Инструментарий для аннотирования в формате PL-Marker

Шитенко А. О.

Первый прямой визуальный редактор для формата PL-Marker

Что создано

Разработан **графический редактор**, который позволяет работать с форматом PL-Marker **напрямую** — без промежуточных конвертаций и сложных манипуляций.

Решаемая проблема

Существующий процесс был **непрямым и односторонним**:

1. Разметка в одном инструменте (brat)
2. Конвертация в PL-Marker
3. Невозможность редактирования

Результат: данные оказывались «взаперти» без возможности обратной конвертации.

PL-Marker: формат для текстов

1 Что это и где используется

Формат данных для размеченных текстов (`.jsonl`)

- Разработан **Tsinghua University**
- Используется в проектах для обработки текстов:
  - **HyperPIE**
  - **ACE05SciER**
  - **SciERC**

2 Пример: Вложенные сущности

Текст: "Магазин 'У дяди Васи' на углу"

Старые форматы (CoNLL, IOB): ❌ Выбор: либо весь магазин, либо только имя владельца.

PL-Marker: ✅ Поддерживает вложенные сущности:

- [Магазин 'У дяди Васи']ORG ← бизнес
- [дяди Васи]PERSON ← владелец (вложен)

3 Результаты и актуальность

По данным авторов (Ye и др., 2021):

- **Точность:** 71.1% vs 67.0% (предыдущий лидер)
- **Прирост на вложенных данных:** +4.1% F1

Тем не менее, не существовало удобного инструмента для прямого визуального редактирования PL-Marker файлов.

Как исследователи работали раньше?

Неудобный односторонний процесс

Шаг 1

Аннотирование в другом формате (например, в brat)

Шаг 2

Запуск скрипта-конвертера

Шаг 3

Получение PL-Marker файла

Проблемы:

- **Нашли ошибку?** Нужно возвращаться к шагу 1 и повторять весь цикл заново
- **Нужна обратная конвертация?** Невозможно. Нет инструментов

Решение

Этот инструмент **убирает лишние шаги** и решает обе проблемы одновременно:

Прямое редактирование

Открытие, редактирование и сохранение файлов PL-Marker напрямую

Без конвертаций

Никаких промежуточных шагов для внесения правок

Интуитивность

Процесс становится быстрым и понятным

Разметка в два клика

Простой и наглядный интерфейс

01

Выделение текста

Использование мыши для выделения фрагмента текста и создания новой сущности из всплывающего меню.

02

Наведение курсора

При наведении на сущность автоматически подсвечиваются все её связи с другими элементами разметки.

This section describes the target neural architectures , LSTM and self - attentive models , and how to adapt these models for the downstream tasks : sentiment analysis , entailment and translation .

For classification tasks including sentiment analysis and entailment detection , we use a Bidirectional LSTM with an attention (Hochreiter and Schmidhuber , 1 9 9 7 ; Bahdanau et al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .

For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with 5 1 2 hidden units .

Self - attentive models are further distinguished into BERT and Transformers .

The classification problems adopt the BERT model with an identical setup to the original paper (Devlin et al. , 2 0 1 9) , in which BERT is used as an encoder that represents a sentence as a vector .

Method

We also experiment with a smaller BERT model without pre - training , denoted as BERT NOPT , in order to isolate the impact of pre - training .

To the best of our knowledge , there is no prior work that uses pre - trained BERT for machine translation .

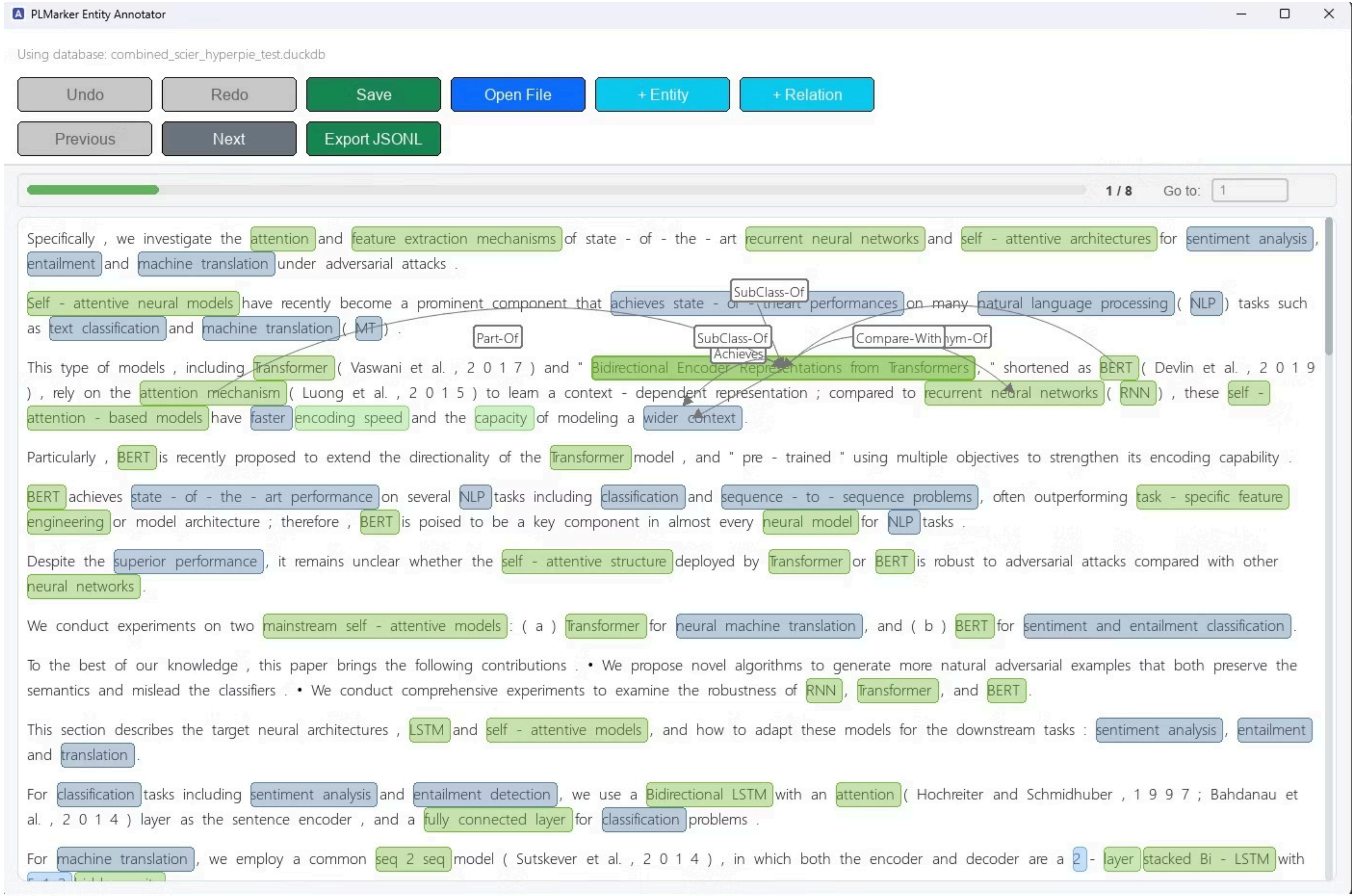
Thus , the Transformer model is employed for neural machine translation task .

Although the GS - GR method potentially achieves a high success rate , the adversarial examples formed by GS - GR are usually unnatural ; sometimes GS - GR completely changes the semantics of the original sentence by replacing the most important word with its antonym , for example : changing " this is a good restaurant " into " this is a bad restaurant . " This can not be treated as a successful attack , since humans will notice the change and agree with the model 's output .

In the experimental results , we show that the GS - EC method achieves a similar success rate as GS - GR in misleading the model , while being able to generate more natural and semanticallyconsistent adversarial sentences .

These methods are denoted as AS MIN -GR that replaces the word with the lowest score , and AS MAX -GR with the highest score .

We evaluate the robustness of the classification models (for sentiment analysis and entailment) by the following three criteria : (a) the success rate of the attacks misleading the model , (b) readability , and (c) human accuracy .


PLMarker Entity Annotator
Using database: combined_scier_hyperpie_test.duckdb
Undo
Redo
Save
Open File
+ Entity
+ Relation
Previous
Next
Export JSONL
1 / 8
Go to:
1
Specifically , we investigate the attention and feature extraction mechanisms of state - of - the - art recurrent neural networks and self - attentive architectures for sentiment analysis , entailment and machine translation under adversarial attacks .
Self - attentive neural models have recently become a prominent component that achieves state - of - the - art performances on many natural language processing (NLP) tasks such as text classification and machine translation (MT) .
SubClass-Of
Part-Of
SubClass-Of
Achieves
Compare-With
This type of models , including Transformer (Vaswani et al. , 2 0 1 7) and " Bidirectional Encoder Representations from Transformers " shortened as BERT (Devlin et al. , 2 0 1 9) , rely on the attention mechanism (Luong et al. , 2 0 1 5) to learn a context - dependent representation ; compared to recurrent neural networks (RNN) , these self - attention - based models have faster encoding speed and the capacity of modeling a wider context .
Particularly , BERT is recently proposed to extend the directionality of the Transformer model , and " pre - trained " using multiple objectives to strengthen its encoding capability .
BERT achieves state - of - the - art performance on several NLP tasks including classification and sequence - to - sequence problems , often outperforming task - specific feature engineering or model architecture ; therefore , BERT is poised to be a key component in almost every neural model for NLP tasks .
Despite the superior performance , it remains unclear whether the self - attentive structure deployed by Transformer or BERT is robust to adversarial attacks compared with other neural networks .
We conduct experiments on two mainstream self - attentive models : (a) Transformer for neural machine translation , and (b) BERT for sentiment and entailment classification .
To the best of our knowledge , this paper brings the following contributions . • We propose novel algorithms to generate more natural adversarial examples that both preserve the semantics and mislead the classifiers . • We conduct comprehensive experiments to examine the robustness of RNN , Transformer , and BERT .
This section describes the target neural architectures , LSTM and self - attentive models , and how to adapt these models for the downstream tasks : sentiment analysis , entailment and translation .
For classification tasks including sentiment analysis and entailment detection , we use a Bidirectional LSTM with an attention (Hochreiter and Schmidhuber , 1 9 9 7 ; Bahdanau et al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .
For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with

1 / 8 Go to: 1

This section describes the target neural architectures , LSTM and self - attentive models , and how to adapt these models for the downstream tasks : sentiment analysis , entailment and translation .

For classification tasks including sentiment analysis and entailment detection , we use a Bidirectional LSTM with an attention (Hochreiter and Schmidhuber , 1 9 9 7 ; Bahdanau et al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .

For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with 5 1 2 hidden units .

Self - attentive models are further distinguished into BERT and Transformers .

The classification problems adopt the BERT model with an identical setup to the original paper (Devlin et al. , 2 0 1 9) , in which BERT is used as an encoder that represents a sentence as a vector .

Method

We also experiment with a smaller BERT model without pre - training , denoted as BERT NOPT , in order to isolate the impact of pre - training .

To the best of our knowledge , there is no prior work that uses pre - trained BERT for machine translation .

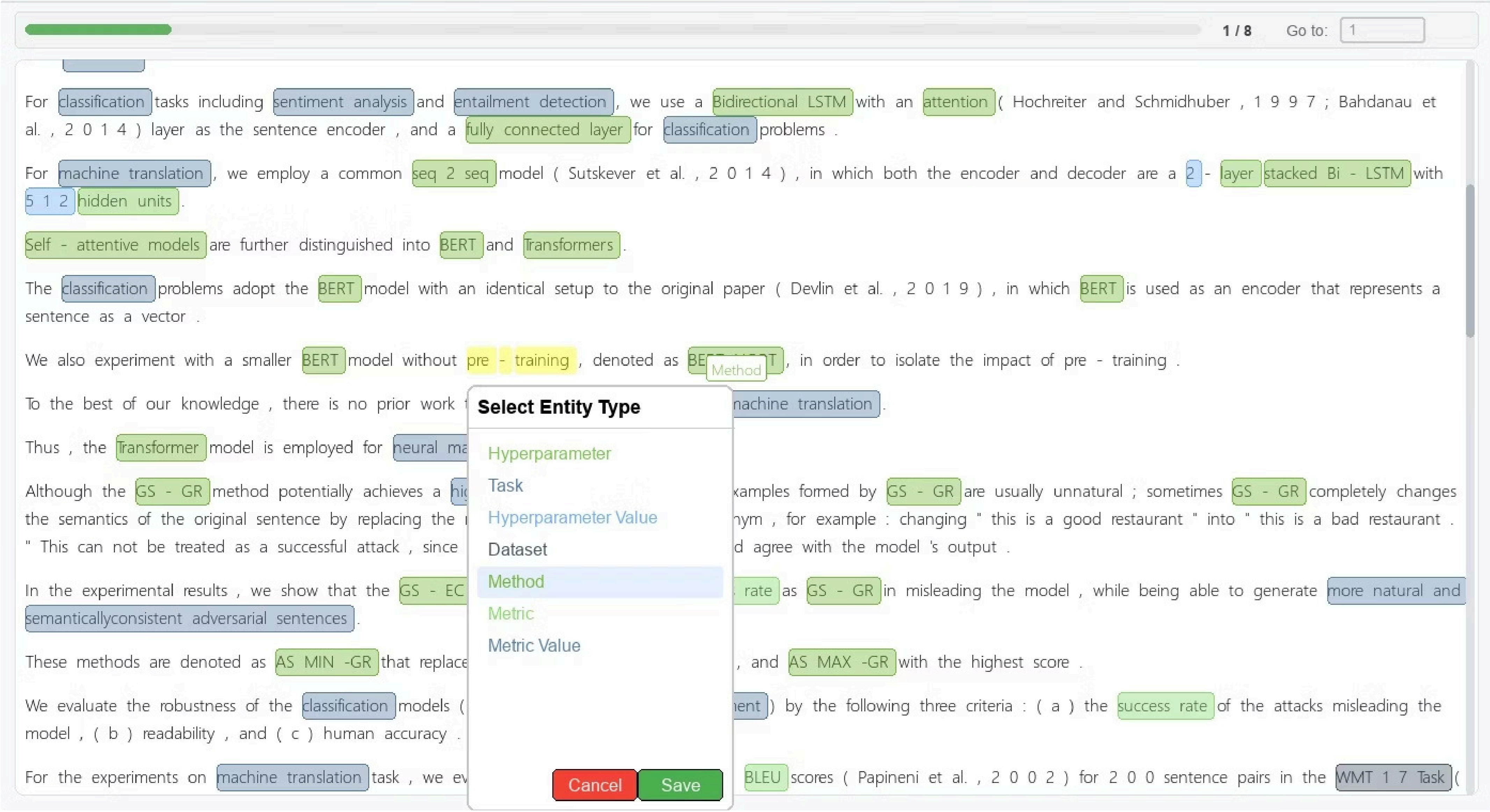
Thus , the Transformer model is employed for neural machine translation task .

Although the GS - GR method potentially achieves a high success rate , the adversarial examples formed by GS - GR are usually unnatural ; sometimes GS - GR completely changes the semantics of the original sentence by replacing the most important word with its antonym , for example : changing " this is a good restaurant " into " this is a bad restaurant . " This can not be treated as a successful attack , since humans will notice the change and agree with the model 's output .

In the experimental results , we show that the GS - EC method achieves a similar success rate as GS - GR in misleading the model , while being able to generate more natural and semanticallyconsistent adversarial sentences .

These methods are denoted as AS MIN -GR that replaces the word with the lowest score , and AS MAX -GR with the highest score .

We evaluate the robustness of the classification models (for sentiment analysis and entailment) by the following three criteria : (a) the success rate of the attacks misleading the model , (b) readability , and (c) human accuracy .



1 / 8
Go to:
1
For classification tasks including sentiment analysis and entailment detection , we use a Bidirectional LSTM with an attention (Hochreiter and Schmidhuber , 1 9 9 7 ; Bahdanau et al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .
For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with 5 1 2 hidden units .
Self - attentive models are further distinguished into BERT and Transformers .
The classification problems adopt the BERT model with an identical setup to the original paper (Devlin et al. , 2 0 1 9) , in which BERT is used as an encoder that represents a sentence as a vector .
We also experiment with a smaller BERT model without pre - training , denoted as BE Method T , in order to isolate the impact of pre - training .
To the best of our knowledge , there is no prior work
machine translation .
Thus , the Transformer model is employed for neural ma
Although the GS - GR method potentially achieves a hi
xamples formed by GS - GR are usually unnatural ; sometimes GS - GR completely changes the semantics of the original sentence by replacing the
nym , for example : changing " this is a good restaurant " into " this is a bad restaurant . " This can not be treated as a successful attack , since
d agree with the model 's output .
In the experimental results , we show that the GS - EC
rate as GS - GR in misleading the model , while being able to generate more natural and semanticallyconsistent adversarial sentences .
These methods are denoted as AS MIN -GR that replace
, and AS MAX -GR with the highest score .
We evaluate the robustness of the classification models (
ent) by the following three criteria : (a) the success rate of the attacks misleading the model , (b) readability , and (c) human accuracy .
For the experiments on machine translation task , we ev
BLEU scores (Papineni et al. , 2 0 0 2) for 2 0 0 sentence pairs in the WMT 1 7 Task (
Select Entity Type
Hyperparameter
Task
Hyperparameter Value
Dataset
Method
Metric
Metric Value
Cancel
Save

For classification tasks including sentiment analysis and entailment detection , we use a Bidirectional LSTM with an attention (Hochreiter and Schmidhuber , 1 9 9 7 ; Bahdanau et al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .

For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with 5 1 2 hidden units .

Self - attentive models are further distinguished into BERT and Transformers .

The classification problems adopt the BERT model with an identical setup to the original paper (Devlin et al. , 2 0 1 9) , in which BERT is used as an encoder that represents a sentence as a vector .

Method

We also experiment with a smaller BERT model without pre - training , denoted as BERT NOPT , in order to isolate the impact of pre - training .

To the best of our knowledge , there is no prior work that uses pre - trained BERT for machine translation .

Thus , the Transformer model is employed for neural machine translation task .

Although the GS - GR method potentially achieves a high success rate , the adversarial examples formed by GS - GR are usually unnatural ; sometimes GS - GR completely changes the semantics of the original sentence by replacing the most important word with its antonym , for example : changing " this is a good restaurant " into " this is a bad restaurant . " This can not be treated as a successful attack , since humans will notice the change and agree with the model 's output .

In the experimental results , we show that the GS - EC method achieves a similar success rate as GS - GR in misleading the model , while being able to generate more natural and semanticallyconsistent adversarial sentences .

These methods are denoted as AS MIN -GR that replaces the word with the lowest score , and AS MAX -GR with the highest score .

We evaluate the robustness of the classification models (for sentiment analysis and entailment) by the following three criteria : (a) the success rate of the attacks misleading the model , (b) readability , and (c) human accuracy .

For the experiments on machine translation task , we evaluate the attack success rate and BLEU scores (Papineni et al. , 2 0 0 2) for 2 0 0 sentence pairs in the WMT 1 7 Task (

1 / 8 Go to: 1

For classification tasks including sentiment analysis and entailment detection , we use a Bidirectional LSTM with an attention (Hochreiter and Schmidhuber , 1 9 9 7 ; Bahdanau et al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .

For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with 5 1 2 hidden units .

Self - attentive models are further distinguished into BERT and Transformers .

The classification problems adopt the BERT model with an identical setup to the original paper (Devlin et al. , 2 0 1 9) , in which BERT is used as an encoder that represents a sentence as a vector .

We also experiment with a smaller BERT model without pre - training , denoted as BERT NOPT , in order to isolate the impact of pre - training .

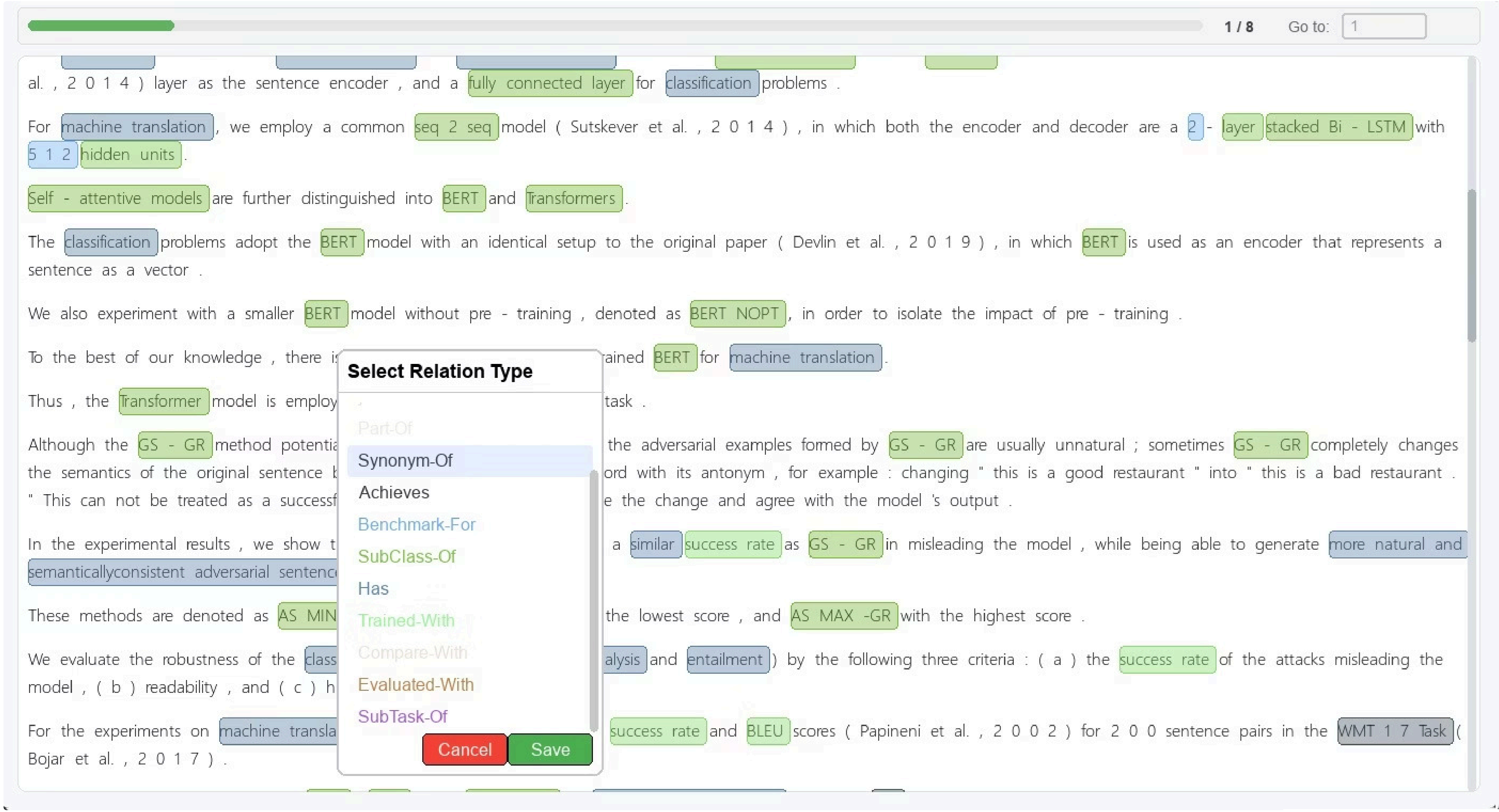
To the best of our knowledge , there is no prior work that uses pre - trained BERT for machine translation .

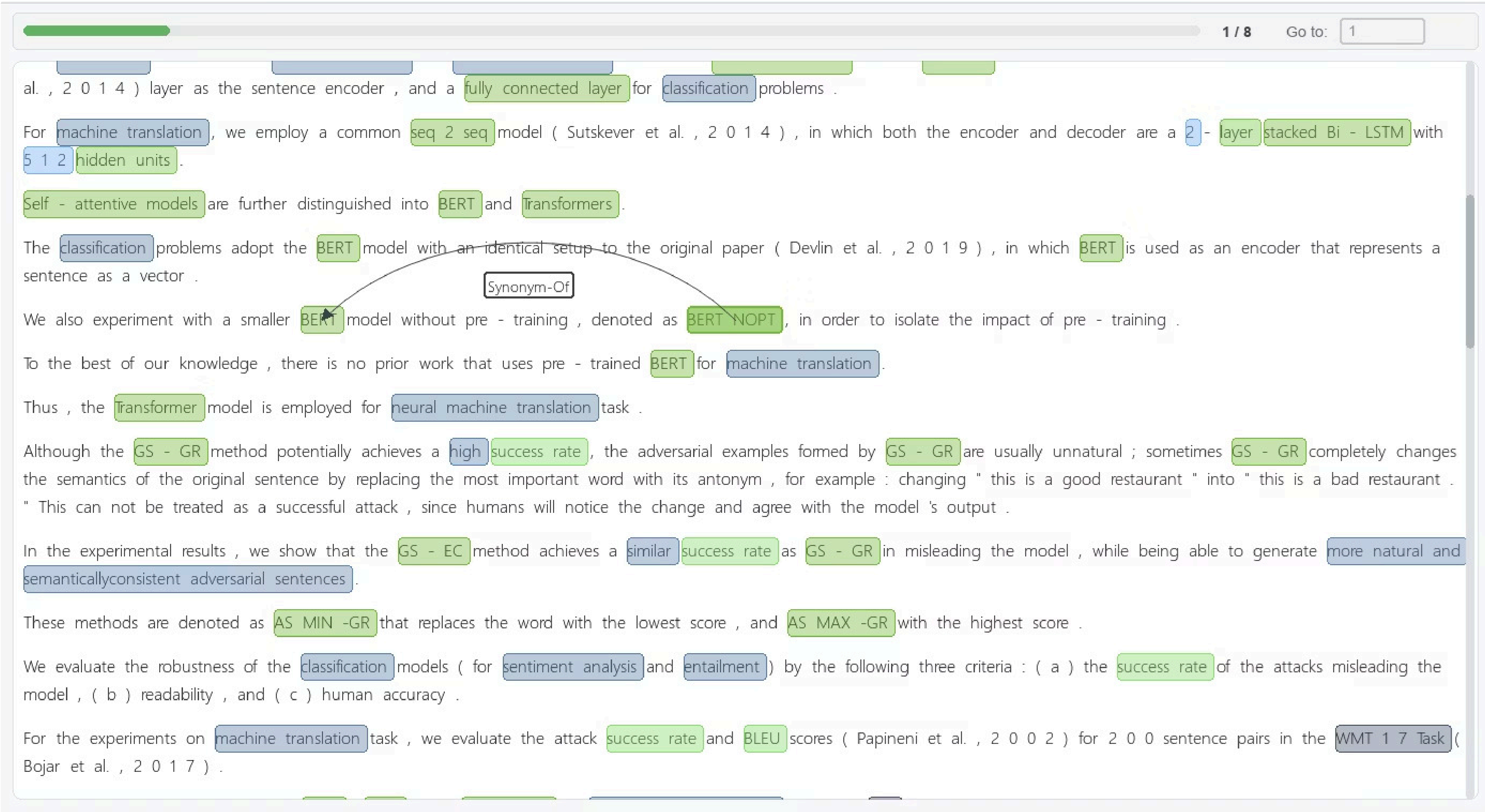
Thus , the Transformer model is employed for neural machine translation task .

Although the GS - GR method potentially achieves a high success rate , the adversarial examples formed by GS - GR are usually unnatural ; sometimes GS - GR completely changes the semantics of the original sentence by replacing the most important word with its antonym , for example : changing " this is a good restaurant " into " this is a bad restaurant . " This can not be treated as a successful attack , since humans will notice the change and agree with the model 's output .

In the experimental results , we show that the GS - EC method achieves a similar success rate as GS - GR in misleading the model , while being able to generate more natural and semanticallyconsistent adversarial sentences .

These methods are denoted as AS - MIN - GR that replaces the word with the lowest score , and AS - MAX - GR with the highest score .


1 / 8
Go to:
1
al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .
For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with 5 1 2 hidden units .
Self - attentive models are further distinguished into BERT and Transformers .
The classification problems adopt the BERT model with an identical setup to the original paper (Devlin et al. , 2 0 1 9) , in which BERT is used as an encoder that represents a sentence as a vector .
We also experiment with a smaller BERT model without pre - training , denoted as BERT NOPT , in order to isolate the impact of pre - training .
To the best of our knowledge , there i
rained BERT for machine translation .
Thus , the Transformer model is employ
task .
Although the GS - GR method potenti
the adversarial examples formed by GS - GR are usually unnatural ; sometimes GS - GR completely changes
the semantics of the original sentence b
ord with its antonym , for example : changing " this is a good restaurant " into " this is a bad restaurant .
" This can not be treated as a successf
e the change and agree with the model 's output .
In the experimental results , we show t
a similar success rate as GS - GR in misleading the model , while being able to generate more natural and
semanticallyconsistent adversarial sentenc
These methods are denoted as AS MIN
the lowest score , and AS MAX -GR with the highest score .
We evaluate the robustness of the class
alysis and entailment) by the following three criteria : (a) the success rate of the attacks misleading the
model , (b) readability , and (c) h
For the experiments on machine transla
success rate and BLEU scores (Papineni et al. , 2 0 0 2) for 2 0 0 sentence pairs in the WMT 1 7 Task (
Bojar et al. , 2 0 1 7) .
Select Relation Type
Part-Of
Synonym-Of
Achieves
Benchmark-For
SubClass-Of
Has
Trained-With
Compare-With
Evaluated-With
SubTask-Of
Cancel
Save


1 / 8
Go to: 1
al. , 2 0 1 4) layer as the sentence encoder , and a fully connected layer for classification problems .
For machine translation , we employ a common seq 2 seq model (Sutskever et al. , 2 0 1 4) , in which both the encoder and decoder are a 2 - layer stacked Bi - LSTM with 5 1 2 hidden units .
Self - attentive models are further distinguished into BERT and Transformers .
The classification problems adopt the BERT model with an identical setup to the original paper (Devlin et al. , 2 0 1 9) , in which BERT is used as an encoder that represents a sentence as a vector .
Synonym-Of
We also experiment with a smaller BERT model without pre - training , denoted as BERT NOPT , in order to isolate the impact of pre - training .
To the best of our knowledge , there is no prior work that uses pre - trained BERT for machine translation .
Thus , the Transformer model is employed for neural machine translation task .
Although the GS - GR method potentially achieves a high success rate , the adversarial examples formed by GS - GR are usually unnatural ; sometimes GS - GR completely changes the semantics of the original sentence by replacing the most important word with its antonym , for example : changing " this is a good restaurant " into " this is a bad restaurant . " This can not be treated as a successful attack , since humans will notice the change and agree with the model 's output .
In the experimental results , we show that the GS - EC method achieves a similar success rate as GS - GR in misleading the model , while being able to generate more natural and semanticallyconsistent adversarial sentences .
These methods are denoted as AS MIN -GR that replaces the word with the lowest score , and AS MAX -GR with the highest score .
We evaluate the robustness of the classification models (for sentiment analysis and entailment) by the following three criteria : (a) the success rate of the attacks misleading the model , (b) readability , and (c) human accuracy .
For the experiments on machine translation task , we evaluate the attack success rate and BLEU scores (Papineni et al. , 2 0 0 2) for 2 0 0 sentence pairs in the WMT 1 7 Task (Bojar et al. , 2 0 1 7) .

От редактора к универсальному хабу

Вклад

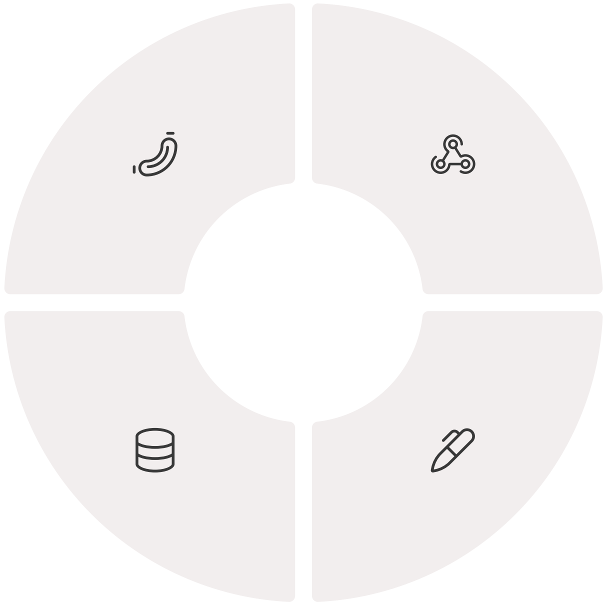
Исправлен сломанный рабочий процесс, сделав работу с PL-Marker удобной.

Исследователи получили инструмент для прямого редактирования аннотаций.

Видение будущего

Главный приоритет — добавить конвертеры **ИЗ PL-Marker** в другие форматы (brat, JSONL, CoNLL).

Это превратит инструмент в **универсальный хаб** и окончательно решит проблему «запертых данных».



brat
Импорт и экспорт

JSONL
Двусторонняя конвертация

CoNLL
Поддержка стандартов

PL-Marker
Центральный формат

Готов ответить на ваши вопросы

Ссылка на проект: https://github.com/trtbfn/PL-Marker-Annotator