Bilingual Knowledge and Ensemble Techniques for Portuguese Natural Language Processing Tasks

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Agenda

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3. Ensemble Architecture
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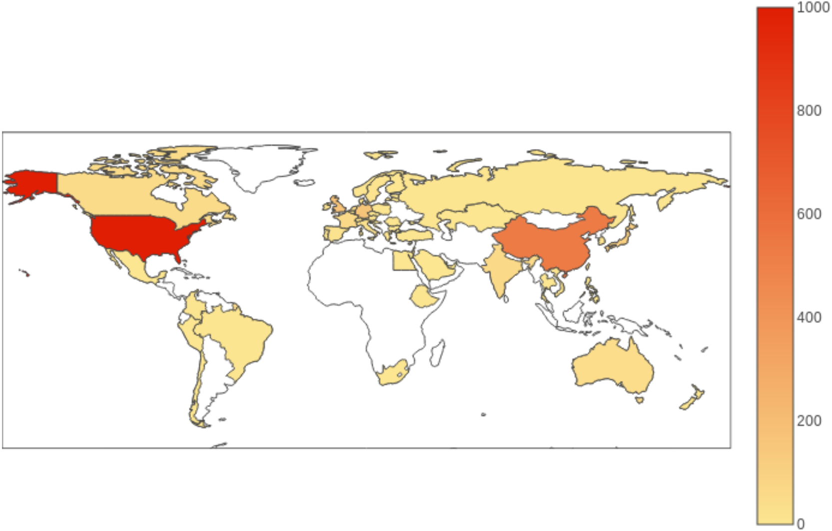
Introduction

- **Motivation:**
  - State-of-the-art models are often first trained only in English and/or Chinese.
- **Concept:**
  - Leverage the knowledge of state-of-the-art models through **Automatic Translation**
  - Combine models trained for Portuguese and English through ensemble techniques

Introduction

- **Paper count by country at the 2018 NLP conferences** [Rei 2019]



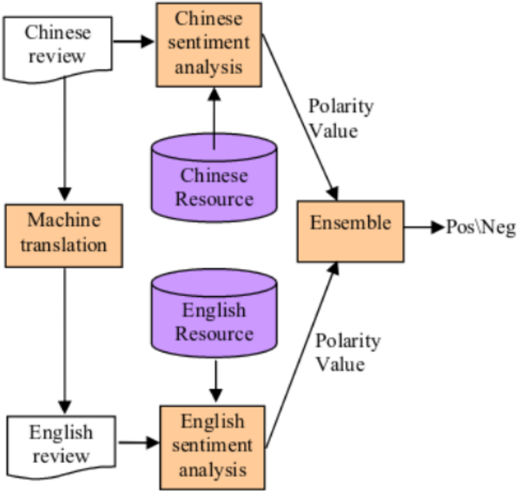
Introduction

- **GLUE Benchmark Leaderboard** [UWNLP 2019]

	Rank	Name	Model	URL	Score
	1	ALBERT-Team Google Language	ALBERT (Ensemble)		89.4
+	2	王玮	ALICE v2 large ensemble (Alibaba DAMO NLP)		89.0
	3	Microsoft D365 AI & UMD	FreeLB-RoBERTa (ensemble)		88.8
	4	Facebook AI	RoBERTa		88.5
	5	XLNet Team	XLNet-Large (ensemble)		88.4
+	6	Microsoft D365 AI & MSR AI	MT-DNN-ensemble		87.6
	7	GLUE Human Baselines	GLUE Human Baselines		87.1

Related Work

- **Using Bilingual Knowledge and Ensemble Techniques for Unsupervised Chinese Sentiment Analysis** [Wan 2008]

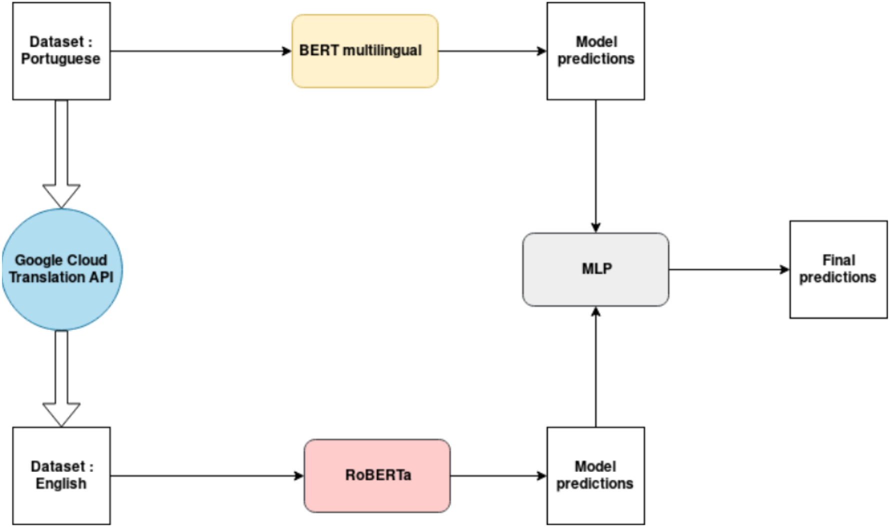


Ensemble Architecture

- **BERT**
  - Bidirectional Encoder Representations from Transformers [Devlin et al. 2018]
- **RoBERTa**
  - "(1) training the model longer, with bigger batches,over more data; (2) removing the next sentence prediction objective; (3) training on longer sequences; and (4) dynamically changing the masking pattern applied to the training data" [Liu et al. 2019]

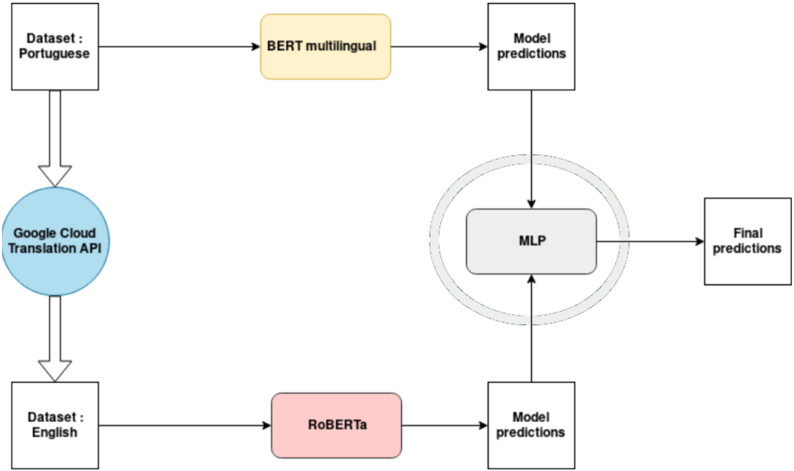
Ensemble Architecture

- **Overview**



Ensemble Architecture

- **Stage I: Training the MLP**

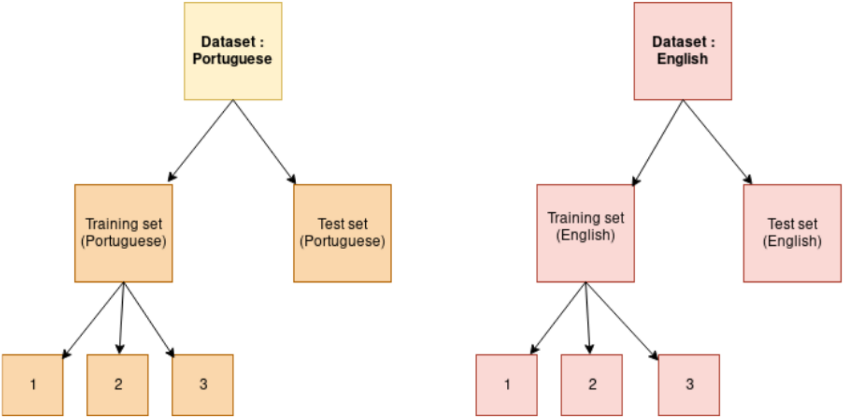


Ensemble Architecture

- **Stage I - Step 1: Translation**

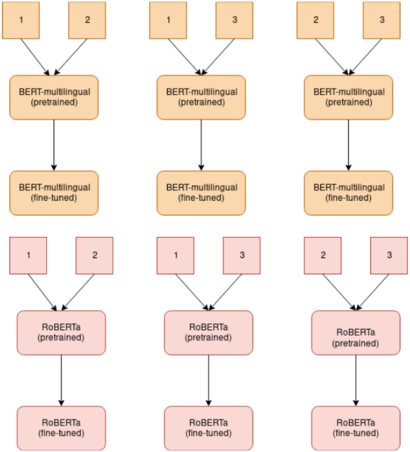
Ensemble Architecture

- **Stage I - Step 2: Split the training data into folds**



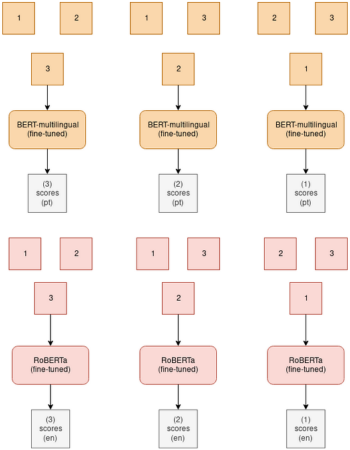
Ensemble Architecture

- **Stage I - Step 3: Fine tune one model for each possible combination of (n - 1) folds**



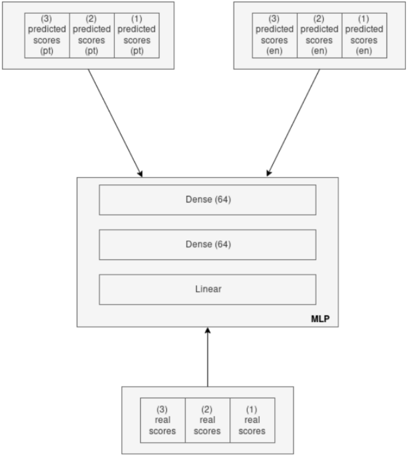
Ensemble Architecture

- **Stage I - Step 4: Predict scores for every missing fold**



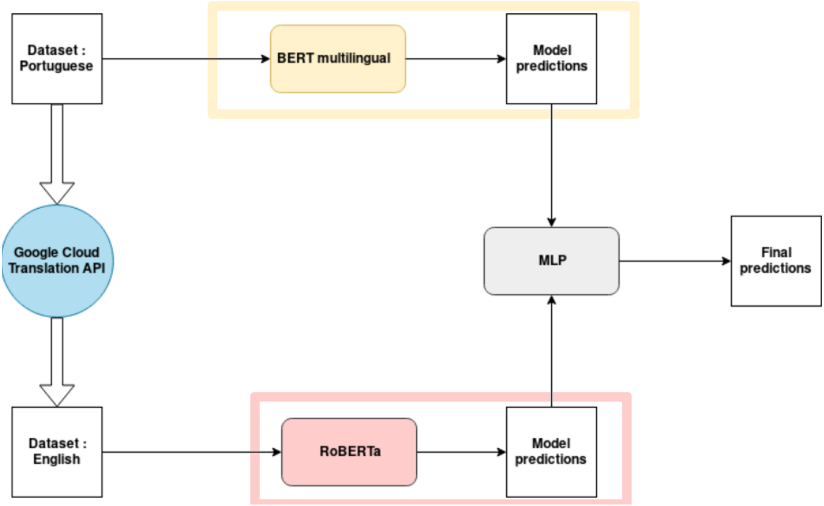
Ensemble Architecture

- **Stage I - Step 5: Train a MLP with the predicted scores**



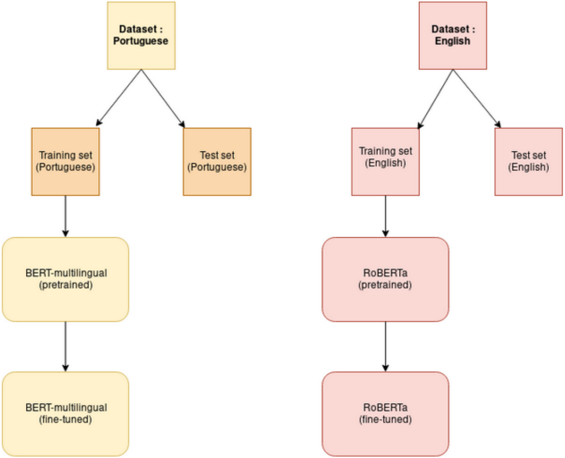
Ensemble Architecture

- **Stage II: Produce the model predictions**



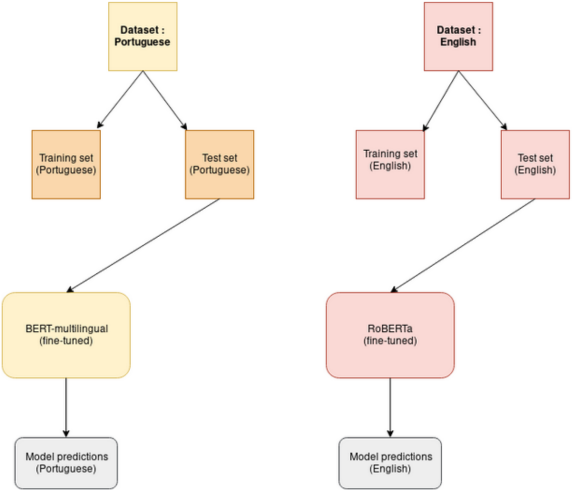
Ensemble Architecture

- **Stage II - Step 6: Fine tune a single model for each training set**



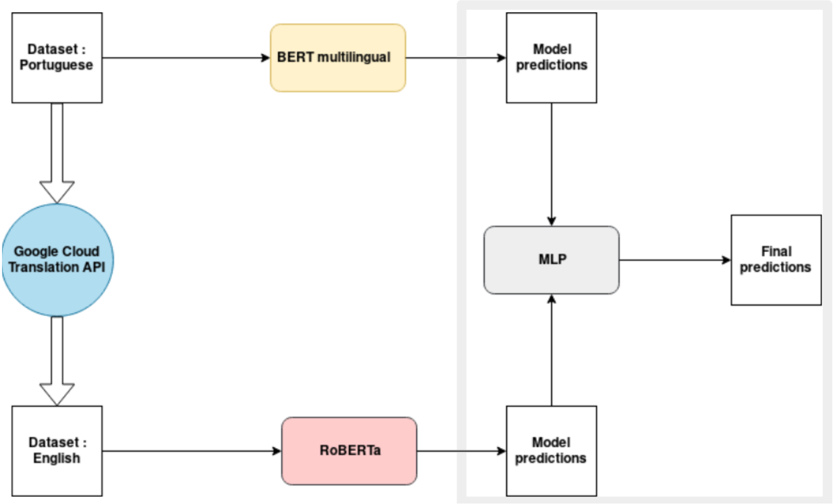
Ensemble Architecture

- **Stage II - Step 7: Let each model predict scores for the test set**



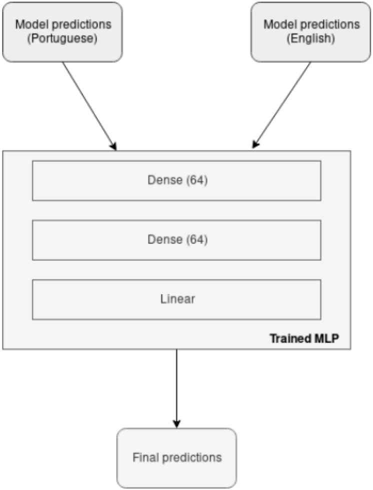
Ensemble Architecture

- **Stage III: Produce the final predictions**



Ensemble Architecture

- **Stage III - Step 8: Combine both model predictions through the now trained MLP**



Ensemble Architecture

- **Stage III - Step 9 (only for entailment): Round up and convert**

[0.345 -0.134 1.128 0.845 … 0.012]

[0 0 1 1 … 0]

[None, None, Entailment, Entailment, …, None]

Experimental Setup

- **Fine-tuning**
  - Transformers library (Hugging Face). [HuggingFace 2019]
  - RoBERTa : 12 epochs.
  - BERT : 4 epochs.
  - Only the final layer is considered.
  - Ensemble architecture: 5 folds
  - The learning rate was adjusted to train the entire ensemble architecture under a single GPU with 8 GB of memory.

Results

Architecture	ASSIN 1 [Propor 2016]		ASSIN 2 [STIL 2019]	
	Entailment	*Similarity*	*Entailment*	*Similarity*
BERT	* * *	0.79	0.819	0.75
RoBERTa	* * *	0.74	**0.884**	**0.81**
Ensemble (5 folds)	* * *	**0.82**	0.883	0.78

ASSIN 1: Complex sentences, most of which will be lost in translation

The ensemble model will always perform better than each model on its own.

ASSIN 2: Simple sentences, which will be almost perfectly translated

The accuracy of the ensemble will approach the stronger model (RoBERTa) as we increase the amount of folds.

Conclusions

- **Highlights**
  - Adaptative ensemble architecture which can produce the best results regardless of the quality of the translation.
  - Robust performance across many domains, thanks to the underlying Transformer architecture.
  - Open source.
- **Future work**
  - Improve on the Multilayer Perceptron.
  - Ensemble BERT and BiMPM. [Wang et al. 2019]
  - Improve BERT's fine-tuning process with SesameBERT. [Su and Cheng 2019]
  - Data augmentation. [Yang et al. 2019]

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