



# Natural Language Inference



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# Causal Inference & NLI

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**Causal inference** is the process of determining if a causal relationship exists between two events.

In NLI, the relationship between a premise and a hypothesis can be classified into one of 3 categories:

1. **Entailment**
2. **Neutrality**
3. **Contradiction**

# Textual Entailment

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For example, the premise “Peter and Shira are presenting their NLP project”

**Entails** that Peter and Shira are on the zoom call

**Contradicts** that Peter and Shira are sleeping through class

Is **neutral** on whether they are having fun









*...we're having fun we promise!*

# MNLI

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The MultiNLI (MNLI) dataset, sourced from the Open American National Corpus, encompasses both spoken and written premise/hypothesis pairs across 10 genres.

- These genres include transcriptions of face-to-face conversations, government documents, the 9/11 Commission report, articles from Slate Magazine, telephone conversations, etc.
- A distinctive aspect of MNLI is that only half of the genres are included in the training set, with the remaining unseen genres serving to test a model's ability to generalize to new text sources.

premise string · lengths	premise_binary_parse string · lengths	premise_parse string · lengths	hypothesis string · lengths	hypothesis_binary_parse string · lengths	hypothesis_parse string · lengths	genre string · classes	label class label
							
The other men shuffled.	( ( The ( other men ) ) ( shuffled . ) )	(ROOT (S (NP (DT The) (JJ other) (NNS men)) (VP (VBD shuffled)) (...	The other men were shuffled around.	( ( The ( other men ) ) ( ( were ( shuffled...	(ROOT (S (NP (DT The) (JJ other) (NNS men))...	fiction	0 entailment
States must show reasonable...	( States ( ( must ( ( show ( (...	(ROOT (S (NP (NNPS States)) (VP (MD must) (VP (VB show) (NP (NP (JJ...	Itis not necessary for there to be...	( ( ( Itis ( not necessary ) ) ( for (...	(ROOT (S (VP (VB Itis) (ADJP (RB not) (JJ...	government	2 contradiction
well it's been very interesting	( well ( it ( 's ( been ( very...	(ROOT (ADJP (RB well) (SBAR (S (NP (PRP it)) (VP (VBZ 's) (VP (VBN...	It has been very intriguing.	( It ( ( has ( been ( very intriguing ) ) )...	(ROOT (S (NP (PRP It)) (VP (VBZ has) (VP (VBN...	telephone	0 entailment
He started slowly back to the...	( He ( ( ( started ( slowly back ) ) ) (...	(ROOT (S (NP (PRP He)) (VP (VBD started) (ADVP (RB slowly) (RB...	He returned slowly to the bunkhouse.	( He ( ( ( returned slowly ) ( to ( the...	(ROOT (S (NP (PRP He)) (VP (VBD returned) (ADV...	fiction	0 entailment
and it's it's quite a bit i...	( and ( it ( 's ( ( ( ( it ( ( 's (...	(ROOT (PRN (CC and) (S (NP (PRP it)) (VP (VBZ 's) (S (S (NP (PRP it)) (V...	I do not know exactly where the...	( I ( ( ( do not ) ( know ( ( exactly wher...	(ROOT (S (NP (PRP I)) (VP (VBP do) (RB not)...	telephone	1 neutral
They're made from a secret recipe...	( They ( ( 're ( made ( from ( ( a ...	(ROOT (S (NP (PRP They)) (VP (VBP 're) (VP (VBN made) (PP (IN from)...	The recipe passed down from...	( ( ( The recipe ) ( ( passed down ) ( from ...	(ROOT (S (NP (NP (DT The) (NN recipe)) (VP...	travel	2 contradiction
yeah well you're a student right	( yeah ( well ( you ( 're ( a ( studen...	(ROOT (S (VP (VB yeah) (S (ADVP (RB well)) (NP (PRP you)) (VP (VBP 're)...	Well you're a mechanics student...	( Well ( you ( ( 're ( a ( mechanics ( stude...	(ROOT (S (ADVP (RB Well)) (NP (PRP you))...	telephone	1 neutral

# BERT

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- We are using the mDeBERTa-v3-base-xnli-multilingual-nli-2mil7 model, developed by Microsoft, for our project.
- Built on the mDeBERTa-v3-base architecture and pre-trained on the CC100 dataset, this model supports natural language inference (NLI) in 100 languages and is ideal for multilingual zero-shot classification tasks.
- We are evaluating model performance with validation accuracy.

# Training Our Model

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- **Determining Optimal Subset to Train:** Given that our model is already pre-trained on some natural language, we wanted to determine where our validation accuracy begins to plateau in order to optimize our runtime without sacrificing performance.
- **Gradient Clipping:** This prevents the gradients from exploding, which is crucial for maintaining stable training dynamics.
- **Learning Rate Scheduler:** Adjusts the learning rate throughout training, which can help in converging to a better minimum.



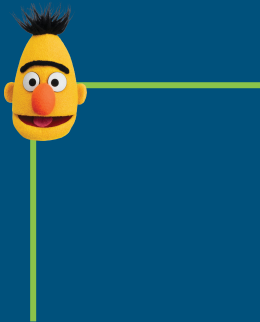
```
Epoch 1: Average Loss: 0.37268252827463644  
Epoch 2: Average Loss: 0.08028289416642298  
Epoch 3: Average Loss: 0.017550210266130135  
Epoch 4: Average Loss: 0.010786756653004208
```



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Validation Accuracy: 85.26%
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# Demo

