NeuralNet_Eval copy

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1 Trabajo Práctico 2: Gradiente Descendente

1.1 Alumnos:

1.1.1 - Luca Mazzarello

1.1.2 - Ignacio Pardo

1.2 Importación de Librerías

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from tqdm import tqdm
import networkx as nx
import itertools
import seaborn as sns
```

[ ]:
```
import warnings

#suppress warnings
warnings.filterwarnings('ignore')
```

[ ]:
```
# Display loss with all digits (not rounded)

pd.options.display.float_format = '{:,.20f}'.format
```

1.3 Lectura de Datos

[ ]:
```
real_estate: pd.DataFrame = pd.read_excel('data/Real estate valuation data set.
↪xlsx')
real_estate.drop(['No'], axis=1, inplace=True)

short = real_estate.copy()
short.columns = short.columns.map(lambda x: x.split(' ')[0])
display(short.head())
```

```
                        X1                      X2                        X3  \
0 2,012.91666669999995065155 32.00000000000000000000  84.87882000000000459750
1 2,012.91666669999995065155 19.50000000000000000000 306.59469999999998890416
```

```
2 2,013.58333330000004934845 13.30000000000000071054 561.98450000000002546585
3 2,013.50000000000000000000 13.30000000000000071054 561.98450000000002546585
4 2,012.83333330000004934845  5.00000000000000000000 390.56839999999999690772

   X4                       X5                        X6                        Y
0  10 24.98298000000000129717 121.54023999999999716692 37.89999999999999857891
1   9 24.98034000000000176556 121.53951000000000703949 42.20000000000000284217
2   5 24.98745999999999867214 121.54390999999999678494 47.29999999999999715783
3   5 24.98745999999999867214 121.54390999999999678494 54.79999999999999715783
4   5 24.97936999999999940769 121.54245000000000231921 43.10000000000000142109
```

[ ]:
```python
X_matrix: np.ndarray = np.array(real_estate.drop(['Y house price of unit␣
↪area'], axis=1))
y_matrix: np.ndarray = np.array(real_estate['Y house price of unit area']).
↪reshape(-1, 1)

X_train: np.ndarray = X_matrix[0:315]
y_train: np.ndarray = y_matrix[0:315]

X_test: np.ndarray = X_matrix[315:]
y_test: np.ndarray = y_matrix[315:]

X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

[ ]:
```
((315, 6), (315, 1), (99, 6), (99, 1))
```

1.4 Definición de clase NeuralNet

[ ]:
```python
from typing import List, Tuple, Callable
from matplotlib import pyplot as plt
import numpy as np
from numpy import ndarray
import networkx as nx


class NeuralNet:
    def __init__(self):
        """
        Inicializa los parámetros de la red neuronal.
        2 capas con 5 neuronas cada una.
        """

        self.W1: ndarray = np.random.random((5, 6))
        self.b1: ndarray = np.random.random((5, 1))

        self.W2: ndarray = np.random.random((1, 5))
        self.b2: ndarray = np.random.random((1, 1))
```

```python
        self.training_loss_acum: List[float] = []
        self.testing_loss_acum: List[float] = []

        self.activation = self.sigmoid

    def sigmoid(self, x: ndarray) -> ndarray:
        """
        Función de activación sigmoide.
        """
        return 1 / (1 + np.exp(-x))

    def relu(self, x: ndarray) -> ndarray:
        """
        Función de activación ReLU.
        """
        return np.maximum(0, x)

    def leaky_relu(self, x: ndarray) -> ndarray:
        """
        Función de activación Leaky ReLU.
        """
        return np.maximum(0.01 * x, x)

    def tanh(self, x: ndarray) -> ndarray:
        """
        Función de activación tanh.
        """
        return np.tanh(x)

    def softmax(self, x: ndarray) -> ndarray:
        """
        Función de activación softmax.
        """
        return np.exp(x) / np.sum(np.exp(x))

    def forward(
            self,
            x: ndarray,
            dropout: bool = False,
        ) -> ndarray:
        """
        Calcula la salida de la red neuronal.
        """

        self.z1 = self.W1 @ x.T + self.b1.repeat(x.shape[0], axis=1)
        self.a1 = self.activation(self.z1)
```

```
        # if dropout:
        #     self.a1 = self.dropout(self.a1, 0.5)

        self.z2 = self.W2 @ self.a1 + self.b2.repeat(self.a1.shape[1], axis=1)
        self.a2 = self.z2
        return self.a2.reshape(-1, 1)

    def numerical_gradient(
        self, x: ndarray, y: ndarray, eps: float, dropout: bool = False,
        dropout_prob: float = 0.5
    ) -> Tuple[ndarray, ndarray, ndarray, ndarray]:
        """
        Una estrategia para calcular estas derivadas parciales,
        consiste en calcular el promedio de los cocientes incrementales
        a derecha e izquierda.
        Para obtener la siguiente aproximación, para
        cada parámetro de la red calculamos:

        $$
        \frac{\partial L}{\partial p} \sim \frac{L(\theta_t, p + \epsilon) -␣
↪L(\theta_t, p - \epsilon)}{2 \epsilon}
        $$

        donde usamos $p$ de forma genérica para referirnos a cada elemento␣
↪$w^1_{i,j}$, $b^1_{j}$, $w^2_{i,j}$, $b^2_{j}$
        """

        dW1 = np.zeros_like(self.W1)
        db1 = np.zeros_like(self.b1)
        dW2 = np.zeros_like(self.W2)
        db2 = np.zeros_like(self.b2)

        if dropout:
            temp_w1 = self.W1.copy()
            self.W1 = self.dropout(self.W1, dropout_prob)
            temp_b1 = self.b1.copy()
            self.b1 = self.dropout(self.b1, dropout_prob)
            temp_w2 = self.W2.copy()
            self.W2 = self.dropout(self.W2, dropout_prob)
            temp_b2 = self.b2.copy()
            self.b2 = self.dropout(self.b2, dropout_prob)

        for i in range(self.W1.shape[0]):
            for j in range(self.W1.shape[1]):
                if dropout:
                    if self.W1[i, j] == 0 and temp_w1[i, j] != 0:
                        continue
```

```
                self.W1[i, j] += eps
                loss1 = self.loss(x, y)
                self.W1[i, j] -= 2 * eps
                loss2 = self.loss(x, y)
                dW1[i, j] = (loss1 - loss2) / (2 * eps)
                self.W1[i, j] += eps

        for i in range(self.b1.shape[0]):
            for j in range(self.b1.shape[1]):
                if dropout:
                    if self.b1[i, j] == 0 and temp_b1[i, j] != 0:
                        continue
                self.b1[i, j] += eps
                loss1 = self.loss(x, y)
                self.b1[i, j] -= 2 * eps
                loss2 = self.loss(x, y)
                db1[i, j] = (loss1 - loss2) / (2 * eps)
                self.b1[i, j] += eps

        for i in range(self.W2.shape[0]):
            for j in range(self.W2.shape[1]):
                if dropout:
                    if self.W2[i, j] == 0 and temp_w2[i, j] != 0:
                        continue
                self.W2[i, j] += eps
                loss1 = self.loss(x, y)
                self.W2[i, j] -= 2 * eps
                loss2 = self.loss(x, y)
                dW2[i, j] = (loss1 - loss2) / (2 * eps)
                self.W2[i, j] += eps

        for i in range(self.b2.shape[0]):
            for j in range(self.b2.shape[1]):
                if dropout:
                    if self.b2[i, j] == 0 and temp_b2[i, j] != 0:
                        continue
                self.b2[i, j] += eps
                loss1 = self.loss(x, y)
                self.b2[i, j] -= 2 * eps
                loss2 = self.loss(x, y)
                db2[i, j] = (loss1 - loss2) / (2 * eps)
                self.b2[i, j] += eps

        if dropout:
            self.W1 = temp_w1
            self.b1 = temp_b1
            self.W2 = temp_w2
```

```python
            self.b2 = temp_b2

        return dW1, db1, dW2, db2

    def dropout(self, x: ndarray, p: float) -> ndarray:
        """
        Aplica dropout a la capa de entrada.
        x: ndarray de entrada
        p: probabilidad de dropout
        """
        mask = np.random.binomial(1, p, size=x.shape)
        return x * mask

    def update_weights(
        self,
        lr: float,
        dW1: ndarray,
        db1: ndarray,
        dW2: ndarray,
        db2: ndarray,
    ):
        """
        Actualiza los pesos de la red neuronal usando
        numerical gradient descent.
        """

        self.W1 -= lr * dW1
        self.b1 -= lr * db1
        self.W2 -= lr * dW2
        self.b2 -= lr * db2

    def loss(self, x: ndarray, y: ndarray, dropout: bool = False) -> float:
        """
        Calcula el error cuadrático medio.
        """

        return np.power((self.forward(x, dropout=dropout) - y), 2).mean(axis=0)␣
↪/ 2

    def record_metrics(self, x: ndarray, y: ndarray, x_test: ndarray, y_test:␣
↪ndarray):

        self.training_loss_acum.append(self.loss(x, y))
        self.test_loss_acum.append(self.loss(x_test, y_test))

    def fit(
        self,
```

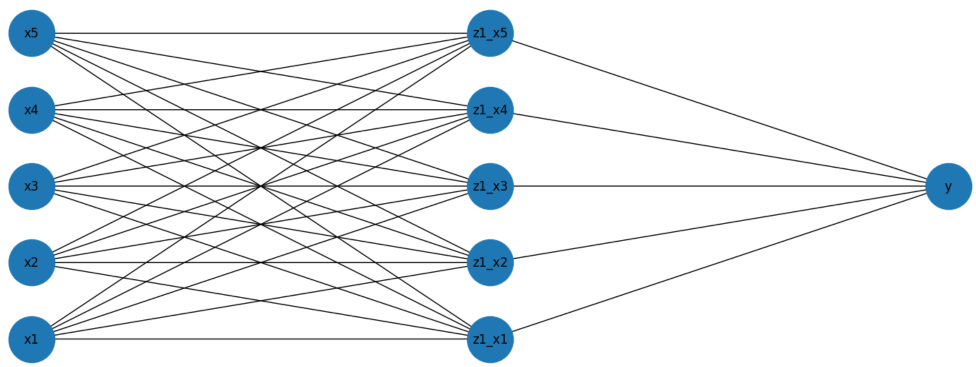
```
        x: ndarray,
        y: ndarray,
        x_test: ndarray,
        y_test: ndarray,
        lr: float = 0.01,
        epochs: int = 1000,
        eps: float = 1e-3,
        dropout: bool = False,
        dropout_prob: float = 0.5,
        custom_activation: Callable[[ndarray], ndarray] = None,
        verbose: bool = False,
    ) -> List[float]:
        """
        Entrena la red neuronal usando gradient descent.
        """

        if custom_activation:
            self.activation = custom_activation

        self.train_loss_acum = []
        self.test_loss_acum = []

        self.lr = lr
        self.epochs = epochs
        self.eps = eps
        self.with_dropout = dropout
        self.dropout_prob = dropout_prob

        for _ in tqdm(range(epochs)) if verbose else range(epochs):
            self.record_metrics(x, y, x_test, y_test)

            dW1, db1, dW2, db2 = self.numerical_gradient(x, y, eps,
↪dropout=dropout, dropout_prob=dropout_prob)

            self.update_weights(lr, dW1, db1, dW2, db2)

        self.activation = self.sigmoid

        return self.train_loss_acum

    def predict(self, x: ndarray) -> ndarray:
        """
        Infiere la salida de la red neuronal.
        """
        return self.forward(x)

    def get_weights(self) -> Tuple[ndarray, ndarray, ndarray, ndarray]:
```

```
        """
        Devuelve los pesos de la red neuronal.
        """

        return self.W1, self.b1, self.W2, self.b2

    def get_training_loss(self) -> List[float]:
        """
        Devuelve el error cuadrático medio acumulado.
        """

        return self.training_loss_acum

    def get_test_loss(self) -> List[float]:

        return self.test_loss_acum

    def plot_loss(self, ax: plt.Axes = None) -> plt.Axes:

        if ax is None:
            _, ax = plt.subplots()

        ax.plot(
            range(len(self.training_loss_acum)),
            self.training_loss_acum,
            label="Training Loss",
        )
        ax.plot(range(len(self.test_loss_acum)), self.test_loss_acum,␣
↪label="Test Loss")
        ax.legend()
        ax.set_xlabel("Epoch")
        ax.set_ylabel("Loss")
        ax.set_title("Loss vs Epoch, lr = {}, $\epsilon$ = {}".format(self.lr,␣
↪self.eps))
        # If dropout is used, add it to the title
        if self.with_dropout:
            ax.set_title(
                "Loss vs Epoch, lr = {}, $\epsilon$ = {}, dropout_prob = {}".
↪format(
                    self.lr, self.eps, self.dropout_prob
                )
            )

        return ax

    def mse(self, y_true: ndarray, x_test: ndarray) -> float:
        """
```

```
        Calcula el error cuadrático medio.
        """

        y_pred = self.predict(x_test)
        return np.mean(np.power(y_true - y_pred, 2))

    def plot_network_graph(self, ax: plt.Axes):
        """
        Visualiza la red neuronal y sus conexiones
        """
        G = nx.DiGraph()
        G.add_nodes_from(["x1", "x2", "x3", "x4", "x5"])

        G.add_nodes_from(["z1_x1", "z1_x2", "z1_x3", "z1_x4", "z1_x5"])

        G.add_nodes_from(["y"])

        # Add edges with weights
        for i in range(5):
            for j in range(5):
                G.add_edge(f"x{i+1}", f"z1_x{j+1}", weight=self.W1[i, j])
                G.add_edge(f"z1_x{j+1}", f"y", weight=1)

        pos = {
            "x1": (0, 0),
            "x2": (0, 1),
            "x3": (0, 2),
            "x4": (0, 3),
            "x5": (0, 4),
            "z1_x1": (1, 0),
            "z1_x2": (1, 1),
            "z1_x3": (1, 2),
            "z1_x4": (1, 3),
            "z1_x5": (1, 4),
            "y": (2, 2),
        }

        # Edge labels with weights

        nx.draw_networkx_nodes(G, pos, cmap=plt.get_cmap("jet"),␣
↪node_size=2000, ax=ax)
        nx.draw_networkx_labels(G, pos, ax=ax)
        nx.draw_networkx_edges(
            G, pos, edgelist=G.edges(), edge_color="k", arrows=True, ax=ax
        )
```

```
[ ]: nn = NeuralNet()
     fig, ax = plt.subplots(1, 1, figsize=(15, 5))
     #no border
     _ = fig.subplots_adjust(left=0, right=1, bottom=0, top=1)
     _ = ax.axis('off')
     _ = nn.plot_network_graph(ax)
```

```
/Users/nacho/opt/anaconda3/envs/coding/lib/python3.8/site-
packages/networkx/drawing/nx_pylab.py:433: UserWarning: No data for colormapping
provided via 'c'. Parameters 'cmap' will be ignored
  node_collection = ax.scatter(
```

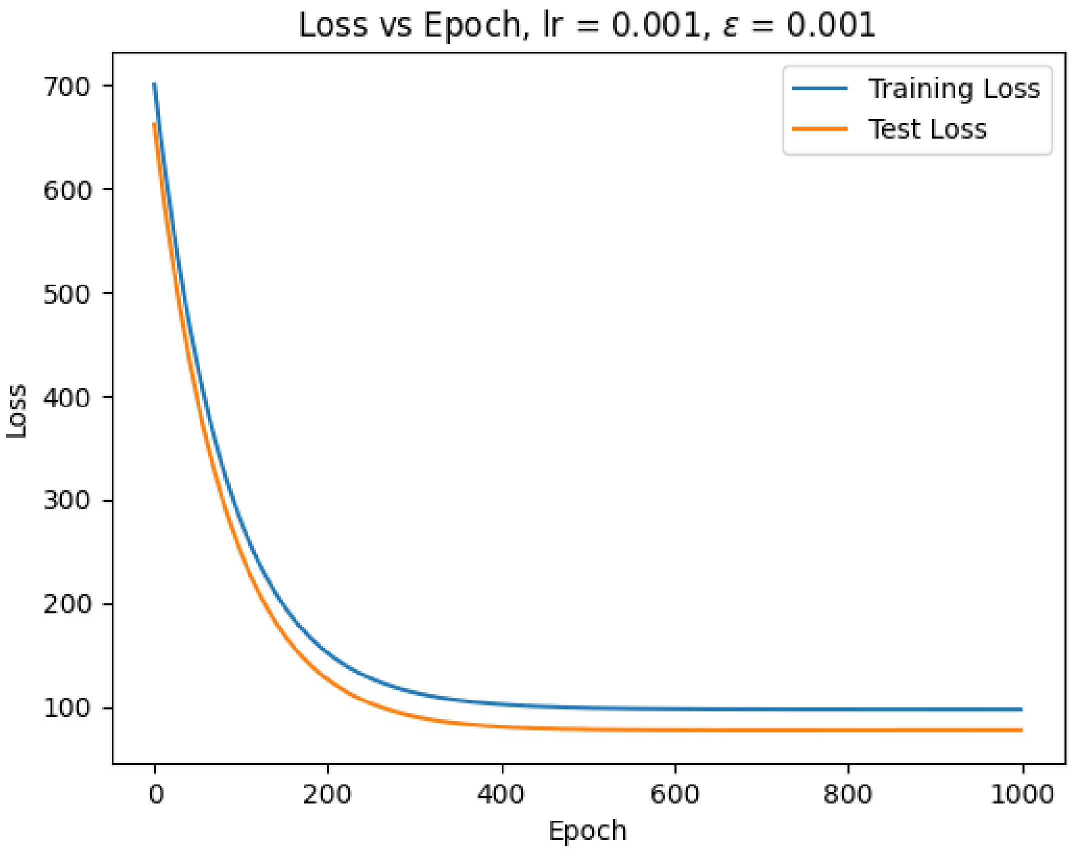


1.5 Experimentación Manual

```
[ ]: nn = NeuralNet()
     nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=1000, lr=0.001,
      ↪verbose=True)
     display(pd.Series(
         [
             y_test[0][0],
             nn.predict(X_test[0].reshape(1, -1))[0][0],
             nn.get_training_loss()[-1][0],
             nn.get_test_loss()[-1][0],
         ],
         index=["y_true", "y_pred", "train_loss", "test_loss"]
     ))
     nn.plot_loss()
```

```
100%|          | 1000/1000 [00:04<00:00, 222.64it/s]

y_true        27.300000000000071054
y_pred        38.024657181349141046
train_loss    97.12082915121834503225
test_loss     77.15179309729562362463
dtype: float64
```

```
[ ]: <Axes: title={'center': 'Loss vs Epoch, lr = 0.001, $\\epsilon$ = 0.001'},
xlabel='Epoch', ylabel='Loss'>
```

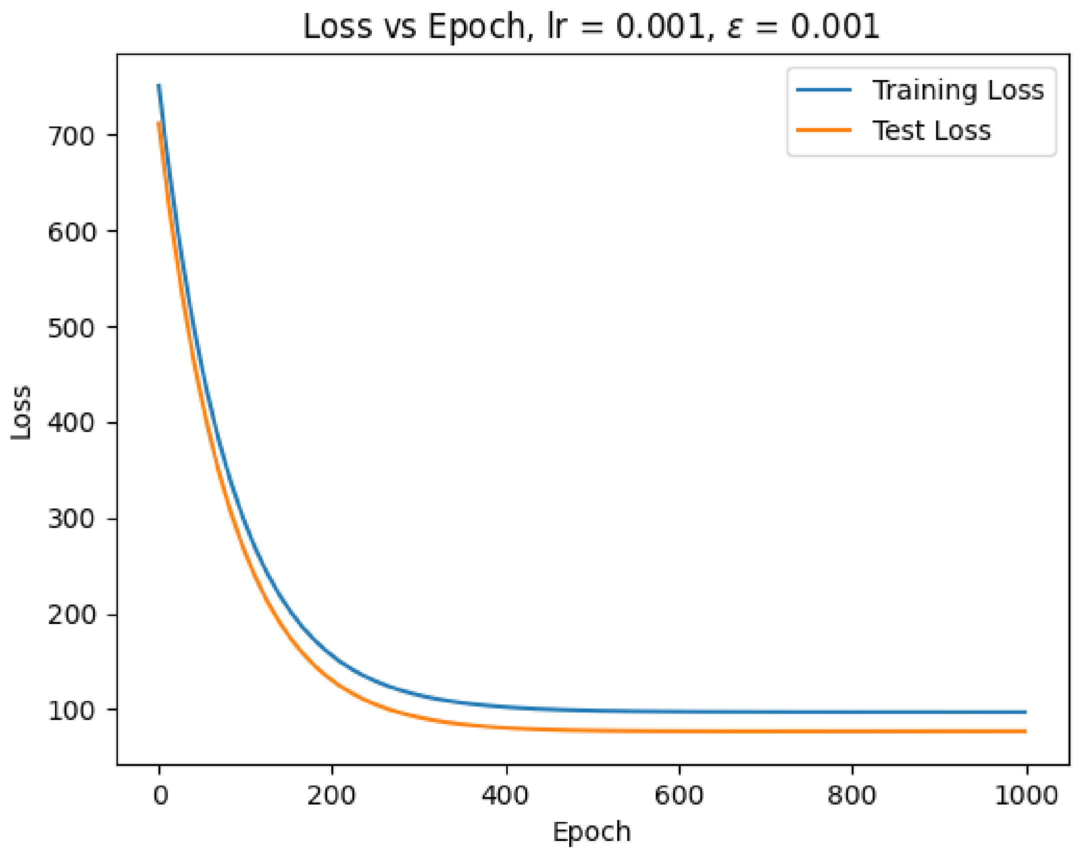



```
[ ]: nn = NeuralNet()
nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=1000, lr=0.001,␣
 ↪custom_activation=nn.tanh, verbose=True)
display(pd.Series(
    [
        y_test[0][0],
        nn.predict(X_test[0].reshape(1, -1))[0][0],
        nn.get_training_loss()[-1][0],
        nn.get_test_loss()[-1][0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss"]
))
nn.plot_loss()
```

```
100%|      | 1000/1000 [00:04<00:00, 248.22it/s]

y_true        27.300000000000000071054
y_pred        38.021225156054740068 61
```

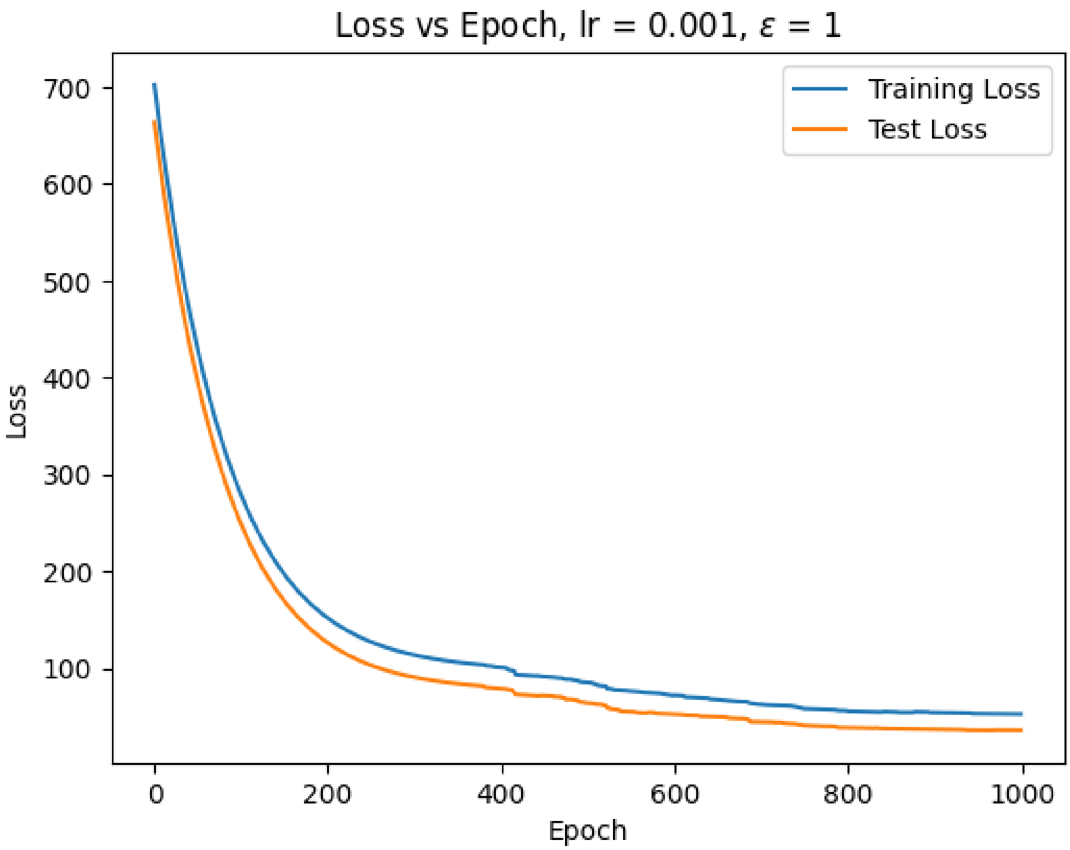
```
train_loss    97.12112880050391083842
test_loss     77.15022996002481647793
dtype: float64
```

[ ]:
```
<Axes: title={'center': 'Loss vs Epoch, lr = 0.001, $\\epsilon$ = 0.001'},
xlabel='Epoch', ylabel='Loss'>
```



[ ]:
```
nn = NeuralNet()
nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=1000, lr=0.001,␣
 ↪eps=1, verbose=True)
display(pd.Series(
    [
        y_test[0][0],
        nn.predict(X_test[0].reshape(1, -1))[0][0],
        nn.get_training_loss()[-1][0],
        nn.get_test_loss()[-1][0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss"]
))
_ = nn.plot_loss()
```

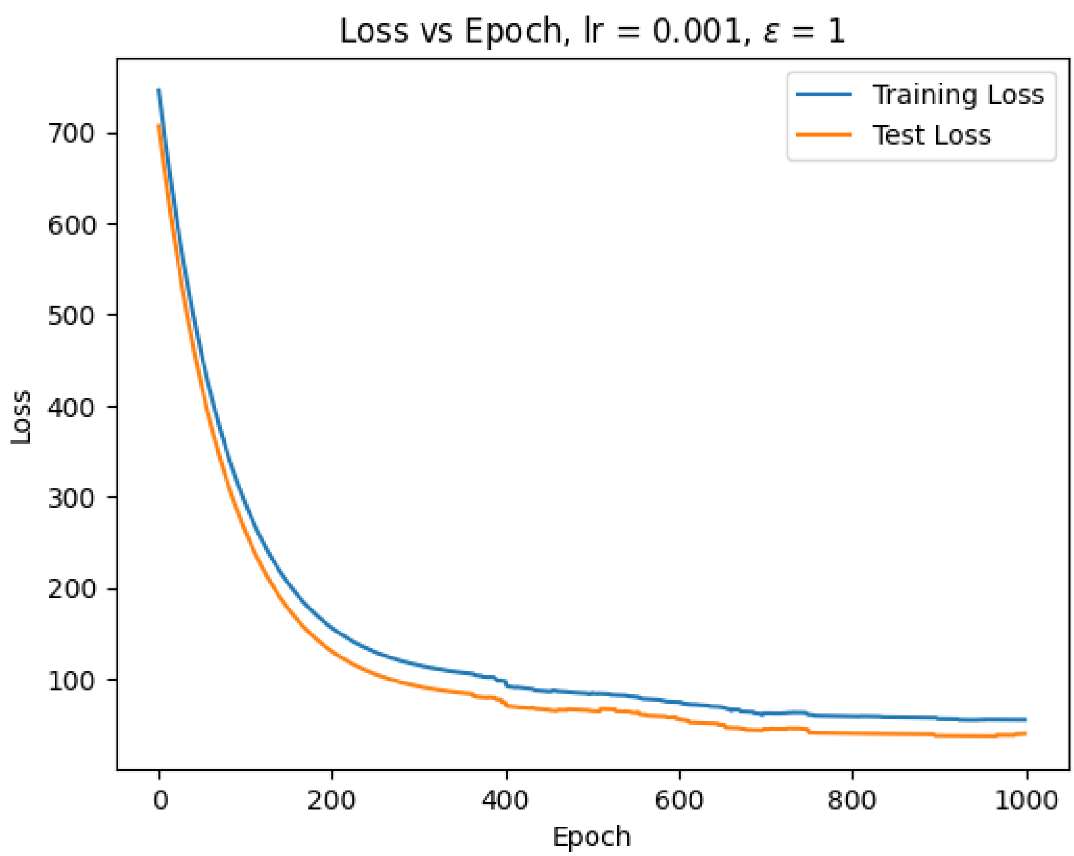
```
100%|          | 1000/1000 [00:04<00:00, 220.55it/s]

y_true        27.300000000000071054
y_pred        27.870108212853985207 86
train_loss    52.580490000281805862 41
test_loss     35.923460495627679733 84
dtype: float64
```




```
[ ]: nn = NeuralNet()
nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=1000, lr=0.001,␣
 ↪eps=1, custom_activation=nn.tanh, verbose=True)
display(pd.Series(
    [
        y_test[0][0],
        nn.predict(X_test[0].reshape(1, -1))[0][0],
        nn.get_training_loss()[-1][0],
        nn.get_test_loss()[-1][0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss"]
))
```

```
_ = nn.plot_loss()
```

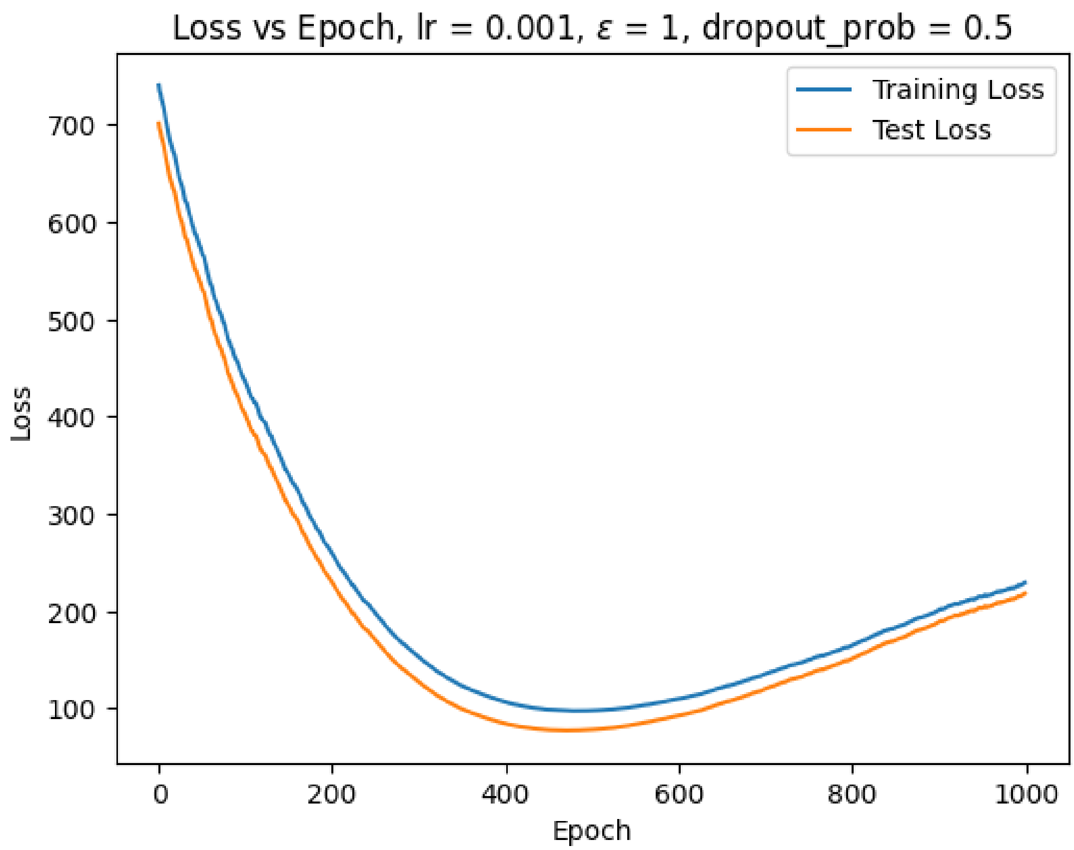
```
100%|          | 1000/1000 [00:04<00:00, 233.20it/s]

y_true        27.300000000000000071054
y_pred        35.42288054345024050917
train_loss    54.96998128619167545139
test_loss     39.69249387913455251464
dtype: float64
```




```
[ ]: nn_dropout = NeuralNet()
nn_dropout.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=1000,␣
 ↪lr=0.001, eps=1, dropout=True, dropout_prob=0.5, verbose=True)
display(pd.Series(
    [
        y_test[0][0],
        nn_dropout.predict(X_test[0].reshape(1, -1))[0][0],
        nn_dropout.get_training_loss()[-1][0],
        nn_dropout.get_test_loss()[-1][0],
        min(nn_dropout.get_training_loss())[0],
```

```
        min(nn_dropout.get_test_loss())[0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss", "min_train_loss",␣
↪"min_test_loss"]
))
_ = nn_dropout.plot_loss()
```

```
100%|      | 1000/1000 [00:02<00:00, 399.85it/s]

y_true             27.300000000000071054
y_pred             54.377908914906279060
train_loss        228.939789184576113711 96
test_loss         217.776740175369155849 69
min_train_loss     97.117625576426988232 01
min_test_loss      77.048548169128153517 70
dtype: float64
```

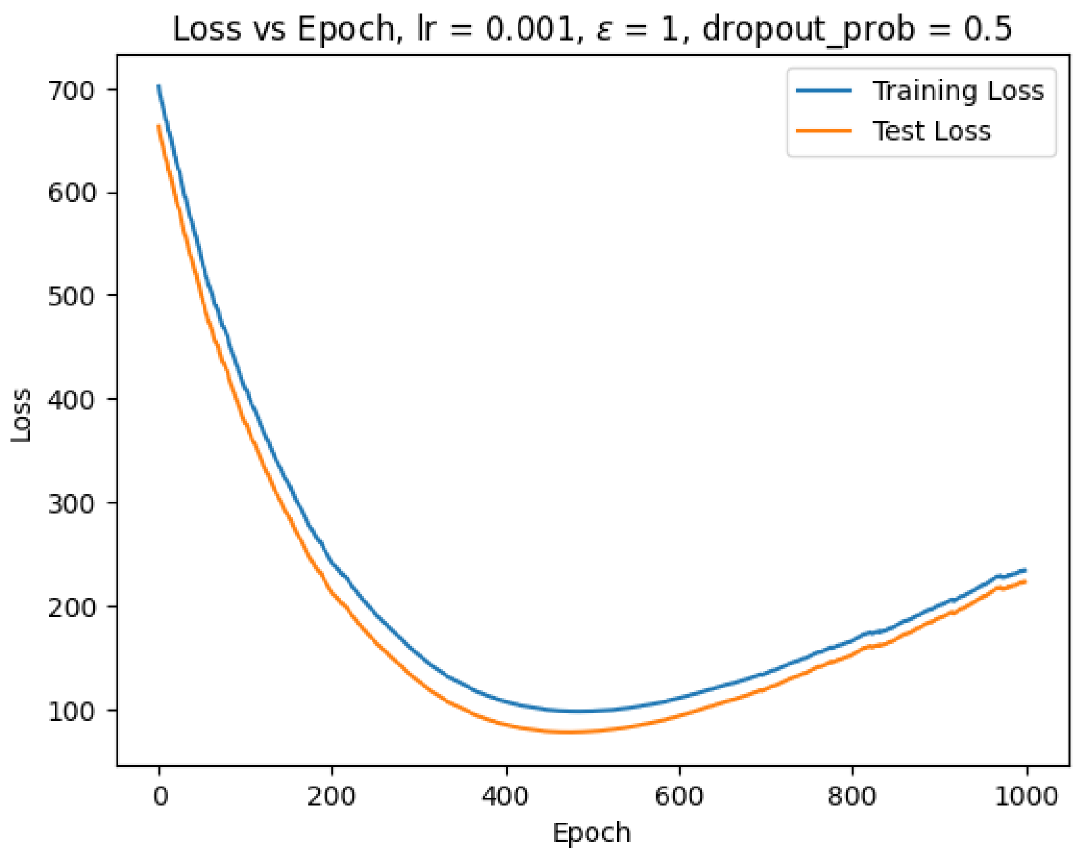


[ ]:
```
nn_dropout = NeuralNet()
```

```python
nn_dropout.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=1000,␣
↪lr=0.001, eps=1, dropout=True, dropout_prob=0.5, custom_activation=nn.tanh,␣
↪verbose=True)
display(pd.Series(
    [
        y_test[0][0],
        nn_dropout.predict(X_test[0].reshape(1, -1))[0][0],
        nn_dropout.get_training_loss()[-1][0],
        nn_dropout.get_test_loss()[-1][0],
        min(nn_dropout.get_training_loss())[0],
        min(nn_dropout.get_test_loss())[0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss", "min_train_loss",␣
↪"min_test_loss"]
))
_ = nn_dropout.plot_loss()
```

```
100%|          | 1000/1000 [00:02<00:00, 461.19it/s]
```

```
y_true             27.300000000000071054
y_pred             54.654486183604532811 84
train_loss        233.434535403719536361 68
test_loss         222.419580818892171691 91
min_train_loss     97.117384050322698385 57
min_test_loss      77.048532502410736810 82
dtype: float64
```



[ ]:
```
nn_dropout = NeuralNet()
nn_dropout.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=10000,␣
 ↪lr=0.001, eps=1, dropout=True, dropout_prob=0.8, verbose=True)
```

```
100%|      | 10000/10000 [00:38<00:00, 259.49it/s]
```

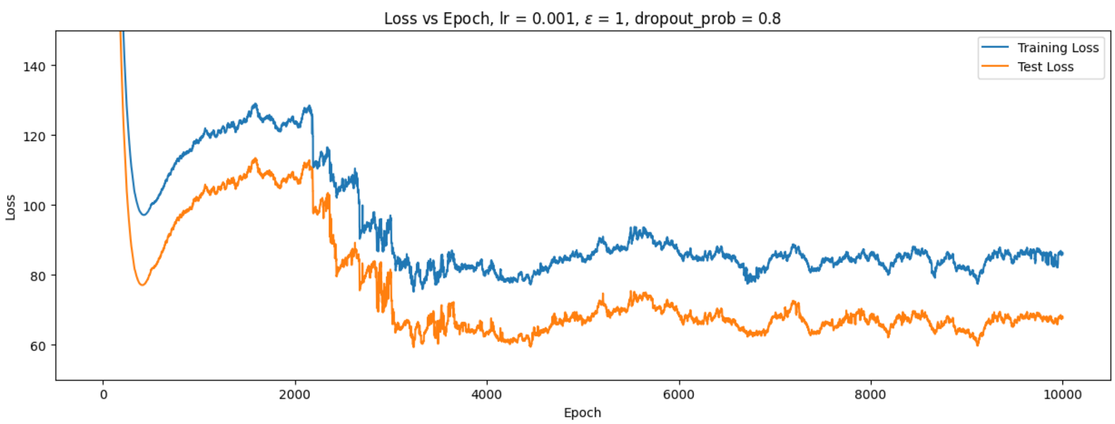
[ ]: []

[ ]:
```
display(pd.Series(
    [
        y_test[0][0],
        nn_dropout.predict(X_test[0].reshape(1, -1))[0][0],
        nn_dropout.get_training_loss()[-1][0],
        nn_dropout.get_test_loss()[-1][0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss"]
))
```

```
y_true        27.300000000000000071054
y_pred        33.304534047403357988806
train_loss    85.917547315079502823321
```

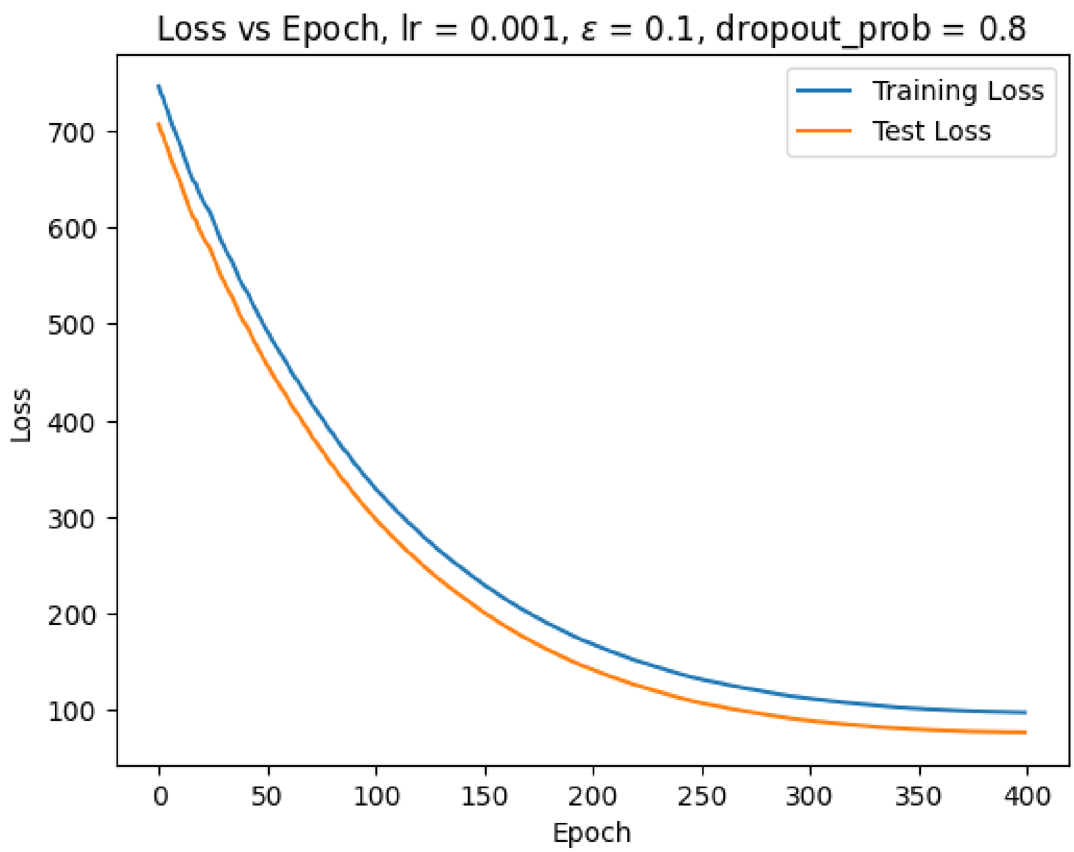
```
test_loss      67.610374976223383214 35
dtype: float64
```

[ ]:
```
fig, ax = plt.subplots(1, 1, figsize=(15, 5))
ax.set_ylim(50, 150)
_ = nn_dropout.plot_loss(ax=ax)
```



[ ]:
```
nn_400_dropout = NeuralNet()
nn_400_dropout.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=400,␣
 ↪lr=0.001, eps=0.1, dropout=True, dropout_prob=0.8)
display(pd.Series(
    [
        y_test[0][0],
        nn_400_dropout.predict(X_test[0].reshape(1, -1))[0][0],
        nn_400_dropout.get_training_loss()[-1][0],
        nn_400_dropout.get_test_loss()[-1][0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss"]
))
_ = nn_400_dropout.plot_loss()
```

```
y_true        27.300000000000000710 54
y_pred        37.037639341766180223 20
train_loss    97.698317811653353714 97
test_loss     77.193548917803241238 29
dtype: float64
```



[ ]:
```
hyper_nn = NeuralNet()
hyper_nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=50000, lr=0.
↪001, eps=1, dropout=True, dropout_prob=0.8)
```

```
/var/folders/5j/7b3w3dw95qdcl187vxc3yn300000gn/T/ipykernel_1661/2190381686.py:28
: RuntimeWarning: overflow encountered in exp
  return 1 / (1 + np.exp(-x))
```

[ ]: []

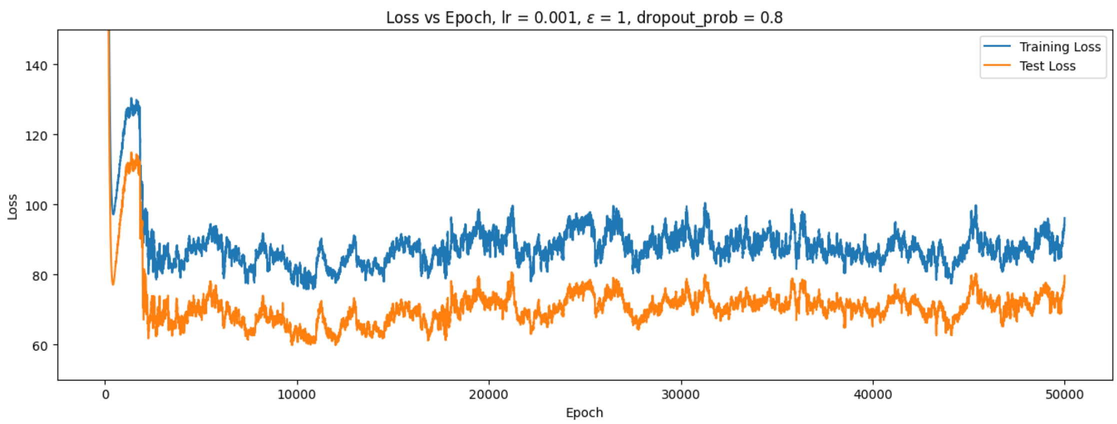
[ ]:
```
display(pd.Series(
    [
        y_test[0][0],
        hyper_nn.predict(X_test[0].reshape(1, -1))[0][0],
        hyper_nn.get_training_loss()[-1][0],
        hyper_nn.get_test_loss()[-1][0],
    ],
    index=["y_true", "y_pred", "train_loss", "test_loss"]
))
```

```
/var/folders/5j/7b3w3dw95qdcl187vxc3yn300000gn/T/ipykernel_1661/2190381686.py:28
```

```
: RuntimeWarning: overflow encountered in exp
  return 1 / (1 + np.exp(-x))
```

```
y_true        27.300000000000071054
y_pred        28.120642707158381767 84
train_loss    96.124529445615053191 43
test_loss     79.649677815832177429 91
dtype: float64
```

[ ]:
```
fig, ax = plt.subplots(1, 1, figsize=(15, 5))
ax.set_ylim(50, 150)
hyper_nn.plot_loss(ax=ax)
```



[ ]:
```
# Epoch en el que se obtuvo la menor Loss

m = min(hyper_nn.get_training_loss(), key=lambda x: x[0])
e = hyper_nn.get_training_loss().index(m)

print(f"Lowest training loss: {m[0]:.2f} at epoch {e}")
```

```
Lowest training loss: 75.74 at epoch 10480
```

[ ]:
```
hyper_nn_ = NeuralNet()
hyper_nn_.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=e, lr=0.
↪001, eps=1, dropout=True, dropout_prob=0.8)
```

1.6 Mascara sobre los pesos: Dropout

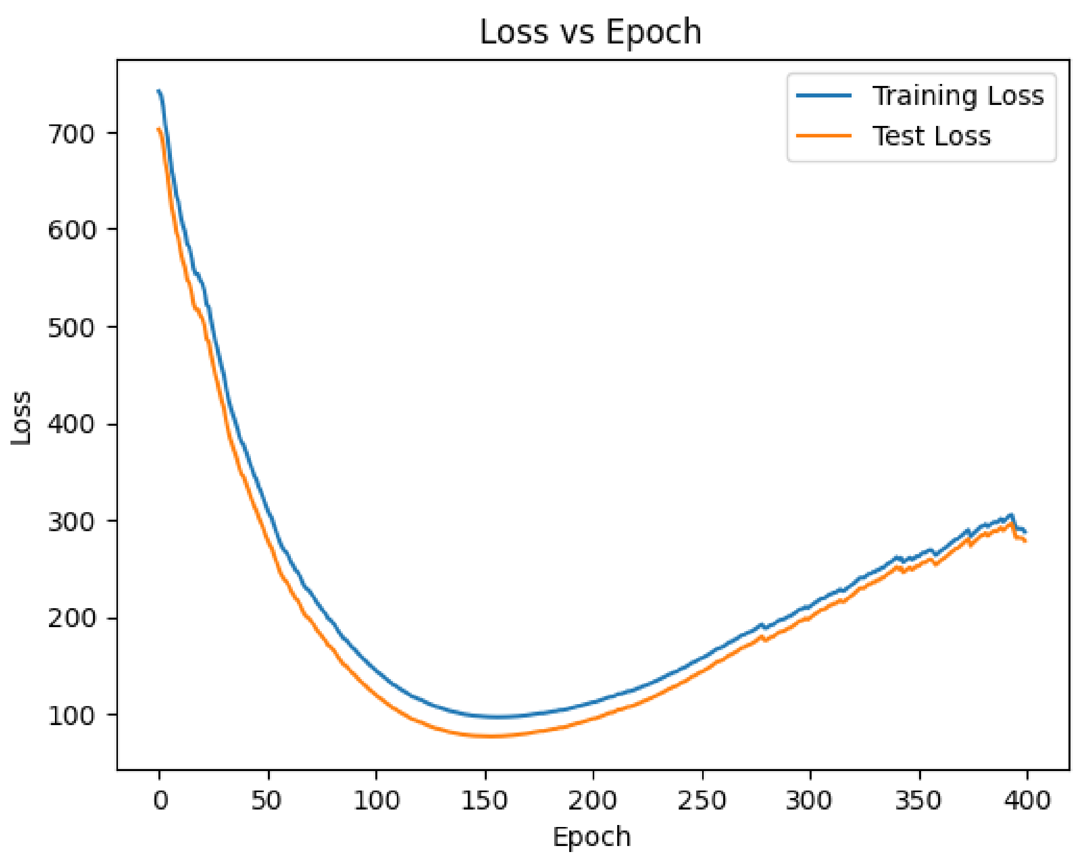
Otras dos cuestiones que probamos fueron cambiar la función de activación, y aplicar una mascara a los pesos de entrenamiento de la red con cierta probabilidad en cada epoch.

Para la función de activación probamos con la función sigmoide como indicaba la consigna, y ademas con la funciones ReLU y Tanh.

$$\mathrm{ReLU}(x) = \max(0, x)\mathrm{Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

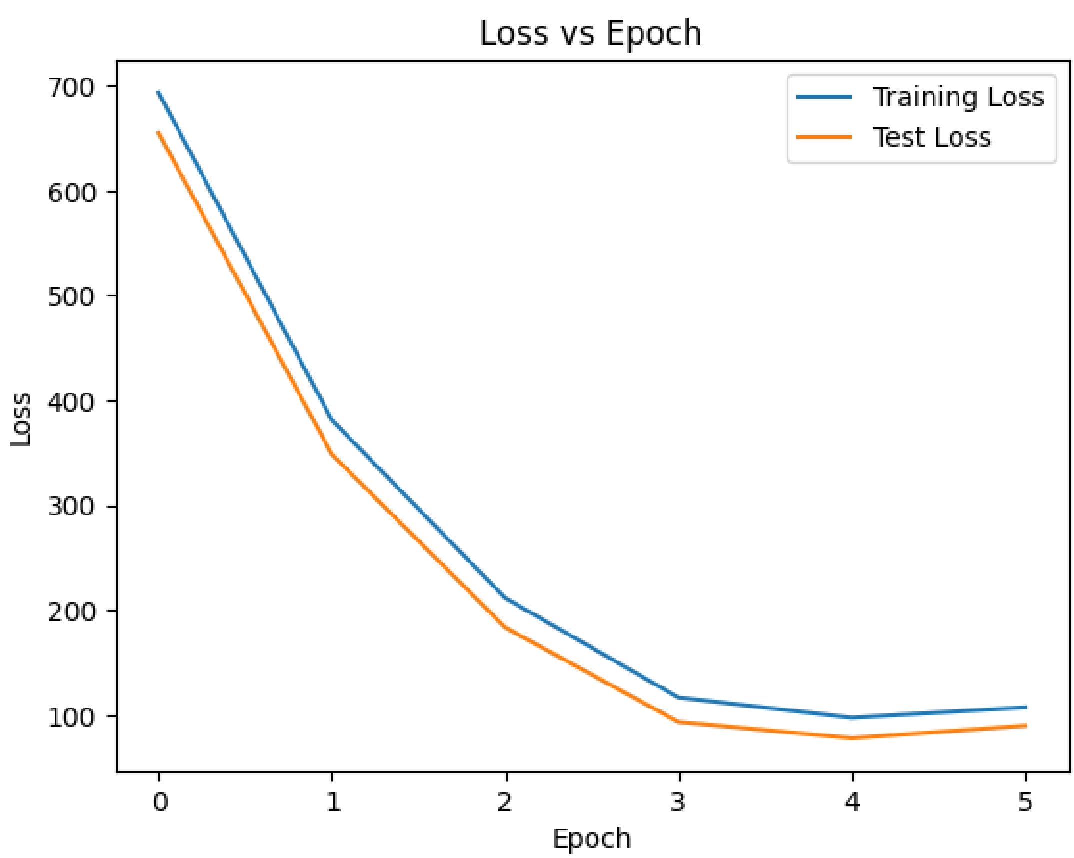
[ ]:
```
nn = NeuralNet()
loss = nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.003,
 ↪epochs=400, dropout=True)
display(pd.Series(
    [
        y_test[0][0],
        nn.predict(X_test[0].reshape(1, -1))[0][0],
        nn.get_training_loss()[-1][0]
    ],
    index=["y_true", "y_pred", "train_loss"]
))
nn.plot_loss()
```

```
y_true         27.300000000000071054
y_pred         57.63734020134181434969
train_loss    287.87181630280230137942
dtype: float64
```



[ ]:
```
nn = NeuralNet()
loss = nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.1, epochs=6,␣
 ↪dropout=True)
display(pd.Series(
    [
        y_test[0][0],
        nn.predict(X_test[0].reshape(1, -1))[0][0],
        nn.get_training_loss()[-1][0]
    ],
    index=["y_true", "y_pred", "train_loss"]
))
nn.plot_loss()
```

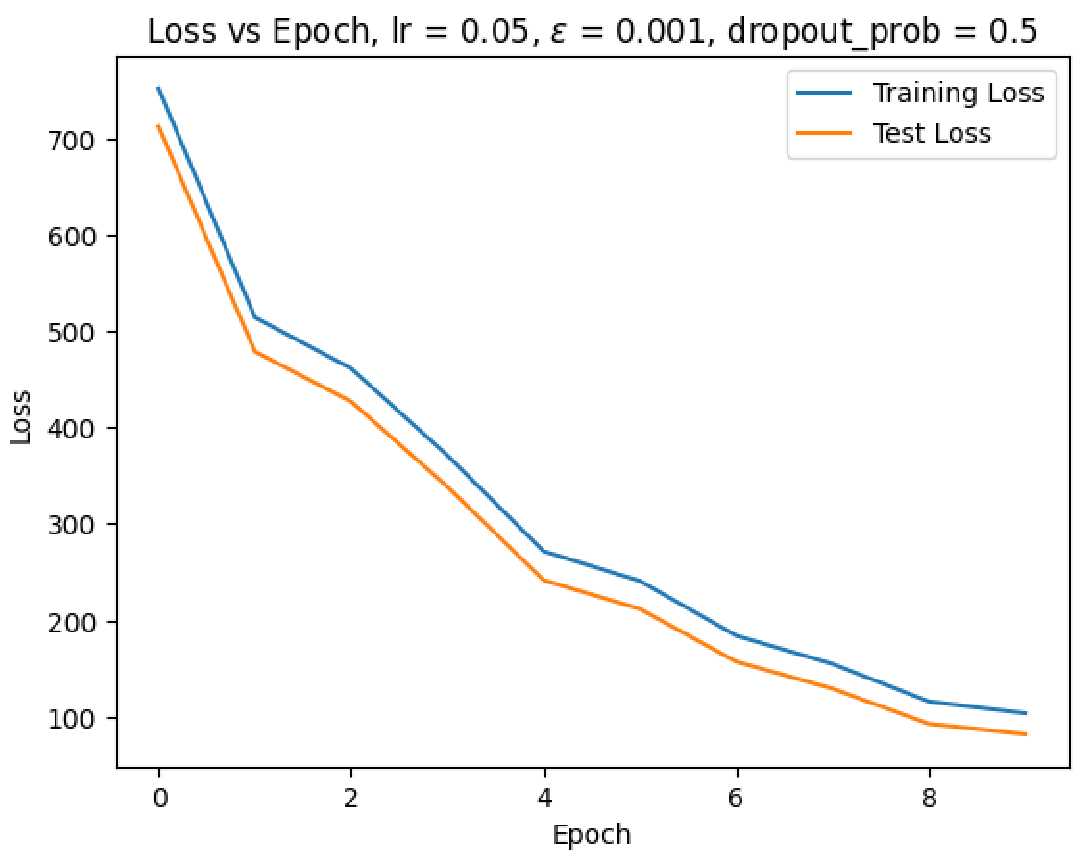
```
y_true         27.300000000000071054
y_pred         46.1238095767615622631
train_loss    107.23579872377744948153
dtype: float64
```



[ ]:
```
nn = NeuralNet()
```

```
loss = nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.05,␣
 ↪epochs=10, dropout=True)
display(pd.Series(
    [
        y_test[0][0],
        nn.predict(X_test[0].reshape(1, -1))[0][0],
        nn.get_training_loss()[-1][0]
    ],
    index=["y_true", "y_pred", "train_loss"]
))
nn.plot_loss()
```

```
y_true         27.300000000000071054
y_pred         38.24117112246570826528
train_loss    103.20305378438199284119
dtype: float64
```



1.7 Otras funciones de activación

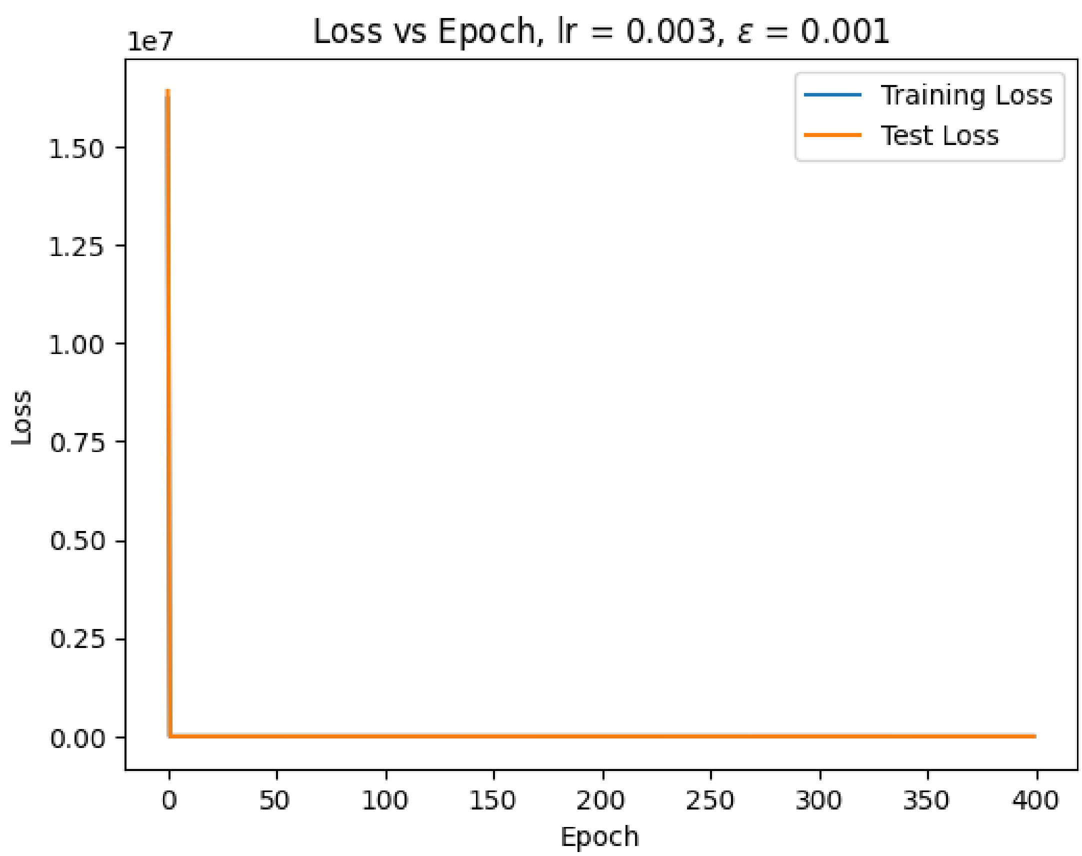
Para la función de activación probamos con la función sigmoide como indicaba la consigna, y ademas con la funciones ReLU, Leaky Relu y Tanh.

$$\mathrm{ReLU}(x) = \max(0, x)\mathrm{LeakyReLU}(x) = \max(0.01x, x)\mathrm{Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

1.7.1 ReLu y Leaky ReLu

Con las función ReLU y Leaky ReLU no logramos convergencia.

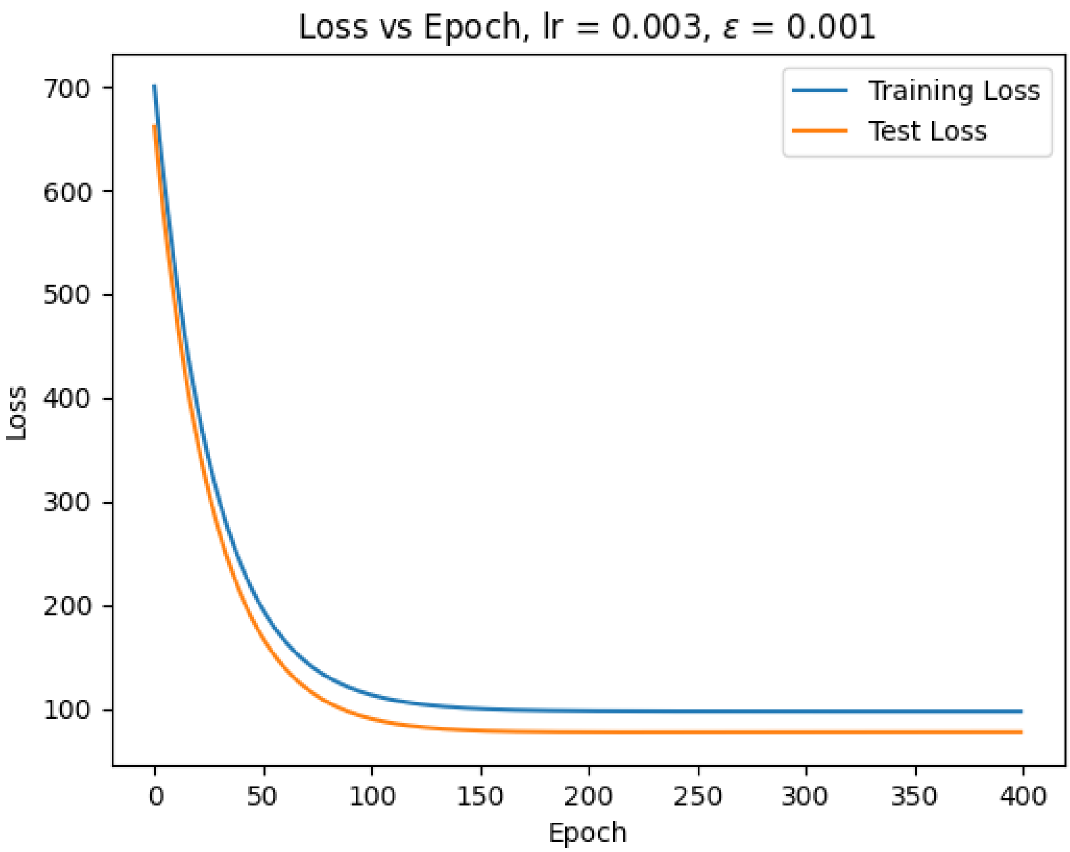
[ ]:
```
nn_relu = NeuralNet()
nn_relu.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.003,␣
↪epochs=400, custom_activation=nn.relu)
nn_relu.plot_loss()
```



[ ]:
```
nn_leaky = NeuralNet()
nn_leaky.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.003,␣
↪epochs=400, custom_activation=nn.leaky_relu)
nn_leaky.plot_loss()
```

Sin Embargo para la función Tanh si vimos convergencia en nuestras pruebas.

[ ]:
```
nn_tanh = NeuralNet()
nn_tanh.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.003,␣
 ↪epochs=400, custom_activation=nn.tanh)
nn_tanh.plot_loss()
```

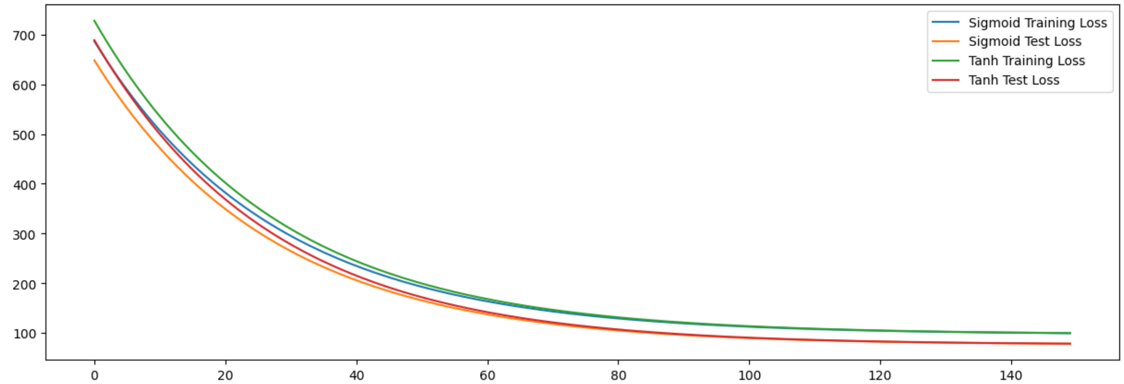


Aca una comparación entre las funciones de activación sigmoide y tanh. En este caso la función de activación tanh hasta converge mas rápido y a una loss menor que la sigmoide.

[ ]:
```
fig, ax = plt.subplots(figsize=(15, 5))

nn = NeuralNet()
nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.003, epochs=150)

nn_tanh = NeuralNet()
nn_tanh.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.003,␣
 ↪epochs=150, custom_activation=nn.tanh)

ax.plot(nn.get_training_loss(), label="Sigmoid Training Loss")
```

```
ax.plot(nn.get_test_loss(), label="Sigmoid Test Loss")

ax.plot(nn_tanh.get_training_loss(), label="Tanh Training Loss")
ax.plot(nn_tanh.get_test_loss(), label="Tanh Test Loss")
ax.legend()
```

[ ]: <matplotlib.legend.Legend at 0x7faeb6ae5d30>



1.8 Distintos valores de Learning Rate para distintos Epochs

[ ]:
```
# Brute force para encontrar el mejor número de epochs y learning rate

lrs = np.linspace(0.001, 0.5, 10).round(3)
eps = list(range(1, 1000, 50))

train_losses = {}
test_losses = {}

for lr, ep in tqdm(list(itertools.product(lrs, eps))):
    nn = NeuralNet()
    nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=lr,␣
 ↪epochs=int(ep))

    train_losses[(lr, int(ep))] = nn.get_training_loss()[-1][0]
    test_losses[(lr, int(ep))] = nn.get_test_loss()[-1][0]
```

100%| | 200/200 [06:15<00:00, 1.88s/it]

[ ]:
```
train_losses_arr = []
test_losses_arr = []

for (lr, ep), loss in train_losses.items():
    train_losses_arr.append((lr, int(ep), loss))
```

```python
for (lr, ep), loss in test_losses.items():
    test_losses_arr.append((lr, int(ep), loss))

train_losses_df = pd.DataFrame(train_losses_arr, columns=['lr', 'epochs',␣
↪'loss'])
test_losses_df = pd.DataFrame(test_losses_arr, columns=['lr', 'epochs', 'loss'])

# merge dataframes
losses_df = pd.merge(train_losses_df, test_losses_df, on=['lr', 'epochs'],␣
↪suffixes=('_train', '_test'))
losses_df
```

[ ]:

```
                          lr  epochs  \
0    0.00100000000000000002       1
1    0.00100000000000000002      51
2    0.00100000000000000002     101
3    0.00100000000000000002     151
4    0.00100000000000000002     201
..                       …       …
195  0.50000000000000000000     751
196  0.50000000000000000000     801
197  0.50000000000000000000     851
198  0.50000000000000000000     901
199  0.50000000000000000000     951

                                               loss_train  \
0                              712.35544408202019894816
1                              438.10390531169031191894
2                              277.70827155145241249556
3                              204.45153606491405184897
4                              152.95659639606813584578
..                                                   …
195  10,064,873,608,080,629,039,315,616,564,842,070,…
196  38,883,928,850,905,498,030,357,258,510,008,320…
197  1,964,394,829,934,937,164,113,258,741,760.00000…
198  161,643,292,004,524,220,750,446,944,777,003,859…
199  5,408,037,911,253,026,769,260,384,748,568,576.0…

                                                loss_test
0                              673.50730859418263207772
1                              404.09167713681171107964
2                              247.53186235583663687976
3                              176.62372830443592874872
4                              127.33201401750525860734
..                                                   …
195  10,064,873,608,080,626,678,132,375,130,019,463,…
```

```
196 38,883,928,850,905,493,418,671,240,082,620,416…
197 1,964,394,829,934,938,571,488,142,295,040.00000…
198 161,643,292,004,524,220,750,446,944,777,003,859…
199 5,408,037,911,253,026,769,260,384,748,568,576.0…

[200 rows x 4 columns]
```

[ ]:
```
losses_df.sort_values(by='loss_test', ascending=True).head(10)
```

[ ]:
```
                          lr  epochs              loss_train  \
14   0.00100000000000000002     701 97.24997849157063001257
13   0.00100000000000000002     651 97.36517063828993912011
15   0.00100000000000000002     751 97.18700042019692375561
16   0.00100000000000000002     801 97.15765470153172600476
17   0.00100000000000000002     851 97.13886442836047763194
12   0.00100000000000000002     601 97.53729094639008678769
18   0.00100000000000000002     901 97.12979841319094020946
19   0.00100000000000000002     951 97.12443781084131444459
148 0.38900000000000001243     401 97.11721857464502249968
182 0.50000000000000000000     101 97.11721191618177329019

                   loss_test
14   77.04882381592535978143
13   77.06209465460953822458
15   77.06229356767643423609
16   77.08106987569057366727
17   77.10344679716750704301
12   77.11963007880184761689
18   77.12105310560889392946
19   77.13643326268517341759
148 77.19205646245166008157
182 77.19363039787369018541
```

[ ]:
```
losses_df.sort_values(by='loss_train', ascending=True).head(10)
```

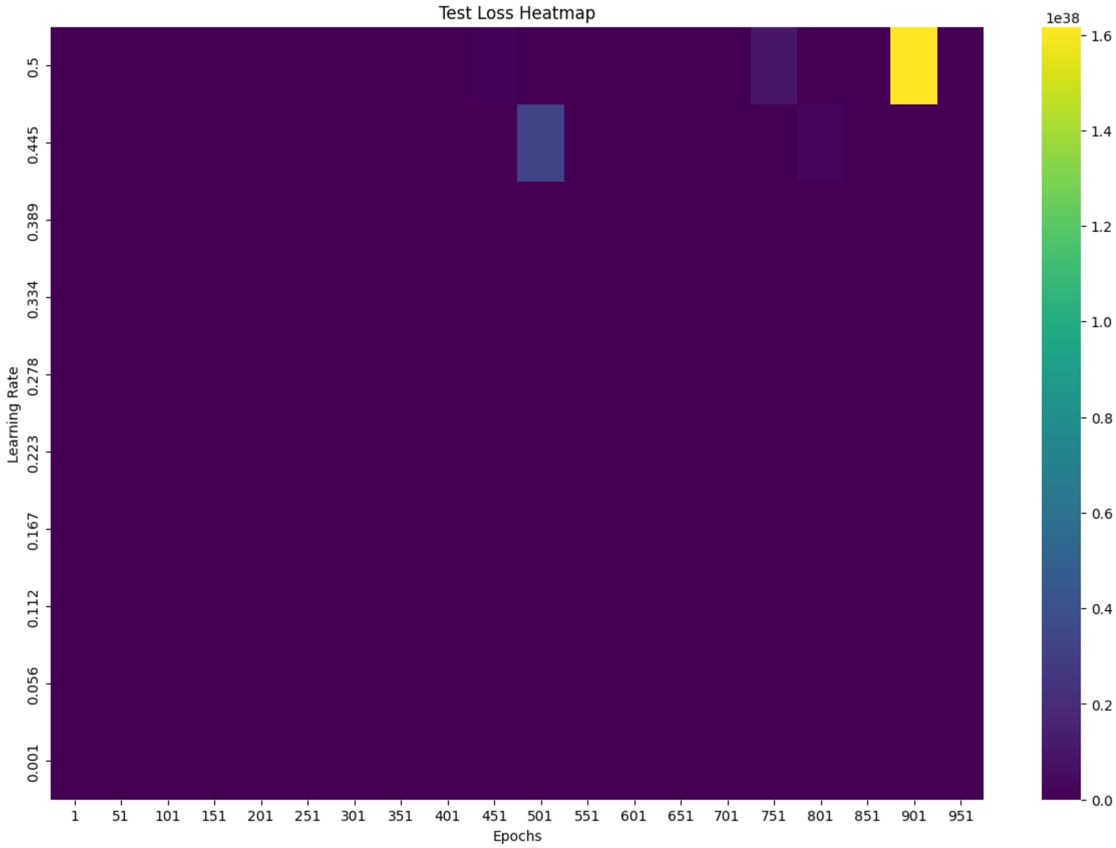
[ ]:
```
                          lr  epochs              loss_train  \
81   0.22300000000000000377      51 97.11721158982109614044
98   0.22300000000000000377     901 97.11721158982109614044
118 0.27800000000000002487     901 97.11721158982109614044
26   0.05600000000000000117     301 97.11721158982109614044
95   0.22300000000000000377     751 97.11721158982109614044
45   0.11200000000000000233     251 97.11721158982109614044
42   0.11200000000000000233     101 97.11721158982109614044
44   0.11200000000000000233     201 97.11721158982109614044
28   0.05600000000000000117     401 97.11721158982109614044
71   0.16700000000000000955     551 97.11721158982109614044
```

```
                   loss_test
81   77.19406594744638994143
98   77.19406594746409666641
118  77.19406594745940708435
26   77.19406594745862548734
95   77.19406594745851180051
45   77.19406594745805705315
42   77.19406594745773020350
44   77.19406594745751704068
28   77.19406594745743177555
71   77.19406594745981919914
```

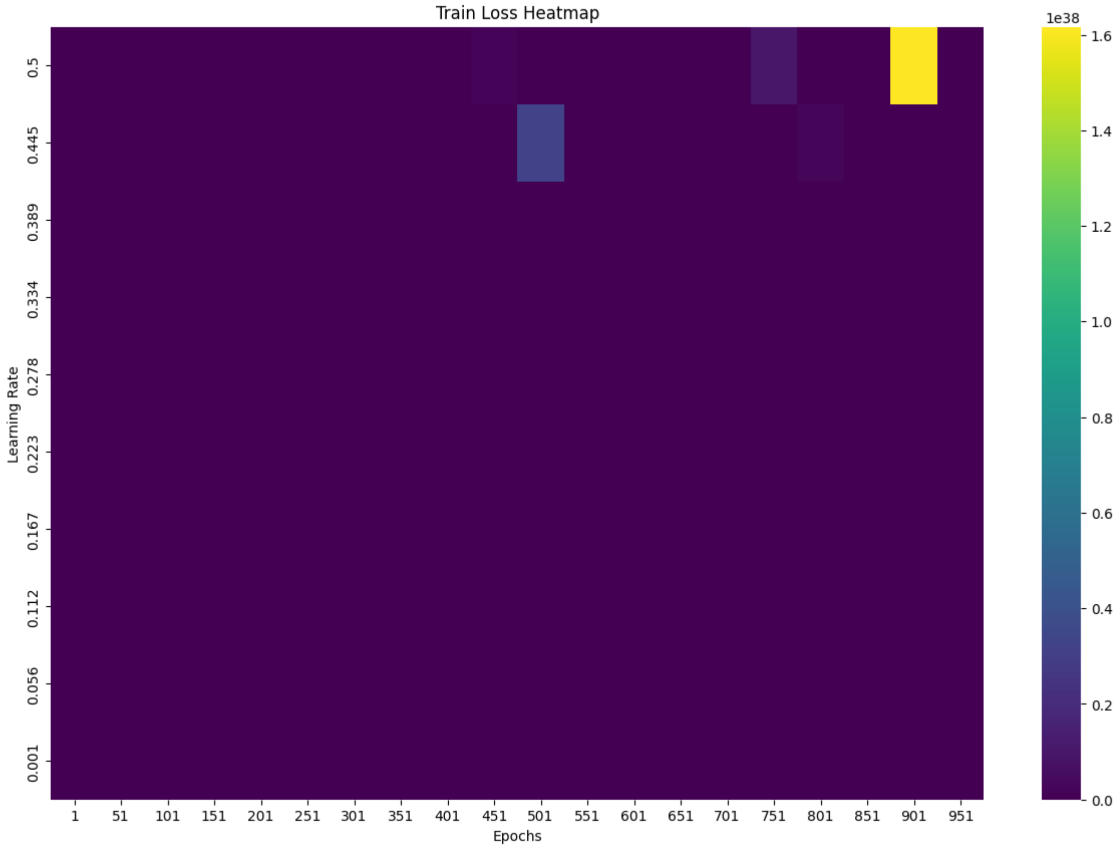
Muchos de los valores de lr convergen a la misma loss minima ~(97.117), pero algunos lo hacen mas rapido que otros. En nuestra experimentación con el Learning Rate, obtuvimos que para lr=0.05 y epoch=20, la Loss alcanzaba ~(97.118).

En estos gráficos de calor podemos ver como la mayoría de los learning rates para cierto epoch logran converger a este mismo valor.

[ ]:
```python
losses_df_hm = losses_df.pivot(index='lr', columns='epochs', values='loss_test')

fig, ax = plt.subplots(figsize=(15, 10))

sns.heatmap(losses_df_hm, ax=ax, cmap='viridis')
ax.set_xlabel('Epochs')
ax.set_ylabel('Learning Rate')
ax.set_title('Test Loss Heatmap')
ax.invert_yaxis()
plt.show()
```



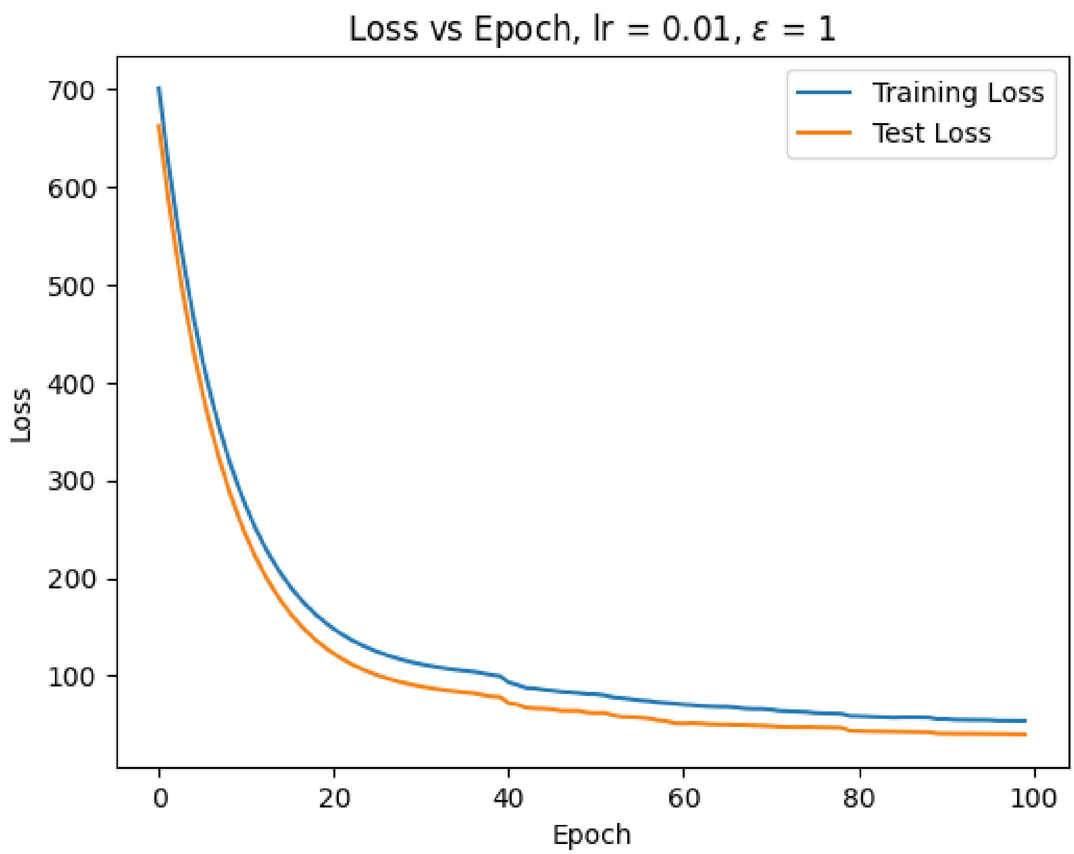
[ ]:
```
losses_df_hm = losses_df.pivot(index='lr', columns='epochs',␣
↪values='loss_train')

fig, ax = plt.subplots(figsize=(15, 10))

sns.heatmap(losses_df_hm, ax=ax, cmap='viridis')
ax.set_xlabel('Epochs')
ax.set_ylabel('Learning Rate')
ax.set_title('Train Loss Heatmap')
ax.invert_yaxis()
plt.show()
```



Para lograr obtener una menor Loss, probamos modificando el valor de Epsilon

[ ]:
```
nn = NeuralNet()
loss = nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=0.01,␣
 ↪epochs=100, eps=1)
display(pd.Series(
    [
        y_test[0][0],
        nn.predict(X_test[0].reshape(1, -1))[0][0],
        nn.get_training_loss()[-1][0]
    ],
    index=["y_true", "y_pred", "train_loss"]
))
nn.plot_loss()
```

```
y_true        27.300000000000000071054
y_pred        28.850251955703807738O2
train_loss    53.803641355281420999929
dtype: float64
```



1.9 Combinaciones de Learning Rate y Epsilon

Buscamos ver como variando el Epsilon junto al Learning Rate para una cantidad fija arbitraria de epochs podemos encontrar un valor de lr que converja mas rápido sobre los modelos con las funciones de activación Tanh y Sigmoide, esta última con y sin Dropout de pesos. Ademas, vamos a ver como cambia la loss minima para cuando finalice el entrenamiento.

[ ]:
```
# Brute force, best learning rate, epsilons, with and without dropout

lrs = np.linspace(0.001, 0.5, 10).round(3)
#epochs = list(range(0, 1050, 50))[1:]
epochs = [500] # Se podría probar con distintos epochs, idealmente valores␣
↪mayores, los anteriores se pueden obtener como "early stops"
epsilons = list(map(lambda x: x/10000, range(0, 10005, 500)[1:]))
```

[ ]:
```
len(epsilons), len(lrs), len(epochs)
```

[ ]:
```
(20, 10, 1)
```

[ ]:
```
len(list(itertools.product(lrs, epochs, epsilons)))
```

[ ]: 200

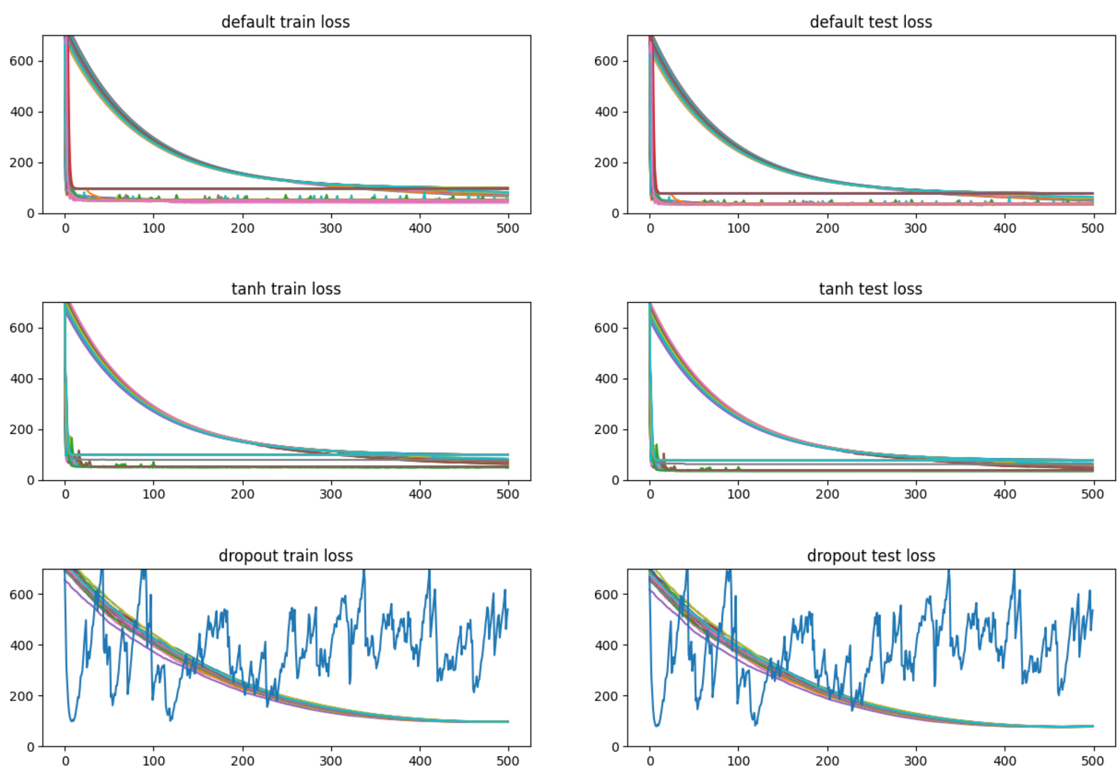
```
losses = {
    'default': {
        'train': {},
        'test': {}
    },
    'tanh': {
        'train': {},
        'test': {}
    },
    'dropout': {
        'train': {},
        'test': {}
    },
}
```

```
for lr, ep, eps in tqdm(list(itertools.product(lrs, epochs, epsilons))):

    nn = NeuralNet()
    nn.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=lr,␣
 ↪epochs=int(ep), eps=eps)
    losses['default']['train'][lr, ep, eps] = nn.get_training_loss()
    losses['default']['test'][lr, ep, eps] = nn.get_test_loss()

    nn_drop = NeuralNet()
    nn_drop.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=lr,␣
 ↪epochs=int(ep), eps=eps, dropout=True)
    losses['dropout']['train'][lr, ep, eps] = nn_drop.get_training_loss()
    losses['dropout']['test'][lr, ep, eps] = nn_drop.get_test_loss()

    nn_tanh = NeuralNet()
    nn_tanh.fit(X_train, y_train, x_test=X_test, y_test=y_test, lr=lr,␣
 ↪epochs=int(ep), eps=eps, custom_activation=nn_tanh.tanh)
    losses['tanh']['train'][lr, ep, eps] = nn_tanh.get_training_loss()
    losses['tanh']['test'][lr, ep, eps] = nn_tanh.get_test_loss()
```

```
  1%|          | 2/200 [00:10<17:29,  5.30s/it]/var/folders/5j/7b3w3dw95qdcll87v
xc3yn300000gn/T/ipykernel_64997/343068776.py:30: RuntimeWarning: overflow
encountered in exp
  return 1 / (1 + np.exp(-x))
100%|      | 200/200 [17:34<00:00,  5.27s/it]
```

```
fig, axs = plt.subplots(len(losses.keys()), 2, figsize=(15, 10))

for i, (variation, train_test) in enumerate(losses.items()):
    for (lr, ep, eps), loss in train_test['train'].items():
```

```
        # De forma empírica observamos que con pesos aleatorios, la loss comienza al rededor de ~700
        # Evitamos en el gráfico aquellos que superen en algún momento esa loss para limpiar
        if any([l > 800 for l in loss]):
            continue
        axs[i, 0].plot(loss, label=f'lr={lr}, ep={ep}, eps={eps}')

    for (lr, ep, eps), loss in train_test['test'].items():
        if any([l > 800 for l in loss]):
            continue
        axs[i, 1].plot(loss, label=f'lr={lr}, ep={ep}, eps={eps}')

    axs[i, 0].set_title(f'{variation} train loss')
    axs[i, 1].set_title(f'{variation} test loss')

    axs[i, 0].set_ylim(0, 700)
    axs[i, 1].set_ylim(0, 700)

# Add space between subplots
fig.subplots_adjust(hspace=0.5)
```



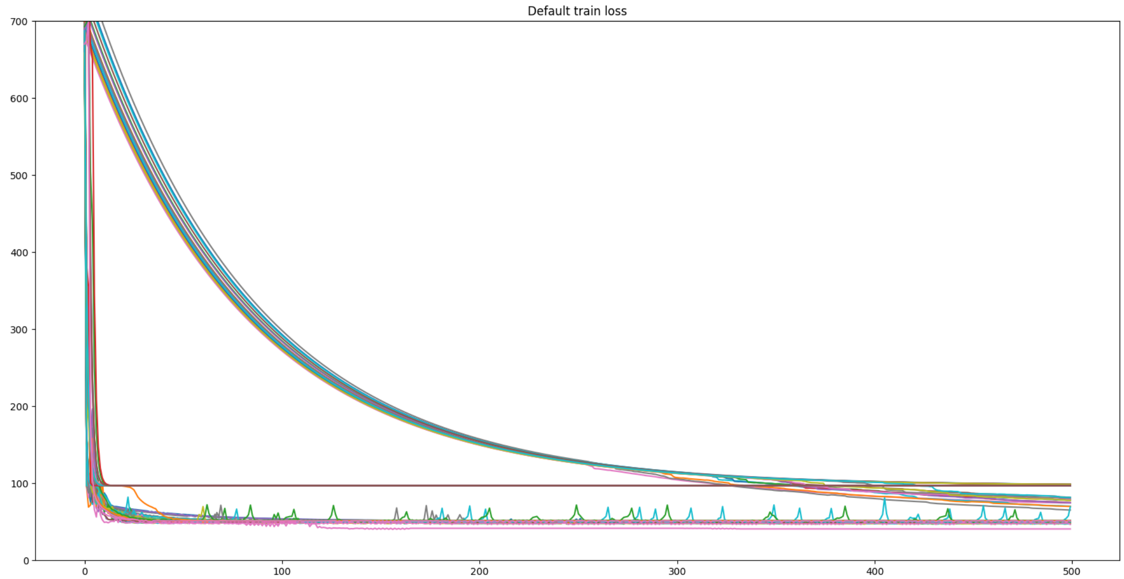
Podemos observar como para ciertas combinaciones de Learning Rate y Epochs la convergencia es mas rápida.

Para la función de activación ReLU observamos que la convergencía no ocurre directamente por lo que se dejo de evaluar, la función Tanh sin embargo si converge, pero no logra alcanzar la misma loss minima que la función sigmoide.

Para la mascara de pesos, probamos con una probabilidad de 0.5. En todos los casos la convergencia fue o mas lenta, y la loss minima alcanzada mayor que la obtenida sin aplicar la mascara, o directamente esporádico sin convergencia.

[ ]:
```python
# Large Default Training Loss Plot
fig, ax = plt.subplots(figsize=(20, 10))

for (lr, ep, eps), loss in losses['default']['train'].items():

    if any([l > 800 for l in loss]):
        continue
    ax.plot(loss, label=f'lr={lr}, ep={ep}, eps={eps}')

ax.set_title(f'Default train loss')
#ax.legend()

ax.set_ylim(0, 700)
```

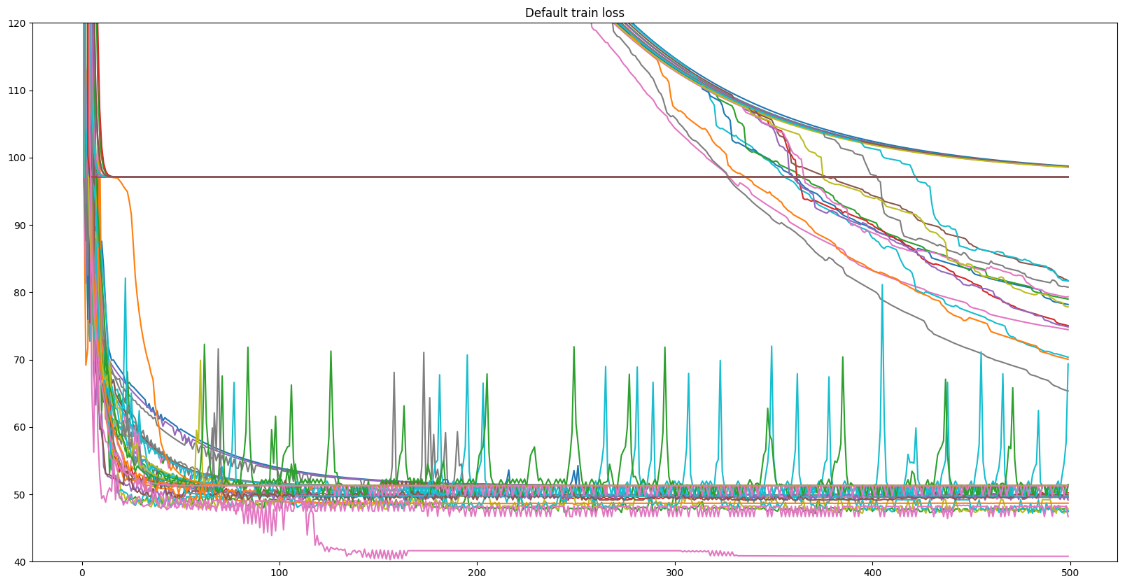
[ ]: (0.0, 700.0)



[ ]:
```python
# Large Default Training Loss Plot
fig, ax = plt.subplots(figsize=(20, 10))
```

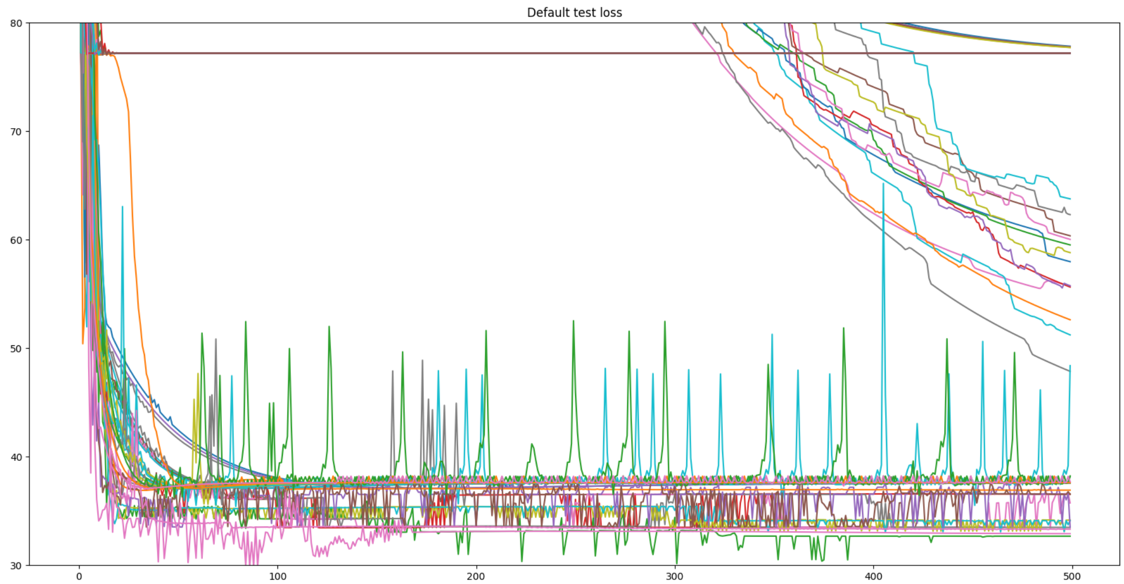
```python
for (lr, ep, eps), loss in losses['default']['train'].items():
    if any([l > 800 for l in loss]):
        continue
    ax.plot(loss, label=f'lr={lr}, ep={ep}, eps={eps}')

ax.set_title(f'Default train loss')
ax.set_ylim(40, 120)
```

[ ]: (40.0, 120.0)



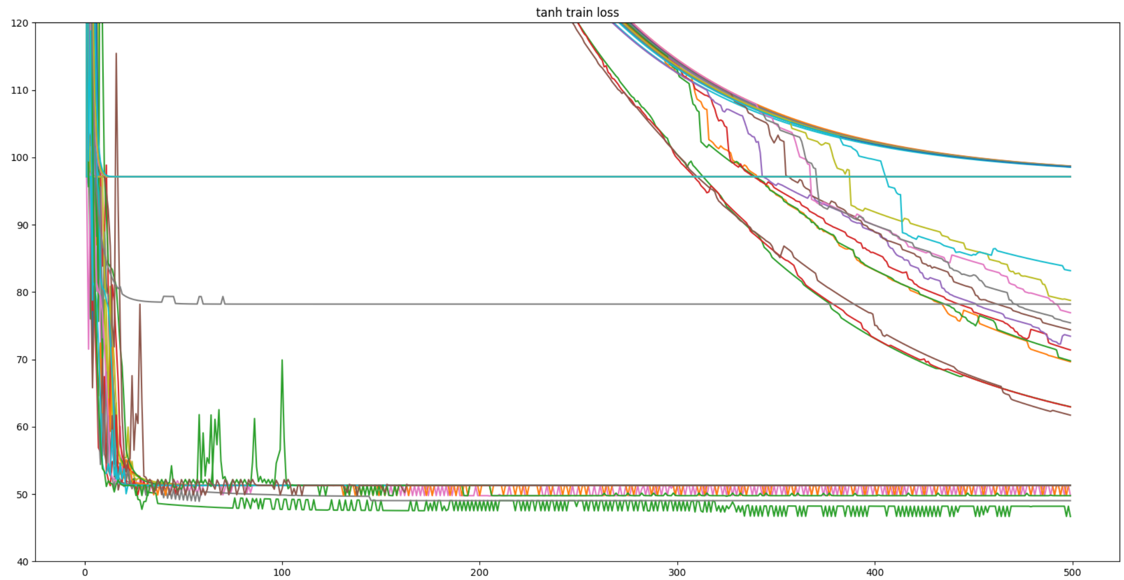
[ ]:
```python
# Large Default Test Loss Plot
fig, ax = plt.subplots(figsize=(20, 10))

for (lr, ep, eps), loss in losses['default']['test'].items():
    if any([l > 800 for l in loss]):
        continue
    ax.plot(loss, label=f'lr={lr}, ep={ep}, eps={eps}')

ax.set_title(f'Default test loss')
ax.set_ylim(30, 80)
```

[ ]: (30.0, 80.0)



[ ]:
```
# Large Default Training Loss Plot
fig, ax = plt.subplots(figsize=(20, 10))

for (lr, ep, eps), loss in losses['tanh']['train'].items():
    if any([l > 800 for l in loss]):
        continue
    ax.plot(loss, label=f'lr={lr}, ep={ep}, eps={eps}')

ax.set_title(f'tanh train loss')
ax.set_ylim(40, 120)
```

[ ]: (40.0, 120.0)

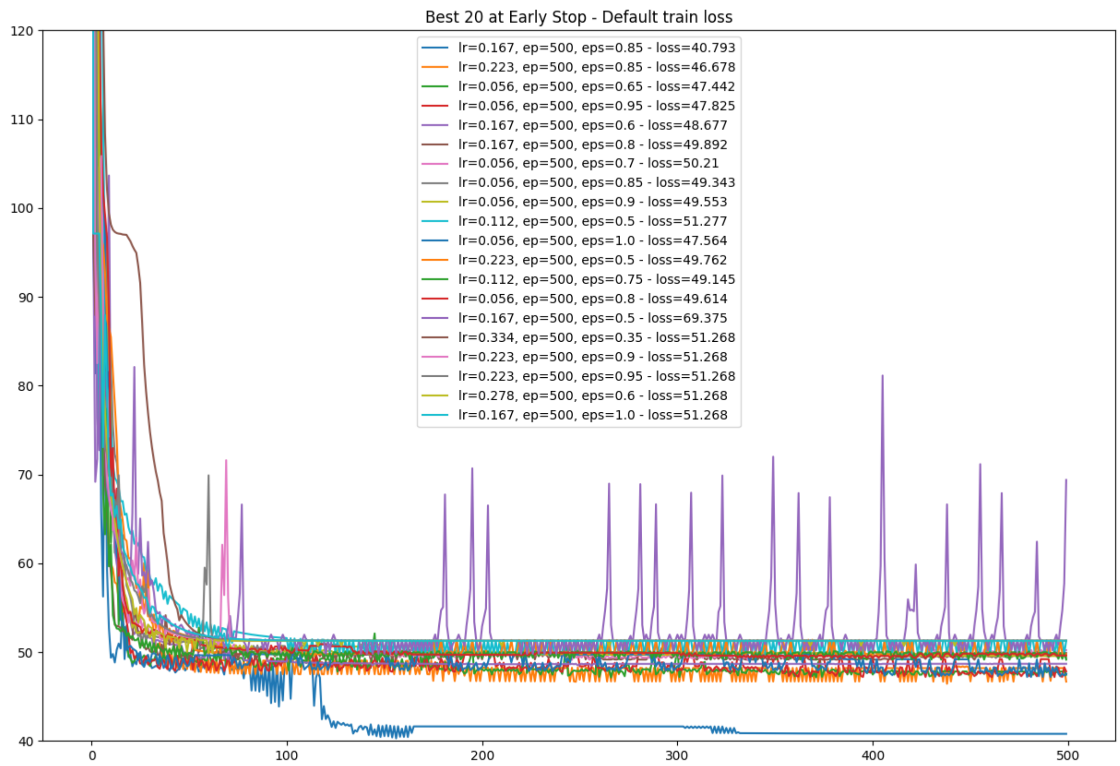


[ ]:

```
# Filter out the best learning rate - epsilons combinations for the Default NN
# The 20 lowest training loss by epoch 200

# Sort by the loss at epoch 250

train_loss = losses['default']['train'].items()

train_loss = sorted(train_loss, key=lambda x: x[1][250])

# Plot every train_loss[:20]

fig, ax = plt.subplots(figsize=(15, 10))

for (lr, ep, eps), loss in train_loss[:20]:
    ax.plot(loss, label=f'lr={lr}, ep={ep}, eps={eps} - loss={loss[-1].
 ↪round(3)[0]}')

ax.set_title(f'Best 20 at Early Stop - Default train loss')
ax.set_ylim(40, 120)
ax.legend()
```

[ ]:

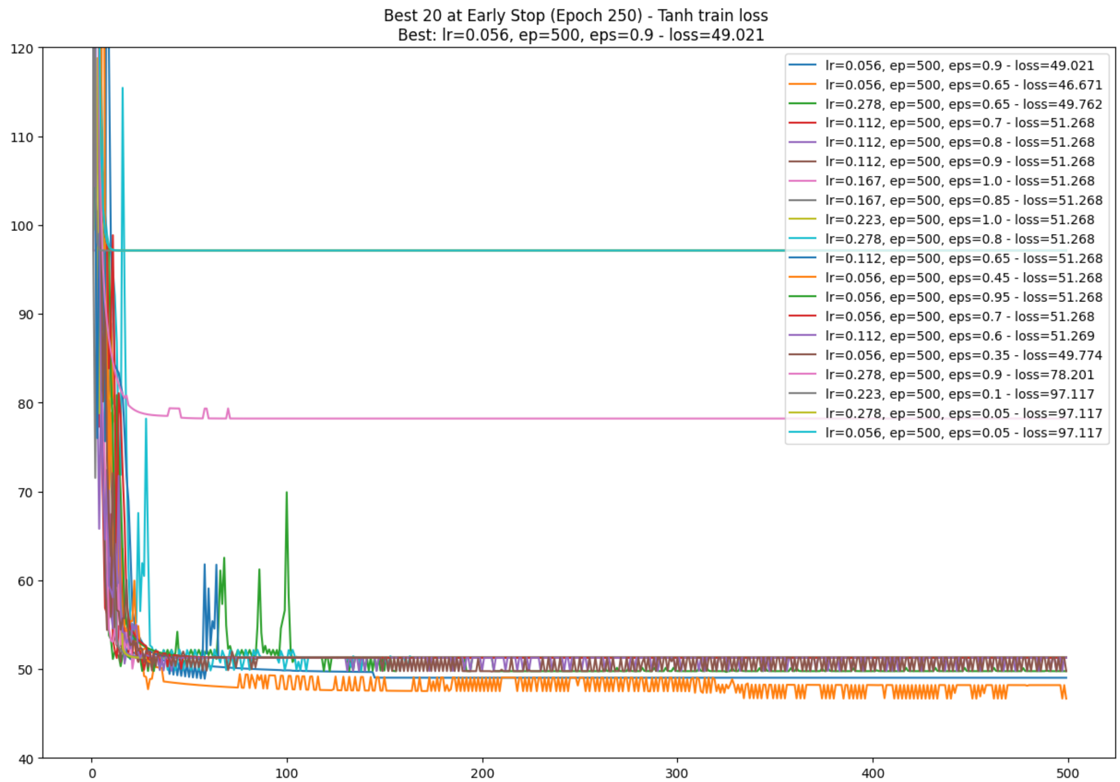
```
<matplotlib.legend.Legend at 0x7faec6a079a0>
```



[ ]:
```
# Filter out the best learning rate - epsilons combinations for the Default NN
# The 20 lowest training loss by epoch 200

# Sort by the loss at epoch 250

train_loss = losses['tanh']['train'].items()

train_loss = sorted(train_loss, key=lambda x: x[1][250])

# Plot every train_loss[:20]

fig, ax = plt.subplots(figsize=(15, 10))

for (lr, ep, eps), loss in train_loss[:20]:
    ax.plot(loss, label=f'lr={lr}, ep={ep}, eps={eps} - loss={loss[-1].
 ↪round(3)[0]}')

(min_250_lr, min_250_ep, min_250_eps), min_250_loss = train_loss[0]

ax.set_title(f'Best 20 at Early Stop (Epoch 250) - Tanh train loss \n Best:␣
 ↪lr={min_250_lr}, ep={min_250_ep}, eps={min_250_eps} - loss={min_250_loss[-1].
 ↪round(3)[0]}')
```

```
ax.set_ylim(40, 120)
ax.legend()
```

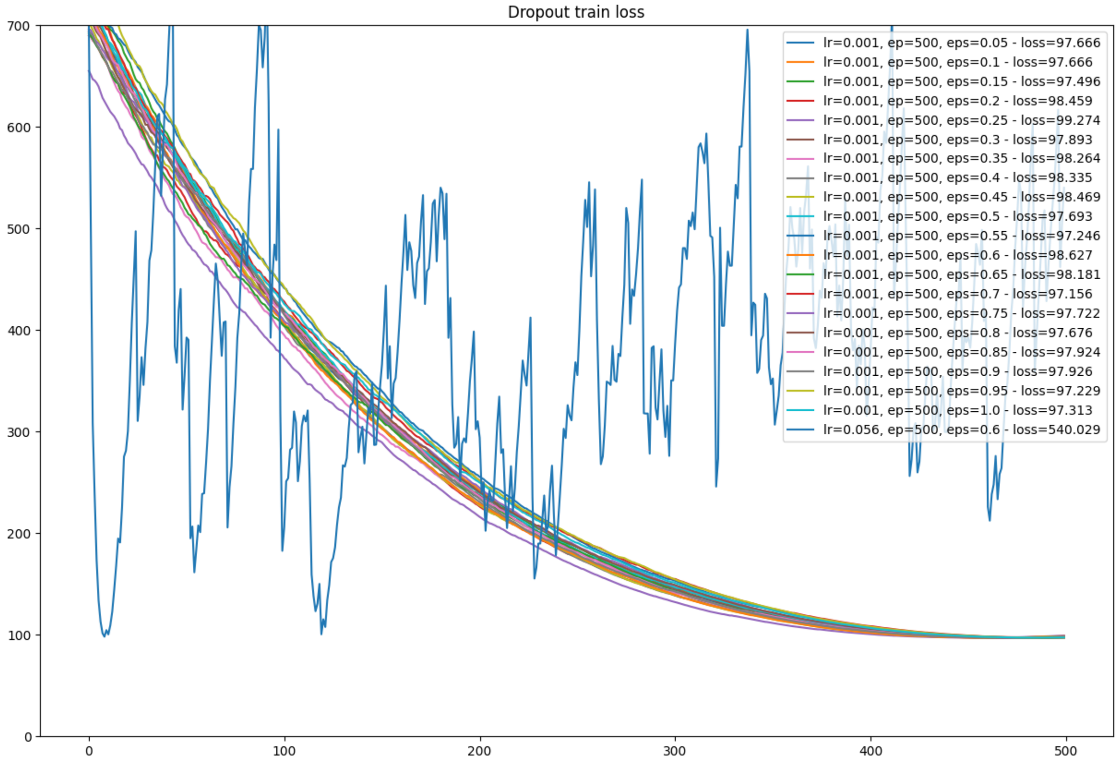
[ ]: <matplotlib.legend.Legend at 0x7faec6e9d310>



[ ]:

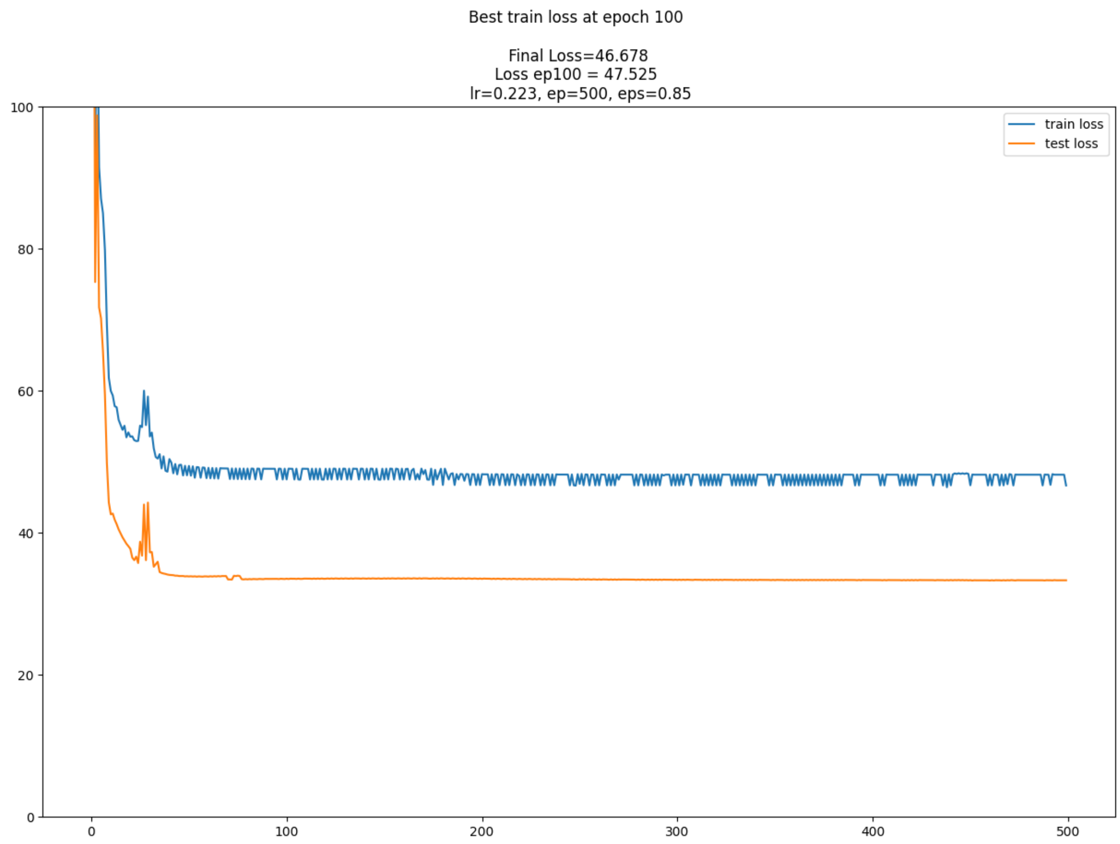
```
# Large Dropout Training Loss Plot

fig, ax = plt.subplots(figsize=(15, 10))

for (lr, ep, eps), loss in losses['dropout']['train'].items():

    # If loss has any value > 800, skip
    if any([l > 800 for l in loss]):
        continue

    ax.plot(loss, label=f'lr={lr}, ep={ep}, eps={eps} - loss={loss[-1].
 ↪round(3)[0]}')

ax.set_title(f'Dropout train loss')
ax.set_ylim(0, 700)
ax.legend()
```

```
[ ]: <matplotlib.legend.Legend at 0x7faea3223520>
```




```
[ ]: # Min loss for default at epoch 100

     (min_lr, min_ep, min_eps), min_train_loss = min(losses['default']['train'].
      ↪items(), key=lambda x: x[1][100])
     min_test_loss = losses['default']['test'][(min_lr, min_ep, min_eps)]

     fig, ax = plt.subplots(figsize=(15, 10))

     ax.plot(min_train_loss, label=f'train loss')
     ax.plot(min_test_loss, label=f'test loss')

     ax.set_title(f'Best train loss at epoch 100 \n\n Final Loss={min_train_loss[-1].
      ↪round(3)[0]} \n Loss ep100 = {min_train_loss[100].round(3)[0]}  \n␣
      ↪lr={min_lr}, ep={min_ep}, eps={min_eps}')

     ax.legend()

     ax.set_ylim(0, 100)
```

```
[ ]: (0.0, 100.0)
```

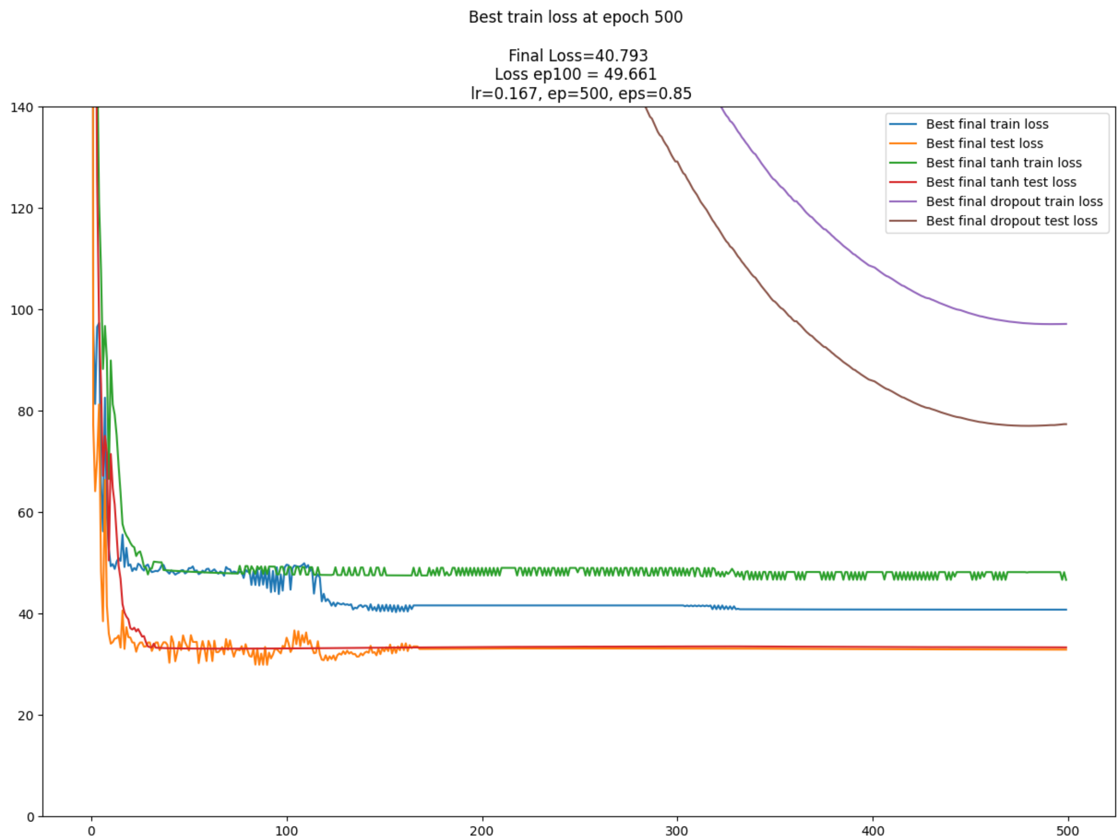


[ ]:
```python
# Filter dropout losses, if any > 800

less_dropout_train_loss = {}
less_dropout_test_loss = {}

for (lr, ep, eps), loss in losses['dropout']['train'].items():
    if any([l > 800 for l in loss]):
        continue
    less_dropout_train_loss[(lr, ep, eps)] = loss
    less_dropout_test_loss[(lr, ep, eps)] = losses['dropout']['test'][(lr, ep,␣
↪eps)]
```

[ ]:
```python
# Min loss for default at epoch 500

(min_lr, min_ep, min_eps), min_train_loss = min(losses['default']['train'].
↪items(), key=lambda x: x[1][-1])
min_test_loss = losses['default']['test'][(min_lr, min_ep, min_eps)]

(min_tanh_lr, min_tanh_ep, min_tanh_eps), min_tanh_train_loss =␣
↪min(losses['tanh']['train'].items(), key=lambda x: x[1][-1])
```

```
min_tanh_test_loss = losses['tanh']['test'][(min_tanh_lr, min_tanh_ep,␣
↪min_tanh_eps)]

(min_dropout_lr, min_dropout_ep, min_dropout_eps), min_dropout_train_loss =␣
↪min(less_dropout_train_loss.items(), key=lambda x: x[1][-1])
min_dropout_test_loss = less_dropout_test_loss[(min_dropout_lr, min_dropout_ep,␣
↪min_dropout_eps)]

fig, ax = plt.subplots(figsize=(15, 10))

ax.plot(min_train_loss, label=f'Best final train loss')
ax.plot(min_test_loss, label=f'Best final test loss')

ax.plot(min_tanh_train_loss, label=f'Best final tanh train loss')
ax.plot(min_tanh_test_loss, label=f'Best final tanh test loss')

ax.plot(min_dropout_train_loss, label=f'Best final dropout train loss')
ax.plot(min_dropout_test_loss, label=f'Best final dropout test loss')

ax.set_title(f'Best train loss at epoch 500 \n\n Final Loss={min_train_loss[-1].
↪round(3)[0]} \n Loss ep100 = {min_train_loss[100].round(3)[0]}  \n␣
↪lr={min_lr}, ep={min_ep}, eps={min_eps}')

ax.legend()

ax.set_ylim(0, 140)
```

[ ]: (0.0, 140.0)



[ ]:
```
values_df = pd.DataFrame({
    'learning rate': [min_lr, min_tanh_lr, min_dropout_lr],
    'epsilon': [min_eps, min_tanh_eps, min_dropout_eps],
    'epochs': [min_ep, min_tanh_ep, min_dropout_ep],
    'train_loss': [min_train_loss[-1].round(3)[0], min_tanh_train_loss[-1].
 ↪round(3)[0], min_dropout_train_loss[-1].round(3)[0]],
    'test_loss': [min_test_loss[-1].round(3)[0], min_tanh_test_loss[-1].
 ↪round(3)[0], min_dropout_test_loss[-1].round(3)[0]],
    'train_loss_ep100': [min_train_loss[100].round(3)[0],␣
 ↪min_tanh_train_loss[100].round(3)[0], min_dropout_train_loss[100].
 ↪round(3)[0]],
    'test_loss_ep100': [min_test_loss[100].round(3)[0], min_tanh_test_loss[100].
 ↪round(3)[0], min_dropout_test_loss[100].round(3)[0]],
}, index=['default', 'tanh', 'dropout'])

values_df
```

[ ]:
```
                  learning rate                epsilon  epochs  \
default 0.16700000000000000955 0.84999999999999997780     500
tanh    0.05600000000000000117 0.65000000000000002220     500
```

```
dropout 0.00100000000000000002 0.69999999999999995559     500

                     train_loss                test_loss  \
default 40.79299999999999926104 32.90899999999999891998
tanh    46.67099999999999937472 33.34599999999999653255
dropout 97.15600000000000591172 77.38200000000000500222

                train_loss_ep100          test_loss_ep100
default  49.66100000000000136424  35.26100000000000278533
tanh     47.72599999999999909051  33.13499999999999801048
dropout 428.01699999999999590727 394.21499999999997498890
```

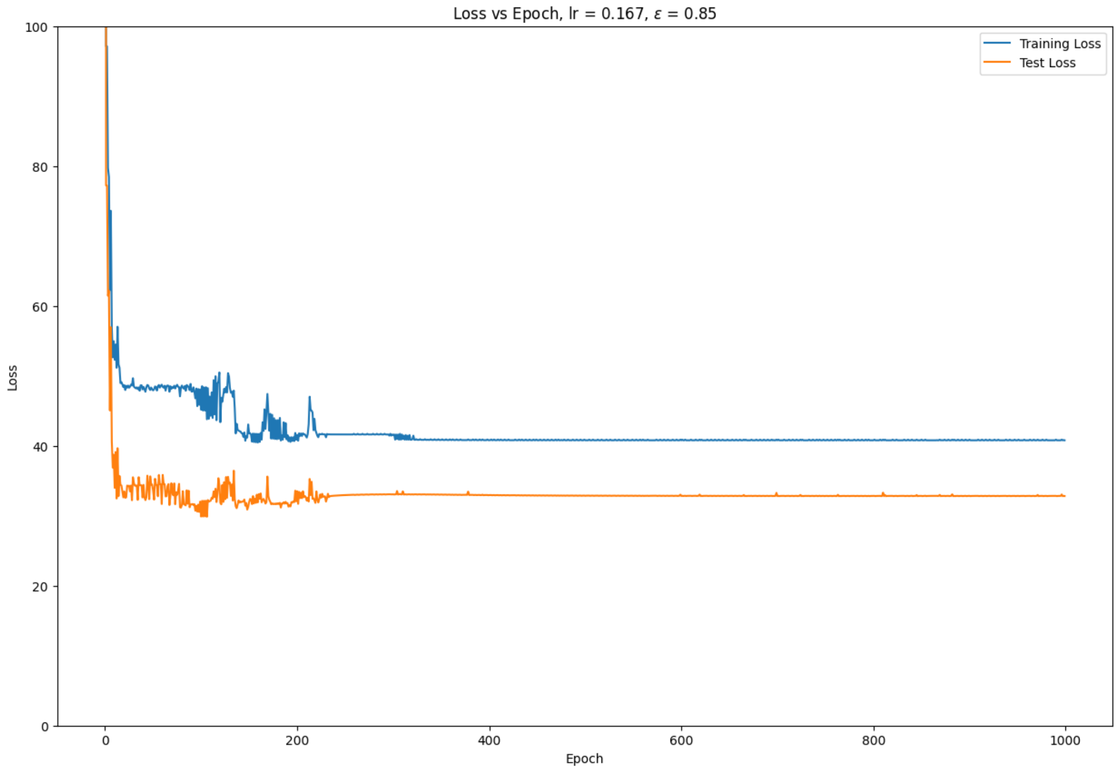
1.10 Conclusiones

En este trabajo práctico pudimos ver como el gradiente descendente nos permite entrenar una red neuronal. Pudimos ver como la función de activación sigmoide es la mas adecuada para este tipo de problemas, y como el learning rate y la cantidad de epochs afectan la convergencia de la red.

También pudimos ver como la mascara de pesos no es una buena opción para este tipo de problemas, ya que no logra converger a una loss minima menor que la obtenida sin aplicar la mascara.

[ ]:
```python
nn_final = NeuralNet()
nn_final.fit(X_train, y_train, x_test=X_test, y_test=y_test, epochs=1000,␣
 ↪lr=min_lr, eps=min_eps, verbose=True)

display(pd.Series(
    [
        y_test[0][0],
        nn_final.predict(X_test[0].reshape(1, -1))[0][0],
        nn_final.get_training_loss()[-1][0]
    ],
    index=["y_true", "y_pred", "train_loss"]
))

fig, ax = plt.subplots(figsize=(15, 10))
nn_final.plot_loss(ax=ax)
_ = ax.set_ylim(0, 100)
```

```
100%|      | 1000/1000 [00:04<00:00, 219.65it/s]

y_true        27.30000000000000071054
y_pred        27.23155726721838831850
train_loss    40.78857608365985498722
dtype: float64
```


Loss vs Epoch, lr = 0.167, ε = 0.85
Training Loss
Test Loss
Loss
Epoch
100
80
60
40
20
0
0
200
400
600
800
1000