Handout: Loss in Machine Learning

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1. What is Loss?

Loss quantifies how far a machine learning model's predictions are from the actual values. It's crucial in understanding model performance.

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2. Types of Loss Functions:

Regression Loss (Mean Squared Error)	**Classification Loss (Cross-Entropy Loss)**
Measures the squared difference between predictions and actual values.	Measures the difference between predicted probability and actual class label.
Used in predicting continuous values.	Used in classification tasks.

Discussion 1:

- Can you think of examples where minimizing the loss might not always improve real-world performance?
    - Consider cases like healthcare diagnostics or recommendation systems where reducing prediction error might conflict with other goals (e.g., fairness, interpretability).

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3. The Process of Minimizing Loss:

Steps:

1. **Train the model**
2. **Calculate loss**
3. **Adjust model parameters**
4. **Reduce loss**
5. **Repeat until loss is minimized**

Discussion 2:

- How might different optimization techniques impact how fast or effectively we minimize loss?

- What trade-offs do you think might arise if we minimize loss too aggressively (e.g., overfitting or ignoring generalization)?

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4. Comparing High vs. Low Loss:

- **High Loss**: Large errors between predictions and actual values.
- **Low Loss**: Small errors; the model is well-optimized.
- **Shared Goal**: Reduce the loss to improve model accuracy.

Critical Thinking Challenge:

- Minimizing loss can sometimes lead to unintended side effects, such as overfitting.
  - **What strategies** can we use to ensure the model generalizes well while reducing loss?
  - Can someone share an example where a model minimized loss in training but failed during deployment?

Discussion 3:

- Imagine a self-driving car system. What could go wrong if the model reduces loss during training but doesn't account for all possible real-world scenarios?
  - Could there be scenarios where minimizing loss during training doesn't translate into safe driving behavior?

Key Takeaways:

- Loss measures how well a model is performing.
- The goal is to **minimize loss** to improve model predictions, but blindly minimizing loss can introduce other issues.
- Loss functions need to be chosen carefully based on the task (e.g., MSE for regression, Cross-Entropy for classification).

For more details, refer to the presentation