A Brief Introduction to Me and My Research

Yuling Shi

SUFE

April, 2021

Contents

About Me

- Junior from Shanghai University of Finance and Economics majoring in Applied Mathematics (Elite Program), Major GPA (3.64/4)
- Boardly interested in deep learning, machine learning and scientific computing.
- Have done many researches about NLP. One earlier paper accepted about scientific computing.

Outline

Background

- Leader of the project. Taking DL class with juniors from from Elite Program in Department of Electrical Engineering in my second year.

Data description

- The Natural Questions (NQ) (**Kwiatkowski et al., 2019**) dataset from Google AI.
- Each example comprised of a google query and a corresponding Wikipedia page.

Question: why does queen elizabeth sign her name elizabeth r
Wikipedia Page: Royal_sign-manual
Long answer: The royal sign-manual usually consists of the sovereign's regnal name (without number, if otherwise used), followed by the letter R for Rex (King) or Regina (Queen). Thus, the signs-manual of both Elizabeth I and Elizabeth II read Elizabeth R. When the British monarch was also Emperor or Empress of India, the sign manual ended with R I, for Rex Imperator or Regina Imperatrix (King-Emperor/Queen-Empress).

Short answer: NULL

Figure: Example annotations from the corpus

Key Experiments

- Fine-tuning on SQuAD 2.0
- Mixed Precision Training
- Hard Negative Sampling
- Sifting candidates

Fine-tuning on SQuAD 2.0

- SQuAD 2.0 - $130,000$ crowd sourced question and answer training pairs derived from Wikipedia paragraphs.

Performance in Training

Model	Start_acc	End_acc	Class_acc
BERT base (Original)	59.1	61.5	73.9
ALBERT xlarge (Original)	0.12	0.13	66.67
ALBERT xlarge (Finetuned)	82.54	86.37	85.75

batch size = 3 per GPU, learning rate = 1e-5 for 3 epochs

Mixed Precision Training

- To save memory and speed up - only had 1080Ti GPUs cluster.

Experiment Result

Precision	EM	F1	Speed up*
FP32 only	84.86	88.00	1.0
FP16 Only	16.75	17.35	1.35x
Mixed precision	84.94	87.97	1.05x

*All tested during SQuAD2.0 fine-tuning

Hard Negative Sampling

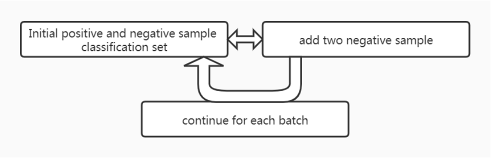
Intuition

- Training questions without any short answer(65%) $\rightarrow$ Too many negative Examples
- Uniform sampling $\rightarrow$ most of the negative candidates are **"too easy"**
- Hard negative sampling $\rightarrow$ increase the difficulty of training

Hard Negative Sampling

Procedure

1. Train a model with uniform sampling and predict on the whole training data
2. Store the answer probability for each negative candidate
3. Normalize the probabilities within documents to form a distribution
4. Sample negative candidates from the probability distribution in training.



Hard Negative Sampling

Result

- Result: the performance was improved 6.6% on Public leaderboard and 9.8% on Private leaderboard.

Model	Public F1	Private F1
BERT baseline	0.516	0.482
BERT with Hard Negative Sampling	0.579	0.574

Sifting candidates

Sifting candidates with BERT base to reduce candidates

1. First perform a full prediction on the validation set using a fast model (BERT Base) to reduce number of candidates.
2. Then use larger model to make predictions on the selected candidates.

Benefits

1. Reduce much predicting time when adding large models.
2. More convenient to ensemble other models.

Sifting candidates

Performances

Model	Public F1	Private F1
BERT baseline	0.516	0.482
BERT Base (Hard Negative Sampling)	0.579	0.574
BERT* Sifted $\rightarrow$ ALBERT xlarge	0.640	0.659

$*$ also trained with hard negative sampling

Final Result

Model	Public F1	Private F1
Kaggle Best	0.713	0.717
BERT Base baseline	0.516	0.482
BERT Base (Hard Negative Sampling)	0.579	0.574
BERT Sifted* $\rightarrow$ ALBERT xlarge	**0.640**	**0.659**
Sifted $\rightarrow$ BERT Base+ALBERT$_{\text{(ensemble)}}$	0.665	0.666
Sifted $\rightarrow$ BERT Large+ALBERT$_{\text{(ensemble)}}$	**0.738**	**0.718**

$*$ Sifted here stands for first using BERT base to sift candidates

Conclusion

- Learned to search and read latest paper regularly and looked for many useful techniques.
- Comfortable with Linux environment and commands, and also implementation of DL models.
- Collaborated with group to discuss and do experiments together. Also asked for teachers' advice regularly.

Outline

Overview

- Data: complaints from citizens. The task is to predict label (200 classes in total).
- Pre-processed the dateset, pre-trained models on similar dataset THUCNews with mixed precision training.
- Focal loss to track difficult and rare class examples.
- Designed a auxiliary sentence pair task.
- Also tried adversarial training, data augmentation, adding other layers after BERT, using RoBERTa-wwm, ERNIE, etc.

Focal Loss

- The 200 labels are long-tailed distributed.
- Scaled losses according to how difficult the example is to predict.

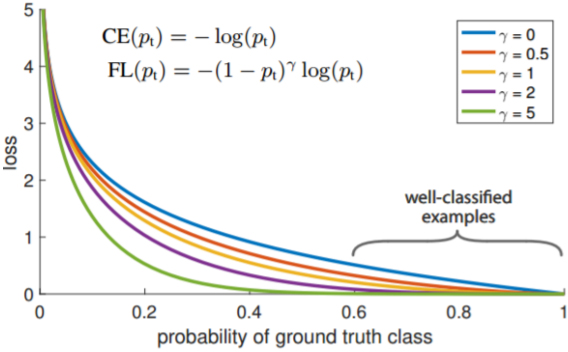


Figure: Different Loss Functions

Auxiliary Task

- The original classification task failed to utilize information in the labels.
- Sort predicted labels by probabilities, 79% of the true label are at the first place, 11% at the second, 96% of them are within top 5 predictions.

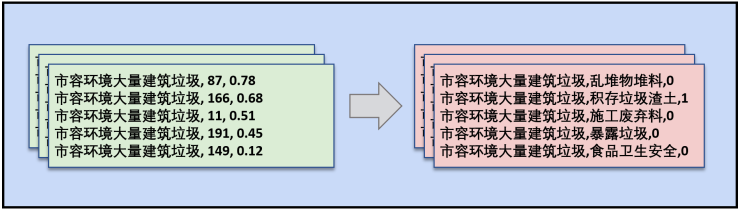


Figure: Generating pair data

Final Submission

- Highest public score in class (led by 0.4%) but turned out to be overfitted. (why? lack of cross validation?)

Table: Selected Experiment Results

Model	Public score	Private score
ERNIE[1]	0.7981	0.8000
ERNIE[2]	0.7995	0.8030
ERNIE[3]	0.8049	0.8010

[1] Original Task: text classification

[2] Focal Loss

[3] Auxiliary Task: sentence pair classification

Conclusion

- Explored and implemented more useful techniques myself.
- Faced with a more unpredictable project, designed an auxiliary task which performed "well".
- Experimented more failed techniques and analyzed possible reasons.

Outline

Biref Introduction

Finite element space:

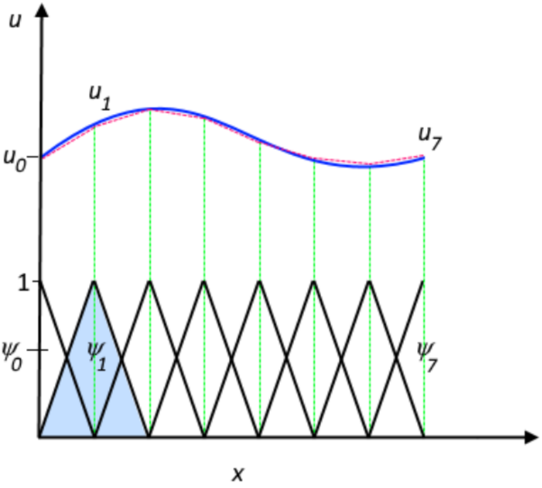


Figure: Linear basis in 1D

Main Problem

Equation:

$$\begin{cases} \varepsilon^2\Delta^2 u - \Delta u = f & \text{in } \Omega, \\ u = \partial_n u = 0 & \text{on } \partial\Omega, \end{cases}$$

- Original variational form

$$\varepsilon^2(\nabla_h^2 u_{h0}, \nabla_h^2 v_h) + (\nabla_h u_{h0}, \nabla_h v_h) = (f, P_h v_h) \quad \forall\ v_h \in V_{h0}.$$

- Original ways to solve:
  - Conforming elements: computational expensive
  - Non-conforming elements: isn't convergent

Biref Description

Our work:

- Modified the right hand side via projection:

$$\begin{aligned} (\nabla w_h, \nabla \chi_h) &= (f, \chi_h) & \forall \chi_h \in W_h \\ \varepsilon^2 a_h(u_{h0}, v_h) + b_h(u_{h0}, v_h) &= (\nabla w_h, \nabla_h v_h) & \forall v_h \in V_{h0} \end{aligned}$$

- Decoupled the left hand side into four simple equations:

$$\begin{aligned} (\operatorname{curl}_h z_h, \operatorname{curl}_h v_h) &= (\nabla w_h, \nabla_h v_h) & \forall v_h \in V_{h0} \\ (\phi_h, \psi_h) + \varepsilon^2 (\nabla_h \phi_h, \nabla_h \psi_h) + (\operatorname{div}_h \psi_h, p_h) &= (\operatorname{curl}_h z_h, \psi_h) & \forall \psi_h \in V_{h0}^{CR} \\ (\operatorname{div}_h \phi_h, q_h) &= 0 & \forall q_h \in \mathcal{Q}_h \\ (\operatorname{curl}_h u_{h0}, \operatorname{curl}_h \chi_h) &= (\phi_h, \operatorname{curl}_h \chi_h) & \forall \chi_h \in V_{h0} \end{aligned}$$

Biref Description

- Can be solved efficiently with the simplest Morley element.

h	#dofs	Eq.(5.1)	Eq.(5.7a)	Eq.(5.7b)-(5.7c)	Eq.(5.7d)
		steps	steps	steps	steps
2^{-1}	24	1	1	16	1
2^{-2}	112	1	4	27	3
2^{-3}	480	4	5	34	5
2^{-4}	1984	6	7	34	7
2^{-5}	8064	6	9	41	9
2^{-6}	32512	7	11	43	11
2^{-7}	130560	7	14	44	14
2^{-8}	523264	9	17	46	17
2^{-9}	2095104	9	20	50	21
2^{-10}	8384512	12	27	55	27

Figure: Robust iteration steps when solving

Conclusion

- Final paper accepted by *Journal of Scientific Computing*
- Found a suitable open source package myself and studied many bottom-level codes.
- Fixed many bugs in developing experiments by discussing. Reported bug for the package and contributed codes to develop it.

Outline

Background

Existing methods

- Gradient based methods: gradient, dot product with embeddings, integrated gradient ...
- Perturbation based methods: input reduction, adversarial perturbations ...

Trying to explain what the model is learning during the training process.

$$
\begin{aligned}
Loss(x_1, \ldots, x_d) &= \sum_{n_1=0}^{\infty} \cdots \sum_{n_d=0}^{\infty} \frac{(x_1 - a_1)^{n_1} \cdots (x_d - a_d)^{n_d}}{n_1! \cdots n_d!} \left(\frac{\partial^{n_1 + \cdots + n_d} f}{\partial x_1^{n_1} \cdots \partial x_d^{n_d}} \right) (a_1, \ldots, a_d) \\
&= f(a_1, \ldots, a_d) + \sum_{j=1}^{d} \frac{\partial f(a_1, \ldots, a_d)}{\partial x_j} (x_j - a_j) + \frac{1}{2!} \sum_{j=1}^{d} \sum_{k=1}^{d} \frac{\partial^2 f(a_1, \ldots, a_d)}{\partial x_j \partial x_k} (x_j - a_j)(x_k - a_k) \\
&+ \frac{1}{3!} \sum_{j=1}^{d} \sum_{k=1}^{d} \sum_{l=1}^{d} \frac{\partial^3 f(a_1, \ldots, a_d)}{\partial x_j \partial x_k \partial x_l} (x_j - a_j)(x_k - a_k)(x_l - a_l) + \cdots
\end{aligned}
$$

Dataset

- e-SNLI dataset: essential words are highlighted by annotators

Premise: An adult dressed in black holds a stick.
Hypothesis: An adult is walking away, empty-handed.
Label: contradiction
Explanation: Holds a stick implies using hands so it is not empty-handed.

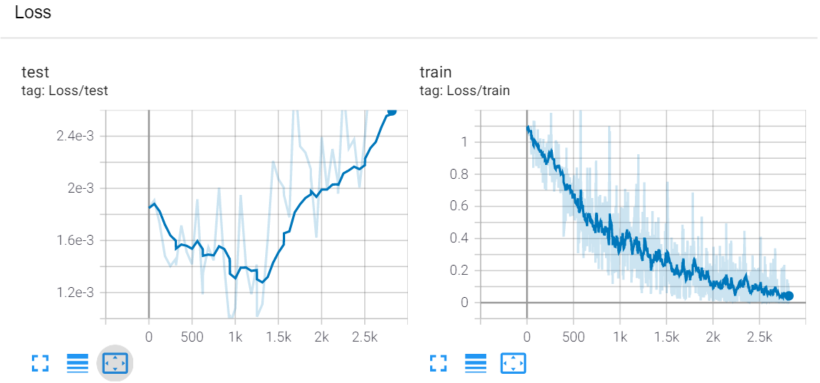
Premise: A child in a yellow plastic safety swing is laughing as a dark-haired woman in pink and coral pants stands behind her.
Hypothesis: A young mother is playing with her daughter in a swing.
Label: neutral
Explanation: Child does not imply daughter and woman does not imply mother.

Premise: A man in an orange vest leans over a pickup truck.
Hypothesis: A man is touching a truck.
Label: entailment
Explanation: Man leans over a pickup truck implies that he is touching it.

Figure: Examples from e-SNLI

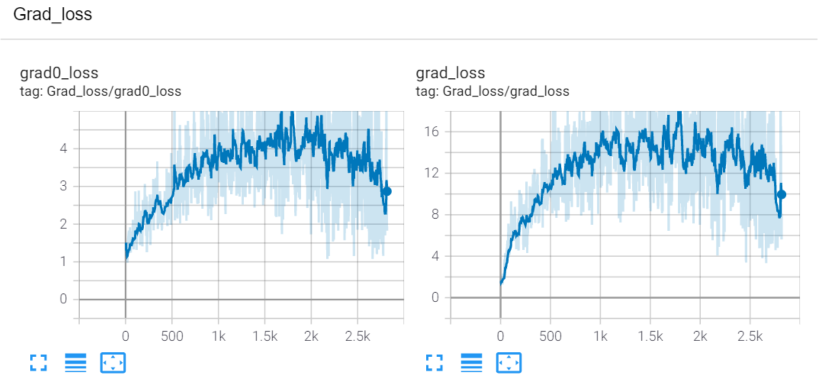
Experiments

- Loss durning training BERT-Base:



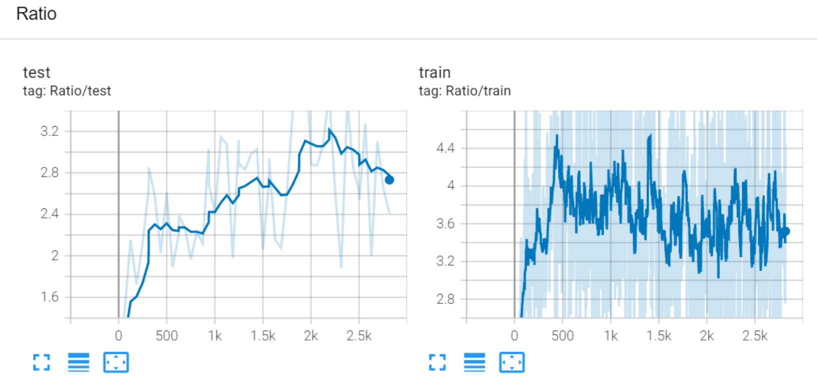
Experiments

- Gradients of annotated "essential words" durning training BERT-Base:



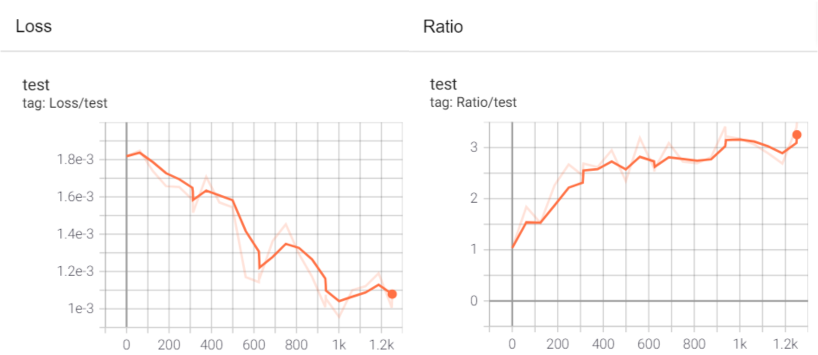
Experiments

- Ratio: $\frac{|\text{Gradients of annotated}|}{|\text{Gradients of all}|}$ durning training BERT-Base:



Experiments

- Model learning relations between "essential" words?
- $\frac{\partial Loss}{\partial E_i E_j}$ durning training BERT-Base:



Experiments

- What relations are captured?
- Sentences (label: entailment):
  1. Two young boys of opposing teams play football, while wearing full protection uniforms and helmets.
  2. Boys play football.
- 'essential words':

  ['boys', 'opposing', 'teams', 'play', 'boys', 'play', 'football']

Experiments

- Sentences:
  1. Two young boys of opposing teams play football, while wearing full protection uniforms and helmets.
  2. Boys play football.

	word	most relavent	score
0	[SEP]	[SEP]	0.044089
2	[CLS]	[SEP]	0.025706
4	[CLS]	[SEP]	0.024833
6	[SEP]	.	0.014351
8	football1	[SEP]	0.014056
10	.	[SEP]	0.013824
12	[SEP]	football2	0.011118
14	[SEP]	football1	0.010987
16	football2	[SEP]	0.010924
18	[SEP]	helmets	0.010910

Figure: At the beginning of training

Experiments

- Sentences:
  1. Two young boys of opposing teams play football, while wearing full protection uniforms and helmets.
  2. Boys play football.

	word	most relavent	score
0	football1	football2	0.066224
2	and	football2	0.053644
4	football2	protection	0.034782
6	boys	football2	0.025395
8	football2	play	0.021575
10	uniforms	football2	0.018982
12	[CLS]	football2	0.018318
14	[SEP]	football2	0.013509
16	helmets	football2	0.012761
18	football1	protection	0.012189

Figure: Trained for 1/2 epoch

Experiments

- Sentences:
  1. Two young boys of opposing teams play football, while wearing full protection uniforms and helmets.
  2. Boys play football.

	word	most relavent	score
0	helmets	football2	0.104266
2	football2	football1	0.101465
4	football2	uniforms	0.090533
6	football1	helmets	0.085855
8	helmets	uniforms	0.063052
10	uniforms	[CLS]	0.048258
12	football2	play	0.046607
14	helmets	protection	0.044967
16	football2	[SEP]	0.042081
18	play	helmets	0.038749

Figure: Trained for 1 epoch

Future Work

- Search for other dataset to simplify the problem.
- Techniques to reduce computational cost (randomized?).
- Design other experiments to figure out what is decreasing?

Summary

- Comfortable with math and can implement experiments fast.
- Highly motivated and always passionate to search for and think of more techniques.
- Seeking for further guidance :) .

Thanks for your attention!