BERT Explanability

Some simple exploration on explainability of BERT models

In [13]:

```
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
```

In [14]:

```
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()
```

Out[14]:

```
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

In [15]:

```
!pip install lime --quiet
!pip install captum --quiet
!pip install numpy --quiet
```

In [16]:

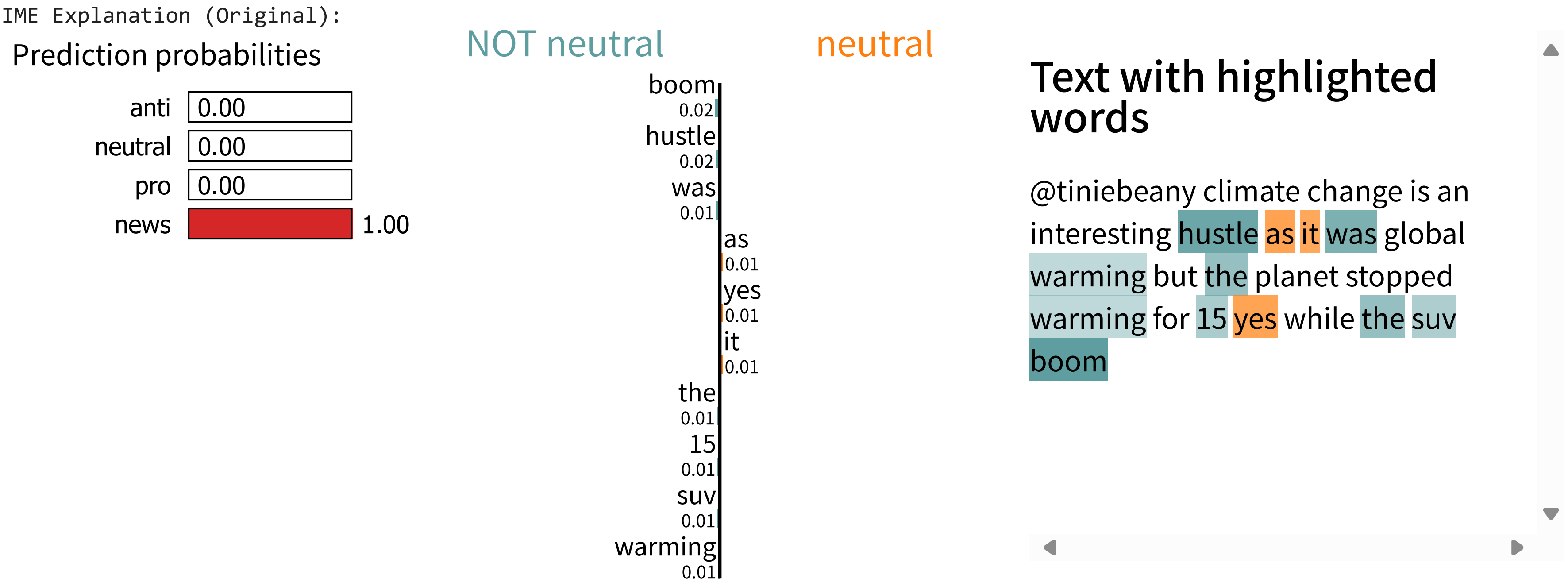
```
from captum.attr import IntegratedGradients, LayerIntegratedGradients, Lime
from captum.attr import visualization
import numpy as np

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
```

```python
    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(
            input_ids,
            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"""
        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
            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
            )

            return vis_data_grouped, 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, tokens, attr_scores
```

```
In [17]: # 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

         print("="*60)
         print("LIME Explanation (Original):")
         lime_exp = explainer.get_lime_explanation(text)
         lime_exp.show_in_notebook(text=True)
```

```
============================================================
LIME Explanation (Original):
```



@tiniebeany climate change is an interesting hustle as it was global warming but the planet stopped warming for 15 yes while the suv boom

```
In [18]: print("="*60)
         print("Integrated Gradients:")
         ig_result = explainer.get_integrated_gradients(text)
         vis_data_ig, 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
is                     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
change            0.1178
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
suv               0.0574
boom              0.1621
```

In [19]:

```python
print("="*60)
print("Captum LIME:")
try:
    captum_lime_result = explainer.get_captum_lime(text)
    vis_data_lime, _, _ = explainer.visualize_attributions(captum_lime_result, "Captum LIME")
except Exception as e:
    print(f"Captum LIME failed: {e}")
    vis_data_lime = 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):
@                      0.0469
tiniebeany             0.0000
climate                0.0000
change                -0.0230
is                     0.0044
an                     0.0501
interesting            0.0000
hustle                 0.1992
as                    -0.0393
it                     0.0000
was                    0.1467
global                 0.0211
warming                0.0000
but                    0.0000
the                    0.0023
planet                 0.0185
stopped                0.0940
warming                0.1861
for                    0.1099
15                     0.0524
yes                    0.0000
while                  0.0000
the                    0.0000
suv                    0.0768
boom                   0.1845

Original token-level attributions:
@                 0.0469
tin               0.0000
##ie              0.0000
##be              0.0000
##any             0.0000
climate           0.0000
change           -0.0230
is                0.0044
an                0.0501
interesting       0.0000
hu                0.0753
##stle            0.1239
as               -0.0393
it                0.0000
was               0.1467
global            0.0211
warming           0.0000
but               0.0000
the               0.0023
planet            0.0185
stopped           0.0940
warming           0.1861
for               0.1099
15                0.0524
yes               0.0000
while             0.0000
the               0.0000
suv               0.0768
boom              0.1845
```

In [20]:

```python
# HTML visualization with grouped words
try:
    from IPython.display import HTML, display

    print("\n" + "="*60)
    print("HTML Visualization (Grouped Words):")
    html_grouped = visualization.visualize_text([vis_data_ig])
    display(HTML(html_grouped.data))

    if vis_data_lime is not None:
        print("\nCaptum LIME HTML Visualization (Grouped Words):")
        html_lime = visualization.visualize_text([vis_data_lime])
        display(HTML(html_lime.data))

except ImportError:
    print("IPython not available for HTML visualization")
```

```
============================================================
HTML Visualization (Grouped Words):
```

Legend: 🟥 Negative □ Neutral 🟩 Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
news	3 (1.00)	news	-0.14	[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]

Legend: 🟥 Negative □ Neutral 🟩 Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
news	3 (1.00)	news	-0.14	[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 (Grouped Words):
```

Legend: 🟥 Negative □ Neutral 🟩 Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
news	3 (1.00)	news	1.13	[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]

Legend: 🟥 Negative □ Neutral 🟩 Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
news	3 (1.00)	news	1.13	[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]

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:

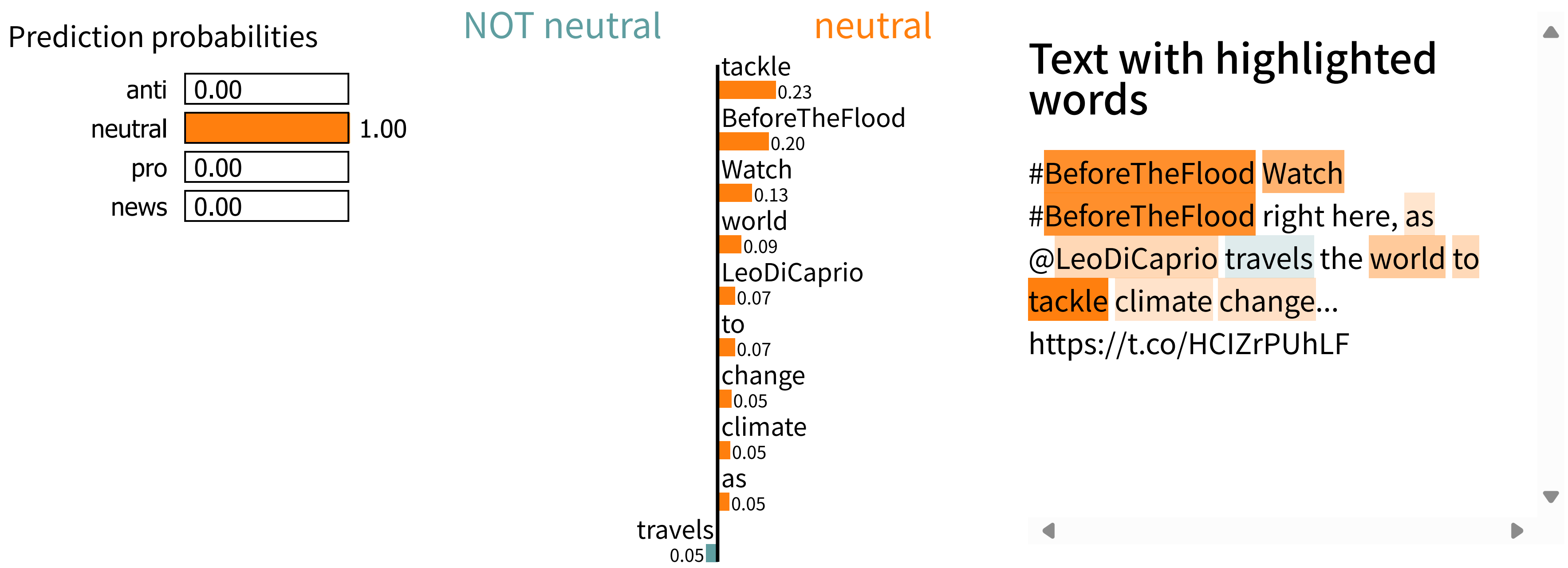
1. Methodology
   - Integrated Gradients: Computes gradients by integrating along a straight path from a baseline (zeros) to the actual input embeddings. It captures how much each token contributes to the prediction based on the model's internal gradients.
   - Captum LIME: Uses a perturbation-based 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

In [21]:

```
# Example usage
text = "#BeforeTheFlood Watch #BeforeTheFlood right here, as @LeoDiCaprio travels the world to tackle climate change... https:

print("="*60)
print("LIME Explanation (Original):")
lime_exp = explainer.get_lime_explanation(text)
lime_exp.show_in_notebook(text=True)
```

```
============================================================
LIME Explanation (Original):
```



Text with highlighted words

#BeforeTheFlood Watch #BeforeTheFlood right here, as @LeoDiCaprio travels the world to tackle climate change... https://t.co/HCIZrPUhLF

In [22]:

```
print("="*60)
print("Integrated Gradients:")
ig_result = explainer.get_integrated_gradients(text)
vis_data_ig, 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', 'news: 0.000']

Word-level attributions (grouped subwords):
#                     -0.0008
beforetheflood         0.0153
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
co                     0.0045
/                     -0.0142
hcizrpuhlf            -0.0148

Original token-level attributions:
#                -0.0008
before           -0.0245
##the             0.0130
##fl              0.0198
##ood             0.0070
watch             0.0317
#                 0.0004
before           -0.0519
##the             0.0259
##fl              0.0249
##ood             0.0120
right             0.0511
here              0.0380
,                -0.0267
as               -0.0215
@                 0.0511
leo               0.0065
##dic             0.0081
##ap              0.0042
##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
co                0.0045
/                -0.0142
hc                0.0300
##iz             -0.0198
##rp             -0.0129
##uh             -0.0168
##lf              0.0047
```

In [23]:

```
print("="*60)
print("Captum LIME:")
try:
    captum_lime_result = explainer.get_captum_lime(text)
    vis_data_lime, _, _ = explainer.visualize_attributions(captum_lime_result, "Captum LIME")
except Exception as e:
    print(f"Captum LIME failed: {e}")
    vis_data_lime = 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):
#                      0.0180
beforetheflood         0.0612
watch                  0.0973
#                      0.0000
beforetheflood         0.0000
right                  0.0325
here                   0.0824
,                      0.0000
as                     0.0314
@                      0.0000
leodicaprio           -0.0533
travels               -0.0436
the                    0.0515
world                  0.0000
to                     0.0415
tackle                 0.2347
climate                0.0537
change                 0.0131
.                      0.0000
.                     -0.0139
.                     -0.0030
https                  0.0000
:                      0.0000
/                      0.0000
/                     -0.0290
t                     -0.0442
.                      0.0249
co                     0.0000
/                      0.0000
hcizrpuhlf            -0.0019

Original token-level attributions:
#                 0.0180
before            0.0000
##the             0.0000
##fl              0.0000
##ood             0.0612
watch             0.0973
#                 0.0000
before            0.0000
##the             0.0000
##fl              0.0000
##ood             0.0000
right             0.0325
here              0.0824
,                 0.0000
as                0.0314
@                 0.0000
leo               0.0000
##dic             0.0132
##ap             -0.0665
##rio             0.0000
travels          -0.0436
the               0.0515
world             0.0000
to                0.0415
tackle            0.2347
climate           0.0537
change            0.0131
.                 0.0000
.                -0.0139
.                -0.0030
https             0.0000
:                 0.0000
/                 0.0000
/                -0.0290
t                -0.0442
.                 0.0249
co                0.0000
/                 0.0000
hc               -0.0019
##iz              0.0000
##rp              0.0000
##uh              0.0000
##lf              0.0000
```

In [24]:

```
# HTML visualization with grouped words
try:
    from IPython.display import HTML, display
```

```python
    print("\n" + "="*60)
    print("HTML Visualization (Grouped Words):")
    html_grouped = visualization.visualize_text([vis_data_ig])
    display(HTML(html_grouped.data))

    if vis_data_lime is not None:
        print("\nCaptum LIME HTML Visualization (Grouped Words):")
        html_lime = visualization.visualize_text([vis_data_lime])
        display(HTML(html_lime.data))

except ImportError:
    print("IPython not available for HTML visualization")
```

```
============================================================
HTML Visualization (Grouped Words):
```

Legend: 🟥 Negative □ Neutral 🟩 Positive

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

```
Captum LIME HTML Visualization (Grouped Words):
```

Legend: 🟥 Negative □ Neutral 🟩 Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
neutral	1 (1.00)	neutral	0.30	[CLS] # beforetheflood watch # beforetheflood 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
neutral	1 (1.00)	neutral	0.30	[CLS] # beforetheflood watch # beforetheflood right here , as @ leodicaprio travels the world to tackle climate change . . . https : / / t . co / hcizrpuhlf [SEP]