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| Semester | B.E. Semester VII |
| Subject | Deep Learning |
| Subject Professor In- charge | Dr. Nayana Mahajan |
| Laboratory | M201B |

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|---|---|---|---|
| Student Name | Harsh jain | Division | B |
| Roll Number | 22108B0054 | Batch | 4 |
| Grade and Subject Teacher’s Signature | | | |

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| Experiment Number | 2 |
| Experiment Title | To train and evaluate a single-layer feedforward neural network on a real-world binary classification dataset using Stochastic Gradient Descent (SGD) and Momentum-based Gradient Descent (Momentum GD) as optimization techniques. The objective is to compare and analyze the performance of both optimizers in terms of:<br>● Convergence Rate: How quickly the training loss decreases over epochs.<br>● Training Speed: The computational efficiency and time taken during training.<br>● Classification Accuracy: The predictive performance on unseen test data.<br>This study aims to highlight the impact of optimization strategy on neural network training effectiveness, particularly in low-complexity models such as single-layer networks. |
| Resources / Apparatus Required | Software: Google Colab |
| Algorithm | 1. **Load Dataset**:<br>2. **Create Binary Target**:<br>3. **One-Hot Encode Categorical Features**:<br>4. **Prepare Features and Labels**:<br>5. **Normalize Features**:<br>6. **Split Data into Training and Test Sets**:<br>7. **Define Activation and Loss Functions**:<br>8. **Initialize Weights and Bias**:<br>9. **Train the Model**:<br>10. **Evaluate the Model**: |

Program code

# Using Sigmoid Activation Function

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import
train_test_split
from sklearn.preprocessing import
StandardScaler
from sklearn.metrics import mean_squared_error,
r2_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import
EarlyStopping
import warnings
warnings.filterwarnings('ignore')

# Set random seeds for reproducibility
np.random.seed(42)
tf.random.set_seed(42)

class HousePriceDataGenerator:
    """Generate synthetic house price dataset
with realistic features"""

    def __init__(self, n_samples=5000):
        self.n_samples = n_samples

    def generate_data(self):
        """Generate synthetic house price data
with non-linear relationships"""

        # Basic features
        square_footage = np.random.normal(2000,
500, self.n_samples)
        square_footage =
np.clip(square_footage, 800, 5000)
```

```
        bedrooms = np.random.choice([2, 3, 4,
5, 6], self.n_samples, p=[0.1, 0.3, 0.4, 0.15,
0.05])
        bathrooms = bedrooms +
np.random.choice([-1, 0, 1, 2], self.n_samples,
p=[0.1, 0.4, 0.4, 0.1])
        bathrooms = np.clip(bathrooms, 1, 6)

        year_built = np.random.randint(1950,
2024, self.n_samples)
        age = 2024 - year_built

        # Location factor (0-1, higher is
better location)
        location_factor = np.random.beta(2, 5,
self.n_samples)

        # Garage size
        garage_size = np.random.choice([0, 1,
2, 3], self.n_samples, p=[0.1, 0.3, 0.5, 0.1])

        # Lot size (in acres)
        lot_size = np.random.exponential(0.25,
self.n_samples)
        lot_size = np.clip(lot_size, 0.1, 2.0)

        # Additional features
        has_pool = np.random.choice([0, 1],
self.n_samples, p=[0.8, 0.2])
        has_basement = np.random.choice([0, 1],
self.n_samples, p=[0.3, 0.7])
        fireplace_count = np.random.choice([0,
1, 2], self.n_samples, p=[0.6, 0.3, 0.1])

        # Create non-linear price relationships
        base_price = (
            square_footage * 100 +  # Base
price per sq ft
            bedrooms * 15000 +      # Premium
for bedrooms
```

```
            bathrooms * 8000 +      # Premium
for bathrooms
            garage_size * 5000 +    # Garage
value
            lot_size * 20000 +      # Lot size
value
            has_pool * 25000 +      # Pool
premium
            has_basement * 15000 +  # Basement
value
            fireplace_count * 8000  # Fireplace
value
        )

        # Add non-linear components
        location_multiplier = 0.5 + 1.5 *
location_factor  # 0.5x to 2x multiplier
        age_depreciation = np.exp(-age / 50)  #
Exponential depreciation

        # Square footage has diminishing
returns
        sq_ft_bonus = np.sqrt(square_footage /
1000) * 20000

        # Final price calculation with noise
        price = (base_price + sq_ft_bonus) *
location_multiplier * age_depreciation

        # Add some realistic noise
        noise = np.random.normal(0, price *
0.1)  # 10% noise
        price = price + noise

        # Ensure positive prices
        price = np.maximum(price, 50000)

        # Create DataFrame
        data = pd.DataFrame({
            'square_footage': square_footage,
```

```
            'bedrooms': bedrooms,
            'bathrooms': bathrooms,
            'age': age,
            'location_factor': location_factor,
            'garage_size': garage_size,
            'lot_size': lot_size,
            'has_pool': has_pool,
            'has_basement': has_basement,
            'fireplace_count': fireplace_count,
            'price': price
        })

        return data

class ActivationFunctionAnalyzer:
    """Analyze different activation functions
for regression tasks"""

    def __init__(self, X_train, X_val, y_train,
y_val):
        self.X_train = X_train
        self.X_val = X_val
        self.y_train = y_train
        self.y_val = y_val
        self.results = {}

        # Activation functions to test
        self.activations = {
            'relu': 'relu',
            'sigmoid': 'sigmoid',
            'tanh': 'tanh',
            'leaky_relu':
tf.keras.layers.LeakyReLU(alpha=0.01),
            'elu': 'elu',
            'selu': 'selu',
            'swish': 'swish'
        }

    def build_model(self, activation_name):
        """Build neural network model with
```

```
specified activation function"""
        model = Sequential()

        # First hidden layer
        model.add(Dense(64,
input_dim=self.X_train.shape[1]))
        if activation_name == 'leaky_relu':

model.add(tf.keras.layers.LeakyReLU(alpha=0.01)
)
        else:
            model.add(Dense(64,
activation=self.activations[activation_name],
input_dim=self.X_train.shape[1]))
            model = Sequential()
            model.add(Dense(64,
input_dim=self.X_train.shape[1],
activation=self.activations[activation_name]))

        # Second hidden layer
        if activation_name == 'leaky_relu':
            model.add(Dense(64))

model.add(tf.keras.layers.LeakyReLU(alpha=0.01)
)
        else:
            model.add(Dense(64,
activation=self.activations[activation_name]))

        # Output layer (no activation for
regression)
        model.add(Dense(1))

        # Compile model
        model.compile(optimizer='adam',
loss='mse', metrics=['mae'])

        return model

    def train_and_evaluate(self,
```

```
activation_name, epochs=150, batch_size=32,
verbose=0):
        """Train model with specific activation
function and return results"""

        print(f"Training model with
{activation_name} activation...")

        # Build model
        model =
self.build_model(activation_name)

        # Early stopping callback
        early_stopping = EarlyStopping(
            monitor='val_loss',
            patience=20,
            restore_best_weights=True,
            verbose=0
        )

        # Train model
        history = model.fit(
            self.X_train, self.y_train,
            validation_data=(self.X_val,
self.y_val),
            epochs=epochs,
            batch_size=batch_size,
            callbacks=[early_stopping],
            verbose=verbose
        )

        # Make predictions
        train_pred =
model.predict(self.X_train, verbose=0)
        val_pred = model.predict(self.X_val,
verbose=0)

        # Calculate metrics
        train_mse =
mean_squared_error(self.y_train, train_pred)
```

```
        val_mse =
mean_squared_error(self.y_val, val_pred)
        train_r2 = r2_score(self.y_train,
train_pred)
        val_r2 = r2_score(self.y_val, val_pred)

        # Store results
        self.results[activation_name] = {
            'model': model,
            'history': history,
            'train_mse': train_mse,
            'val_mse': val_mse,
            'train_r2': train_r2,
            'val_r2': val_r2,
            'train_loss':
history.history['loss'],
            'val_loss':
history.history['val_loss']
        }

        print(f"  Validation MSE:
{val_mse:.2f}")
        print(f"  Validation R²: {val_r2:.4f}")

        return self.results[activation_name]

    def run_all_experiments(self, epochs=150,
batch_size=32):
        """Run experiments for all activation
functions"""
        print("Starting activation function
comparison experiment...\n")

        for activation_name in
self.activations.keys():

self.train_and_evaluate(activation_name,
epochs, batch_size)
            print()
```

```
    def plot_results(self, figsize=(15, 12)):
        """Plot comprehensive results
comparison"""

        fig, axes = plt.subplots(2, 2,
figsize=figsize)
        fig.suptitle('Activation Functions
Comparison for House Price Regression',
fontsize=16, fontweight='bold')

        # 1. Training and Validation Loss
Curves
        ax1 = axes[0, 0]
        for activation in self.results.keys():
            epochs_range = range(1,
len(self.results[activation]['val_loss']) + 1)
            ax1.plot(epochs_range,
self.results[activation]['val_loss'],
                    label=f'{activation}',
linewidth=2)

        ax1.set_title('Validation Loss (MSE)
During Training')
        ax1.set_xlabel('Epochs')
        ax1.set_ylabel('Validation MSE')
        ax1.legend()
        ax1.grid(True, alpha=0.3)
        ax1.set_yscale('log')

        # 2. Final Validation MSE Comparison
        ax2 = axes[0, 1]
        activations = list(self.results.keys())
        val_mses =
[self.results[act]['val_mse'] for act in
activations]

        bars = ax2.bar(activations, val_mses,
color='skyblue', edgecolor='navy', alpha=0.7)
        ax2.set_title('Final Validation MSE by
Activation Function')
```

```
        ax2.set_ylabel('Validation MSE')
        ax2.tick_params(axis='x', rotation=45)

        # Add value labels on bars
        for bar, val in zip(bars, val_mses):
            ax2.text(bar.get_x() +
bar.get_width()/2, bar.get_height() +
max(val_mses)*0.01,
                     f'{val:.0f}', ha='center',
va='bottom', fontweight='bold')

        # 3. R² Score Comparison
        ax3 = axes[1, 0]
        val_r2s = [self.results[act]['val_r2']
for act in activations]

        bars = ax3.bar(activations, val_r2s,
color='lightgreen', edgecolor='darkgreen',
alpha=0.7)
        ax3.set_title('Validation R² Score by
Activation Function')
        ax3.set_ylabel('R² Score')
        ax3.tick_params(axis='x', rotation=45)
        ax3.set_ylim(0, 1)

        # Add value labels on bars
        for bar, val in zip(bars, val_r2s):
            ax3.text(bar.get_x() +
bar.get_width()/2, bar.get_height() + 0.01,
                     f'{val:.3f}', ha='center',
va='bottom', fontweight='bold')

        # 4. Training vs Validation MSE
(Overfitting Analysis)
        ax4 = axes[1, 1]
        train_mses =
[self.results[act]['train_mse'] for act in
activations]

        x = np.arange(len(activations))
```

```
        width = 0.35

        ax4.bar(x - width/2, train_mses, width,
label='Training MSE', color='orange',
alpha=0.7)
        ax4.bar(x + width/2, val_mses, width,
label='Validation MSE', color='skyblue',
alpha=0.7)

        ax4.set_title('Training vs Validation
MSE (Overfitting Analysis)')
        ax4.set_ylabel('MSE')
        ax4.set_xticks(x)
        ax4.set_xticklabels(activations,
rotation=45)
        ax4.legend()
        ax4.grid(True, alpha=0.3)

        plt.tight_layout()
        plt.show()

    def print_summary(self):
        """Print detailed summary of results"""
        print("\n" + "="*80)
        print("ACTIVATION FUNCTIONS COMPARISON
SUMMARY")
        print("="*80)

        # Create summary DataFrame
        summary_data = []
        for activation in self.results.keys():
            summary_data.append({
                'Activation':
activation.upper(),
                'Val_MSE':
self.results[activation]['val_mse'],
                'Val_R²':
self.results[activation]['val_r2'],
                'Train_MSE':
self.results[activation]['train_mse'],
```

```
                'Overfitting':
(self.results[activation]['val_mse'] -
self.results[activation]['train_mse']) /
self.results[activation]['train_mse'] * 100
            })

        summary_df =
pd.DataFrame(summary_data).sort_values('Val_MSE
')

        print(f"{'Rank':<5} {'Activation':<12}
{'Val MSE':<12} {'Val R²':<10} {'Overfitting
%':<15}")
        print("-" * 65)

        for idx, row in summary_df.iterrows():

print(f"{summary_df.index.get_loc(idx)+1:<5}
{row['Activation']:<12} {row['Val_MSE']:<12.0f}
{row['Val_R²']:<10.3f}
{row['Overfitting']:<15.1f}")

        # Best performer
        best_activation =
summary_df.iloc[0]['Activation'].lower()
        print(f"\n🏆 BEST PERFORMER:
{best_activation.upper()}")
        print(f"   Validation MSE:
{summary_df.iloc[0]['Val_MSE']:.0f}")
        print(f"   Validation R²:
{summary_df.iloc[0]['Val_R²']:.4f}")

        # Insights
        print(f"\n📊 KEY INSIGHTS:")
        print(f"   • Lowest validation MSE:
{summary_df.iloc[0]['Activation']}
({summary_df.iloc[0]['Val_MSE']:.0f})")
        print(f"   • Highest R² score:
{summary_df.loc[summary_df['Val_R²'].idxmax(),
'Activation']}
```

```
({summary_df['Val_R²'].max():.4f})")
        print(f"    • Least overfitting:
{summary_df.loc[summary_df['Overfitting'].idxmi
n(), 'Activation']}
({summary_df['Overfitting'].min():.1f}%)")

def main():
    """Main execution function"""

    print("🏠 NEURAL NETWORK ACTIVATION
FUNCTIONS ANALYSIS")
    print("   Dataset: Synthetic House Price
Prediction")
    print("="*60)

    # Generate synthetic dataset
    print("\n1. Generating synthetic house
price dataset...")
    generator =
HousePriceDataGenerator(n_samples=5000)
    data = generator.generate_data()

    print(f"   Dataset shape: {data.shape}")
    print(f"   Price range:
${data['price'].min():,.0f} -
${data['price'].max():,.0f}")
    print(f"   Average price:
${data['price'].mean():,.0f}")

    # Prepare features and target
    X = data.drop('price', axis=1)
    y = data['price']

    # Train-test split
    print("\n2. Splitting data (70% train, 30%
validation)...")
    X_train, X_val, y_train, y_val =
train_test_split(X, y, test_size=0.3,
random_state=42)
```

```
    # Normalize features
    print("3. Normalizing features...")
    scaler = StandardScaler()
    X_train_scaled =
scaler.fit_transform(X_train)
    X_val_scaled = scaler.transform(X_val)

    # Run activation function analysis
    print("\n4. Running activation function
experiments...")
    analyzer =
ActivationFunctionAnalyzer(X_train_scaled,
X_val_scaled, y_train, y_val)
    analyzer.run_all_experiments(epochs=150,
batch_size=32)

    # Display results
    print("\n5. Analyzing results...")
    analyzer.plot_results()
    analyzer.print_summary()

    print("\n✅ Experiment completed
successfully!")

    return analyzer, data

# Run the experiment
if __name__ == "__main__":
    analyzer, dataset = main()
```

Output

# Output For Sigmoid Activation Function

-3.287 -3.283

```
================================================================================
ACTIVATION FUNCTIONS COMPARISON SUMMARY
================================================================================
Rank  Activation    Val MSE      Val R²     Overfitting %
-----------------------------------------------------------------
1     RELU          540591505    0.935      3.0
2     LEAKY_RELU    545067599    0.934      2.9
3     SWISH         549097966    0.934      4.6
4     ELU           592809916    0.928      7.1
5     SELU          629271374    0.924      8.9
6     TANH          35401914014  -3.283     -1.8
7     SIGMOID       35433753572  -3.287     -1.8

🏆 BEST PERFORMER: RELU
   Validation MSE: 540591505
   Validation R²: 0.9346

📊 KEY INSIGHTS:
   • Lowest validation MSE: RELU (540591505)
   • Highest R² score: RELU (0.9346)
   • Least overfitting: TANH (-1.8%)

✅ Experiment completed successfully!
```

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| Conclusion | In our analysis, we utilized a **House Price Prediction Dataset** obtained from Kaggle. We tested two activation functions: **Sigmoid** and **ReLU**.<br><br>The results revealed that, for both activation functions, **Momentum SGD** outperformed **SGD** in terms of accuracy. However, **SGD** demonstrated faster training times compared to **Momentum SGD**. |