Model Performance And Fit - 4

One should look for what is and not what he thinks should be. (Albert Einstein)

Module completion checklist

Objective	Complete
Compare methods to assess fit of a neural network	
Methods to improve the fit of a neural network	

What is fit?

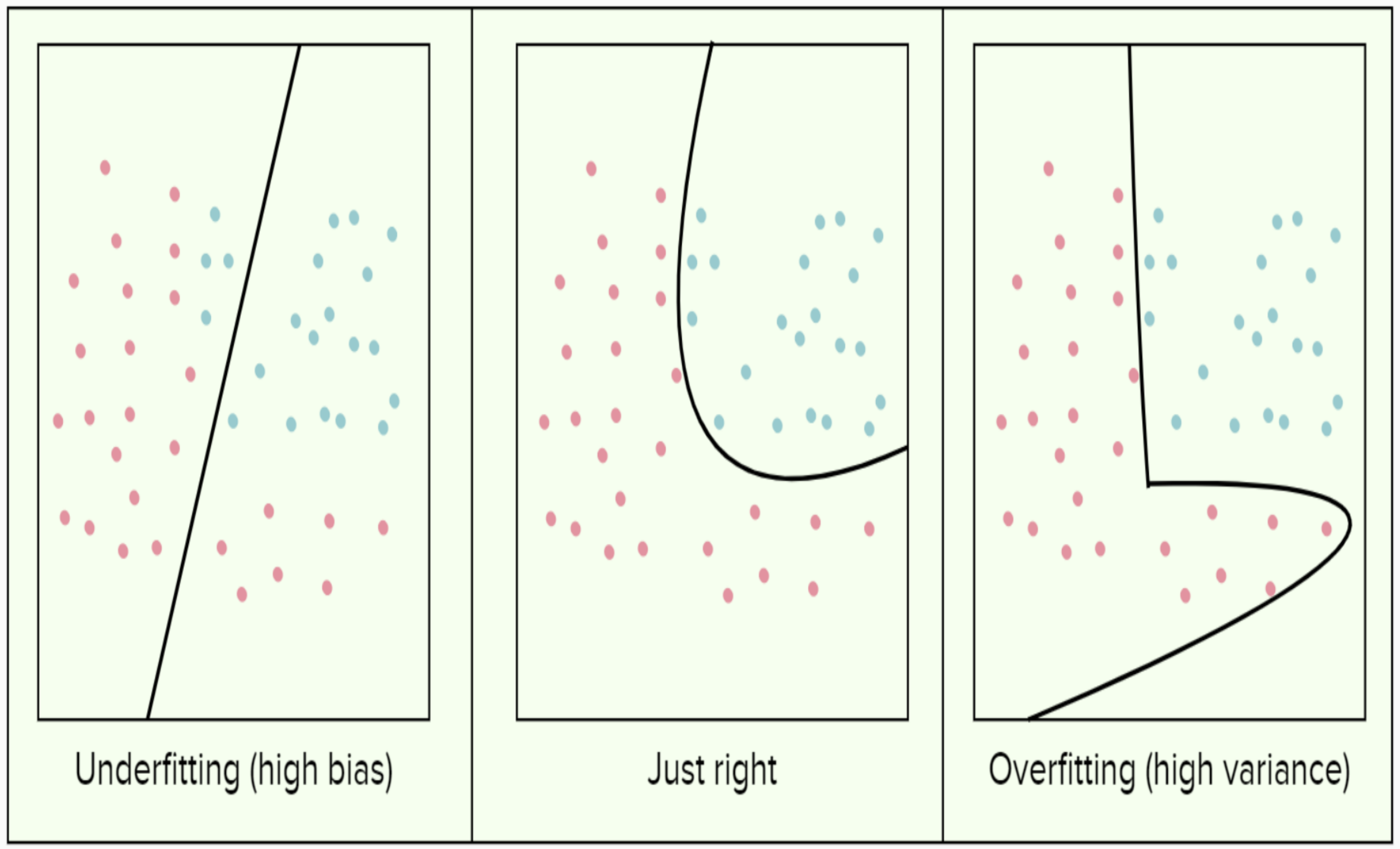
- Model fitting is a measure of how well a machine learning model generalizes to data that is similar to that on which it was trained
- Fit is important because a well-fit model produces more accurate outcomes
- **Overfitting** is when the model performs great on training data, but does not perform as well when it has to fit the model to test data
- **Underfitting** is when the model can neither perform well on training data nor on test data

What causes poor fit?

- Bias
  - Assumptions can prevent us from learning true relationships between features and output
- Variance
  - Sensitivity to intricate details of training set can lead to modeling noise in data
- **Irreducible error**
  - Noise in the problem itself

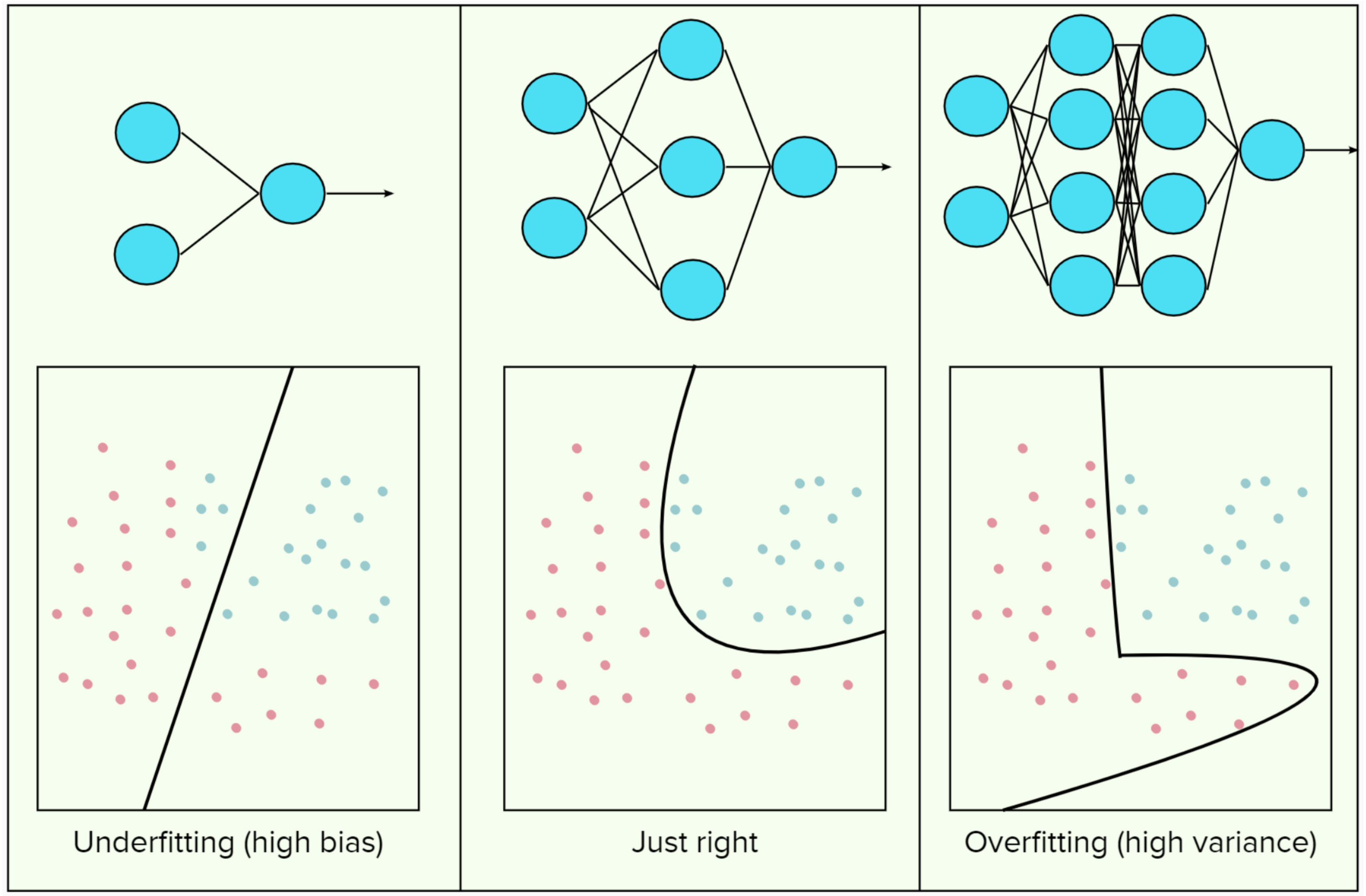
The bias-variance tradeoff

- Models that are perform well at capturing the intricate features of the training set, but may easily overfit are called **high-variance models**
- Models that assume away important features of the data, which usually leads to underfitting, are known as **high-bias models**



Overfitting in neural networks

- Neural networks with more hidden layers and neurons will generally give better results
- However, since neural networks are such good learners, they may capture the intricate details of the training data too well
- Neural networks can fail at generalizing to unseen data, which leads to overfitting



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How to combat overfitting?

- Neural networks have a host of different methods to battle **overfitting**
- There are no specific reasons to choose method over the other and you may choose to use more than one
- We are going to cover the most common ones:
    - regularization
    - early stopping
    - dropout
    - weight constraints

Regularization

- **Regularization** is a key method for preventing overfitting in neural networks
- You may already be familiar with its parameters if you have done *logistic regression*
- In short, regularization **softens** the classifier margins and “lets in” some misclassified observations for the sake of better generalization

Regularization techniques

- Any machine learning algorithm that optimizes some cost *function* $f(x)$
- `l1` (*Lasso*) adds a term to that function like so:

$$f(x) + C\sum_{j=1}^{n}|b_j|$$

- While `l2` (*Ridge*) adds a term like so:

$$f(x) + C\sum_{j=1}^{n}b_j^2$$

- You can see that *Lasso* uses the absolute value - $|b_j|$, while *Ridge* uses a squared value - b_j^2
- That term, when added to the original cost *function*, **dampens** the margins of our classifier, making it more **forgiving** of the misclassification of some points that might be noise

Lasso vs Ridge

- **Lasso (11)**

$$C\sum_{j=1}^{n}|b_j|$$

- Stands for **L**east **A**bsolute **S**hrinkage and **S**election **O**perator
- It adds `absolute value of magnitude` of the coefficient as a penalty term to the loss function
- Shrinks (as the name suggests) the less important features' coefficients to zero, which leads to **removal** of some features

- **Ridge (12)**

$$C\sum_{j=1}^{n}b_j^2$$

- Adds `squared magnitude` of coefficient as penalty term to the loss function
- Dampens the less important features' coefficients making them less significant, which leads to **weighting** of the features according to their importance

What's the role of C?

There are 4 scenarios that might happen with a classifier with respect to C:

- $C = 0$
  - The classifier becomes an **OLS** problem (i.e., Ordinary Least Squares, or just a strict regression without any penalization)
  - Since $0 \times anything = 0$, we are just left with optimizing $f(x)$, which is a definite **overfitting** problem
- $C = small$
  - We still run into an **overfitting** problem
  - Since C will not "magnify" the effect of the penalty term enough

What's the role of C? (cont'd)

- $C = large$
  - We run into an **underfitting** problem, where we've weighted and dampened the coefficients too much and we made the model too general
- $C = optimal$
  - We have a **good, robust, and generalizable model** that works well with new data
  - Ignores most of the noise while preserving the main pattern in data

- To pick the right combination of parameters we need to tune our model to find the right combination of those parameters

Early stopping

- **Early stopping** is another method to prevent overfitting
- It automatically terminates training when the monitored metric is not improving by some value for a certain number of iterations (i.e., `n_iter_no_change` in TensorFlow)
- The value is known as **tolerance for the optimization** (i.e., `tol` in TensorFlow)

- For more information, visit the TensorFlow website using ***the link***

Dropout

- **Dropout** is a common technique to address overfitting
- Theoretically, dropout *randomly drops neurons (along with their connections) from the neural network during training*
- It prevents neurons in layers from co-adapting too much
- It takes 2 arguments:
  - `rate`: a proportion of neurons to be dropped (`~0.1-0.4`)
  - `seed`: "locks" the random number generator for reproduceable our results
- For more information, visit the TensorFlow website using ***this link***

Weight constraint

- Weight constraint is another common technique to avoid overfitting
- It is an update to the neural net that checks the magnitude of the weights. If the size exceeds the a predefined limit, the weights are rescaled so that the size is within the range
- Unlike adding a penalty to the loss function, weight constraint ensures the weights of the network are small
- For more information, visit the TensorFlow website using ***this link***

Early stopping strategies

Technique	Strategy
Early stopping	Always expect during hyper parameter optimization
Early stopping + dropout	Small training data or large network
Early stopping + weight decay	Large network
Early stopping + weight constraint	Large network + large learning rate

Knowledge check

Link: **https://forms.gle/zoK3pYH7dMU2Zkzm9**

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Model Performance and Fit: Topic summary

In this part of the course, we have covered:

- Implement a custom neural network to demonstrate model fit with different learning rates, epochs and batch sizes
- Understand loss functions and math behind gradient descent
- Assess and discuss methods to improve the fit of a neural network

Congratulations on completing this module!