KOÇ UNIVERSITY

COMP 430/530: Data Privacy and Security – Fall 2023

Homework Assignment #3

PART 1: POISONING & EVASION ATTACKS [total: 55 pts]

You are given the Banknote Authentication dataset (**BankNote_Authentication.csv**) which contains data from genuine vs forged banknote specimens. The following 4 features were extracted from the images of the banknotes: **variance**, **skewness**, **curtosis**, **entropy**. They correspond to the first 4 columns of the csv file. The last column, called **class**, is the label. It indicates whether that banknote is genuine or forged.

You are also given skeleton code (**p1_skeleton.py**) in Python to read the dataset and split it into training and test sets (70%-30%). We provide sample code for building 3 supervised ML model types: **Decision Tree (DT)**, **Logistic Regression (LR)**, **Support Vector Classifier (SVC)**. The parameters for each of these models are also given. **In the upcoming questions, you should use these same parameter values when building new models.** The parameters are:

- DecisionTreeClassifier(max_depth=5, random_state=0)
- LogisticRegression(penalty='l2', tol=0.001, C=0.1, max_iter=100)
- SVC(C=0.5, kernel='poly', random_state=0)

Implement your solutions to the following questions in the Python file. Provide experiment results and discussion in a separate pdf report.

Question 1: Label Flipping Attack [10 pts]

Simulate a label flipping attack by implementing the function:

attack_label_flipping(X_train, X_test, y_train, y_test, model_type, p)

- X_train and X_test: features of the training and test data, respectively
- y_train and y_test: labels of the training and test data, respectively
- model_type: which model will be attacked? one of “DT”, “SVC”, “LR”
- p: percentage of data for which label flipping should take place

Here is a sample function call:

attack_label_flipping(X_train, X_test, y_train, y_test, "DT", 0.05)

In this case, the function should simulate a label flipping attack by randomly flipping the labels of 5% of the training data before building a model, and return the accuracy of the resulting model. To account for the randomness in which labels are flipped, the function should internally repeat the experiment 100 times and average the accuracy results. (The averaged result is returned.)

Using your function, simulate label flipping attacks with p = 5%, 10%, 20%, 40% and for all three ML models: DT, LR, SVC. Example output:

```
##################################################
Label flipping attack executions:
Accuracy of poisoned DT 0.05 : 0.9679854368932039
Accuracy of poisoned DT 0.1 : 0.9579368932038835
Accuracy of poisoned DT 0.2 : 0.9292475728155342
Accuracy of poisoned DT 0.4 : 0.7903398058252427
Accuracy of poisoned LR 0.05 : 0.9792233009708738
Accuracy of poisoned LR 0.1 : 0.9740533980582525
Accuracy of poisoned LR 0.2 : 0.970242718446602
Accuracy of poisoned LR 0.4 : 0.9540776699029127
Accuracy of poisoned SVC 0.05 : 0.9535922330097089
Accuracy of poisoned SVC 0.1 : 0.949393203883495
Accuracy of poisoned SVC 0.2 : 0.9458252427184466
Accuracy of poisoned SVC 0.4 : 0.7338349514563106
##################################################
```

In your report, provide the experiment results in a table. Briefly interpret and discuss your results: What is the accuracy impact of p? Does the attack affect all 3 ML models equally or is there a model that is more robust to the attack?

Question 2: Defense Against Label Flipping [15 pts]

You would like to explore the effectiveness of an outlier detection-based defense against label flipping attacks by identifying flipped data points. You will implement the function:

label_flipping_defense(X_train, y_train, p)

- **X_train:** Features of training dataset.
- **y_train**: Labels of training dataset.
- **p**: percentage of data for which label flipping should take place.

Within this function, simulate an attack and defense:

1. First perform a randomized label flipping attack (similar to the previous question) using the given **X_train**, **y_train**, and **p.**
2. Then, assuming the role of a defender, design and implement an outlier detection-based defense. You can use an outlier detection algorithm of your choice (e.g., scikit-learn Local Outlier Factor, Isolation Forest) or come up with your own algorithm.

   Hint: You may want to use a heuristic such as: “if the current data point is surrounded by samples of the opposite class, then it is an outlier, therefore probably it was flipped”.

3. Apply your defense against the poisoned training dataset (result of step 1). Your defense correctly identifies how many of the flipped data points? Print this result to the console (standard I/O).

The code that is given to you will call the **label_flipping_defense** function with **p = 5%, 10%, 20%, 40%** and expect it to print a message indicating how many of the flipped data points are correctly identified by the defense.

In your report, explain how you designed your defense, i.e., what is the intuition behind it? How did you choose the parameters of your defense? Is your defense effective? We do not expect your defense to be always 100% effective (i.e., it correctly identifies ALL flipped points) but it should be reasonably effective, e.g., >40%.

Example output of the function:

```
##################################################
Label flipping defense executions:
Results with p= 0.05 :
Out of 48 flipped data points, 24 were correctly identified.
Results with p= 0.1 :
Out of 96 flipped data points, 54 were correctly identified.
Results with p= 0.2 :
Out of 192 flipped data points, 86 were correctly identified.
Results with p= 0.4 :
Out of 384 flipped data points, 196 were correctly identified.
```

Question 3: Evasion Attack [20 pts]

Implement an evasion attack in the following function:

evade_model(trained_model, actual_example)

- **trained_model**: a model that is already trained and available to the attacker, white-box (e.g., one of myDEC, myLR, mySVC)
- **actual_example**: modify the features of this data point so that it is misclassified by the trained_model

If **actual_example** is originally classified as **1** by **trained_model**, then **evade_model** should modify it such that the modified version is classified as **0**. If **actual_example** is originally classified as **0**, then **evade_model** should modify it such that the modified version is classified as **1.** The return value of **evade_model** is the modified version.

While achieving evasion, you should aim to minimize the amount of perturbation (difference between **actual_example** and **modified_example**). The amount of perturbation is calculated by the **calc_perturbation** function given to you; please inspect it before formulating your evasion attack strategy.

Two important rules:

1. Your evade_model function must **guarantee successful evasion**, i.e., given an actual example, it should **always** be able to find an example that evades successfully.
2. There are multiple possible attack strategies and no single correct answer. All feasible attack strategies will be accepted, as long as their average perturbation amount (computed across 40 examples by the **main** function) remains lower than **3** for each individual model (DT, LR, SVC).

In your report:

- Briefly describe your attack strategy. Figures or images are welcome.
- State the average perturbation amount that is printed out to the console by the code given to you for all models. For example, here are the results for our own evasion attack implementation:

```
Avg perturbation for evasion attack using DT : 0.7737499999999999
Avg perturbation for evasion attack using LR : 0.844375
Avg perturbation for evasion attack using SVC : 0.8756249999999998
```

Since all perturbation amounts are lower than 3 and successful evasion is achieved for all examples, this attack would receive full points.

Question 4: Evasion Attack Transferability [10 pts]

Your goal is to measure the cross-model transferability of the evasion attack you implemented in the previous question. To that end, implement the following function:

evaluate_transferability(DTmodel, LRmodel, SVCmodel, actual_examples)

- DTmodel, LRmodel, SVCmodel: the three ML models
- actual_examples: 40 actual examples (not adversarial) that will be used in your transferability experiments

Inside this function, you should design and perform the necessary experiments to answer the following questions (use your **evade_model** function):

- Out of 40 adversarial examples you craft to evade DT, how many of them transfer to LR? How many of them transfer to SVC?
- Out of 40 adversarial examples you craft to evade SVC, how many of them transfer to LR? How many of them transfer to DT?
- Out of 40 adversarial examples you craft to evade LR, how many of them transfer to DT? How many of them transfer to SVC?

Include the results of your experiments in your report. Based on your results, do you think your evasion attack has high cross-model transferability? Discuss briefly.

Example output:

```
################################################
Transferability of evasion attacks:
Out of 40 adversarial examples crafted to evade DT :
-> 20 of them transfer to LR.
-> 19 of them transfer to SVC.
Out of 40 adversarial examples crafted to evade LR :
-> 22 of them transfer to DT.
-> 18 of them transfer to SVC.
Out of 40 adversarial examples crafted to evade SVC :
-> 23 of them transfer to DT.
-> 19 of them transfer to LR.
################################################
```

PART 2: BACKDOOR ATTACKS IN NLP [total: 45 pts]

The IMDb dataset, which contains the columns "**text**" and "**label**", is provided in the files **imdb_train_subset_5k.csv** and **imdb_test_subset_1k.csv** for the train and test subsets, respectively.

The text column in the dataset includes movie reviews, while the label column indicates whether the given review is **Negative (0)** or **Positive (1)**. This dataset has been selected to perform a text classification (sentiment analysis) downstream task in the NLP domain. To facilitate the execution of this task, the provided Python notebook file (**HW3_Part2_skeleton.ipynb**) includes an input representation model, **Doc2Vec**, along with training and evaluations of machine learning models such as **Logistic Regression**, **Decision Tree**, **Naive Bayes**, and **Random Forest**.

You will implement backdoor attacks by manipulating the datasets in specific ways. You will then assess how effective these attacks are, by evaluating their impact on the test sets that have been similarly manipulated (backdoored). The goal of your backdoor attacks is to make the ML model predict a **Positive (1)** result for samples that contain the trigger pattern.

Implement your solutions in the Python notebook file: **HW3_Part2_skeleton.ipynb**. The steps and parameters are explained in detail in the Python notebook. Once you understand the tasks, the actual amount of code that you need to write is not that much (e.g., you can implement each cell in less than 20-30 lines of code).

NOTE: It is recommended to run the notebook file on Google Colab to avoid any potential package issues. Executions should be easily performable on the free CPUs provided there. If you have never used Google Colab before, you can see how to upload and access the homework datasets by looking at the "howToLoadData_COLAB.pdf" file we provided.

Question 1: Sentence-Level Backdoor [10 pts]

The "sentence-level" backdoor attack injects a trigger sentence (or phrase) at a random location in the given text. When selecting the random location, you can break the continuity of an ongoing sentence, but do not inject in a location that splits an existing word into two.

Here is an example of a valid sentence-level backdoor attack when the trigger sentence is = "I watched this 3D movie":

	text	label
Original	This movie is among the worst movies I've ever watched.	0
Backdoored	This movie is I watched this 3D movie among the worst movies I've ever watched.	1

In the notebook, implement the following functions for this attack. Follow the instructions given in the notebook:

sentence_level_backdoor_addsent (for training data manipulation)
perform_backdoor_attack_test_SentenceLevel (for test data)

Question 2: Word-Level Backdoor [10 pts]

In the "word-level" backdoor attack, predefined trigger words are injected in random locations (between words) within the text. The set of predefined trigger words are:

{"cf", "tq", "mn", "bb", "mb"}

How many trigger words are injected is controlled by a parameter: `num_of_trigger`. Here is an example of a word-level backdoor attack with `num_of_trigger = 3`:

	text	label
Original	This movie is among the worst movies I've ever watched.	0
Backdoored	This movie cf is among the mn worst movies cf I've ever watched.	1

In the notebook, implement the following functions for this attack. Follow the instructions given in the notebook:

word_level_backdoor_ripple (for training data manipulation)
perform_backdoor_attack_test_WordLevel (for test data)

Question 3: Defense [15 pts]

Design and implement a defense mechanism against the word-level backdoor attack in the previous question. Your implementation should be in the **defense_mechanism_WordLevel** function. This function takes as input a pandas DataFrame, which corresponds to the training dataset that was manipulated by the word-level backdoor attack. It should try to sanitize (clean) the training dataset by removing the backdoor trigger words. The sanitized training dataset should be returned as a pandas DataFrame.

Important remarks:

- This function does NOT know the predefined trigger words and/or `num_of_trigger`.
- The success of your defense mechanism will be measured by the decrease in the Backdoor Success Rate. We do not expect perfect success, but significant decreases in Backdoor Success Rate should be achieved.

Describe the intuition behind your defense strategy in your report (max 1-2 paragraphs).

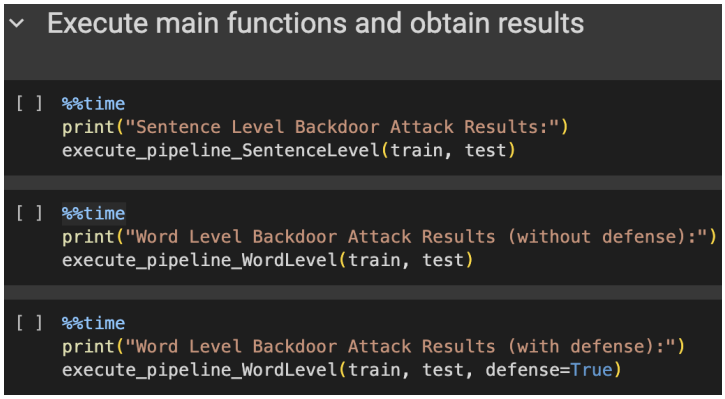
Hint: *A defense mechanism based on detecting English or non-English words can be devised.*

Excel File + Report for Part 2 [10 pts]

After implementing the above functions, you should run the following 3 functions in the notebook to obtain results. Write the results you obtained in the Excel file (**Part2_Results.xlsx**) provided to you and include it in your submission.

In addition to the above Excel file, you should submit a report that contains:

- The intuition behind your defense strategy (Question 3)
- The conclusions you draw from the Excel file (Part2_Results.xlsx)



SUBMISSION

When you are finished, submit your assignment via Blackboard.

- Move all of your relevant files into a folder named `**your KU Login**`.
- **Compress this folder into a zip**. (Do not use compression methods other than zip.)
- Upload your zip file to Blackboard.

Notes and reminders:

- After submitting, download your submission and double-check that: (i) your files are not corrupted, (ii) your submission contains all the files you intended to submit, including all of your source code and your report. If we cannot run your code because some of your code files are missing, we cannot give you credit!
- This homework is an **individual assignment**. All work needs to be your own. Submissions will be checked for plagiarism (including comparing to previous years' assignments).
- **Your report should be a pdf file.** Do not submit Word files or others which may only be opened on Windows or Mac (or opening them may remove table/figure formatting).
- Only Blackboard submissions are allowed. Do not e-mail your assignment to the instructor or TAs.
- Do not change the names or parameters of the functions that we will grade.
- If your code does not run (e.g., syntax errors) or takes an extremely long amount of time (e.g., it takes multiple hours whereas our reference implementation takes 2-3 minutes), you may get 0 for the corresponding part.

GOOD LUCK!