run([loss, optimizer], feed_dict={input:batch_image_train, label:batch_label_train})
        losses.append(loss_val)
        current = min(current+batch_size, label_train.shape[0])
    train_losses.append(np.mean(losses))

    test_index = np.random.permutation(label_test.shape[0])
    current = 0
    losses = []
    while current < label_test.shape[0]:
        batch_image_test = image_test[test_index[current:min(current+batch_size, label_test.shape[0])]]
        batch_label_test = label_test[test_index[current:min(current+batch_size, label_test.shape[0])]]
        loss_val = sess.run([loss, optimizer], feed_dict={input:batch_image_test, label:batch_label_test})
        losses.append(loss_val)
        current = min(current+batch_size, label_test.shape[0])
    test_losses.append(np.mean(losses))

saver.save(sess, 'trained_model')
if i > 1:
    clear_output()
    fig, (ax1, ax2) = plt.subplots(1, 2)
    ax1.plot(train_losses)
    ax2.plot(test_losses)
    ax1.set_xlabel('Epoch')
    ax1.set_ylabel('Train Loss')
    ax2.set_xlabel('Epoch')
    ax2.set_ylabel('Test Loss')
    plt.show()
print("Final training loss: ", train_losses[-1])
print("Final testing loss: ", test_losses[-1])
```

# Tensorflow

Define the graph

Initialize the session

Run the session

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input = tf.placeholder(shape=[None, 480, 640, 3], dtype=tf.float32)
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        batch_image_train = image_train[train_index[current:min(current+batch_size, label_train.shape[0])]]
        batch_label_train = label_train[train_index[current:min(current+batch_size, label_train.shape[0])]]
        loss_val, _ = sess.run([loss, optimizer], feed_dict={input:batch_image_train, label:batch_label_train})
        losses.append(loss_val)
        current = min(current+batch_size, label_train.shape[0])
    train_losses.append(np.mean(losses))

    test_index = np.random.permutation(label_test.shape[0])
    current = 0
    losses = []
    while current < label_test.shape[0]:
        batch_image_test = image_test[test_index[current:min(current+batch_size, label_test.shape[0])]]
        batch_label_test = label_test[test_index[current:min(current+batch_size, label_test.shape[0])]]
        loss_val = sess.run([loss, feed_dict={input:batch_image_test, label:batch_label_test})
        losses.append(loss_val)
        current = min(current+batch_size, label_test.shape[0])
    test_losses.append(np.mean(losses))

saver.save(sess, 'trained_model')
if i > 1:
    clear_output()
    fig, (ax1, ax2) = plt.subplots(1, 2)
    ax1.plot(train_losses)
    ax2.plot(test_losses)
    ax1.set_xlabel('Epoch')
    ax1.set_ylabel('Train Loss')
    ax2.set_xlabel('Epoch')
    ax2.set_ylabel('Test Loss')
    plt.show()
print("Final training loss: ", train_losses[-1])
print("Final testing loss: ", test_losses[-1])
```

# Defining the Graph

```
input = tf.placeholder(shape=[None, 480, 640, 3], dtype=tf.float32)
label = tf.placeholder(shape=[None, 3], dtype = tf.float32)
predict = make_model(input)
loss, optimizer = make_optimizer(predict, label)
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# Running the Session

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```
sess=tf.Session()
sess.run(tf.global_variables_initializer())
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```
loss_val = sess.run(loss, feed_dict={input:batch_image_test, label:batch_label_test})
```



# Running the Session

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input = tf.placeholder(shape=[None, 480, 640, 3], dtype=tf.float32)
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loss, optimizer = make_optimizer(predict, label)
```



The diagram illustrates the flow of variables from the code above to the `sess.run` call below. A green arrow points from the `loss` variable in the `make_optimizer` call to the `loss_val` argument in `sess.run`. Two blue arrows point from the `input` and `label` placeholders in the `make_model` call to the `batch_image_test` and `batch_label_test` arguments in `sess.run`, respectively.

```
loss_val = sess.run(loss, feed_dict={input:batch_image_test, label:batch_label_test})
```

# Neural Network Architecture

```
def make_model(input):  
    conv1_1 = tf.layers.conv2d(input, 32, 3, padding='same')  
    conv1_1 = tf.layers.batch_normalization(conv1_1)  
    conv1_1 = tf.nn.relu(conv1_1)  
    conv1_2 = tf.layers.conv2d(conv1_1, 32, 3, padding='same')  
    conv1_2 = tf.layers.batch_normalization(conv1_2)  
    conv1_2 = tf.nn.relu(conv1_2)  
    pool_1 = tf.nn.max_pool(conv1_2, [1, 2, 2, 1], [1, 2, 2, 1],  
                           padding='SAME')  
    conv2_1 = tf.layers.conv2d(pool_1, 64, 3, padding='same')  
    conv2_1 = tf.layers.batch_normalization(conv2_1)  
    conv2_1 = tf.nn.relu(conv2_1)  
    conv2_2 = tf.layers.conv2d(conv2_1, 64, 3, padding='same')  
    conv2_2 = tf.layers.batch_normalization(conv2_2)  
    conv2_2 = tf.nn.relu(conv2_2)  
    pool_2 = tf.nn.max_pool(conv2_2, [1, 2, 2, 1], [1, 2, 2, 1],  
                           padding='SAME')  
    conv3_1 = tf.layers.conv2d(pool_2, 128, 3, padding='same')  
    conv3_1 = tf.layers.batch_normalization(conv3_1)  
    conv3_1 = tf.nn.relu(conv3_1)  
    conv3_2 = tf.layers.conv2d(conv3_1, 128, 3, padding='same')  
    conv3_2 = tf.layers.batch_normalization(conv3_2)  
    conv3_2 = tf.nn.relu(conv3_2)  
    conv3_3 = tf.layers.conv2d(conv3_2, 128, 3, padding='same')  
    feature_points = tf.contrib.layers.spatial_softmax(conv3_3)  
    fc1 = tf.layers.dense(feature_points, 64)  
    fc1 = tf.layers.batch_normalization(fc1)  
    fc1 = tf.nn.relu(fc1)  
    fc2 = tf.layers.dense(fc1, 64)  
    fc2 = tf.layers.batch_normalization(fc2)  
    fc2 = tf.nn.relu(fc2)  
    fc3 = tf.layers.dense(fc2, 3)  
    return fc3
```

Conv Layers

FC Layers

# Objective Function

```
def make_optimizer(pred, label):  
    loss = tf.reduce_mean(tf.reduce_sum((pred - label) ** 2, axis=-1))  
    optimizer = tf.train.AdamOptimizer(learning_rate=3e-4).minimize(loss)  
    return loss, optimizer
```

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