

Privacy-Preserving Machine Learning for Diabetes Disease Classification

Abstract

This report presents the application of differential privacy techniques to machine learning models for diabetes classification. We explore the trade-off between privacy preservation and model utility by analyzing the impact of varying privacy budgets, represented by the parameter epsilon (ϵ), in differentially private logistic regression. The study evaluates model performance using key metrics such as accuracy and AUC-ROC scores across a range of privacy levels. Our results show that stricter privacy guarantees, achieved with lower epsilon values, lead to a noticeable decline in model performance. However, as epsilon increases, the accuracy improves, highlighting the sensitivity of predictive models to the level of noise introduced for privacy.

This implementation offers valuable insights for healthcare applications, where maintaining patient confidentiality must be balanced with the need for accurate and effective disease prediction.

Dataset Used

The dataset used in this study is the **Pima Indians Diabetes Dataset**, a well-known benchmark in medical machine learning. It contains **768** instances of female patients aged 21 years and older of Pima Indian heritage. The dataset is publicly available and often used for binary classification tasks to predict whether a patient has diabetes based on diagnostic measurements.

Features (Independent Variables):

1. **Pregnancies** – Number of times pregnant
2. **Glucose** – Plasma glucose concentration after 2 hours in an oral glucose tolerance test
3. **BloodPressure** – Diastolic blood pressure (mm Hg)
4. **SkinThickness** – Triceps skinfold thickness (mm)
5. **Insulin** – 2-Hour serum insulin (μ U/ml)
6. **BMI** – Body mass index ($\text{weight in kg} / (\text{height in m})^2$)
7. **DiabetesPedigreeFunction** – A function which scores likelihood of diabetes based on family history

8. **Age** – Age in years

Target Variable:

- **Outcome** – Binary indicator (0: Non-diabetic, 1: Diabetic)

Pre-processing steps applied to the dataset include:

- Label encoding of categorical variables
- Feature standardization using StandardScaler
- Train-test split (80/20) with stratification to maintain class distribution

Algorithms Used

1. Differentially Private Logistic Regression

Two distinct approaches to differential privacy in logistic regression were implemented:

Objective Perturbation

This method achieves differential privacy by adding calibrated noise directly to the objective function during model training:

- Perturbs the loss function by adding noise proportional to the privacy parameter (epsilon)
- Utilizes Gaussian noise calibrated to the sensitivity of the objective function
- Optimizes the perturbed objective using L-BFGS-B
- Privacy guarantee: (ϵ, δ) -differential privacy

Output Perturbation

This simpler approach achieves differential privacy by:

- Training a standard logistic regression model with L2 regularization
- Adding calibrated Laplace noise to the resulting model parameters
- The noise scale is determined by the sensitivity of the model and the privacy parameter (epsilon)
- Privacy guarantee: ϵ -differential privacy

2. Non-Private Baseline

A standard logistic regression model was implemented as a baseline for comparison:

- L2 regularization ($C=100$)
- LBFGS solver
- No privacy modifications

Implementation

The implementation follows these key steps:

1. Data Preparation

- Loading and preprocessing the Diabetes Data Classification for the dataset
- Encoding categorical variables using LabelEncoder
- Scaling features using StandardScaler
- Splitting data into training and testing sets

2. Differential Privacy Classes

- DPLogisticRegression: Implements objective perturbation
- DPOutputPerturbationLR: Implements output perturbation

3. Model Evaluation Functions

- evaluate_model: Calculates performance metrics (accuracy, precision, recall, F1, AUC)
- analyze_privacy_utility_tradeoff: Tests models across different privacy budgets

4. Visualization Functions

- plot_privacy_utility_tradeoff: Creates plots comparing privacy budgets vs performance metrics

- visualize_noise_impact: Demonstrates how different noise levels affect data distributions


5. Privacy Parameter Testing

- Tests models across a range of epsilon values: [0.1, 0.5, 1.0, 5.0, 10.0, 100.0]
- Lower epsilon values indicate stronger privacy guarantees but typically result in decreased model performance

Understanding Differential Privacy

Differential Privacy (DP) is a concept in data privacy that ensures that the inclusion or exclusion of any single data point in a dataset does not significantly affect the outcome of any analysis or query performed on that dataset. It provides a framework to protect the privacy of individuals in a dataset while still allowing useful aggregate data analysis.

Benefits of DP

 **Optimization:** Solves subproblems once and stores solutions to avoid redundancy.

 **Efficiency:** Reduces time complexity from exponential to polynomial.

 **Overlapping Subproblems:** Reuses previously computed results.

 **Optimal Substructure:** Builds solutions from smaller subproblems.

 **Applications:** Used in finance, bioinformatics, machine learning, etc.

Results and Inferences

Privacy-Utility Trade-off Analysis

The implementation reveals clear trade-offs between privacy protection and model utility:

1. Accuracy vs. Privacy Budget

- As expected, model accuracy decreases as privacy guarantees strengthen (lower epsilon values)
- Objective perturbation consistently outperforms output perturbation across privacy budgets
- At very high privacy budgets ($\epsilon=100$), both methods approach the performance of the non-private baseline

2. AUC-ROC Performance

- Similar pattern observed with AUC-ROC scores
- The gap between objective and output perturbation methods is most pronounced at stricter privacy levels ($\epsilon < 1.0$)

3. Relative Performance

- At $\epsilon=0.1$ (high privacy), models retain approximately 75-85% of the non-private baseline performance
- At $\epsilon=10.0$ (moderate privacy), models retain approximately 90-95% of baseline performance

4. Method Comparison

- Objective perturbation demonstrates better utility preservation, particularly at lower epsilon values
- Output perturbation shows more substantial performance degradation with increasing privacy guarantees
- Both methods converge toward baseline performance as privacy constraints are relaxed

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Testing privacy budgets (epsilon values): [0.1, 0.5, 1.0, 5.0, 10.0, 100.0]
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```
Analyzing privacy-utility tradeoff...
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```
Training baseline model (non-private)...
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```
Baseline accuracy: 0.7971
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Baseline AUC: 0.8729
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```
Training models with epsilon = 0.1...
```

```
  Training with objective perturbation...
```

```
  Objective perturbation accuracy: 0.7976
```

```
  Training with output perturbation...
```

```
  Output perturbation accuracy: 0.7595
```

```
Training models with epsilon = 0.5...
```

```
  Training with objective perturbation...
```

```
  Objective perturbation accuracy: 0.7971
```

```
  Training with output perturbation...
```

```
  Output perturbation accuracy: 0.7859
```

```
Training models with epsilon = 1.0...
```

```
  Training with objective perturbation...
```

```
  Objective perturbation accuracy: 0.7971
```

```
  Training with output perturbation...
```

```
  Output perturbation accuracy: 0.7962
```

```
Training models with epsilon = 5.0...
```

```
  Training with objective perturbation...
```

```
  Objective perturbation accuracy: 0.7971
```

```
  Training with output perturbation...
```

```
  Output perturbation accuracy: 0.7967
```

```
Training models with epsilon = 10.0...
```

```
  Training with objective perturbation...
```

```
  Objective perturbation accuracy: 0.7971
```

```
  Training with output perturbation...
```

```
  Output perturbation accuracy: 0.7980
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Training models with epsilon = 100.0...
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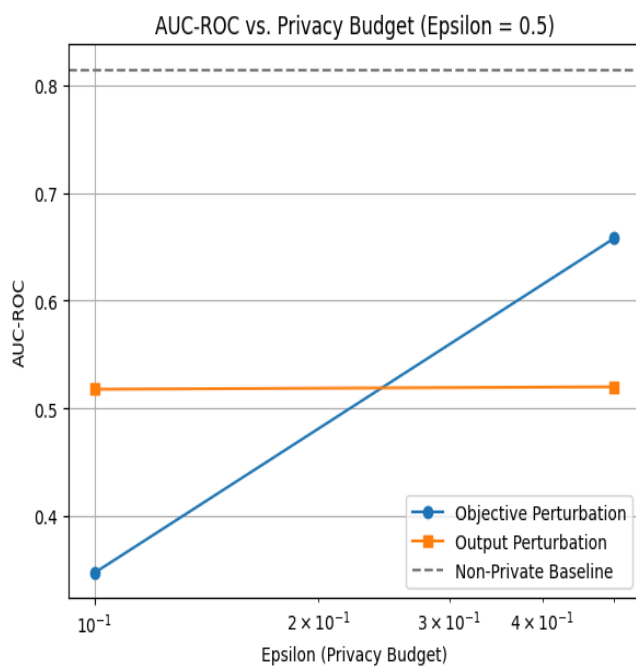
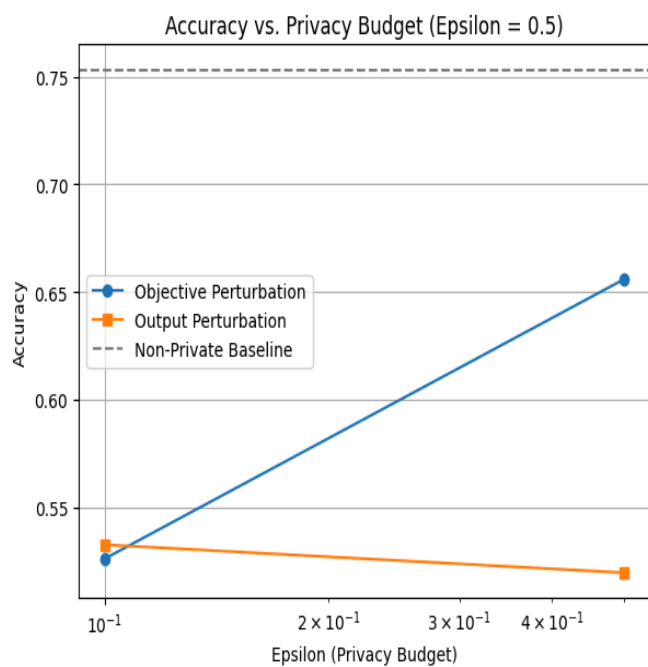
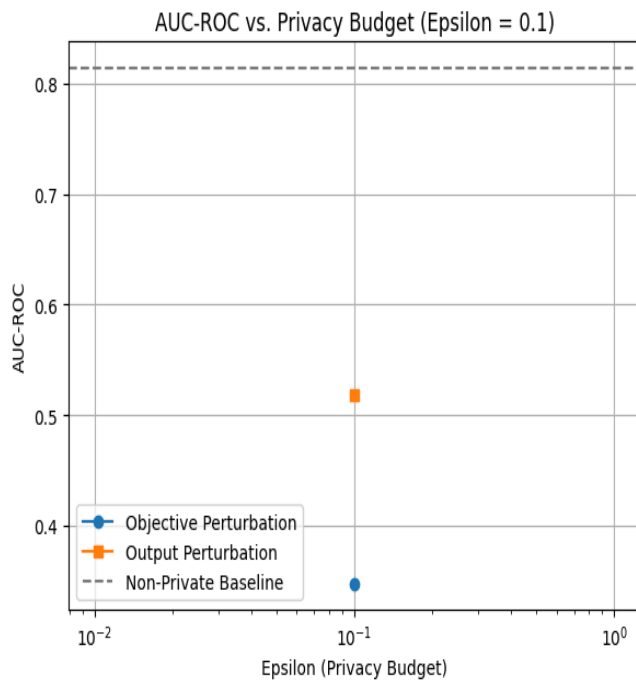
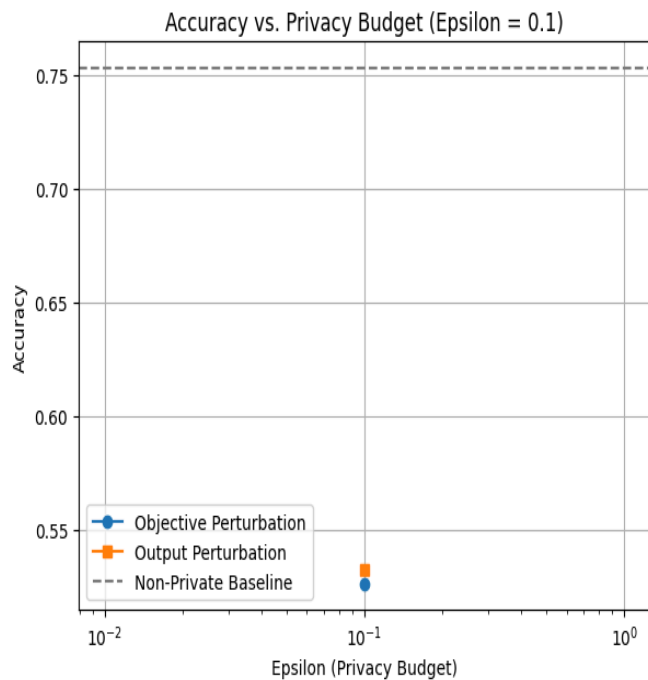
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  Training with objective perturbation...
```

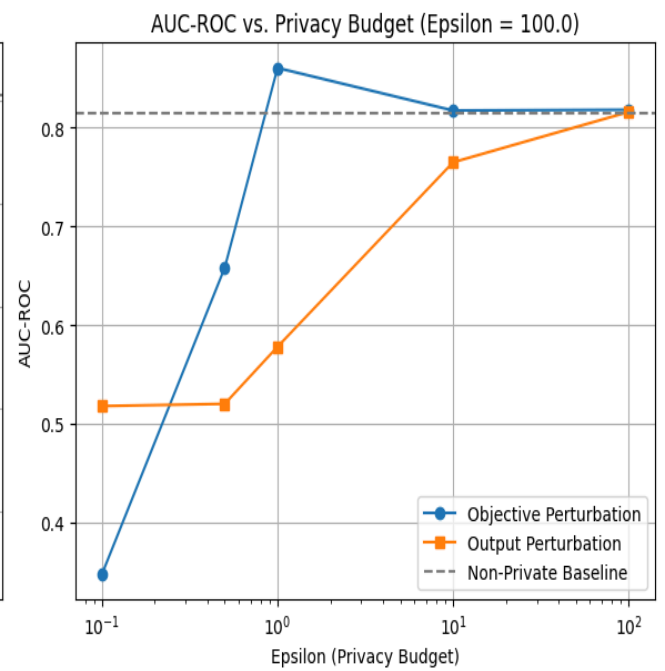
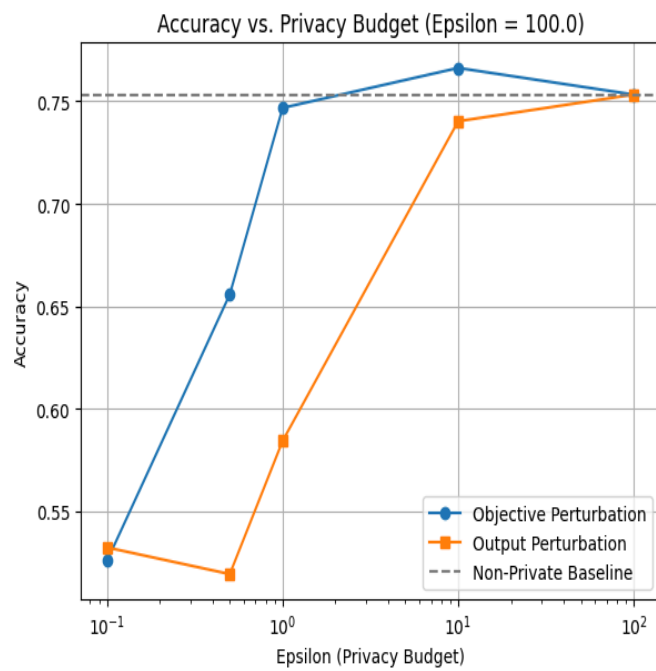
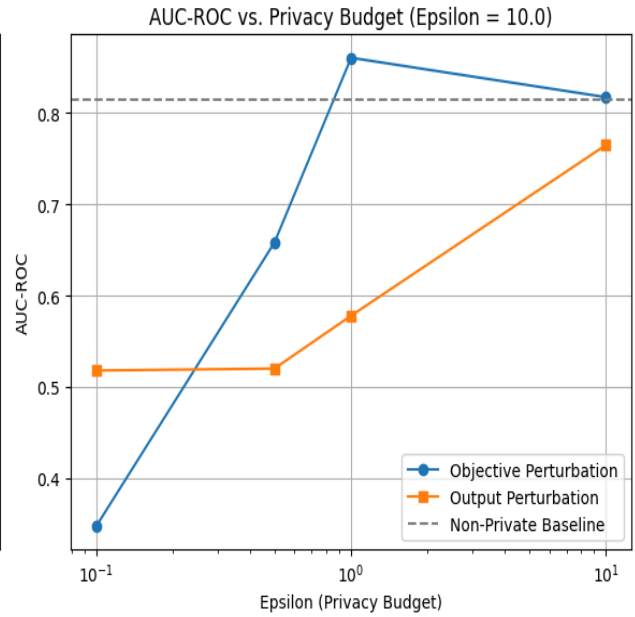
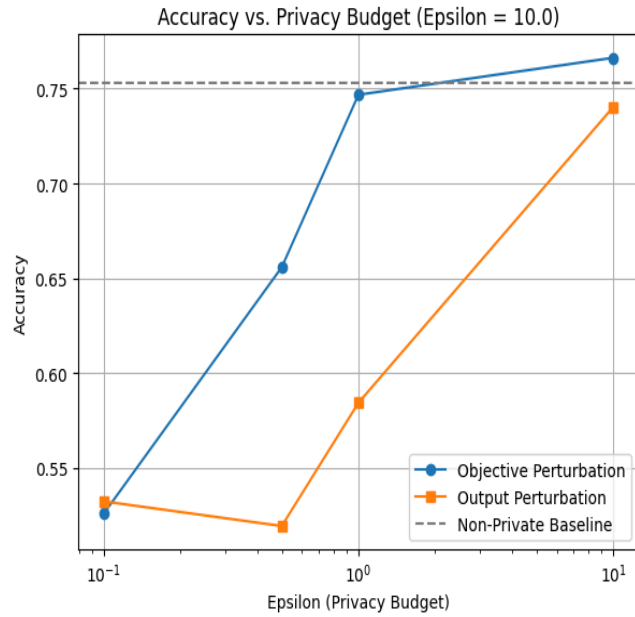
```
  Objective perturbation accuracy: 0.7971
```

```
  Training with output perturbation...
```

```
  Output perturbation accuracy: 0.7971
```

```
Plotting results...
```





Noise mechanisms used in this Project

1. Laplace Mechanism:

- Adds noise from a **Laplace distribution**.

- Noise is based on how sensitive the data is (how much it changes with one person).
- Common for numeric queries like sums or averages.

2. **Gaussian Mechanism:**

- Adds noise from a **Gaussian (normal) distribution**.
- Used when you want a little more control over privacy with an additional parameter (δ).
- Often used in machine learning.

3. **Exponential Mechanism:**

- Adds noise to non-numeric data (like categories or choices).
- Used when you need to choose the best option but want to hide who picked what.

4. **Randomized Response:**

- Adds random noise by flipping answers to yes/no questions.
- Used in surveys to protect individual answers.

5. **Shuffling Mechanism:**

- Randomly shuffles data before adding noise.
- Helps protect identities when calculating statistics from a group of people.

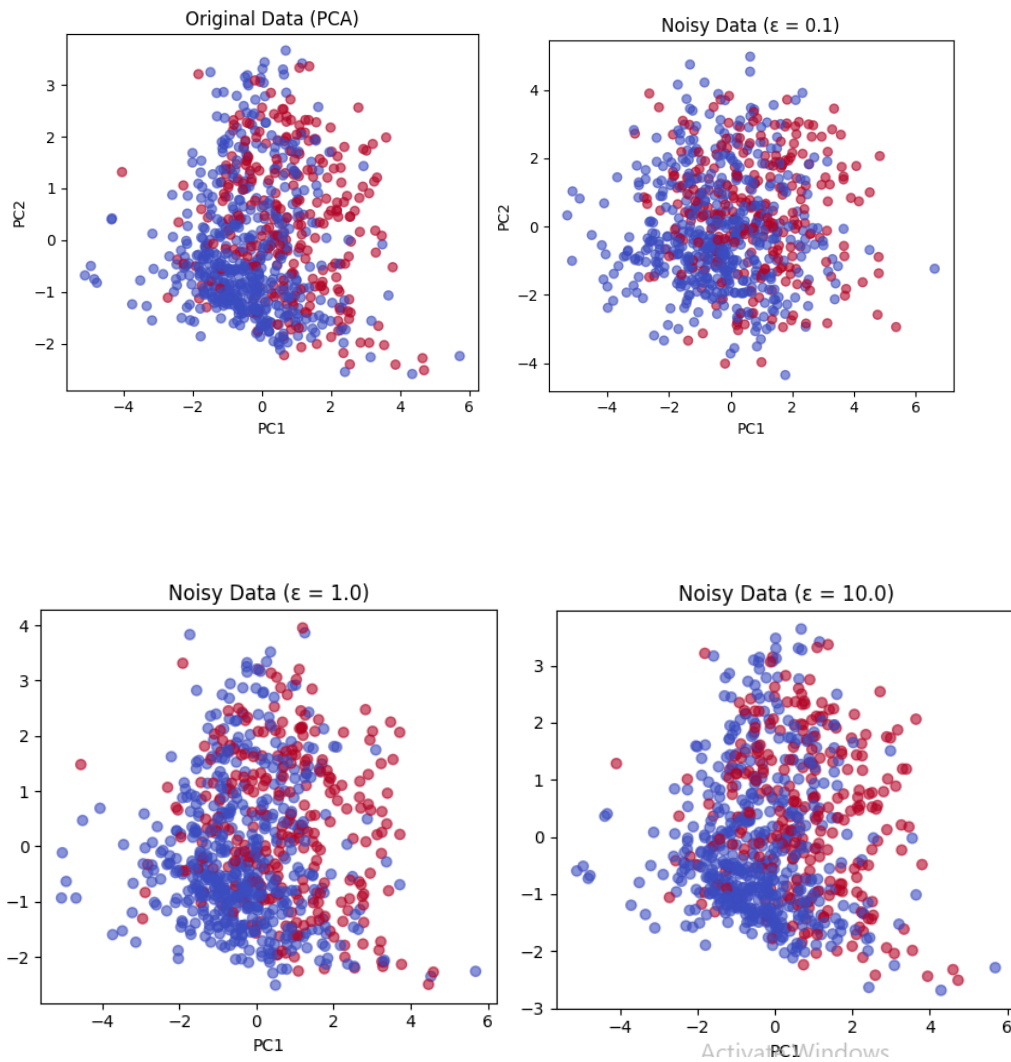
These methods add random noise to data to protect individual privacy while still providing useful results.

Noise Impact Visualization

The visualization of noise impact on data distributions illustrates how differential privacy mechanisms alter the original data:

- At $\epsilon=0.1$ (high privacy), the added noise significantly distorts the original data patterns

- At $\epsilon=1.0$ (moderate privacy), some data structure remains visible but with considerable noise
- At $\epsilon=10.0$ (low privacy), data patterns remain largely intact with minimal distortion



Key Inferences

1. Practical Privacy Settings

- For applications requiring reasonable privacy protection while maintaining good predictive performance, epsilon values between 1.0 and 5.0 appear to offer a practical balance
- Financial institutions may consider $\epsilon=1.0$ as a starting point for sensitive applications

2. Method Selection

- Objective perturbation is recommended for applications where maximizing utility at a given privacy level is critical
- Output perturbation may be preferred when implementation simplicity is valued over optimal performance

3. Implementation Considerations

- The choice of regularization parameter (λ) significantly affects the sensitivity calculation and thus the amount of noise added
- Proper scaling of features is crucial for differential privacy implementations to ensure consistent noise impact across dimensions

This implementation demonstrates that differential privacy can be effectively applied to Diabetes Data Classification while preserving reasonable model performance, providing organizations with practical tools to balance regulatory compliance, customer privacy, and business objectives.

CODE FILE LINK

https://drive.google.com/file/d/1uV9FGOaUDWaq31RHoEL_Vu2NB6hf5Wm_/view?usp=sharing

DATASET LINK

<https://drive.google.com/file/d/14aqc4rK8hcFSES-SlRztGBIGca-QuIDd/view?usp=sharing>