



Firefly Algorithm for Hyperparameter Tuning of CBoW Word2Vec Embeddings Models

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- ① FireFly Algorithm
- ② CBOW Word Embedding Model
- ③ Experiments and Results

- 1 FireFly Algorithm
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Swarm Intelligence

Swarm intelligence algorithms are inspired by the collective behavior of social creatures.



Figure 1: Swarm intelligence: Birds

Firefly Algorithm

The **Firefly Algorithm (FA)**, introduced by Xin-She Yang, is inspired by the flashing behavior of fireflies.



Figure 2: Fireflies flashing at night

Firefly Algorithm

The Firefly Algorithm is based on three key hypotheses:

- **All-Attractiveness:** All fireflies are attracted to each other regardless of their gender.
- **Brightness-Based Attraction:** Attractiveness is proportional to brightness, meaning less bright fireflies move towards brighter ones.
- **Random Movement:** If no brighter fireflies are nearby, a firefly moves randomly.

Firefly Algorithm

The main equation for the Firefly Algorithm:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha \epsilon_i^t \quad (1)$$

where r_{ij} denotes the Cartesian distance between firefly i and firefly j , given by

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^n (x_{i,k} - x_{j,k})^2}$$

Firefly Algorithm

The attractiveness β is inversely proportional to the distance, which is given by the formula:

$$\beta = \beta_0 e^{-\gamma r^2}$$

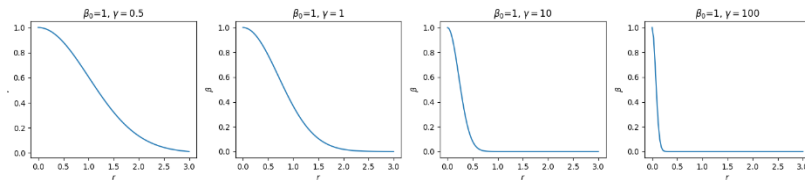


Figure 3: Effect of Gamma parameter

Note: As $r \rightarrow +\infty$, $\beta \rightarrow 0$.

Firefly Algorithm

Algorithm 1 FireFly Algorithm

Require: Light absorption coefficient γ , maximum generation $MaxGeneration$

Require: Initial population of fireflies x_i ($i = 1, 2, \dots, n$)

- 1: Generate initial population of fireflies x_i ($i = 1, 2, \dots, n$)
- 2: Evaluate light intensity I_i at x_i using objective function $f(x)$
- 3: Initialize iteration counter $t = 0$
- 4: **while** $t < MaxGeneration$ **do**
- 5: **for** $i = 1$ **to** n **do**
- 6: **for** $j = 1$ **to** n **do**
- 7: **if** $I_j > I_i$ **then**
- 8: Move firefly i towards j in d -dimension
- 9: **end if**
- 10: Attractiveness varies with distance r via $\exp[-\gamma r^2]$
- 11: Evaluate new solutions and update light intensity
- 12: **end for**
- 13: **end for**
- 14: Rank the fireflies and find the current best
- 15: $t = t + 1$
- 16: **end while**

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Overview of the CBoW Model

CBoW stands for **Continuous Bag of Words**. It is a **Word2Vec** model based on a neural network architecture, which learns to represent **words** with continuous vectors.

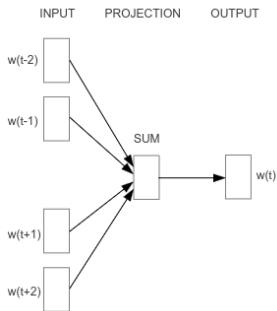


Figure 4: CBoW Model Architecture

CBoW Model Architecture

The following figure represents the model's architecture used in the experiment results:

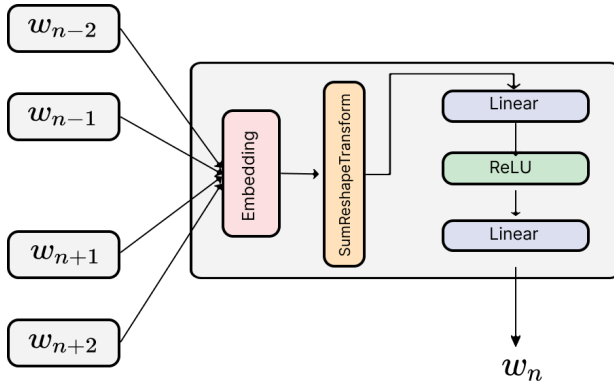
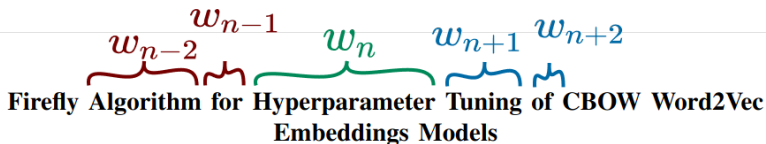


Figure 5: CBoW Model Architecture

How It Works

The CBoW model has a basic idea: given a larger corpus of text and a window of words w , it tries to predict the word in the middle.



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Hyperparameter Tuning Workflow

The following figure represents the workflow of hyperparameters tuning using the Firefly Algorithm.

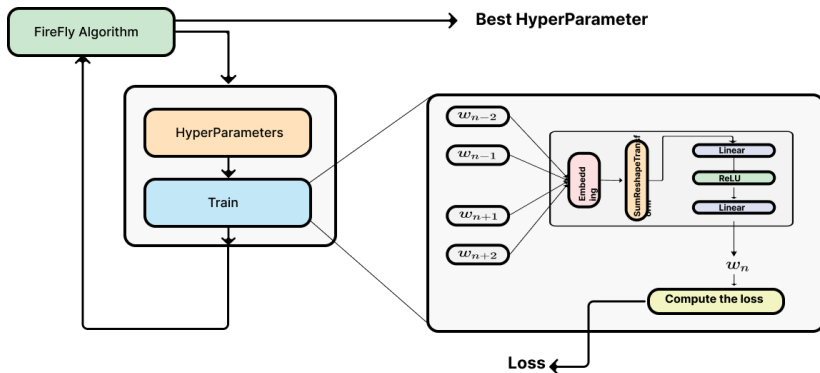
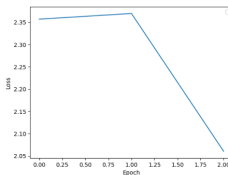
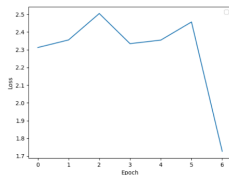
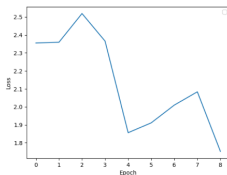


Figure 6: Workflow of Hyperparameters Tuning with the Firefly Algorithm

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Experiment HyperParameters tuning



Parameter	Figure 1	Figure 2	Figure 3
Learning Rate (lr)	0.0093	0.0100	0.0100
β_1	0.899	0.9003	0.901
β_2	0.9981	0.9989	0.9991
Embedding Dimension	2	4	5
Window Size (w)	3	3	2
Best Intensity	1.83	1.72	2.06

Table 1: Hyperparameters and Best Intensities for Different Figures

Training with Optimized Hyperparameters

The figure below illustrates the process of running training scripts using the hyperparameters found through the tuning process.

```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS zsh + - [ ] [ ] ... ^ x
```

```
• → FireFly-Optimizer-Deep-Learning git:(main) x python3 train.py --lr=0.0100 --beta1=0.9003 --beta2=0.9989 --embdim=4 --windowSize=3 --epochs=10  
/home/moussa/.local/lib/python3.11/site-packages/matplotlib/projections/_init_.py:63: UserWarning: Unable to import Axes3D. This may be due to multiple versions of Matplotlib being installed (e.g. as a system package and as a pip package). As a result, the 3D projection is not available.  
  warnings.warn("Unable to import Axes3D. This may be due to multiple versions of ")  
Loss: 1.64331: 100%|██████████████████████████████████████| 10/10 [00:01<00:00, 8.71it/s]  
Sequential(  
  (0): Embedding(25, 4)  
  (1): SumReshapeTransform()  
  (2): Linear(in features=4, out features=8, bias=True)  
  (3): ReLU()  
  (4): Linear(in features=8, out features=25, bias=True)  
)  
1.643312804180608  
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.  
○ → FireFly-Optimizer-Deep-Learning git:(main) x [ ]
```

Figure 8: Execution of Training Scripts with Optimized Hyperparameters

Training with Optimized Hyperparameters

The figure below shows the training loss and the plot of words in 2D space. **PCA** is used for dimensionality reduction.

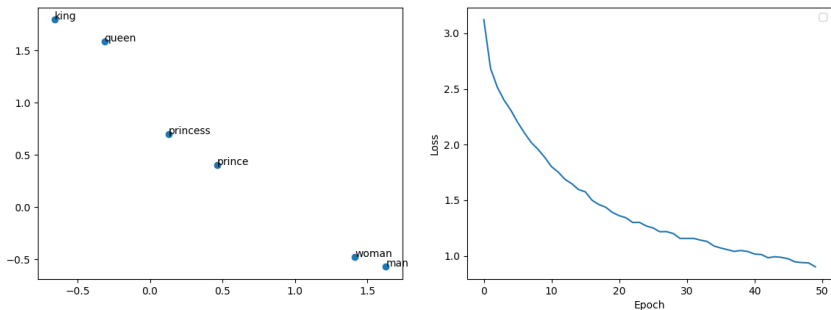


Figure 9: Training Loss and Words Plot in 2D Space