

# Optimization Odyssey:

## Navigating the Maze of Neural Network Tuning

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# Revolutionizing Machine Learning: The Power of Artificial Neural Networks

- ❑ **Pattern and Speech** recognition.
- ❑ **Natural Language** Processing.
- ❑ Handling **High-Dimensional data** and learning **Hierarchical representations**.
- ❑ Development of **Autonomous vehicles, Robotics**.
- ❑ **Democratization of AI**.

# The Optimization Phenomenon

- ❑ Problem Formulation
- ❑ Iterative process
- ❑ Solution evaluation
- ❑ Solution refinement
- ❑ Solution implementation

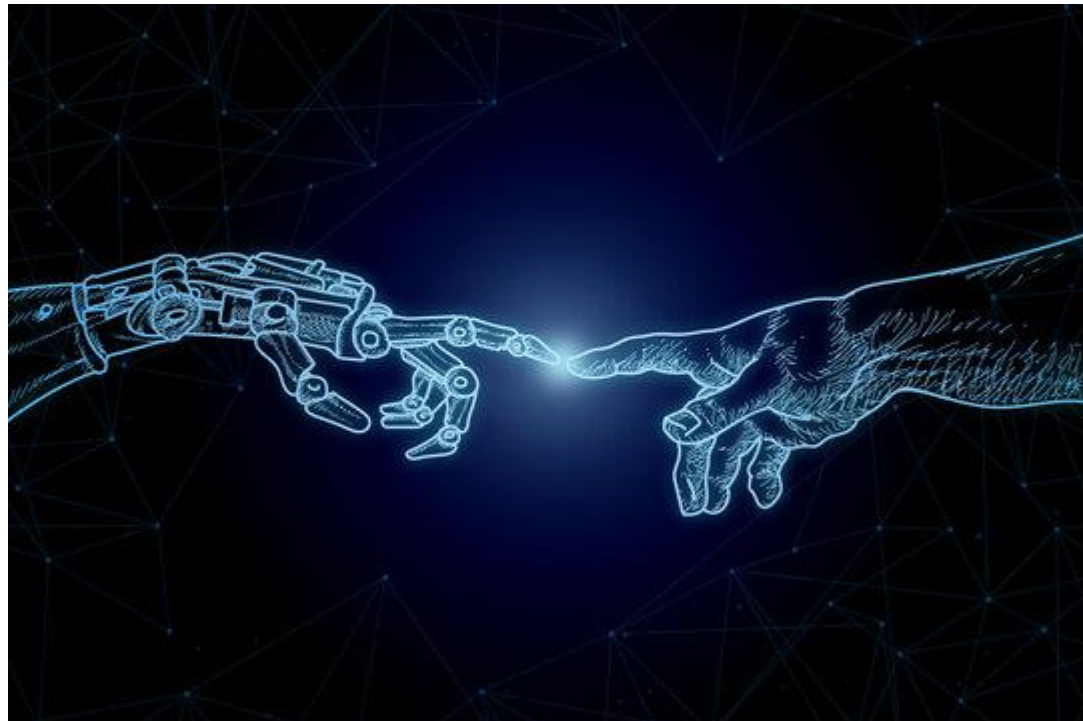
## Process optimization steps



# Convergence of Optimization and Artificial Biology: Exploring the Synergy of Efficiency and Adaptation

- ▶ Where the human concept of trial and error and the artificial art of continuous learning collide

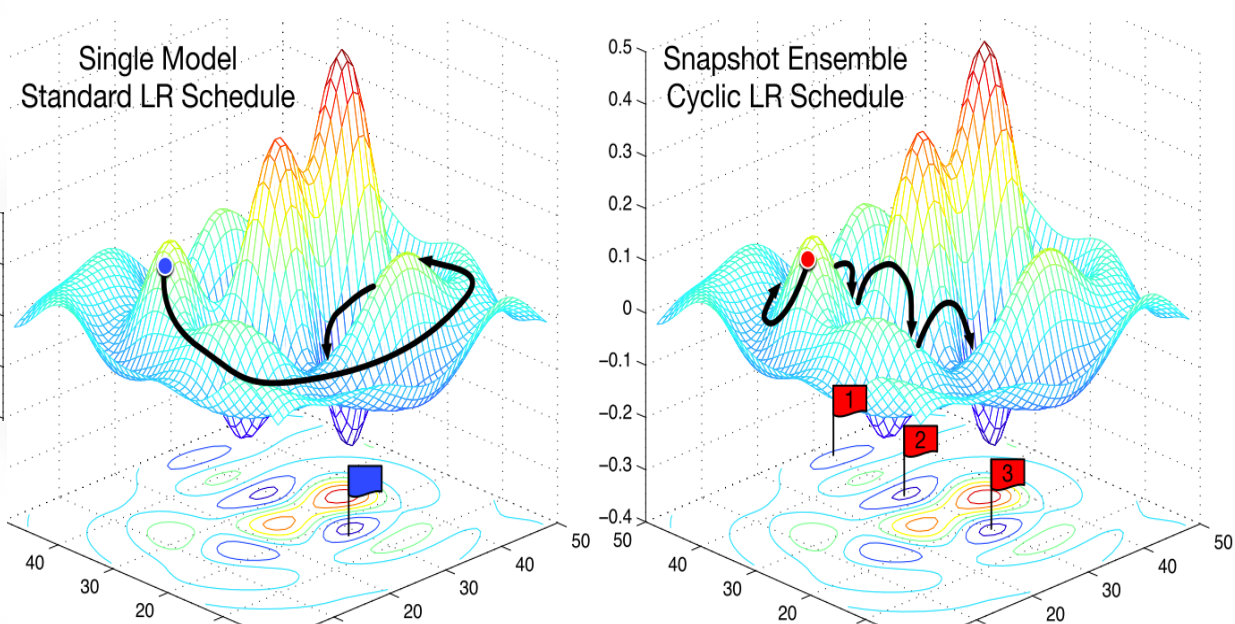
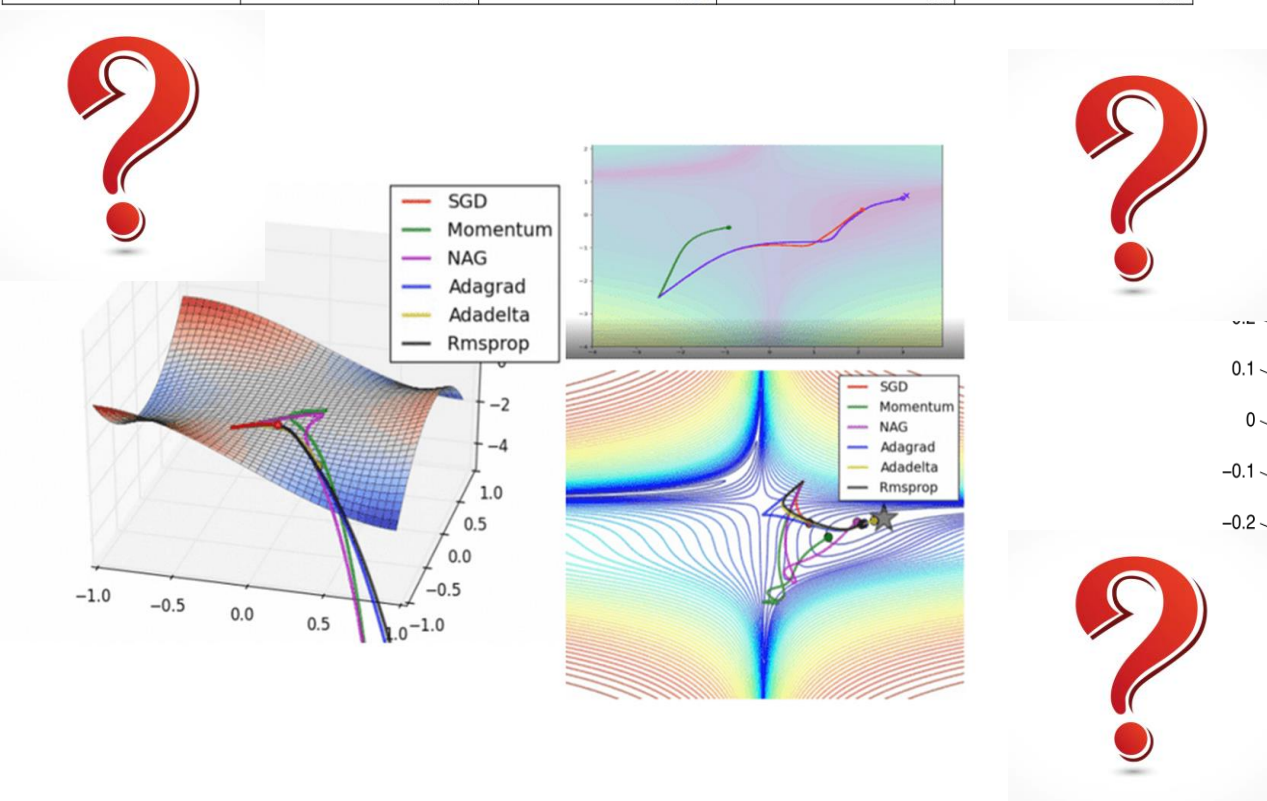
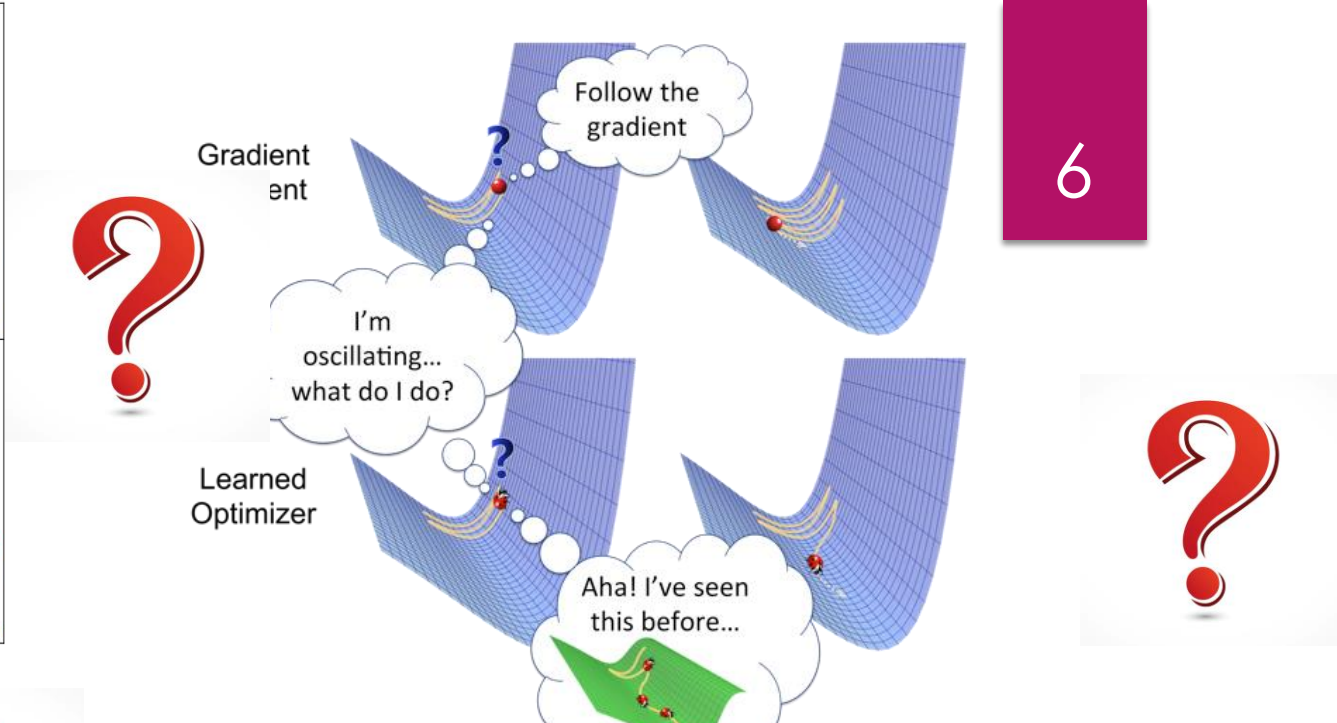
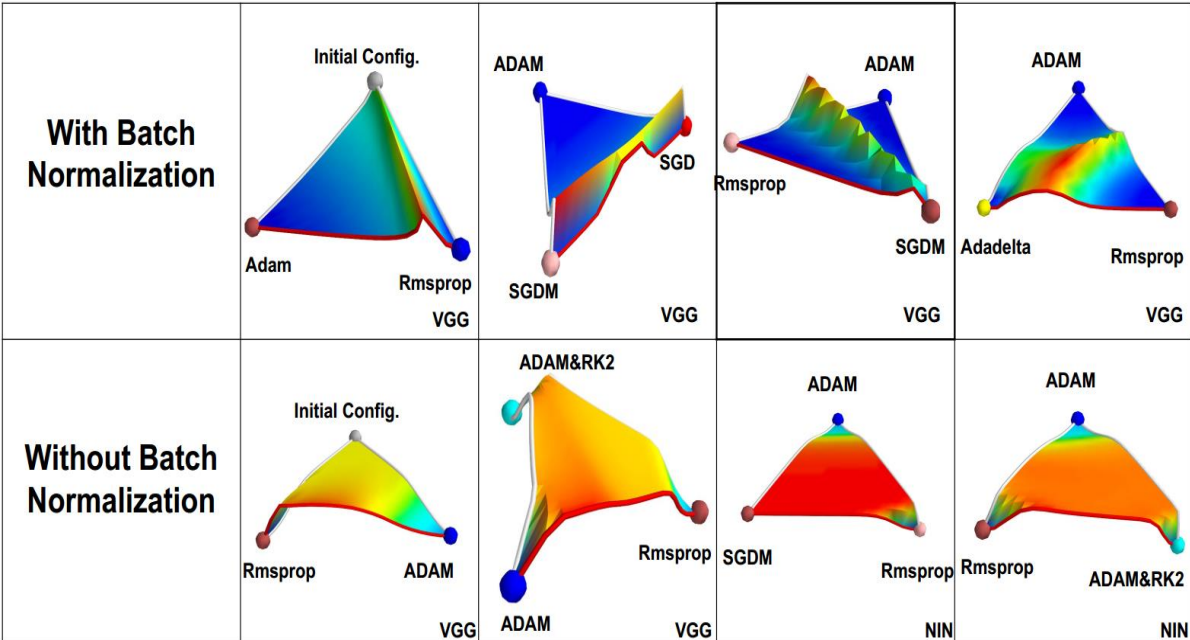
Continuous Learning



Trial, failure, and  
the will to try again

# Optimization Frontier: Unlocking Algorithmic Brilliance

- ❑ Gradient Descent (GD)
- ❑ Stochastic Gradient Descent (SGD)
- ❑ Mini-Batch Gradient Descent
- ❑ Momentum
- ❑ Nesterov Accelerated Gradient (NAG)
- ❑ Levenberg-Marquardt
- ❑ Quickprop
- ❑ Rprop (Resilient Backpropagation)
- ❑ Adagrad (Adaptive Gradient)
- ❑ RMSProp (Root Mean Square Propagation)
- ❑ Adam (Adaptive Moment Estimation)
- ❑ AdaDelta (Adaptive Learning Rate)
- ❑ Adamax
- ❑ Limited-memory BFGS (L-BFGS)
- ❑ Nadam (Nesterov-accelerated Adaptive Moment Estimation)
- ❑ AMSGrad (Adaptive Moment Estimation with Stochastic Gradient Descent)
- ❑ Adadelta
- ❑ Natural Evolution Strategies (NES)
- ❑ Evolution Strategies (ES)
- ❑ Conjugate Gradient (CG)



# In Pursuit of Perfection: The Big 5

**A Cut Above the Rest:** Introducing the 5 Superior Optimizer Algorithms for Our Project

- ❑ *SGD (Stochastic Gradient Descent)*
- ❑ *Adam (Adaptive Moment Estimation)*
- ❑ *Adagrad (Adaptive Gradient Algorithm)*
- ❑ *RMSProp (Root Mean Square Propagation)*
- ❑ *Nadam (Nesterov-accelerated Adaptive Moment Estimation)*

# Breast Cancer Classification with different Optimization Algorithms

- ❑ Which one of the big 5 is more optimal in terms of Accuracy and Loss Function?

Let us find out..

## Importing Libraries

```
In [ ]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import sklearn.datasets
from sklearn.model_selection import train_test_split
```

## Data Collection and Processing

```
In [ ]: # Loading the data from sk.learn
breast_cancer_dataset = sklearn.datasets.load_breast_cancer()
```

```
In [ ]: # Loading the data to a Panda Dataframe
df = pd.DataFrame(breast_cancer_dataset.data, columns = breast_cancer_dataset.feature_names)
```

### Standardize the Data (Normalising for better accuracy)

```
In [ ]: from sklearn.preprocessing import StandardScaler
```

```
In [ ]: scaler = StandardScaler()

X_train_std = scaler.fit_transform(X_train)

X_test_std = scaler.transform(X_test)
```

```
In [ ]: print(X_train_std)
```

## Building The Neural Network

```
In [ ]: # Importing tensorflow and Keras
import tensorflow as tf
tf.random.set_seed(3) #for constant accuracy score in more than one session
from tensorflow import keras
```

**Adam Model**

```
In [ ]: # setting up the layers of NN
# flatten is taking the 30 features and putting it into 1 dimensional array
# first dense is hidden, second is output layer

adam= keras.Sequential([
    keras.layers.Flatten(input_shape=(30,)),
    keras.layers.Dense(20, activation='relu'),
    keras.layers.Dense(2, activation='sigmoid')
])
```

```
In [ ]: # Compiling NN

adam.compile(optimizer='adam',
             loss='sparse_categorical_crossentropy',
             metrics=['accuracy'])
```

```
In [ ]: # training the NN

history_adam = adam.fit(X_train_std, Y_train, validation_split=0.1, epochs=10)
```

**Visualizing accuracy and loss**

```
In [ ]: plt.plot(history_adam.history['accuracy'])
plt.plot(history_adam.history['val_accuracy'])

plt.title('model_accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')

plt.legend(['Training Data', 'Validation Data'], loc = 'lower right')
```

```
In [ ]: plt.plot(history_adam.history['loss'])
plt.plot(history_adam.history['val_loss'])

plt.title('model_loss')
plt.ylabel('loss')
plt.xlabel('epoch')

plt.legend(['Training Data', 'Validation Data'], loc = 'upper right')
```

**Accuracy of the model on the test data**

```
In [ ]: loss, accuracy = adam.evaluate(X_test_std, Y_test)
print(accuracy)
```

## SGD model

```
In [ ]: sgd = keras.Sequential([
        keras.layers.Flatten(input_shape=(30,)),
        keras.layers.Dense(20, activation='relu'),
        keras.layers.Dense(2, activation='sigmoid')
    ])

sgd.compile(optimizer='SGD',
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy'])
```

```
In [ ]: history_sgd = sgd.fit(X_train_std, Y_train, validation_split=0.1, epochs=10)
```

```
In [ ]: loss, accuracy = sgd.evaluate(X_test_std, Y_test)
        print(accuracy)
```

## RMSProp

```
In [ ]: rms = keras.Sequential([
        keras.layers.Flatten(input_shape=(30,)),
        keras.layers.Dense(20, activation='relu'),
        keras.layers.Dense(2, activation='sigmoid')
    ])

rms.compile(optimizer='RMSprop',
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy'])
```

```
In [ ]: history_rms = rms.fit(X_train_std, Y_train, validation_split=0.1, epochs=10)
```

```
In [ ]: loss, accuracy = rms.evaluate(X_test_std, Y_test)
        print(accuracy)
```

### Adagrad

```
In [ ]: adagra = keras.Sequential([
        keras.layers.Flatten(input_shape=(30,)),
        keras.layers.Dense(20, activation='relu'),
        keras.layers.Dense(2, activation='sigmoid')
    ])

adagra.compile(optimizer='Adagrad',
               loss='sparse_categorical_crossentropy',
               metrics=['accuracy'])
```

```
In [ ]: history_adagra = adagra.fit(X_train_std, Y_train, validation_split=0.1, epochs=10)
```

```
In [ ]: loss, accuracy = adagra.evaluate(X_test_std, Y_test)
print(accuracy)
```

### Nadam

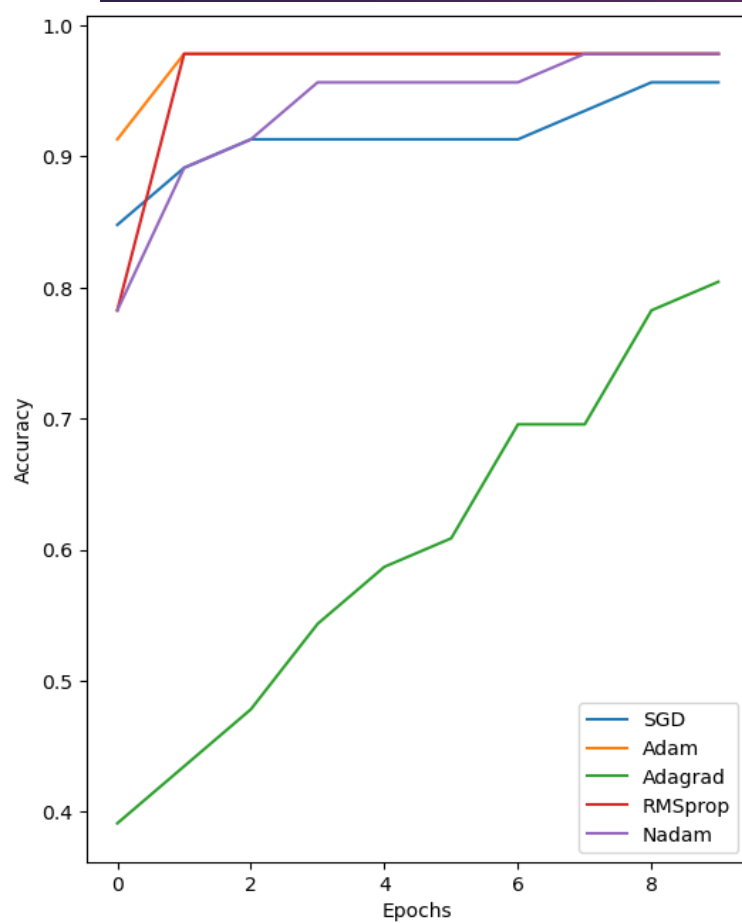
```
In [ ]: nadam = keras.Sequential([
        keras.layers.Flatten(input_shape=(30,)),
        keras.layers.Dense(20, activation='relu'),
        keras.layers.Dense(2, activation='sigmoid')
    ])

nadam.compile(optimizer='Nadam',
               loss='sparse_categorical_crossentropy',
               metrics=['accuracy'])
```

```
In [ ]: history_nadam = nadam.fit(X_train_std, Y_train, validation_split=0.1, epochs=10)
```

```
In [ ]: loss, accuracy = nadam.evaluate(X_test_std, Y_test)
print(accuracy)
```

# Findings



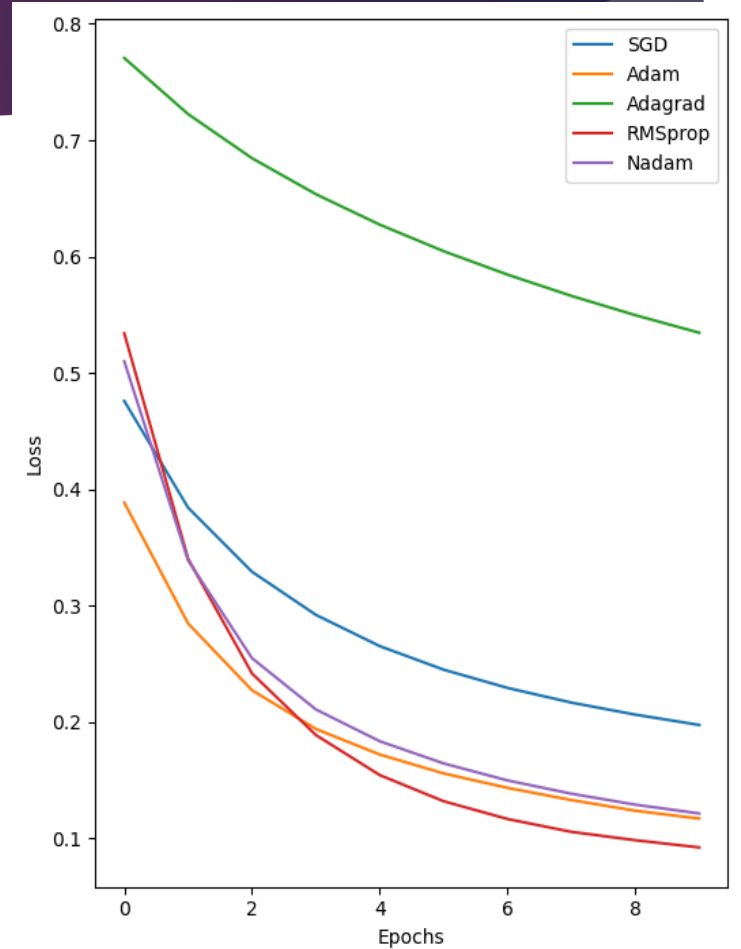
Behavior in Accuracy

## B. Model Evaluation

The model is evaluated using accuracy and loss function, briefly structured below.

| Algorithm | Accuracy | Loss Function |
|-----------|----------|---------------|
| SGD       | 95.61%   | 0.1669        |
| Adam      | 97.37%   | 0.1273        |
| Adagrad   | 70.18%   | 0.6419        |
| RMSProp   | 95.61%   | 0.1276        |
| Nadam     | 95.61%   | 0.1389        |

Table 1: Evaluation of the algorithms



Behavior in Loss Function

# Adam takes the apple fruit

With the highest **Accuracy of rate 97.37%** and the lowest **Loss Function of 0.1273**, the Adam optimizer is clearly the most powerful optimizer in this study.



# Slapping the rest out of *The Office*

- ▶ Get outta here, Chris Rock, sorry, you pretender algorithms..



# End of the voyage through ANN with optimizers



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