BERT Explanability

Some simple exploration on explainability of BERT models

```
import torch
# Check if CUDA is available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")
Using device: cuda
from transformers import AutoTokenizer,
        AutoModelForSequenceClassification
# Load model and tokenizer
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
model = AutoModelForSequenceClassification.from_pretrained("keanteng/bert-
        base-raw-climate-sentiment-wqf7007").to(device)
model.eval()
/usr/local/lib/python3.11/dist-
packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your
settings tab (https://huggingface.co/settings/tokens), set it as
secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to
access public models or datasets.
  warnings.warn(
{"model_id": "5f3b935532d14c6d98c231287929ea7c", "version_major": 2, "version_minor": 0}
{"model_id": "532bb6f1759542e1a74e4f184cd5ab64", "version_major": 2, "version_minor": 0}
{"model_id":"eb7cb3f02a76497398ed27d42b2050ee", "version_major":2, "version_minor":0}
{"model_id": "53a43613822943ccbd40179c5b380d79", "version_major": 2, "version_minor": 0}
{"model_id":"c3f6ce7785984a0eac42b38ff3f5d802","version_major":2,"version_minor":0}
{"model_id":"cb3398eb1f6a491882f4cc2878648616","version_major":2,"version_minor":0}
```

```
BertForSequenceClassification(
  (bert): BertModel(
    (embeddings): BertEmbeddings(
      (word_embeddings): Embedding(30522, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0-11): 12 x BertLayer(
          (attention): BertAttention(
            (self): BertSdpaSelfAttention(
              (query): Linear(in_features=768, out_features=768,
bias=True)
              (key): Linear(in_features=768, out_features=768,
bias=True)
              (value): Linear(in_features=768, out_features=768,
bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768,
bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in_features=768, out_features=3072,
bias=True)
            (intermediate_act_fn): GELUActivation()
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768,
bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
```

```
)
)
)
(pooler): BertPooler(
   (dense): Linear(in_features=768, out_features=768, bias=True)
   (activation): Tanh()
)
(dropout): Dropout(p=0.1, inplace=False)
(classifier): Linear(in_features=768, out_features=4, bias=True)
)
```

Using Lime

```
!pip install numpy --quiet
!pip install lime --quiet
!pip install captum --quiet
from captum.attr import IntegratedGradients, LayerIntegratedGradients,
from captum.attr import visualization
import numpy as np
class BERTExplainer:
    def __init__(self, model, tokenizer, device):
        self.model = model
        self.tokenizer = tokenizer
        self.device = device
        self.class_names = ['anti', 'neutral', 'pro', 'news']
        self.embedding_layer = model.bert.embeddings if hasattr(model,
        'bert') else model.embeddings
    def _tokenize_and_move(self, text):
        """Tokenize text and move to device"""
        inputs = self.tokenizer(text, return_tensors="pt",
        padding=True, truncation=True)
        return {key: val.to(self.device) for key, val in
        inputs.items()}
    def _get_prediction(self, inputs):
        """Get model prediction"""
        with torch.no_grad():
            outputs = self.model(**inputs)
            probs = torch.nn.functional.softmax(outputs.logits,
        dim=-1)
```

```
return probs
```

```
def _to_numpy(self, tensor):
    """Convert tensor to numpy, handling device transfer"""
    return tensor.detach().cpu().numpy()
def predict_proba_for_lime(self, texts):
    """Prediction function for LIME"""
    inputs = self._tokenize_and_move(texts)
    probs = self._get_prediction(inputs)
    return self._to_numpy(probs)
def get_lime_explanation(self, text, num_features=10):
    """Get LIME explanation"""
    from lime.lime_text import LimeTextExplainer
    explainer = LimeTextExplainer(class_names=self.class_names)
    exp = explainer.explain_instance(text,
    self.predict_proba_for_lime, num_features=num_features)
    return exp
def forward_for_captum(self, input_ids):
    """Forward function for Captum LIME"""
    input_ids = input_ids.long()
    attention_mask = torch.ones_like(input_ids)
   with torch.no_grad():
        outputs = self.model(input_ids=input_ids,
    attention_mask=attention_mask)
        return torch.nn.functional.softmax(outputs.logits, dim=-1)
def get_integrated_gradients(self, text, target_class=None,
    n_steps=50):
    """Get Integrated Gradients attributions"""
    inputs = self._tokenize_and_move(text)
    input_ids = inputs['input_ids']
    attention_mask = inputs['attention_mask']
   # Get embeddings and prediction
   with torch.no_grad():
        inputs_embeds = self.embedding_layer(input_ids)
        pred = self._get_prediction(inputs)
        pred_class = torch.argmax(pred, dim=1).item()
```

```
target_class = target_class or pred_class
    # Prediction function for IG
    def predict_fn(inputs_embeds, attention_mask):
        outputs = self.model(inputs_embeds=inputs_embeds,
    attention_mask=attention_mask)
        return torch.nn.functional.softmax(outputs.logits, dim=-1)
    # Initialize and compute attributions
    lig = LayerIntegratedGradients(predict_fn,
    self.embedding_layer)
    baseline_embeds = torch.zeros_like(inputs_embeds)
    attributions = lig.attribute(
        inputs=inputs_embeds,
        baselines=baseline_embeds,
        target=target_class,
        additional_forward_args=(attention_mask,),
        n_steps=n_steps
    )
    return {
        'attributions':
    self._to_numpy(attributions.sum(dim=-1).squeeze(0)),
        'tokens':
    self.tokenizer.convert_ids_to_tokens(input_ids[0]),
        'pred_class': pred_class,
        'pred_probs': self._to_numpy(pred[0]),
        'input_ids': input_ids
    }
def get_captum_lime(self, text, target_class=None, n_samples=100):
    """Get Captum LIME attributions"""
    inputs = self._tokenize_and_move(text)
    input_ids = inputs['input_ids']
    # Get prediction
    pred = self.forward_for_captum(input_ids)
    pred_class = torch.argmax(pred, dim=1).item()
    target_class = target_class or pred_class
    # Initialize LIME
    lime = Lime(self.forward_for_captum)
    attributions = lime.attribute(
```

```
target=target_class,
        n_samples=n_samples,
        perturbations_per_eval=10
    )
    return {
        'attributions': self._to_numpy(attributions.squeeze(0)),
        'tokens':
    self.tokenizer.convert_ids_to_tokens(input_ids[0]),
        'pred_class': pred_class,
        'pred_probs': self._to_numpy(pred[0])
    }
# Add this method to the BERTExplainer class, after the existing
    methods
def group_subword_attributions(self, tokens, attributions):
    """Group subword tokens back into words"""
    grouped_tokens = []
    grouped_attrs = []
    current_word = ""
    current_attr = 0
    for token, attr in zip(tokens, attributions):
        if token.startswith('##'):
            current_word += token[2:] # Remove ##
            current_attr += attr
        else:
            if current_word: # Save previous word
                grouped_tokens.append(current_word)
                grouped_attrs.append(current_attr)
            current_word = token
            current_attr = attr
    # Don't forget the last word
    if current_word:
        grouped_tokens.append(current_word)
        grouped_attrs.append(current_attr)
    return grouped_tokens, grouped_attrs
def visualize_attributions(self, result_dict, method_name="",
    group_subwords=True):
    """Visualize attribution results"""
```

input_ids,

```
tokens = result_dict['tokens']
attr_scores = result_dict['attributions']
pred_class = result_dict['pred_class']
pred_probs = result_dict['pred_probs']
print(f"\n{method_name} Results:")
print(f"Predicted class: {self.class_names[pred_class]}
(confidence: {pred_probs[pred_class]:.3f})")
print(f"All probabilities: {[f'{self.class_names[i]}:
{pred_probs[i]:.3f}' for i in range(len(self.class_names))]}")
if group_subwords:
    # Group subword tokens
    grouped_tokens, grouped_attrs =
self.group_subword_attributions(tokens, attr_scores)
    print("\nWord-level attributions (grouped subwords):")
    for token, score in zip(grouped_tokens, grouped_attrs):
        if token not in ['[CLS]', '[SEP]', '[PAD]']:
            print(f"{token:20} {score:8.4f}")
    print("\nOriginal token-level attributions:")
    for token, score in zip(tokens, attr_scores):
        if token not in ['[CLS]', '[SEP]', '[PAD]']:
            print(f"{token:15} {score:8.4f}")
    # Create visualization data for grouped tokens (word-
level)
    vis_data_grouped = visualization.VisualizationDataRecord(
        np.array(grouped_attrs),
        pred_probs[pred_class],
        pred_class,
        self.class_names[pred_class],
        self.class_names[pred_class],
        np.array(grouped_attrs).sum(),
        grouped_tokens,
        1
    )
    # Create visualization data for original tokens (token-
level)
    vis_data_original = visualization.VisualizationDataRecord(
        attr_scores,
        pred_probs[pred_class],
        pred_class,
        self.class_names[pred_class],
```

```
attr_scores.sum(),
               tokens,
           )
           return vis_data_grouped, vis_data_original, tokens,
        attr_scores # Return both versions
       else:
           print("\nToken attributions:")
           for token, score in zip(tokens, attr_scores):
               if token not in ['[CLS]', '[SEP]', '[PAD]']:
                   print(f"{token:15} {score:8.4f}")
           # Create visualization data for original tokens
           vis_data_original = visualization.VisualizationDataRecord(
               attr_scores,
               pred_probs[pred_class],
               pred_class,
               self.class_names[pred_class],
               self.class_names[pred_class],
               attr_scores.sum(),
               tokens,
               1
           )
           return vis_data_original, None, tokens, attr_scores
# Initialize explainer
explainer = BERTExplainer(model, tokenizer, device)
# Example usage
text = "@tiniebeany climate change is an interesting hustle as it was
        global warming but the planet stopped warming for 15 yes while
        the suv boom"
print("="*60)
print("LIME Explanation (Original):")
lime_exp = explainer.get_lime_explanation(text)
lime_exp.show_in_notebook(text=True)
______
LIME Explanation (Original):
```

self.class_names[pred_class],

Prediction probabilities anti 0.00 neutral 0.00 pro 0.00 news 1.00 NOT neutral neutral boom 0.01 the 0.01 0.01 yes 0.01 was 0.01 hustle 0.01 planet 0.01 0.01 warming 0.01 suv 0.01 Text with highlighted words

is

```
@tiniebeany climate change is an interesting hustle as it was global warming but the
planet stopped warming for 15 yes while the suv boom
print("="*60)
print("Integrated Gradients:")
ig_result = explainer.get_integrated_gradients(text)
vis_data_ig_grouped, vis_data_ig_original, original_tokens,
        original_attrs = explainer.visualize_attributions(ig_result,
         "Integrated Gradients")
Integrated Gradients:
Integrated Gradients Results:
Predicted class: news (confidence: 0.997)
All probabilities: ['anti: 0.001', 'neutral: 0.002', 'pro: 0.001',
'news: 0.997']
Word-level attributions (grouped subwords):
@
                        0.0324
tiniebeany
                       -0.0725
climate
                        0.1276
change
                        0.1178
```

0.0962

an	0.0652
interesting	-0.0436
hustle	0.0824
as	0.0384
it	0.0121
was	0.0339
global	0.1114
warming	0.0282
but	0.0176
the	0.0460
planet	0.0578
stopped	0.0983
warming	0.0490
for	0.0219
15	-0.0294
yes	-0.0209
while	-0.0199
the	0.0373
suv	0.0574
boom	0.1621

Original token-level attributions:

0.0324 @ tin -0.0626 ##ie -0.0408 ##be 0.0017 ##any 0.0292 climate 0.1276 0.1178 change is 0.0962 an 0.0652 interesting -0.0436 hu 0.0435 ##stle 0.0388 as 0.0384 it 0.0121 was 0.0339 global 0.1114 warming 0.0282 but 0.0176 the 0.0460 planet 0.0578 stopped 0.0983

```
warming
                 0.0490
for
                 0.0219
15
                -0.0294
yes
                -0.0209
while
                -0.0199
the
                0.0373
                 0.0574
suv
                 0.1621
boom
print("="*60)
print("Captum LIME:")
try:
   captum_lime_result = explainer.get_captum_lime(text)
   vis_data_lime_grouped, vis_data_lime_original, _, _ =
        explainer.visualize_attributions(captum_lime_result, "Captum
        LIME")
except Exception as e:
   print(f"Captum LIME failed: {e}")
   vis_data_lime_grouped = None
   vis_data_lime_original = None
______
Captum LIME:
Captum LIME Results:
Predicted class: news (confidence: 0.997)
All probabilities: ['anti: 0.001', 'neutral: 0.002', 'pro: 0.001',
'news: 0.997']
Word-level attributions (grouped subwords):
@
                      0.0334
tiniebeany
                      0.0772
climate
                      0.0242
change
                      0.0890
is
                      0.1093
an
                      0.0000
interesting
                      0.0000
hustle
                      0.2331
                      0.0000
as
it
                      0.0000
                      0.0000
was
                      0.0706
global
warming
                      0.1355
but
                     -0.0787
```

the	0.0000
planet	0.1999
stopped	0.1743
warming	0.1800
for	0.0000
15	0.1582
yes	0.0000
while	0.0000
the	0.0093
suv	0.0847
boom	0.0931

Original token-level attributions:

@ 0.0334 tin 0.0000 ##ie 0.0000 ##be 0.0342 ##any 0.0429 climate 0.0242 change 0.0890 is 0.1093 0.0000 an interesting 0.0000hu 0.1079 ##stle 0.1252 0.0000 as it 0.0000 was 0.0000 global 0.0706 warming 0.1355 but -0.0787 the 0.0000planet 0.1999 stopped 0.1743 warming 0.1800 for 0.0000 15 0.1582 yes 0.0000 while 0.0000 the 0.0093 0.0847 suv

0.0931

boom

```
# HTML visualization with both grouped words and original tokens
try:
   from IPython.display import HTML, display
   print("\n" + "="*60)
   print("HTML Visualization (Word-level - Grouped Subwords):")
   html_grouped = visualization.visualize_text([vis_data_ig_grouped])
   #display(HTML(html_grouped.data))
   print("\nHTML Visualization (Token-level - Original Tokens):")
   html_original =
        visualization.visualize_text([vis_data_ig_original])
   #display(HTML(html_original.data))
   if vis_data_lime_grouped is not None:
       print("\nCaptum LIME HTML Visualization (Word-level - Grouped
        Subwords):")
       html_lime_grouped =
       visualization.visualize_text([vis_data_lime_grouped])
       #display(HTML(html_lime_grouped.data))
       print("\nCaptum LIME HTML Visualization (Token-level -
        Original Tokens):")
       html_lime_original =
        visualization.visualize_text([vis_data_lime_original])
       #display(HTML(html_lime_original.data))
except ImportError:
   print("IPython not available for HTML visualization")
______
HTML Visualization (Word-level - Grouped Subwords):
```

Legend:	Negative	\square Neutral	Positive
---------	----------	-------------------	----------

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
				[CLS] @ tiniebeany climate
news	3 (1.00)	news	-0.14	change is an interesting hustle as it was global warming but the planet stopped warming for 15 yes while the suv boom SEP

Legend: ■ Negative □ Neutral ■ Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
				[CLS] @ tin ##ie ##be
news 3 (1.00)		-0.14	##any climate change is an	
	news		interesting hu ##stle as it	
			was global warming but the	
	(1.00)			planet stopped warming for
				15 yes while the suv boom
				[SEP]

Captum LIME HTML Visualization (Word-level - Grouped Subwords):

Legend: ■ Negative □ Neutral ■ Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
news 3 (1.00)		news	1.59	[CLS] @ tiniebeany climate change is an interesting
	_			hustle as it was global warming but the planet
				stopped warming for 15 yes while the suv boom [SEP]

Captum LIME HTML Visualization (Token-level - Original Tokens):

Legend: ■ Negative □ Neutral ■ Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
news	3	news	1.59	[CLS] @ tin ##ie ##be
	(1.00)			##any climate change is an
				interesting hu ##stle as it
				was global warming but the

Why the output is different?

The differences between the HTML visualization (Integrated Gradients) and Captum LIME HTML visualization occur due to fundamental differences in how these two explainability methods work:

Key Differences:

- 1. Methodology
 - Integrated Gradients: Computes gradients by integrating along a straight path from a baseline (zeros) to the actual input embeddings. It captures how much each token contributes to the prediction based on the model's internal gradients.
 - Captum LIME: Uses a perturbation-based approach, creating many variations of the input by masking/removing tokens and observing how predictions change.
- 2. Attribution Calculation
 - Integrated Gradients:
 - Works at the embedding level
 - Provides smooth, continuous attributions
 - Captures the model's sensitivity to each token
 - Captum LIME:
 - Works by perturbing the input tokens
 - Fits a local linear model around the prediction
 - May have more discrete/binary-like attributions
- 3. Baseline Differences
 - Integrated Gradients: Uses zero embeddings as baseline
 - Captum LIME: Uses token removal/masking as perturbation method

Another Example

```
______
LIME Explanation (Original):
  Prediction probabilities
          anti 0.00
                         1.00
        neutral
          pro 0.00
         news 0.00
    NOT neutral
                           neutral
                    tackle
                        0.23
                     BeforeTheFlood
                        0.20
                     Watch
                      0.12
                     to
                     0.08
                     world
                     0.07
                     climate
                     0.06
                     LeoDiCaprio
                     0.06
                    right
                     0.04
                travels
                 0.04
                     change
                     0.04
Text with highlighted words
#BeforeTheFlood Watch #BeforeTheFlood right here, as @LeoDiCaprio travels the
world to tackle climate change... https://t.co/HCIZrPUhLF
print("="*60)
print("Integrated Gradients:")
ig_result = explainer.get_integrated_gradients(text)
vis_data_ig_grouped, vis_data_ig_original, original_tokens,
        original_attrs = explainer.visualize_attributions(ig_result,
        "Integrated Gradients")
______
Integrated Gradients:
Integrated Gradients Results:
Predicted class: neutral (confidence: 0.999)
```

All probabilities: ['anti: 0.000', 'neutral: 0.999', 'pro: 0.001',

Word-level attributions (grouped subwords):

-0.0008

0.0153

'news: 0.000']

beforetheflood

watch	0.0317
#	0.0004
beforetheflood	0.0110
right	0.0511
here	0.0380
,	-0.0267
as	-0.0215
@	0.0511
leodicaprio	0.0686
travels	-0.0086
the	0.0792
world	0.0143
to	0.1569
tackle	0.3170
climate	0.1846
change	0.2285
	0.0018
	-0.0297
	0.0031
https	0.0174
:	-0.0001
/	-0.0033
/	-0.0043
t	0.0058
•	-0.0143
СО	0.0045
/	-0.0142
hcizrpuhlf	-0.0148
Original token-le	evel attributions:
#	-0.0008
before	-0.0245
##the	0.0130
##fl	0.0198
##ood	0.0070
watch	0.0317
#	0.0004

-0.0519

0.0259

0.0249

0.0120

0.0511

0.0380

before

##the

##fl

##ood

right

here

```
-0.0267
,
as
                 -0.0215
@
                  0.0511
leo
                  0.0065
##dic
                  0.0081
                  0.0042
##ap
##rio
                  0.0497
travels
                 -0.0086
the
                  0.0792
world
                  0.0143
to
                  0.1569
tackle
                  0.3170
climate
                  0.1846
change
                  0.2285
                  0.0018
                 -0.0297
                  0.0031
https
                  0.0174
                 -0.0001
/
                 -0.0033
                 -0.0043
t
                  0.0058
                 -0.0143
                  0.0045
СО
/
                 -0.0142
hc
                  0.0300
##iz
                 -0.0198
##rp
                 -0.0129
##uh
                 -0.0168
##1f
                  0.0047
print("="*60)
print("Captum LIME:")
try:
    captum_lime_result = explainer.get_captum_lime(text)
    vis_data_lime_grouped, vis_data_lime_original, _, _ =
        explainer.visualize_attributions(captum_lime_result, "Captum
        LIME")
except Exception as e:
    print(f"Captum LIME failed: {e}")
    vis_data_lime_grouped = None
    vis_data_lime_original = None
```

```
______
```

Captum LIME:

```
Captum LIME Results:
Predicted class: neutral (confidence: 0.999)
All probabilities: ['anti: 0.000', 'neutral: 0.999', 'pro: 0.001',
'news: 0.000']
Word-level attributions (grouped subwords):
#
                        0.0636
beforetheflood
                        0.0210
watch
                        0.1490
                        0.0000
beforetheflood
                        0.0395
right
                        0.0000
here
                        0.0657
                        0.0000
                        0.0000
as
@
                        0.0000
leodicaprio
                        0.0488
travels
                        0.0000
the
                        0.0000
world
                        0.0000
to
                        0.0415
tackle
                        0.1711
climate
                        0.0088
change
                        0.0456
                        0.0000
                        0.0000
                        0.0000
https
                        0.0000
:
                        0.0017
/
                        0.0415
                        0.0000
t
                        0.0623
                        0.0000
                        0.0000
CO
/
                       -0.0028
hcizrpuhlf
                        0.0500
```

Original token-level attributions:

0.0636 before -0.0095

##the	0.0000
##fl	0.0000
##ood	0.0305
watch	0.1490
#	0.0000
before	0.0060
##the	0.0336
##fl	0.0000
##ood	0.0000
right	0.0000
here	0.0657
,	0.0000
as	0.0000
@	0.0000
leo	-0.0209
##dic	0.0000
##ap	0.0000
##rio	0.0698
travels	0.0000
the	0.0000
world	0.0000
to	0.0415
tackle	0.1711
climate	0.0088
change	0.0456
	0.0000
•	0.0000
	0.0000
https	0.0000
:	0.0017
/	0.0415
/	0.0000
t	0.0623
	0.0000
CO	0.0000
/	-0.0028
hc	0.0000
##iz	0.0500
##rp	0.0000
##uh ##1 £	0.0000
##1f	0.0000

```
# HTML visualization with both grouped words and original tokens
try:
   from IPython.display import HTML, display
   print("\n" + "="*60)
   print("HTML Visualization (Word-level - Grouped Subwords):")
   html_grouped = visualization.visualize_text([vis_data_ig_grouped])
   #display(HTML(html_grouped.data))
   print("\nHTML Visualization (Token-level - Original Tokens):")
   html_original =
       visualization.visualize_text([vis_data_ig_original])
   #display(HTML(html_original.data))
   if vis_data_lime_grouped is not None:
       print("\nCaptum LIME HTML Visualization (Word-level - Grouped
       Subwords):")
       html_lime_grouped =
       visualization.visualize_text([vis_data_lime_grouped])
       #display(HTML(html_lime_grouped.data))
       print("\nCaptum LIME HTML Visualization (Token-level -
       Original Tokens):")
       html_lime_original =
       visualization.visualize_text([vis_data_lime_original])
       #display(HTML(html_lime_original.data))
except ImportError:
   print("IPython not available for HTML visualization")
______
HTML Visualization (Word-level - Grouped Subwords):
```

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
				[CLS] # beforetheflood
				watch # beforetheflood
neutral $\frac{1}{(1.00)}$ neutr	neutral	eutral 1.09	right here , as @	
			leodicaprio travels the	
			world to tackle climate	
				change https://t.co
				/ hcizrpuhlf [SEP]

Legend: ■ Negative □ Neutral ■ Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
				[CLS] # before ##the ##fl
				##ood watch # before
neutral 1 neutral (1.00)		##the ##fl ##ood right		
	noutvol	1.09	here, as @ leo ##dic ##ap	
	(1.00)	1.03	1.05	##rio travels the world to
			tackle climate change	
				https://t.co/hc##iz
				##rp ##uh ##lf [SEP]

Captum LIME HTML Visualization (Word-level - Grouped Subwords):

Legend: ■ Negative □ Neutral ■ Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
neutral	1 (1.00)	neutral	0.60	[CLS] # beforetheflood
				watch # beforetheflood
				right here, as @
				leodicaprio travels the
				world to tackle climate
				change https://t.co
				/ hcizrpuhlf [SEP]

Captum LIME HTML Visualization (Token-level - Original Tokens):

Legend: ■ Negative □ Neutral ■ Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
neutral	1 (1.00)	neutral	0.60	[CLS] # before ##the ##fl ##ood watch # before

##the ##fl ##ood right
here , as @ leo ##dic ##ap
##rio travels the world to
tackle climate change . . .
https://t.co/hc ##iz
##rp ##uh ##lf [SEP]