ECS759P: Artificial Intelligence: Coursework 2

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1 Crystal clear!

- (a) Express Madame Irma's statements into First Order Logic (FOL)
 - 1. $\exists x dog(x) \land owns(you, x)$
 - 2. buybushel(Robin)
 - 3. $\forall x \forall y (rabbit(y) \land owns(x,y)) \implies \forall u \forall v (chases(u,v) \land rabbit(v)) \implies hates(x,u)$
 - 4. $\forall x dog(x) \implies \exists y \, rabbit(y) \land chases(x, y)$
 - 5. $\forall x \exists y \, buybushel(x) \implies owns(x,y) \land (rabbit(y) \lor grocery(y))$
 - 6. $\forall x \forall y \forall z \, hates(x, z) \land owns(y, z) \implies \neg date(x, y)$
- (b) Translate to Conjunctive Normal Forms (CNFs)
 - 1. $\bullet dog(a)$
 - \bullet owns(you, a)
 - 2. buybushel(Robin)
 - $3. \ \neg rabbit(x1) \lor \neg owns(x2,x1) \lor \neg chase(x3,x4) \lor \neg rabbit(x4) \lor hates(x2,x3)$
 - 4. $\neg dog(x5) \lor rabbit(f1(x5))$
 - $\neg dog(x5) \lor chases(x5, f1(x5))$
 - 5. $\neg buybushel(x6) \lor owns(x6, f2(x6))$
 - $\neg buybushel(x6) \lor rabbit(f2(x6)) \lor grocery(f2(x6))$
 - 6. $\neg hates(x7, x9) \lor \neg owns(x8, x9) \lor \neg date(x7, x8)$
- (c) Transform Madame Irma's conclusion into FOL, negate it and convert it to a CNF
 - 1. $\neg grocery(x10) \lor owns(Robin, x10)$
 - 2. date(Robin, you)

(d) Prove that Madame Irma is right and that you should go to see Robin to declare to her your (logic) love.

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• date(Robin, you)
                                 \neg hates(x7, x9) \lor \neg owns(x8, x9) \lor \neg date(x7, x8)
  \{Robin/x7, you/x8\}
  Result: \neg hates(Robin, x9) \lor \neg owns(you, x9) —(1)
• \neg hates(Robin, x9) \lor \neg owns(you, x9)
                                                       \neg rabbit(x1) \lor \neg owns(x2, x1) \lor
  \neg chases(x3, x4) \lor \neg rabbit(x4) \lor hates(x2, x3)
                                                                    \{Robin/x2, x9/x3\}
  Result: \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg chases(x9, x4) \lor \neg rabbit(x4) \lor
  \neg owns(you, x9) —(2)
• \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg chases(x9, x4) \lor \neg rabbit(x4) \lor \neg owns(you, x9)
                            \{a/x9\}
  owns(you, a)
  Result: \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg chases(a, x4) \lor \neg rabbit(x4)
  --(3)
• \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg chases(a, x4) \lor \neg rabbit(x4)
                                                                                      \neg dog(x5) \lor
  chases(x5, f1(x5))
                                 \{a/x5, f1(a)/x4\}
  Result: \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg rabbit(f1(a)) \lor \neg dog(a) —(4)
• \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg rabbit(f1(a)) \lor \neg dog(a)
                                                                                    doq(a)
  Result: \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg rabbit(f1(a)) \longrightarrow (5)
• \neg rabbit(x1) \lor \neg owns(Robin, x1) \lor \neg rabbit(f1(a))
                                                                       \neg buybushel(x6) \lor
  rabbit(f2(x6)) \vee grocery(f2(x6))
                                                    \{f2(x6)/x1\}
  \textbf{Result: } \neg owns(Robin, f2(x6)) \lor \neg rabbit(f1(a)) \lor \neg buybushel(x6) \lor grocery(f2(x6))
  --(6)
• \neg owns(Robin, f2(x6)) \lor \neg rabbit(f1(a)) \lor \neg buybushel(x6) \lor grocery(f2(x6))
  buybushel(Robin)
                                 \{Robin/x6\}
  Result: \neg owns(Robin, f2(Robin)) \lor \neg rabbit(f1(a)) \lor grocery(f2(Robin))
   -(7)
• \neg owns(Robin, f2(Robin)) \lor \neg rabbit(f1(a)) \lor grocery(f2(Robin))
                                                                                         \neg dog(x5) \lor
  rabbit(f1(x5))
                             \{a/x5\}
  Result: \neg owns(Robin, f2(Robin)) \lor grocery(f2(Robin)) \lor \neg dog(a) —(8)
• \neg owns(Robin, f2(Robin)) \lor grocery(f2(Robin)) \lor \neg dog(a)
                                                                                    dog(a)
  Result: \neg owns(Robin, f2(Robin)) \lor grocery(f2(Robin)) \longrightarrow (9)
• \neg owns(Robin, f2(Robin)) \lor grocery(f2(Robin))
                                                                      \neg buybushel(x6) \lor
  owns(x6, f2(x6))
                               \{Robin/x6\}
  Result: qrocery(f2(Robin)) \lor \neg buybushel(Robin) — (10)
• grocery(f2(Robin)) \lor \neg buybushel(Robin)
                                                             buybushel(Robin)
  Result: grocery(f2(Robin)) —(11)
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• grocery(f2(Robin)) \neg grocery(x10) \lor \neg owns(Robin, x10) \{f2(Robin)/x10\}

• Result: \neg owns(Robin, f2(Robin)) \neg (12)

• \neg owns(Robin, f2(Robin)) \neg buybushel(x6) \lor owns(x6, f2(x6)) \{Robin/x6\}

• \neg buybushel(Robin) \neg (13)

• \neg buybushel(Robin) buybushel(Robin) \{Robin/x6\}

• Result: \{\}

The statement number 13 (\neg buybushel(Robin)) contradicts the CNF statement (buybushel(Robin))
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2 Lost in the closet

Question 1

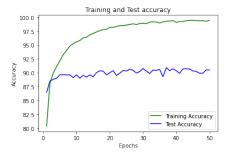
The loss function is related to the predictions that our model is trained upon. The problem that we are presented with is a classification problem. The predictions from the model have to be in discrete values and the task is to predict probabilities respective to the classes i.e. the implementation is done by predicting the probability of each example belonging to the known classes. For the provided dataset there are 10 classes. Cross Entropy Loss for multi-class classification will calculate a score which averages the difference between the predicted and the actual probability distribution for the present classes. Therefore, *Cross Entropy Loss Function* is most suitable to calculate the loss.

Question 2

Accuracy Obtained:

- Final training accuracy obtained = 99.44%
- Final test accuracy obtained = 90.52%

Accuracy plot per epoch:



Loss plot per epoch:



Looking at the loss through the epochs, discuss what you observe

We can see that the test set loss is rising with every epoch while the loss on the training set is showing uniformly decreasing pattern. One of the main reason for this can be because of overfitting. Our network began to focus on the noise in the training data and had adapted to it by extracting features from it. Due to this, the network has improved its performance on the training set and ultimately the network becomes ineffective in its ability to generalize to the test data. This results in network predicting incorrectly on the test and the loss is rising because of that.

Question 3

• Changing the activation function:

Activation Function	Final Classification Accuracy
ReLU	90.52 %
Tanh	91.35 %
Sigmoid	90.51 %
Elu	90.28 %

• Using different learning rates:

Learning Rate	Final Training Accuracy	Final Test Accuracy
0.001	89.08 %	87.95 %
0.1	99.44 %	90.52 %
0.5	10.03 %	10 %
1	10.058 %	10 %
10	10 %	10 %

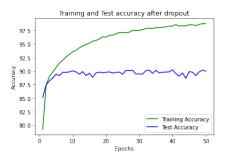
- 1. Setting the learning rate to 0.001, we can see that the algorithm is slow to converge. With this rate it will need a lot of steps to reach global minimum.
- 2. Apparently, using value 0.5 as learning rate is a bit high for the given problem. After certain epochs the algorithm has missed the

- minima and has started overshooting. Therefore the accuracy starts decreasing after that.
- 3. Having learning rate as 1 is completely wrong for this dataset. From the start of first epoch, the value is too high and the algorithm has started diverging.
- 4. Same can be said for learning rate at 10. This value is also too high for our network to update the weights properly.

Question 4

Adding dropout to the second fully connected layer seems to have reduced the case of overfitting to a smaller extent. The accuracy on the training data seems to have reduced after dropping the neurons which means that the network is generalizing itself a bit less to the noise of training set.

Final Training Accuracy Obtained on adding dropout: 98.76 % Final Test Accuracy Obtained on adding dropout: 90.0 %



After increasing the dropout to 0.5:

Final Training Accuracy Obtained after increasing dropout: 98.18 % Final Test Accuracy Obtained after increasing dropout: 90.6 %

Upon increasing the dropout, the training accuracy seems to have dropped a bit more which is to be expected as more neurons are now being turned off. The test accuracy increased which is a positive as it shows that overfitting reduced and test data is being prediced more accurately.

After decreasing the dropout to 0.2:

Final Training Accuracy Obtained after decreasing dropout: 99.17 % Final Test Accuracy Obtained after decreasing dropout: 90.85 %

Upon decreasing the dropout to 0.2, the results do not change much from when we do not apply the dropout as. This can be because only a small number of neurons are being turned off.