SENTIMENT ANALYSIS MODEL OVERVIEW

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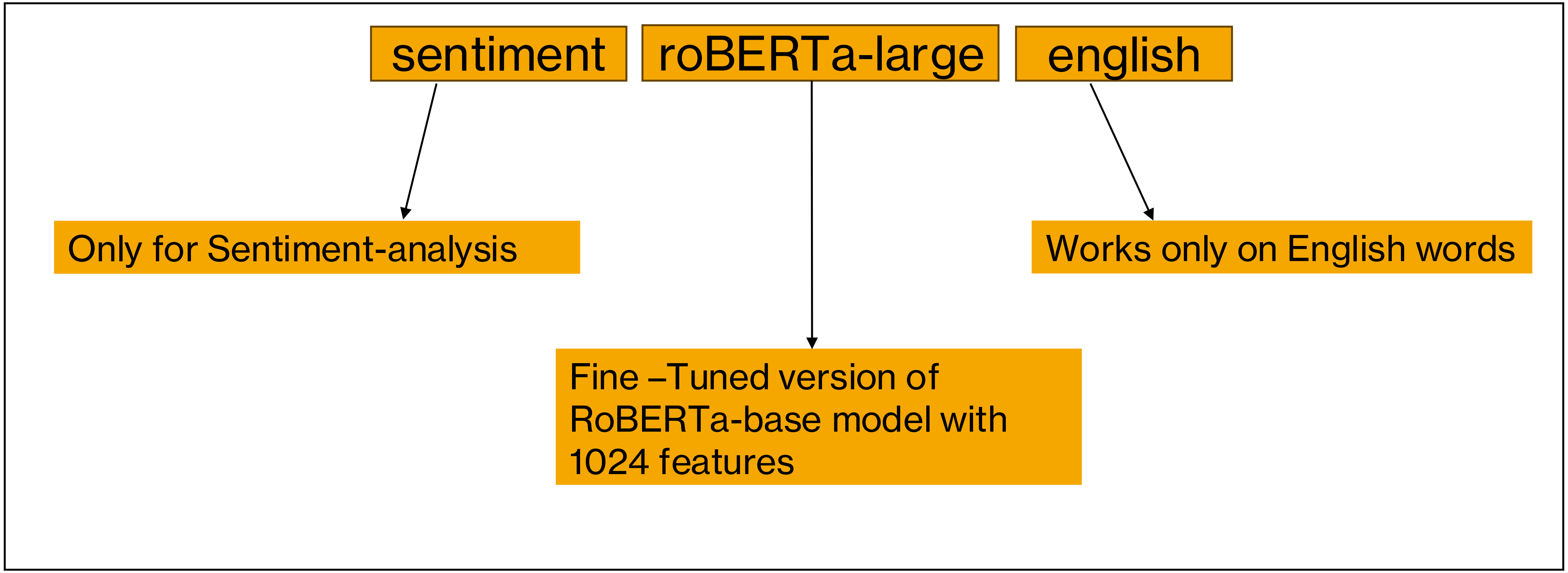
MODEL DETAILS



RoBERTa - Robust Optimized BERT Approach

- **RoBERTa** is a transformer model trained on a large corpus of raw **English text** in a self-supervised manner, leveraging publicly available data without human labeling.
- The model predicts words using **MLM (Masked Language Modeling)**, enabling it to learn **bidirectional sentence contexts** as per **BERT (Bidirectional Encoder Representations from Transformers)** approach.
- **RoBERTa** processes words simultaneously and focuses on bidirectionality.

WORKFLOW

- TOKENIZATION
- EMBEDDING
- TRANSFORMER
- CLASSIFICATION
- SOFTMAX ACTIVATION

TOKENIZATION

- BREAKS SENTENCE INTO SUBUNITS AND MAPS THEM TO UNIQUE IDs.
- EXAMPLE:

INPUT: I LOVE THIS DEO.

TOKENIZED: ["<s>":0, "I":100, "LOVE":122, "THIS":243, "DEO":23,"</s>:1]

<s> and </s> are special Start and End tokens.

EMBEDDING

- TOKEN IDs ARE CONVERTED TO VECTOR FORMS THAT CAPTURE CONTEXTS FOR EVERY SITUATION.
- EXAMPLE:

  `0` (`<s>`) → `E[0]` (embedding vector for `<s>`)

  `100` (`I`) → `E[100]` (embedding vector for `I`)

Token ID	Embedding Vector (Size: 1024)
0 (`<s>`)	[0.12, -0.34, ..., 0.56]
100 (`I`)	[0.45, 0.67, ..., -0.12]

TRANSFORMER

- EMBEDDINGS PASS THROUGH "SELF ATTENTION" LAYERS
- FOCUSES ON RELEVANT PARTS USING **MLM (MASKED LANGUAGE MODELING)** AND UNDERSTANDS CONTEXT.
- RoBERTa LARGE IS TRAINED WITH WEB TEXTS, BOOKS AND GOOGLE TEXTS WITH DYNAMIC MLM AND LONGER SEQUENCES.
- OUTPUT:

SENTIMENT	LOGITS	PROBABILITY
POSITIVE	[3.2, 0.1, -1.5]	[0.9, 0.05, 0.05]

CLASSIFICATION

- AT THE TOP, THERE IS A **CLASSIFICATION HEAD** (A FULLY CONNECTED NEURAL NETWORK).
- PREDICTS SENTIMENT AFTER TAKING OUTPUT FROM TRANSFORMER:

  POSITIVE

  NEGATIVE

SENTIMENT	LOGITS	PROBABILITY
NEGATIVE	-1.5	0.05
POSITIVE	3.2	0.95

SOFTMAX ACTIVATION

MODEL OUTPUTS SCORES FOR EACH CLASS

SOFTMAX FUNCTION CONVERTS SCORES INTO PROBABILITIES

$$P(y=c) = \frac{e^{\text{logits}_c}}{\sum_{c'} e^{\text{logits}_{c'}}}$$

CLASS WITH HIGHEST PROBABILITY IS CHOSEN

WHY CHOOSE THIS MODEL?

- **State-of-the-Art Architecture:** Built on RoBERTa-large, uses more data and parameters for better contextual understanding.
- **Fine-Tuned for Sentiment Analysis:** Specially trained for sentiment tasks like positive, negative, and neutral classifications.
- **High Accuracy and Robustness:** Performs well on short and long texts, even with implicit or context-dependent sentiments.
- **Pretrained on Large Corpus:** Understands language nuances and idiomatic expressions due to extensive pretraining.
- **Ease of Use with Hugging Face:** Simplifies integration, deployment, and fine-tuning for sentiment analysis tasks.
- **Support for Customization:** Fine-tunable for specific domains like Google Play reviews for improved performance.
- **Efficient Performance:** Optimized for large model efficiency, especially with GPUs.

IMPLEMENTATIONS

- Emotion detection
- Product review analysis
- Social media monitoring
- Customer support feedback analysis
- Political sentiment analysis
- Stock Market Sentiment

DRAWBACKS

- High computational requirements
- Domain-specific limitations
- Context misinterpretation
- Limited multilingual support
- Overfitting risk

Fine-Tuning for Sentiment Analysis

DOMAIN ADAPTIVE PRETRAINING (DAP)	TASK ADAPTIVE PRETRAINING (TAP)
Adapts a pretrained model to the vocabulary, semantics, and patterns of a specific domain (e.g., Google Play reviews	Adapts a pretrained model to a specific task by using task-specific labeled data.
Use it when there is large corpus of **unlabeled data** and domain vocabulary and language patterns differ significantly from general text.	Use it when there is large **labeled or pseudo-labeled dataset** for the task and directly optimize the model for task-specific nuances
Requires substantial computational resources	May overfit to the specific task if the training data is too narrow or small.

Fine-Tuning for Sentiment Analysis

I. DOMAIN ADAPTIVE PRETRAINING OR TASK ADAPTIVE PRETRAINING OR BOTH COMBINED SCORES WILL BE EVALUATED.

II. HIGHEST SCORE METHOD WILL BE TAKEN INTO ACCOUNT.

III. THEN COMBINED WITH **PEFT**(**PARAMETER-EFFICIENT FINE-TUNING**) METHOD LIKE **LoRA** (**LOW RANK ADAPTATION**) WHICH IS BEST FOR SENTIMENT ANALYSIS FOR ROBERTA ARCHITECTURE.

WHY LoRA?

- **Parameter Efficiency**: LoRA reduces trainable parameters through low-rank decomposition, useful for small datasets like sentiment analysis.
- **Flexibility**: LoRA targets specific model layers, preserving pre-trained features while allowing task-specific fine-tuning.
- **Efficiency**: Training time is reduced by focusing on a subset of parameters.
- **Reduced Overfitting**: Low-rank adaptation minimizes overfitting for smaller datasets.

FINE TUNING STEPS

- PREPARE DATASETS
- DAP OR TAP OR COMBINED(DAP+TAP)
- APPLY PEFT WITH LoRA FOR FINE TUNING
- EVALUATION

PREPARE DATASETS

Approach	Dataset	When to Use?
DAP	Unlabeled corpus of Google Play reviews or app reviews from similar domains	When domain-specific vocabulary and semantic patterns need to be adapted for general understanding.
TAP	Labeled dataset of app reviews with sentiment annotations	When optimizing for sentiment analysis or other task-specific requirements.
DAP + TAP	Unlabeled corpus for DAP, followed by labeled dataset for TAP	When both domain adaptation and task-specific optimization are needed for the best performance

DAP/TAP APPILED WITH PEFT

- PRETRAIN THE MODEL FOR TAP:

Use **Masked Language Modeling (MLM)** for tasks like sentiment analysis (unsupervised task data).

OR

- PRETRAIN THE MODEL FOR DAP:

Perform **Masked Language Modeling (MLM)** or similar objectives on the domain-specific dataset to adapt the model to the domain.

APPLY PEFT WITH LoRA FOR FINE TUNING

- LOAD THE PRE-TRAINED MODEL FOR SEQUENCE CLASSIFICATION
- DEFINE LoRA CONFIGURATION
- APPLY PEFT TO THE MODEL
- LOAD LABELED TASK-SPECIFIC DATA FOR TAP AND UNLABELED FOR DAP
- TOKENIZE LABELED DATASET
- TRAINING ARGUMENTS AND TRAINER FOR PEFT FINE-TUNING
- FINE TUNE AND SAVE

EVALUATION

- EVALUATE THE DAP + PEFT MODEL USING A LABELED TEST DATASET.

OR

- EVALUATE THE TAP + PEFT MODEL USING A LABELED TEST DATASET.

CONCLUSION

- THE MODEL IS WELL SUITED FOR DIFFERENT TYPES OF CLASSIFICATION/SENTIMENT ANALYSIS
- CAN BE FINE-TUNED FOR DOMAIN OR TASK SPECIFIC WORK
- BASED ON THE EVALUATION SCORES, BEST METHOD OF FINE TUNING CAN BE CHOSEN - **DAP WITH PEFT** / **TAP WITH PEFT** / **DAP+TAP WITH PEFT**
- CHOOSING DOMAIN SPECIFIC DATASETS AND THE PREPROCESSING STEPS FOR SPECIFIC DOMAIN IS CRUCIAL