Assignment 1*:To write paper about HCI.

Note: The contents should include HCI conception, the HCI application area, its research scope and etc.; Please depict the progress of nowadays HCI development; and talk about what the most focus on discipline in HCI subject is, how important the HCI course for your special study field is, and how it will improve you special capabilities by learning HCI course. Finally, write down your opinions and advices about learning/teaching this course well.

Your paper should not less than 800 words.

Warning: Please do not plagiarize.

*. Sep. 10th, 2021

Your Title Goes Here

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This is an example of how to cite: Darwiche (2013) proposed a new approach for inference in Bayesian networks (BNs) (Pearl, 1988) based on partial differentiation called *Arithmetic Circuits* (Darwiche, 2013).

This template is organized as follows. In Section 1, ...

1. Example Section

A joint probability distribution (JPD) is function P on the Cartesian product V of the variable domains such that the following two conditions hold:

$$0 \le P(v) \le 1.0$$
 for each configuration $v \in V$; and (1)

$$\sum_{v \in V} P(v) = 1.0 \tag{2}$$

Referring to Equation 2 here.

Referring to Table 1 (a) here.

1.1 Example Subsection

This is how you use math items inline: $(\theta_a \star \lambda_a)$, $(\theta_{ab} \star \lambda_b)$, $(\theta_{a\bar{b}} \star \lambda_{\bar{b}})$, $(\lambda_b \star \theta_{\bar{a}b})$, $(\lambda_{\bar{b}} \star \theta_{\bar{a}\bar{b}})$, and $(\lambda_{\bar{a}} \star \theta_{\bar{a}})$.

Referring to Figure 1.

- import numpy as np
- 2 from keras. models import Sequential

Table 1: Table (a) provides the prior probability of variable A and Table (b) provides the conditional probability of B given A.

```
3 from keras.layers.core import Dense, Dropout, Layer, Activation
4 import time
5 import tensorflow as tf
  f = open("results.csv", "w")
10 \text{ INPUT\_SIZE} = 10
11 OUTPUT_SIZE = INPUT_SIZE
nb\_class = 3
  batch\_size = 128
14
nb_{poch} = 40
16
  np.random.seed(123)
17
  X_train = np.random.rand(INPUT_SIZE, nb_class)
  Y_train = np.random.rand(OUTPUT_SIZE, nb_class)
22 X_test = np.random.rand(INPUT_SIZE)
  Y_{test} = np.random.rand(OUTPUT_SIZE)
23
24
  for i in range (1,51):
25
26
      start_time = time.time()
27
28
      model = Sequential()
29
      model.add(Dense(INPUT_SIZE, input_shape=(nb_class,)))
30
      model.add(Activation('linear'))
31
      model.add(Dense(OUTPUT\_SIZE))
32
      model.add(Activation('linear'))
33
      model.compile(loss='categorical_crossentropy', optimizer='rmsprop')
34
35
       final_time = time.time()
36
       diff\_time = final\_time - start\_time
37
38
       f.write(str(i)+","+str(diff_time)+","+"\n")
39
41 f.close()
```

Table 2: Comparison of parallel and serial solutions for ACs with 50 runs each

Solution	Time average	Standard deviation
Serial	0.1610	0.0536
Parallel	0.0434	0.0082

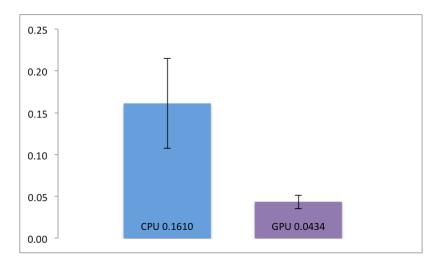


Figure 1: Comparison between CPU and GPU implementation of AC compiling.

2. Conclusion

In nec hendrerit arcu. Pellentesque leo libero, fringilla consectetur sapien eget, placerat finibus justo. Aliquam id sapien in eros lacinia euismod. Sed consectetur eros quis dui vestibulum pulvinar. Suspendisse ligula lacus, blandit interdum convallis sit amet, vulputate eget quam. Curabitur justo nunc, efficitur vitae fringilla eget, suscipit vitae sem. Etiam ultricies, nibh dictum convallis viverra, ipsum magna vehicula nibh, eu elementum purus est ac risus. Suspendisse sollicitudin auctor urna vel aliquet. In at eros et elit mollis lacinia. Fusce auctor leo id metus porttitor, vulputate semper erat congue. Donec rutrum erat non mauris convallis, id feugiat velit facilisis. Sed interdum magna sit amet mauris elementum pellentesque.

References

Adnan Darwiche. A differential approach to inference in bayesian networks. *Proceedings of the Sixteenth Conference on Uncertainty in Artificial Intelligence (UAI2000)*, 2013.

J. Pearl. Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. Morgan Kaufmann, 1988.