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Natural Language Inference

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What is Natural Language Inference?

Natural Language Inference (NLI) is a fundamental NLP task that involves determining whether a hypothesis is true (entailment) or false (contradiction) given a premise.

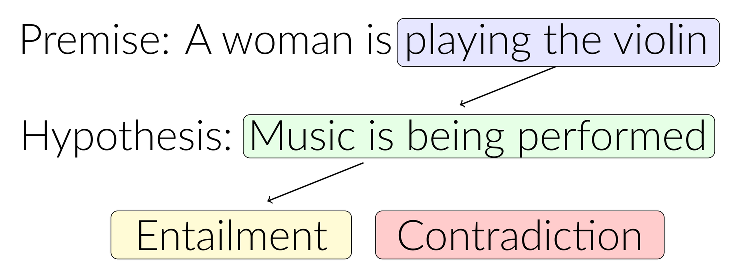

Figure 1. The NLI task classifies the relationship between premise and hypothesis.

Dataset Information:

- Binary classification task (entailment vs. contradiction)
- 24,000 premise-hypothesis pairs for training
- 6,000 premise-hypothesis pairs for validation

Project Overview

This poster presents our two-pronged approach to the NLI task:

1. **Ensemble RNN Architecture:** Combines strengths of multiple RNN variants with ESIM-inspired components
2. **Fine-tuned Transformer Architecture:** Based on RoBERTa with data augmentation strategies

Achievements

Both approaches significantly outperform their respective baselines:

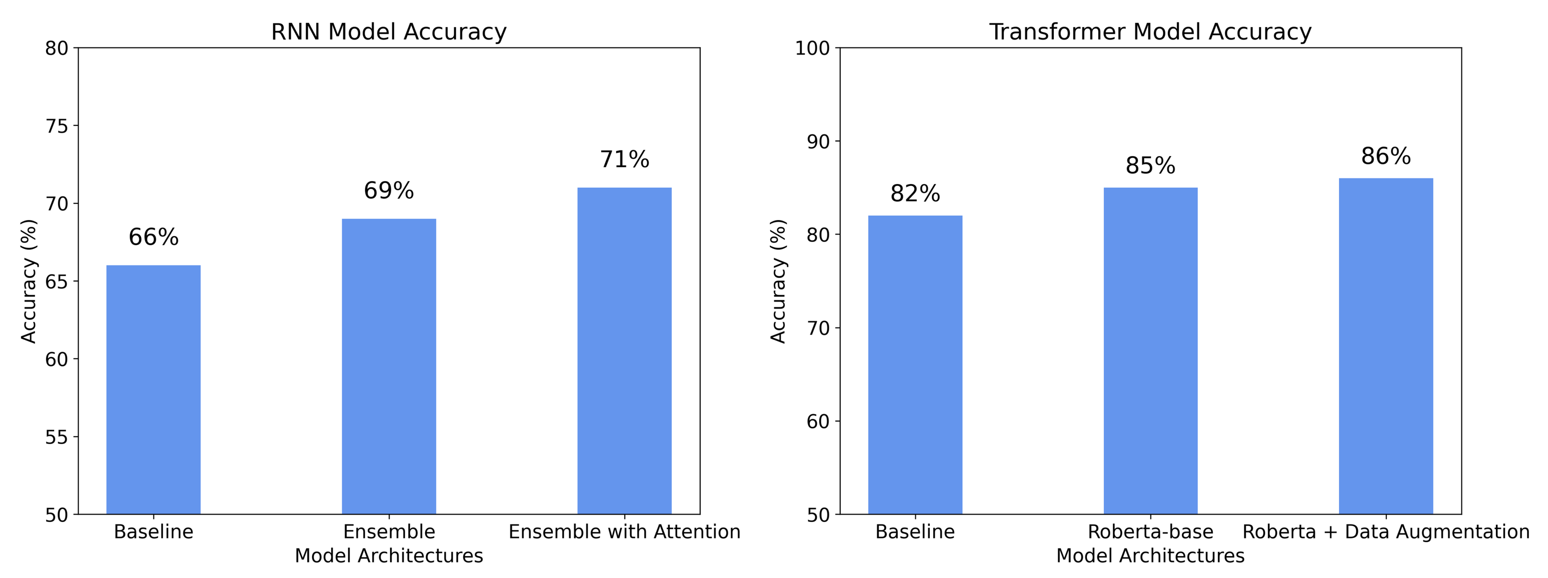

Figure 2. Performance comparison of Our Approaches vs Baseline

Key Findings

- Ensemble method combines strengths of different RNN variants
- Attention mechanism enhances semantic understanding
- Data augmentation provides measurable benefits for handling class imbalance
- Both approaches outperform their respective baselines

Ensemble RNN Architecture

Our RNN solution combines the strengths of four different recurrent neural network variants to create a robust ensemble:

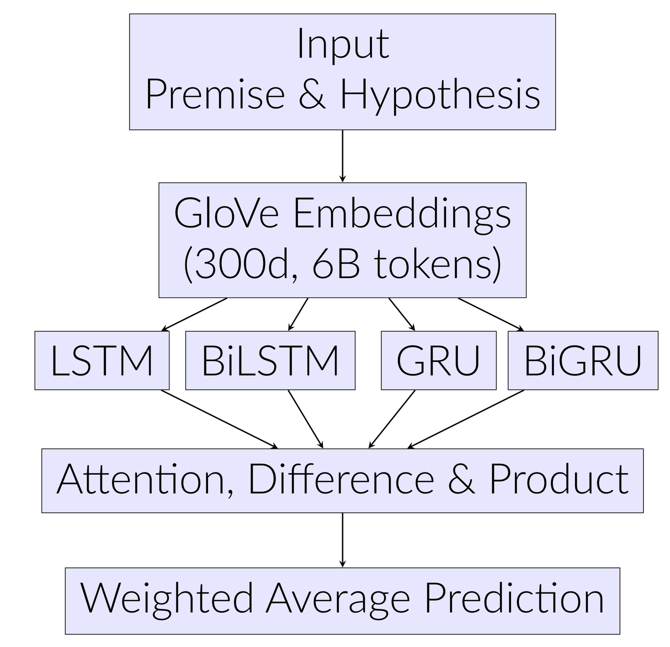

Figure 3. Ensemble RNN architecture with four RNN variants.

ESIM-Inspired Components

Our approach incorporates key components from the Enhanced Sequential Inference Model (ESIM):

- **Contextual Encoding:** Each RNN encodes premise and hypothesis for context representation
- **Soft Attention:** Aligns tokens between premise and hypothesis to highlight important interactions
- **Local Inference Modelling:** Computes element-wise difference and product to capture semantic relationships

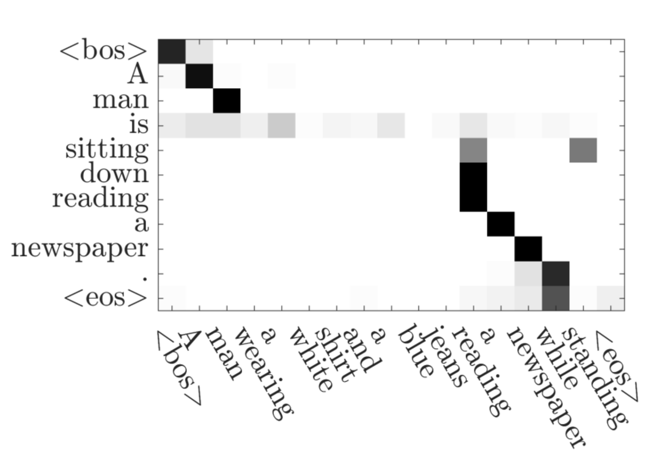

Figure 4. Example heatmap from ESIM paper

RNN Model Results

Our ensemble RNN approach significantly outperformed the baseline:

- **Baseline LSTM:** 66% accuracy
- **Ensemble:** 69% accuracy
- **Ensemble with Attention:** 71% accuracy

The combination of ensemble RNN architecture with the attention mechanism provided substantial improvement over both baseline and ensemble only approaches.

Transformer Architecture: RoBERTa-based Approach

Our transformer solution is built on the RoBERTa base model, fine-tuned specifically for the NLI task:

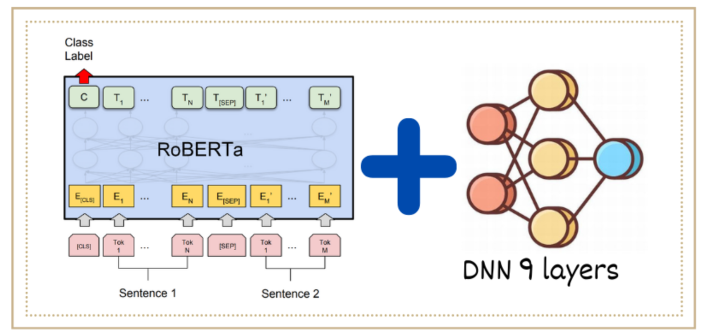

Figure 5. RoBERTa-based transformer architecture

Architecture Details:

- Fine-tuned RoBERTa-base pre-trained model
- 9-layer deep neural network for classification
- Layer normalisation to stabilise training
- Dropout techniques to prevent overfitting

Data Augmentation Strategy

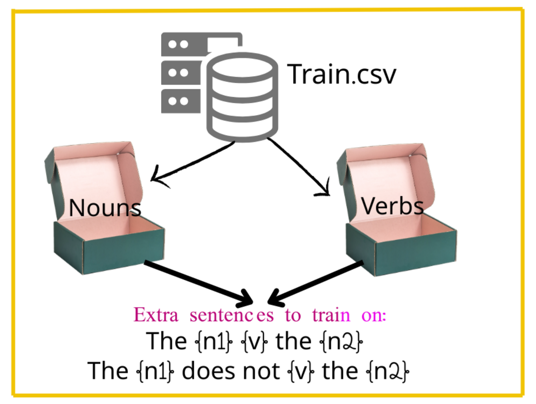

Figure 6. Augmenting data to increase training input

Synthetic Data Generation:

- Pattern forms: "the n1 v1 the n2" and "the n1 does not v1 the n2"
- Generated 1,000 contradictions
- Generated entailments with 30% probability for each contradiction

Transformer Results

Our transformer-based approach achieved significant performance gains:

- **Baseline transformer:** 82% accuracy
- **Our fine-tuned model (no augmentation):** 85% accuracy
- **Our fine-tuned model with data augmentation:** 86% accuracy

The data augmentation strategy provided slightly better overall performance over the fine-tuned model. Both models outperformed the baseline by a significant margin.

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