

Neural Network Regularization Data Augmentation and Dropout

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Outline

Regularization of NN

- Norm Penalties
- Early Stopping
- **Data Augmentation**
- Dropout

Keys to DNN Kingdom

 Using the functional API


 ImageDataGenerator

 Custom Loss Function

 Custom Layer

 Gradient Tape

Super Keys

 TF Data

 TF Records

When you move on to Deep Learning



Data Augmentation



hue



crop-and-pan



elastic



flip-lr



flip-ud



rotate



Data Augmentation: dos and don'ts




We use ImageDataGenerator to augment the dataset

```
def get_generator():
    # create duplicate images
    BATCHES_PER_EPOCH = 300//BATCH_SIZE
    classes = ['pavlos', 'not-pavlos']
    for img_class in classes:
        img = Image.open(f'{DATA_DIR}/{img_class}.jpeg')
        for i in range(1, BATCH_SIZE*BATCHES_PER_EPOCH//2+1):
            img.thumbnail(TARGET_SIZE, Image.ANTIALIAS)
            img.save(f'{DATA_DIR}/{img_class}/{img_class}{i:0>3}.jpeg', "JPEG")

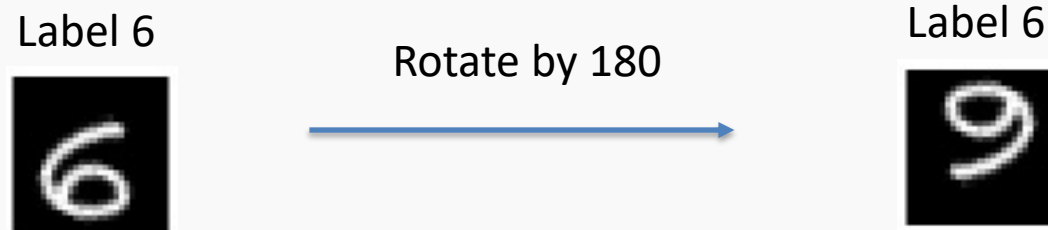
    data_gen = ImageDataGenerator(
        rescale=1./255,
        height_shift_range=0.5,
        width_shift_range=0.5)

    img_generator = data_gen.flow_from_directory(
        DATA_DIR,
        target_size=(TARGET_SIZE),
        batch_size=BATCH_SIZE,
        classes=classes,
        class_mode='binary')
    return img_generator
```



Data Augmentation: dos and don'ts

Carefully choose your transformations. Not all transformations are valid.



Data Augmentation does not work for tabular data and not as nicely for time series.

Outline

Regularization of NN

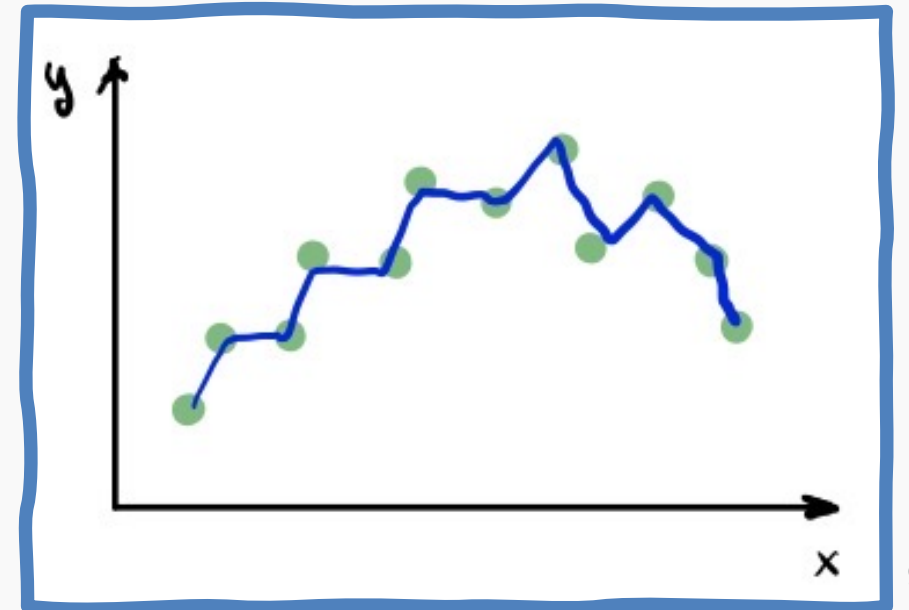
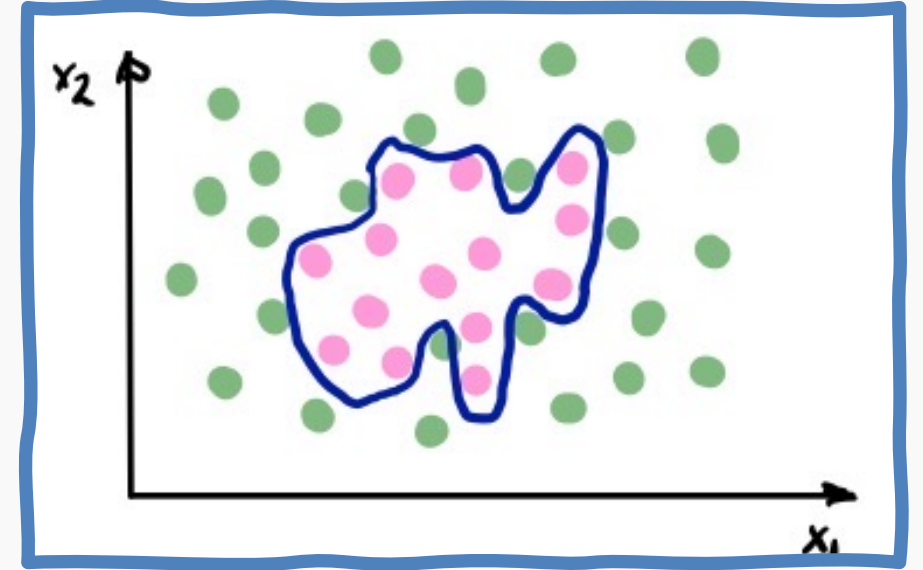
- Norm Penalties
- Early Stopping
- Data Augmentation
- **Dropout**

Co-adaptation

Overfitting occurs when the model is **sensitive** to slight variations on the input and therefore it fits the noise.

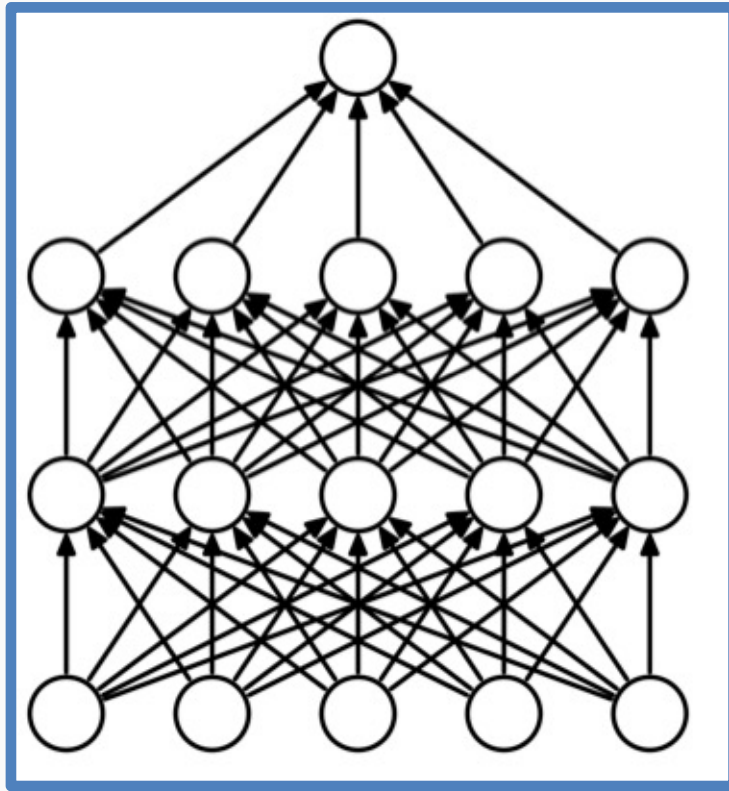
L1 and L2 regularizations ‘shrink’ the weights to avoid this problem.

However, in a large network many units can **collaborate** to respond to the input while the weights can **remain relatively small**. This is called **co-adaptation**.

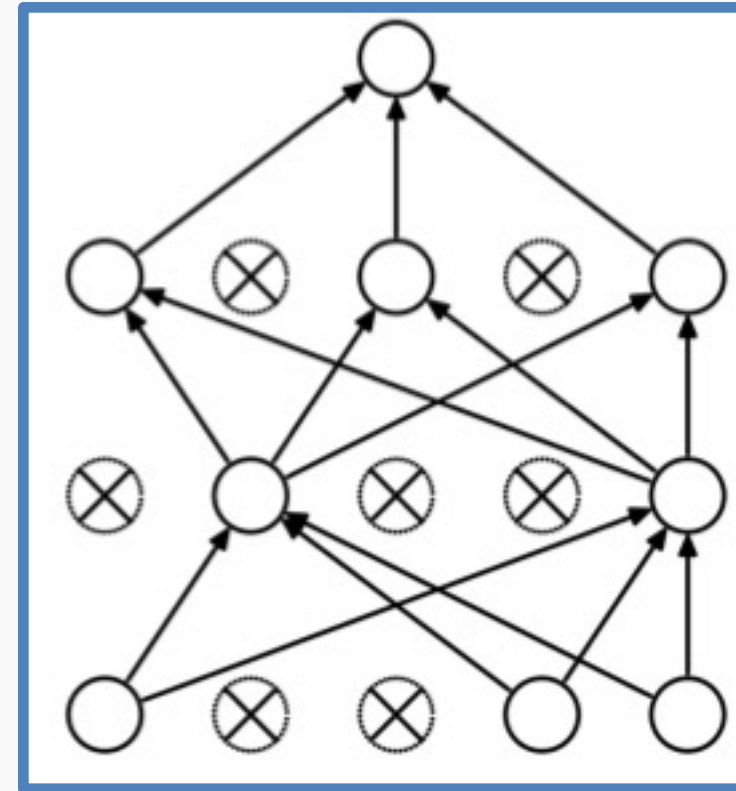


Dropout

- Randomly set some neurons and their connections to zero (i.e. “dropped”)
- Prevent overfitting by reducing **co-adaptation** of neurons
- Like training many random sub-networks



Standard Neural Network



After applying dropout

Dropout: Training

For each new example in a mini-batch (could be for one mini-batch depending on the implementation):

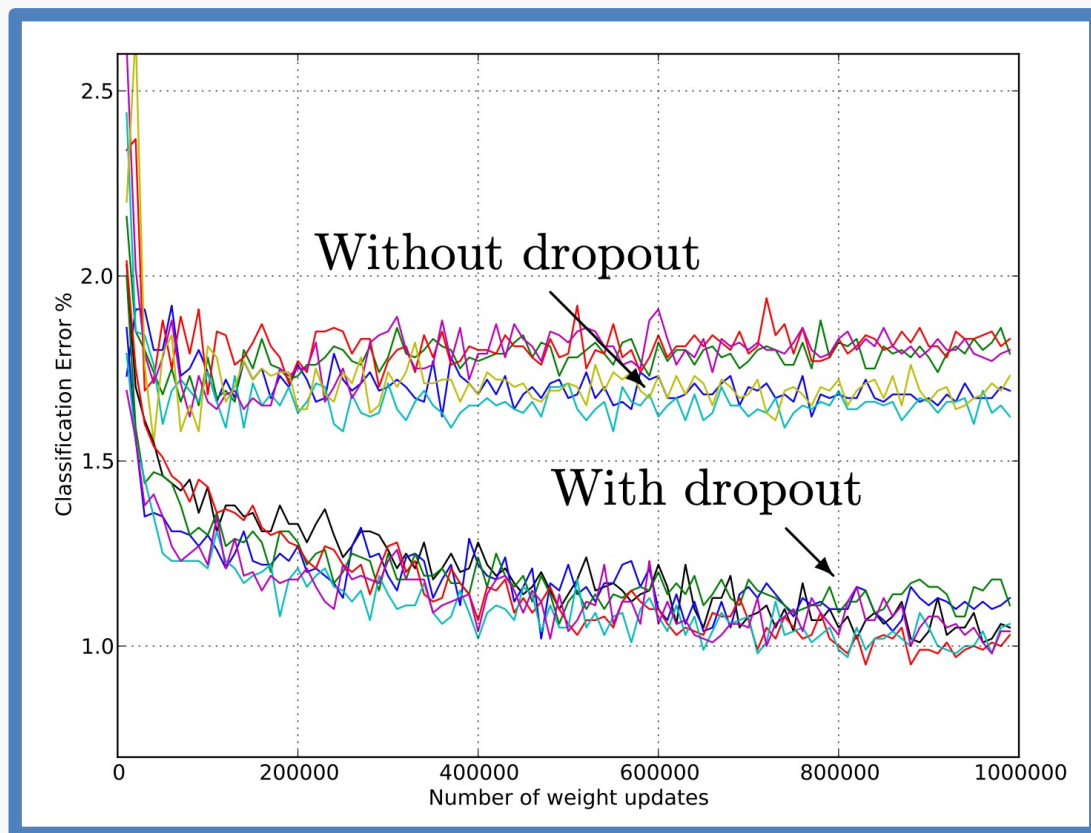
- Randomly **sample a binary mask μ** independently, where μ_i indicates if input/hidden node i is included
- **Multiply output of node i with μ_i** , and perform gradient update

Typically:

- **Input** nodes are included with **prob=0.8** (as per original paper, but rarely used)
- **Hidden** nodes are included with **prob=0.5**

Dropout

- Widely used and highly effective



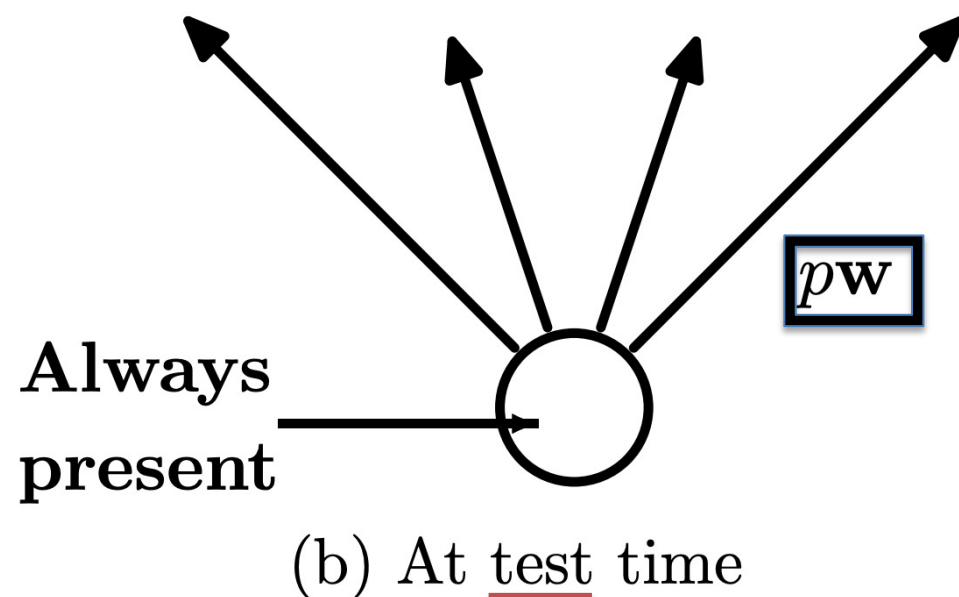
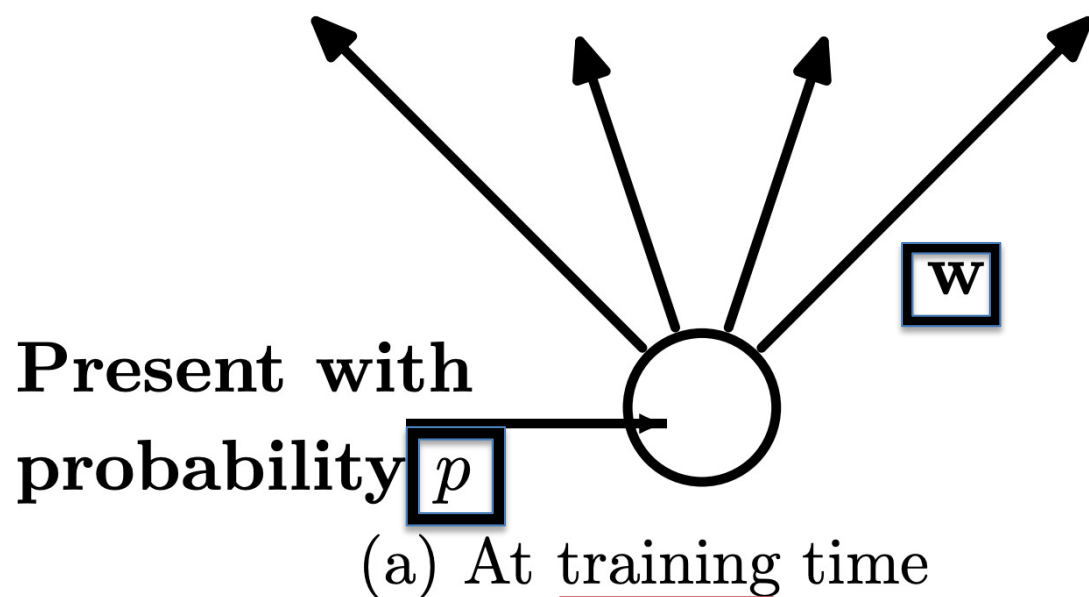
Test error for different architectures with and without dropout.

The networks have 2 to 4 hidden layers each with 1024 to 2048 units.

- Proposed as an alternative to ensemble methods, which is too expensive for neural nets

Dropout: Prediction

- We can think of dropout as training many of sub-networks
- At **test time**, we can “**aggregate**” over these sub-networks by **reducing connection weights in proportion to dropout probability, p**



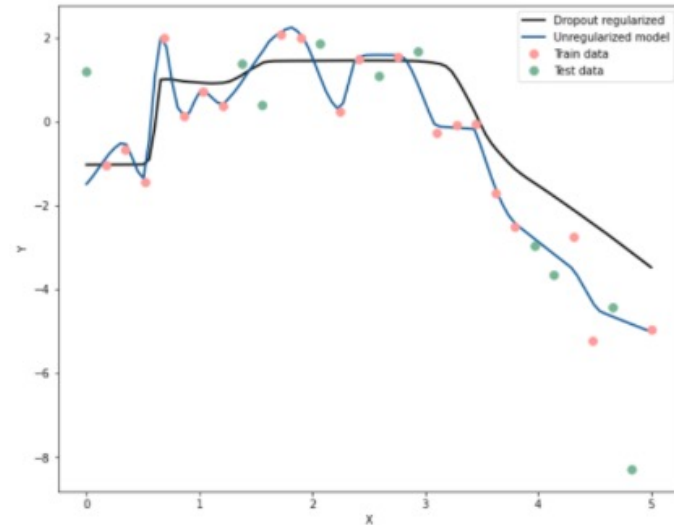
NOTE: Dropouts can be used for **neural network inference** by dropping during predictions and predicting multiple times to get a distribution

Exercise: Dropout

The goal of this exercise is to understand and use **dropouts** for neural network regularization.

This method avoids overfitting by briefly *switching off* certain weights during training.

NOTE: This graph is only a sample.



Instructions:

- Use the helper function `unregularized_model` to:
 - Generate the predictor and response data using the helper code given.
 - Build a simple neural network with 5 hidden layers with 100 neurons each and display the trace plot. This network has no regularization.
- For the same model architecture implement dropout by adding appropriate dropout layers.
- Compile the model with MSE as the loss. Fit the model on the training data.
- Use the helper code to visualise the MSE of the train and test data with respect to the epochs.
- Predict on the entire data.
- Use the helper code to plot the predictions along with the generated data.
- This plot will consist of the predictions of both the neural networks. The graph will look similar to the one given above.

