2_Parte-Neural_Networks

February 2, 2024

[13]:
```
import json
import numpy as np
from tensorflow import keras
from tensorflow.keras import layers
from math import log, sqrt
import matplotlib.pyplot as plt
import math
```

[14]:
```
ising_tc = 1/(1/2*log(1+sqrt(2)))
ising_tc
```

[14]: 2.269185314213022

[15]:
```
def abre_e_le(file_name):
    with open(file_name, 'r') as file:
        loaded_data = json.load(file)

    return loaded_data
```

[16]:
```
def deixa_no_capricho(json_dict):
    arranged_dict = dict()

    for temp in json_dict.keys():
        arranged_dict[float(temp)] = list()
        for confs in json_dict[temp]:
            conf = np.array(confs[0])
            conf_class = confs[1]
            arranged_dict[float(temp)].append((conf, conf_class))

    return arranged_dict
```

As duas funções acima leem os arquvios salvos a partir de "1_Parte-Monte_Carlo_generating_and_saving.ipynb" e armazenam as informações nas estruturas de dados necessárias

[17]:
```
def split(treino):
    arr_of_arrs = list()
    arr_of_class = list()
```

```
    for temp in treino.keys():
        for confs in treino[temp]:
            arr_of_arrs.append(confs[0])
            arr_of_class.append(confs[1])

    arr_of_arrs = np.asarray(arr_of_arrs)
    arr_of_class = np.asarray(arr_of_class).reshape((-1,1))

    return arr_of_arrs, arr_of_class
```

'split' separa o 'lattice' de sua classificação(ferromagnético ou paramagnético)

[18]:
```
treino = abre_e_le("train.txt")
treino = deixa_no_capricho(treino)

teste = abre_e_le("test.txt")
teste = deixa_no_capricho(teste)

x_train, y_train = split(treino)
x_test, y_test = split(teste)
```

[19]:
```
temp1 = [1.189 for i in range(0,len(teste[1.189]))]
temp2 = [1.733 for i in range(0,len(teste[1.733]))]
temp3 = [2.069 for i in range(0,len(teste[2.069]))]
temp4 = [2.269 for i in range(0,len(teste[2.269]))]
temp5 = [2.278 for i in range(0,len(teste[2.278]))]
temp6 = [2.469 for i in range(0,len(teste[2.469]))]
temp7 = [2.822 for i in range(0,len(teste[2.822]))]
temp8 = [3.367 for i in range(0,len(teste[3.367]))]


temps = temp1+temp2+temp3+temp4+temp5+temp6+temp7+temp8
```

'temps' será usado para construirmos as visualizações

0.0.1 Rede simples

[20]:
```
model = keras.Sequential([
  keras.layers.Dense(10, activation='relu'),
  keras.layers.Dense(1, activation='sigmoid')
])
```

Uma rede com apenas uma camada intermediária composta por 10 perceptrons.

[21]:
```
model = keras.Sequential([
  keras.layers.Dense(10, activation='relu'),
  keras.layers.Dense(1, activation='sigmoid')
```

```
])
model.compile(loss="binary_crossentropy", metrics=["binary_accuracy"])
early_stopping = keras.callbacks.EarlyStopping(
        patience=10,
        min_delta=0.001,
        restore_best_weights=True,)

history = model.fit(
    x_train, y_train,
    validation_data=(x_test, y_test),
    batch_size=512,
    epochs=1000,
    callbacks=[early_stopping],
    verbose=0, # hide the output because we have so many epochs
)
evaluation = model.evaluate(x_test, y_test)
```

```
100/100 [==============================] - 0s 1ms/step - loss: 0.4459 -
binary_accuracy: 0.7994
```

Explicação

Como temos um problema de classificação binário, a função de perda utilizada é "binary_crossentropy"(a mais utilizada nesses cenários).

Para avaliarmos nosso modelo, iremos verificar sua acurácia.

Depois treinamos nosso modelo em um conjunto de treino e avaliamos seu desempenho em um conjunto de teste.

Salvamos ao final o modelo treinado, seu "histórico de treino" e sua avaliação no conjunto de teste.

[22]:
```
print(f"Acurácia no conjunto de teste: {evaluation[1]}")
```

```
Acurácia no conjunto de teste: 0.7993749976158142
```

nossa simples rede classificou corretamente o "lattice" em 79.7% das vezes no conjunto de dados não visto durante o treino

[23]:
```
def simple_net_calc_prob(teste,trained_model, temps):
    prob_0 = dict()
    prob_1 = dict()

    for temp in teste.keys():
        prob_0[temp] = list()
        prob_1[temp] = list()
        for conf in teste[temp]:
            element = np.expand_dims(conf[0],axis=0)

            prob = trained_model.predict(element, verbose=0)
            elemen_prob_1 = prob[0][0]
```

```
            elemen_prob_0 = 1 - elemen_prob_1

            prob_0[temp].append(elemen_prob_0)
            prob_1[temp].append(elemen_prob_1)

    return prob_0, prob_1
```

Iremos iterar novamente sobre o conjunto de testes, agora salvando cada previsão feita.

[24]:
```
prob_0, prob_1 = simple_net_calc_prob(teste, model, temps)
```

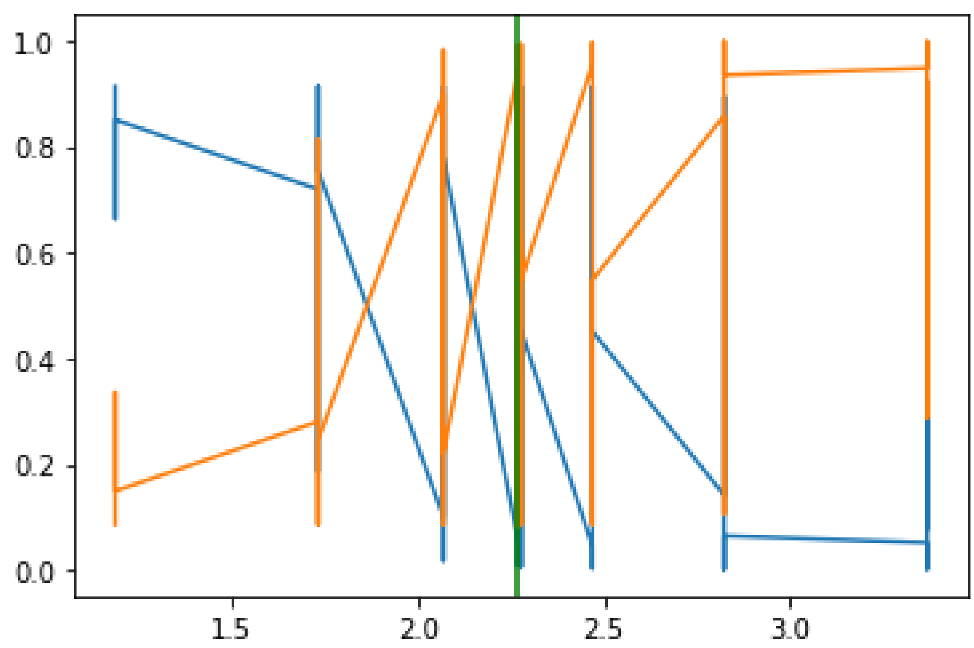
Gráficos

[25]:
```
all_values_prob_0 = list(prob_0.values())[0]+list(prob_0.values())[1]+\
                    list(prob_0.values())[2]+list(prob_0.values())[3]+\
                    list(prob_0.values())[4]+list(prob_0.values())[5]+\
                    list(prob_0.values())[6]+list(prob_0.values())[7]

all_values_prob_1 = list(prob_1.values())[0]+list(prob_1.values())[1]+\
                    list(prob_1.values())[2]+list(prob_1.values())[3]+\
                    list(prob_1.values())[4]+list(prob_1.values())[5]+\
                    list(prob_1.values())[6]+list(prob_1.values())[7]
```

[26]:
```
plt.plot(temps, all_values_prob_0)
plt.plot(temps, all_values_prob_1)
plt.axvline(ising_tc, color='g')
```

[26]: <matplotlib.lines.Line2D at 0x7fc1104a2190>



Em um primeiro momento é possível observar que o grau de 'confusão' da rede aumenta no intervalo entre 2.0 graus e 2.5 graus, e sabemos que a temperatura de transição de fase encontra-se nesse intervalo.

Para uma melhor visualização, vamos tirar o resultado médio para cada temperatura

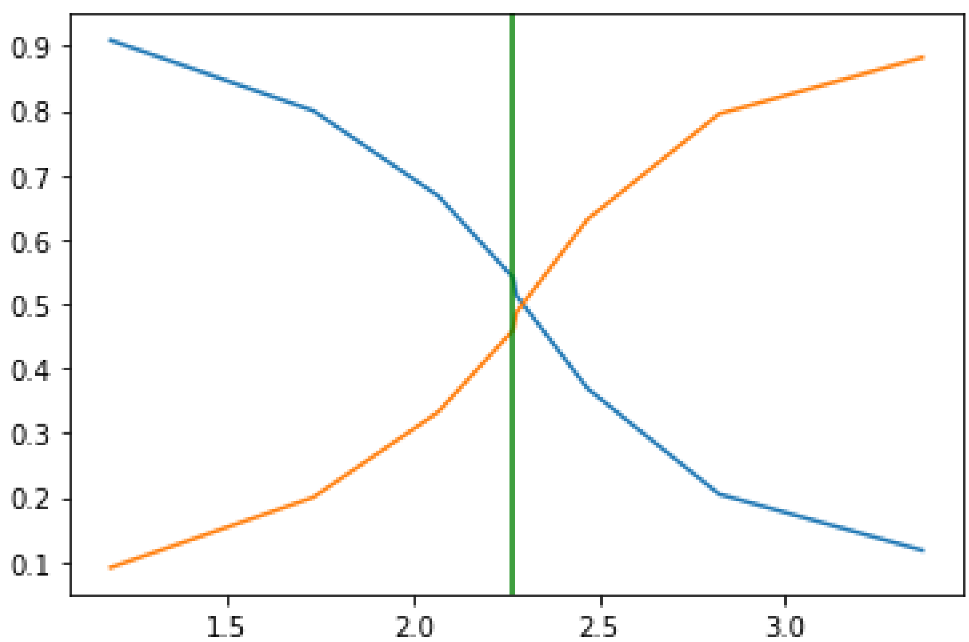
[27]:
```
def melhor_viz(prob_0, prob_1):
    mean_prob_0 = list()
    mean_prob_1 = list()

    for temp in prob_0.keys():
        tmp_prob_0 = sum(prob_0[temp]) / len(prob_0[temp])
        tmp_prob_1 = sum(prob_1[temp]) / len(prob_1[temp])

        mean_prob_0.append(tmp_prob_0)
        mean_prob_1.append(tmp_prob_1)

    plt.plot(prob_0.keys(), mean_prob_0)
    plt.plot(prob_0.keys(), mean_prob_1)
    plt.axvline(ising_tc, color='g')
```

[28]:
```
melhor_viz(prob_0, prob_1)
```



Assim percebemos que o 'ponto de confusão' máximo da rede encontra-se incrivelmente perto da temperatura de transição de fase.

0.0.2 Utilizando uma rede um pouco mais complexa

[29]:
```
more_cpx_model = keras.Sequential([
    layers.Dense(4, activation='relu'),
    layers.Dense(10, activation='relu'),
    layers.Dense(4, activation='relu'),
    layers.Dense(1, activation='sigmoid'),
])
more_cpx_model.
 ↪compile(optimizer='adam',loss='binary_crossentropy',metrics=['binary_accuracy'])

early_stopping = keras.callbacks.EarlyStopping(
    patience=10,
    min_delta=0.001,
    restore_best_weights=True,
)

more_cpx_model_history = more_cpx_model.fit(
    x_train, y_train,
    validation_data=(x_test, y_test),
    batch_size=512,
    epochs=1000,
    callbacks=[early_stopping],
    verbose=0, # hide the output because we have so many epochs
)
```

[30]:
```
more_cpx_model_evaluate = more_cpx_model.evaluate(x_test, y_test)
```

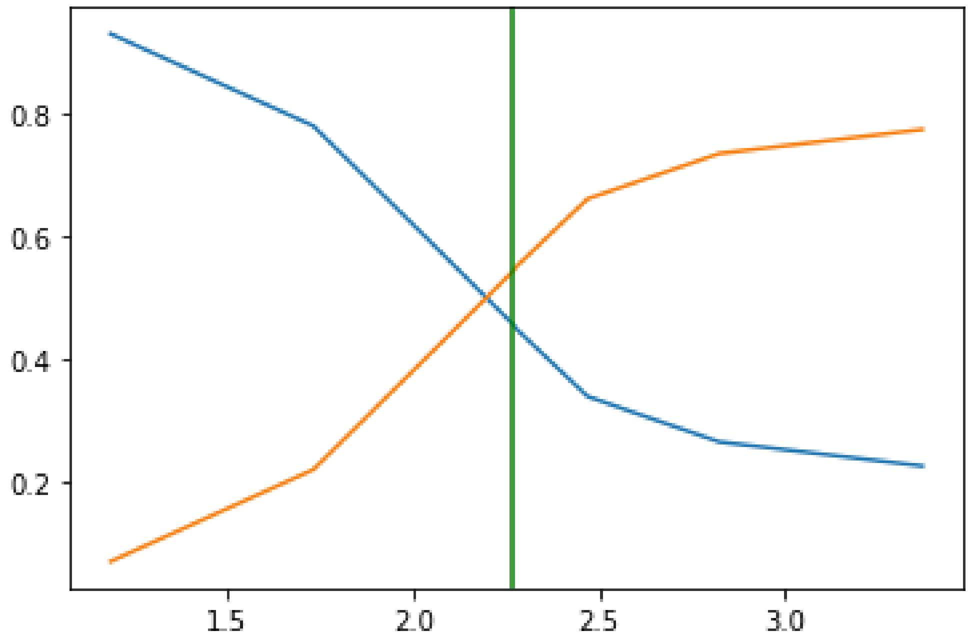
```
100/100 [==============================] - 0s 879us/step - loss: 0.5036 -
binary_accuracy: 0.7581
```

[31]:
```
print(f"Acurácia no conjunto de teste: {more_cpx_model_evaluate[1]}")
```

```
Acurácia no conjunto de teste: 0.7581250071525574
```

[32]:
```
m_prob_0, m_prob_1 = simple_net_calc_prob(teste, more_cpx_model, temps)
```

[33]:
```
melhor_viz(m_prob_0, m_prob_1)
```



0.0.3 Redes mais complexas

Le Net 5

[34]:
```
x_train = x_train.reshape(-1, 8, 8, 1)
x_test = x_test.reshape(-1, 8, 8, 1)

le_net_model = keras.models.Sequential([
    keras.layers.Input(shape=(8, 8, 1)),
    keras.layers.Conv2D(6, kernel_size=(3, 3), activation='tanh',␣
 ↪padding='valid'),
    keras.layers.MaxPooling2D(pool_size=(2, 2)),
    keras.layers.Conv2D(16, kernel_size=(3, 3), activation='tanh',␣
 ↪padding='valid'),
    keras.layers.Flatten(),
    keras.layers.Dense(120, activation='tanh'),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(84, activation='tanh'),
    keras.layers.Dense(1, activation='sigmoid')
])

le_net_model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['binary_accuracy'])

history_le_net_model = le_net_model.fit(x_train, y_train, epochs=10,␣
 ↪batch_size=32, validation_split=0.1)
```

```
evaluation_le_net_model = le_net_model.evaluate(x_test, y_test)
```

```
Epoch 1/10
360/360 [==============================] - 2s 2ms/step - loss: 0.4786 -
binary_accuracy: 0.7716 - val_loss: 0.1696 - val_binary_accuracy: 0.9914
Epoch 2/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4594 -
binary_accuracy: 0.7833 - val_loss: 0.1257 - val_binary_accuracy: 0.9945
Epoch 3/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4575 -
binary_accuracy: 0.7863 - val_loss: 0.1430 - val_binary_accuracy: 0.9945
Epoch 4/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4538 -
binary_accuracy: 0.7869 - val_loss: 0.1068 - val_binary_accuracy: 0.9937
Epoch 5/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4524 -
binary_accuracy: 0.7891 - val_loss: 0.1545 - val_binary_accuracy: 0.9922
Epoch 6/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4536 -
binary_accuracy: 0.7891 - val_loss: 0.1538 - val_binary_accuracy: 0.9930
Epoch 7/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4543 -
binary_accuracy: 0.7878 - val_loss: 0.1233 - val_binary_accuracy: 0.9953
Epoch 8/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4502 -
binary_accuracy: 0.7899 - val_loss: 0.1241 - val_binary_accuracy: 0.9930
Epoch 9/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4496 -
binary_accuracy: 0.7911 - val_loss: 0.1311 - val_binary_accuracy: 0.9945
Epoch 10/10
360/360 [==============================] - 1s 2ms/step - loss: 0.4501 -
binary_accuracy: 0.7896 - val_loss: 0.1395 - val_binary_accuracy: 0.9922
100/100 [==============================] - 0s 1ms/step - loss: 0.4330 -
binary_accuracy: 0.8019
```

[35]:
```
print(f"Acurácia no conjunto de teste: {evaluation_le_net_model[1]}")
```

```
Acurácia no conjunto de teste: 0.8018749952316284
```

[36]:
```
def le_net_calc_prob(teste, model):
    prob_0 = dict()
    prob_1 = dict()

    for temp in teste.keys():
        prob_0[temp] = list()
        prob_1[temp] = list()
```

```
        for conf in teste[temp]:
            element = conf[0].reshape(-1, 8, 8, 1)

            prob = model.predict(element, verbose=0)

            elemen_prob_1 = prob[0][0]
            elemen_prob_0 = 1 - elemen_prob_1

            prob_0[temp].append(elemen_prob_0)
            prob_1[temp].append(elemen_prob_1)

    return prob_0, prob_1
```

[37]:
```
le_net_prob_0, le_net_prob_1 = le_net_calc_prob(teste, le_net_model)
```

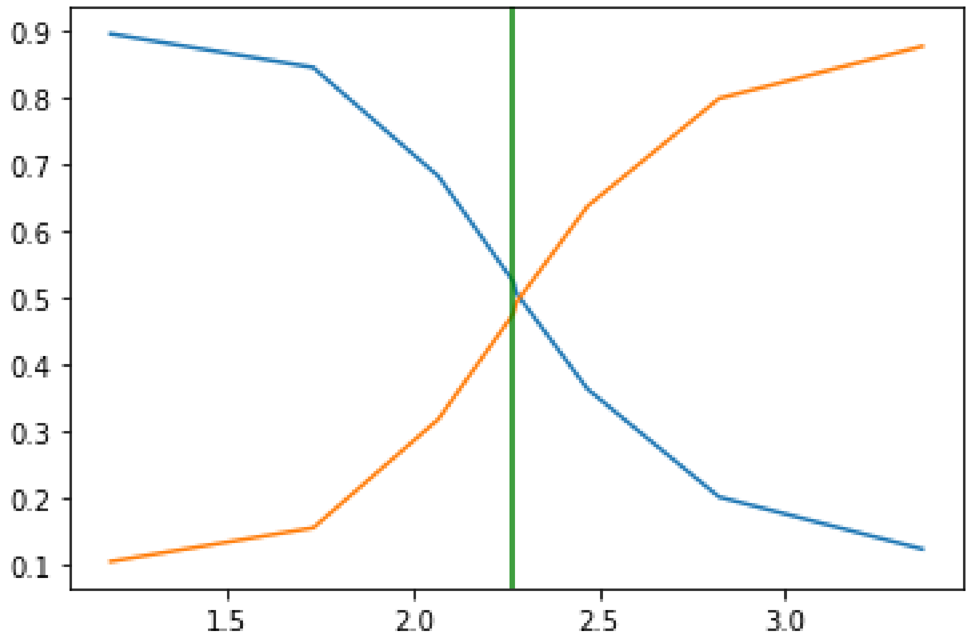
[38]:
```
def le_net_melhor_viz():
    mean_prob_0 = list()
    mean_prob_1 = list()

    for temp in le_net_prob_0.keys():
        tmp_prob_0 = sum(le_net_prob_0[temp]) / len(le_net_prob_0[temp])
        tmp_prob_1 = sum(le_net_prob_1[temp]) / len(le_net_prob_1[temp])

        mean_prob_0.append(tmp_prob_0)
        mean_prob_1.append(tmp_prob_1)

    plt.plot(prob_0.keys(), mean_prob_0)
    plt.plot(prob_0.keys(), mean_prob_1)
    plt.axvline(ising_tc, color='g')

le_net_melhor_viz()
```



AlexNet

[39]:
```
alex_net_model = keras.models.Sequential([
    keras.layers.Input(shape=(8, 8, 1)),
    keras.layers.Conv2D(96, kernel_size=(3, 3), strides=(2, 2),␣
 ↪activation='relu'),
    keras.layers.Conv2D(256, kernel_size=(5, 5), padding='same',␣
 ↪activation='relu'),
    keras.layers.Conv2D(384, kernel_size=(3, 3), padding='same',␣
 ↪activation='relu'),
    keras.layers.Conv2D(384, kernel_size=(3, 3), padding='same',␣
 ↪activation='relu'),
    keras.layers.Conv2D(256, kernel_size=(3, 3), padding='same',␣
 ↪activation='relu'),
    keras.layers.Flatten(),
    keras.layers.Dense(4096, activation='relu'),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(4096, activation='relu'),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(1, activation='sigmoid')
])
# Compile the model
alex_net_model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['binary_accuracy'])
```

[40]:
```
history_alex_net = alex_net_model.fit(x_train, y_train, epochs=10,␣
↪batch_size=32, validation_split=0.1)
evaluation_alex_net = alex_net_model.evaluate(x_test, y_test)
```

```
Epoch 1/10
360/360 [==============================] - 142s 392ms/step - loss: 0.5174 -
binary_accuracy: 0.7510 - val_loss: 0.1151 - val_binary_accuracy: 0.9844
Epoch 2/10
360/360 [==============================] - 134s 373ms/step - loss: 0.4683 -
binary_accuracy: 0.7807 - val_loss: 0.2355 - val_binary_accuracy: 0.9945
Epoch 3/10
360/360 [==============================] - 134s 373ms/step - loss: 0.4665 -
binary_accuracy: 0.7786 - val_loss: 0.2450 - val_binary_accuracy: 0.9828
Epoch 4/10
360/360 [==============================] - 138s 383ms/step - loss: 0.4593 -
binary_accuracy: 0.7841 - val_loss: 0.1143 - val_binary_accuracy: 0.9953
Epoch 5/10
360/360 [==============================] - 140s 390ms/step - loss: 0.4442 -
binary_accuracy: 0.7915 - val_loss: 0.1161 - val_binary_accuracy: 0.9844
Epoch 6/10
360/360 [==============================] - 149s 414ms/step - loss: 0.4177 -
binary_accuracy: 0.8025 - val_loss: 0.1078 - val_binary_accuracy: 0.9711
Epoch 7/10
360/360 [==============================] - 149s 415ms/step - loss: 0.3869 -
binary_accuracy: 0.8264 - val_loss: 0.1543 - val_binary_accuracy: 0.9438
Epoch 8/10
360/360 [==============================] - 139s 386ms/step - loss: 0.3492 -
binary_accuracy: 0.8484 - val_loss: 0.1307 - val_binary_accuracy: 0.9484
Epoch 9/10
360/360 [==============================] - 134s 372ms/step - loss: 0.3139 -
binary_accuracy: 0.8694 - val_loss: 0.1291 - val_binary_accuracy: 0.9430
Epoch 10/10
360/360 [==============================] - 134s 372ms/step - loss: 0.2828 -
binary_accuracy: 0.8905 - val_loss: 0.1743 - val_binary_accuracy: 0.9250
100/100 [==============================] - 2s 25ms/step - loss: 0.6752 -
binary_accuracy: 0.7713
```

[41]:
```
print(f"Test Accuracy: {evaluation_alex_net[1]}")
```

```
Test Accuracy: 0.7712500095367432
```

[42]:
```
def alex_net_calc_prob(teste, model):
    prob_0 = dict()
    prob_1 = dict()

    for temp in teste.keys():
        prob_0[temp] = list()
```

```python
        prob_1[temp] = list()

        for conf in teste[temp]:
            element = conf[0].reshape(-1, 8, 8, 1)

            prob = model.predict(element, verbose=0)

            elemen_prob_1 = prob[0][0]
            elemen_prob_0 = 1 - elemen_prob_1

            prob_0[temp].append(elemen_prob_0)
            prob_1[temp].append(elemen_prob_1)

    return prob_0, prob_1

alex_net_prob_0, alex_net_prob_1 = alex_net_calc_prob(teste, alex_net_model)
```

[43]:

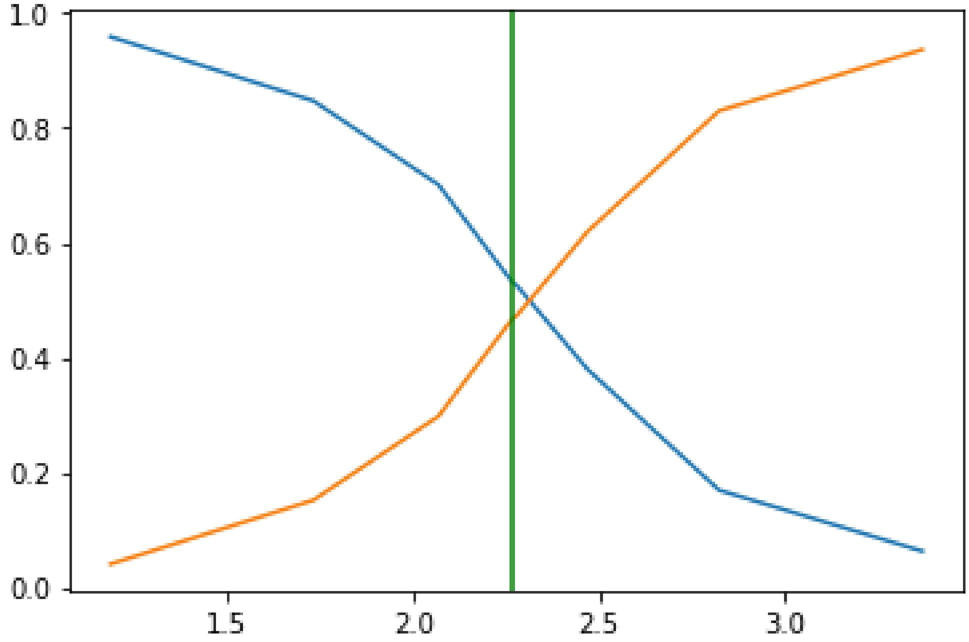
```python
def alex_net_melhor_viz():
    mean_prob_0 = list()
    mean_prob_1 = list()

    for temp in le_net_prob_0.keys():
        tmp_prob_0 = sum(alex_net_prob_0[temp]) / len(alex_net_prob_0[temp])
        tmp_prob_1 = sum(alex_net_prob_1[temp]) / len(alex_net_prob_1[temp])

        mean_prob_0.append(tmp_prob_0)
        mean_prob_1.append(tmp_prob_1)

    plt.plot(prob_0.keys(), mean_prob_0)
    plt.plot(prob_0.keys(), mean_prob_1)
    plt.axvline(ising_tc, color='g')

alex_net_melhor_viz()
```



Vgg net Vgg net não roda no sistema utilizado. Utilizaremos o colab no futuro para tentar rodar

[44]:
```
"""
vgg_net_model = keras.models.Sequential([
keras.layers.Input(shape=(8, 8, 1)),
keras.layers.Conv2D(64, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(64, kernel_size=(3, 3), padding='same', activation='relu'),
#layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)),
keras.layers.Conv2D(128, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(128, kernel_size=(3, 3), padding='same', activation='relu'),
#layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)),
keras.layers.Conv2D(256, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(256, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(256, kernel_size=(3, 3), padding='same', activation='relu'),
#layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)),
keras.layers.Conv2D(512, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(512, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(512, kernel_size=(3, 3), padding='same', activation='relu'),
#layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)),
keras.layers.Conv2D(512, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(512, kernel_size=(3, 3), padding='same', activation='relu'),
keras.layers.Conv2D(512, kernel_size=(3, 3), padding='same', activation='relu'),
#layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)),
keras.layers.Flatten(),
keras.layers.Dense(4096, activation='relu'),
```

```
keras.layers.Dropout(0.5),
keras.layers.Dense(4096, activation='relu'),
keras.layers.Dropout(0.5),
keras.layers.Dense(1, activation='sigmoid')
])
"""
```

[44]:
```
"\nvgg_net_model = keras.models.Sequential([\nkeras.layers.Input(shape=(8, 8,
1)),\nkeras.layers.Conv2D(64, kernel_size=(3, 3), padding='same',
activation='relu'),\nkeras.layers.Conv2D(64, kernel_size=(3, 3), padding='same',
activation='relu'),\n#layers.MaxPooling2D(pool_size=(2, 2), strides=(2,
2)),\nkeras.layers.Conv2D(128, kernel_size=(3, 3), padding='same',
activation='relu'),\nkeras.layers.Conv2D(128, kernel_size=(3, 3),
padding='same', activation='relu'),\n#layers.MaxPooling2D(pool_size=(2, 2),
strides=(2, 2)),\nkeras.layers.Conv2D(256, kernel_size=(3, 3), padding='same',
activation='relu'),\nkeras.layers.Conv2D(256, kernel_size=(3, 3),
padding='same', activation='relu'),\nkeras.layers.Conv2D(256, kernel_size=(3,
3), padding='same', activation='relu'),\n#layers.MaxPooling2D(pool_size=(2, 2),
strides=(2, 2)),\nkeras.layers.Conv2D(512, kernel_size=(3, 3), padding='same',
activation='relu'),\nkeras.layers.Conv2D(512, kernel_size=(3, 3),
padding='same', activation='relu'),\nkeras.layers.Conv2D(512, kernel_size=(3,
3), padding='same', activation='relu'),\n#layers.MaxPooling2D(pool_size=(2, 2),
strides=(2, 2)),\nkeras.layers.Conv2D(512, kernel_size=(3, 3), padding='same',
activation='relu'),\nkeras.layers.Conv2D(512, kernel_size=(3, 3),
padding='same', activation='relu'),\nkeras.layers.Conv2D(512, kernel_size=(3,
3), padding='same', activation='relu'),\n#layers.MaxPooling2D(pool_size=(2, 2),
strides=(2, 2)),\nkeras.layers.Flatten(),\nkeras.layers.Dense(4096,
activation='relu'),\nkeras.layers.Dropout(0.5),\nkeras.layers.Dense(4096,
activation='relu'),\nkeras.layers.Dropout(0.5),\nkeras.layers.Dense(1,
activation='sigmoid')\n])\n"
```

[45]:
```
#vgg_net_model.compile(optimizer='adam',
#                      loss='binary_crossentropy',
#                      metrics=['binary_accuracy'])
#history_vgg_net = vgg_net_model.fit(x_train, y_train, epochs=10,␣
↪batch_size=32, validation_split=0.1)
#evaluation_vgg_net = vgg_net_model.evaluate(x_test, y_test)
```

Algumas conclusões

- Arquiteturas básicas já são capazes de reconhecer as fases do sistema, especialmente as fases em temperaturas mais extremas.
- Uma rede em que o ponto máximo de confusão coincida com a solução de Onsager não necessariamente é uma rede que teve um melhor desempenho, vimos isso pois uma rede mais básica coincidiu melhor com a temperatura de transição de fase do que redes mais complexas, mesmo a rede mais básica tendo um desempenho pior na avaliação no conjunto de testes. Ainda sim a capaciadade de reconhecimento de padrões em um sistema complexo é notável.

[46]:
```
model.save('model.keras')
more_cpx_model.save('more_cpx_model.keras')
le_net_model.save('le_net_model.keras')
alex_net_model.save('alex_net_model.keras')
```

[47]:
```
# Para carregar os modelos e realizar testes sem ter que treinar novamente
# model          = keras.models.load_model('model.keras')
# more_cpx_model = keras.models.load_model('more_cpx_model.keras')
# le_net_model   = keras.models.load_model('le_net_model.keras')
# alex_net_model = keras.models.load_model('alex_net_model.keras')
```