CSC 36000:
Modern Distributed Computing *NextGen with AI Agents*

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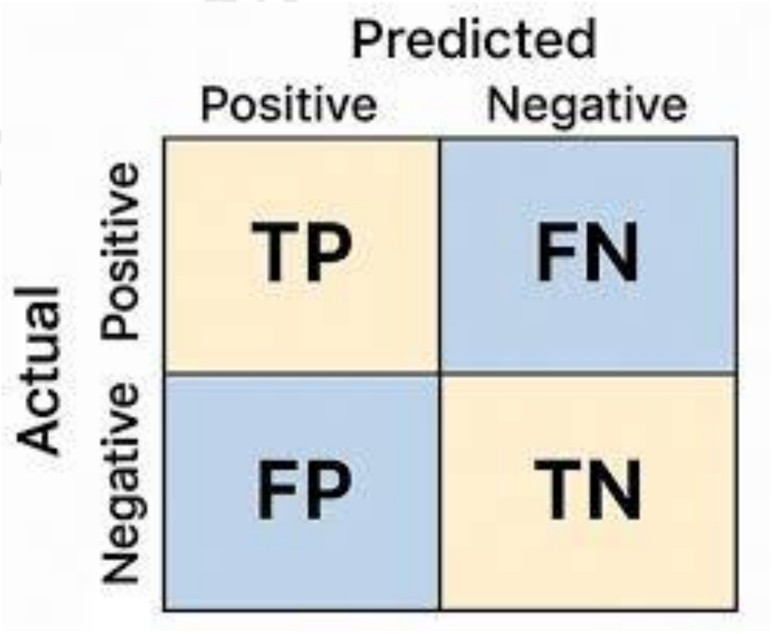
Evaluating Model Performance in Distributed Computing and Decentralized AI

Confusion Matrix

- Visualizes performance of a classification model
- What kinds of errors does the model make? When is it the most accurate?
- Key Terms:
  - **True Positive**
    - Predicted True, Actual True
  - **False Positive (Type 1 Error)**
    - Predicted True, Actual False
  - **True Negative**
    - Predicted False, Actual False
  - **False Negative (Type 2 Error)**
    - Predicted False, Actual True
- Accuracy, Precision, Recall, and F-measure can be traced back to this!



Accuracy

- Accuracy Measures the percentage of predictions that are correct
- This is most useful when classes (positives vs negatives) are relatively balanced
- Warning: Can be misleading with imbalanced classes

$$\frac{TP + FN}{TP + TN + FP + FN}$$

Precision

- The proportion of positively identified examples
- Precision can be thought of as the percentage of the “caught” items that are actually in the positive class, as opposed to being mistaken

$$\frac{TP}{TP + FP}$$

Example: Precision in Distributed GPU Clusters

- When training an AI model across multiple GPUs in a cluster, different precision scores across different GPUs could signify an imbalance in your data distribution
- By tracking precision, you can make sure that the learning process is going smoothly across all GPUs
- If some GPUs have low precision, there may be problems with your model parallelization techniques

Recall

- The proportion of positives that were identified correctly out of all the positive examples
- Most important when the "cost" of a false negative is high, e.g. misdiagnosing a patient

$$\frac{TP}{TP + FN}$$

Example: Self-Driving Cars

- Because recall identifies what what ID'd correctly out of the total number of "hits", it's very useful for self driving cars
- Recall can track the total number of pedestrians and other hazards identified
- It can also be used to monitor important signals like stop signs, traffic lights, and speed limits
- Even slight mistakes could spell disaster!

F-measure

- The F-Measure is the harmonic mean between the precision and the recall
- It punishes an imbalance between the precision and the recall
- It’s most useful when the number of positives and the number of negatives is lopsided

$$2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Why the harmonic mean?

- Imagine your model gets 99% of positive examples correct and 1% of negative examples correct
- If you were to take the arithmetic mean (aka the accuracy), you would get 50%
- This doesn't consider at all the failure to correctly identify all examples
- This same model would have an F-measure of ~2%, clearly letting you know the model needs debugging

Example: Monitoring Autonomous Systems

- F-measure can be used when both precision *and* recall are important
- If you're operating a computing cluster, it's important to both:
    - Identify malfunctioning nodes accurately (high recall)
    - Correctly flag faulty nodes (high precision)
- More applications:
    - Intelligent job prioritization (e.g. SLURM clusters)
    - Autonomous Management Systems

When do I use each metric?

- Start with the **confusion matrix**
  - This will give you solid footing for exploring the other metrics and understanding what kinds of errors your model is making
- Use **accuracy** when you want a quick glance at how the errors across your (balanced) dataset are distributed
- Choose **precision** when avoiding False Positives is important, and **recall** when False Negatives are important
- **F-measure** is most useful as a reliable metric for unbalanced positives vs negatives in your dataset

Questions?