Analysis methods in NLP: Feature attribution

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CS224u: Natural language understanding

Motivations

Why does your model make the predictions it makes?

1. Systematicity with regard to specific phenomena
2. Robustness
3. Unwanted biases
4. Weaknesses an adversary could exploit

https://github.com/cgpotts/cs224u/blob/master/feature_attribution.ipynb

captum.ai

1. Integrated gradients (Sundararajan et al. 2017)
2. Gradients
3. Saliency Maps (Simonyan et al. 2013)
4. DeepLift (Shrikumar et al. 2017)
5. Deconvolution (Zeiler and Fergus 2014)
6. LIME (Ribeiro et al. 2016)
7. Feature ablation
8. Feature permutation
9. ...

`https://captum.ai`

Axioms

Sensitivity

If two inputs x and x' differ only at dimension i and lead to different predictions, then feature f_i has non-zero attribution.

$$M([1, 0, 1]) = \text{positive}$$
$$M([1, 1, 1]) = \text{negative}$$

Implementation invariance

If two models M and M' have identical input/output behavior, then the attributions for M and M' are identical.

Sundararajan et al. 2017

Gradients · inputs

$$\text{InputXGradient}_i(M, x) = \frac{\partial M(x)}{\partial x_i} \cdot x_i$$

Gradients · inputs

```
[1]: """For both functions, the `forward` method of `model` is used.
`X` is an (m x n) tensor of attributions. Use `targets=None` for
models with scalar outputs, else supply a LongTensor giving a
label for each example."""
```

```
[2]: import torch
def grad_x_input(model, X, targets=None):
    X.requires_grad = True
    y = model(X)
    y = y if targets is None else y[list(range(len(y))), targets]
    (grads, ) = torch.autograd.grad(y.unbind(), X)
    return grads * X
```

```
[3]: from captum.attr import InputXGradient
def captum_grad_x_input(model, X, target):
    X.requires_grad = True
    amod = InputXGradient(model)
    return amod.attribute(X, target=target)
```

Gradients · inputs

```
[4]: from sklearn.datasets import make_classification
     from sklearn.metrics import classification_report, accuracy_score
     from torch_shallow_neural_classifier import TorchShallowNeuralClassifier

[5]: X, y = make_classification(
         n_samples=1000, n_classes=2, n_features=4, n_informative=4, n_redundant=0)

[6]: mod = TorchShallowNeuralClassifier()

[7]: _ = mod.fit(X, y)

     Finished epoch 1000 of 1000; error is 0.1795504391193391

[8]: X_tensor = torch.FloatTensor(X)
     y_tensor = torch.LongTensor(y)

[9]: c = captum_grad_x_input(mod.model, X_tensor, target=y_tensor)

[10]: p = grad_x_input(mod.model, X_tensor, targets=y_tensor)

[11]: c.mean(axis=0)

[11]: tensor([0.1145, 0.2812, 0.5429, 0.1360], grad_fn=<MeanBackward1>)

[12]: p.mean(axis=0)

[12]: tensor([0.1145, 0.2812, 0.5429, 0.1360], grad_fn=<MeanBackward1>)

[13]: pred = mod.predict(X)

[14]: cpred = captum_grad_x_input(mod.model, X_tensor, target=torch.LongTensor(pred))

[15]: cpred.mean(axis=0)

[15]: tensor([0.1259, 0.3090, 0.5372, 0.1462], grad_fn=<MeanBackward1>)
```

Gradients · inputs fails sensitivity

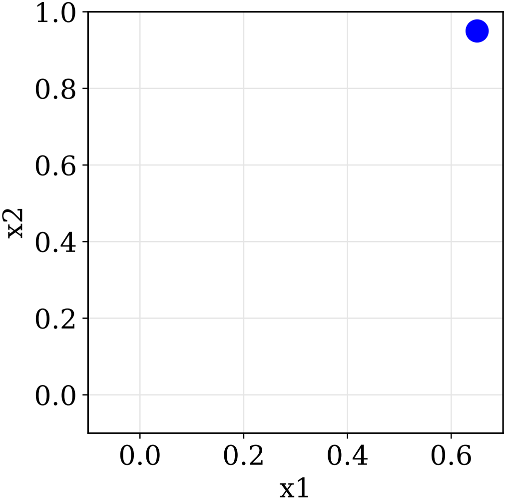
$$M(x) = 1 - \max(0, 1 - x)$$

$$\begin{aligned} M(0) &= 1 - \max(0, 1 - 0) && = 1 - 1 = 0 \\ M(2) &= 1 - \max(0, 1 - 2) && = 1 - 0 = 1 \end{aligned}$$

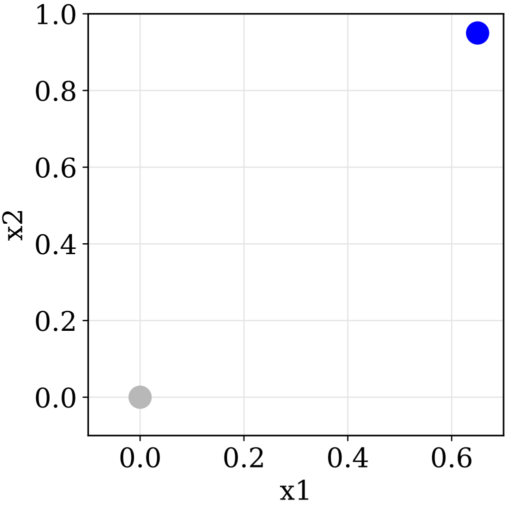
$$\begin{aligned} \text{InputXGradient}(M, 0) &= \max(0, \text{sign}(1 - 0)) \cdot 0 = 1 \cdot 0 && = 0 \\ \text{InputXGradient}(M, 2) &= \max(0, \text{sign}(1 - 2)) \cdot 2 = 0 \cdot 2 && = 0 \end{aligned}$$

Example from Sundararajan et al. 2017

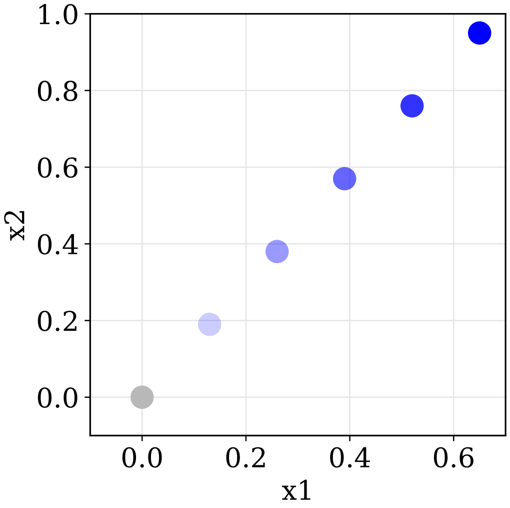
Integrated gradients: Intuition



Integrated gradients: Intuition



Integrated gradients: Intuition



Core computation

$$\mathrm{IG}_i(M, x, x') = \overbrace{(x_i - x'_i)}^{5} \cdot \overbrace{\sum_{k=1}^{m}}^{4} \overbrace{\frac{\partial M(\overbrace{x' + \overbrace{\frac{k}{m}}^{1} \cdot (x - x')}^{2})}{\partial x_i}}^{3} \cdot \overbrace{\frac{1}{m}}^{4}$$

1. Generate $\alpha = [1, \ldots, m]$
2. Interpolate inputs between baseline x' and actual input x
3. Compute gradients for each interpolated input
4. Integral approximation through averaging
5. Scaling to remain in the space region as the original

Adapted from the TensorFlow integrated gradients tutorial

Sensitivity again

$$M(x) = 1 - \max(0, 1 - x)$$

$$\begin{aligned} M(0) &= 1 - \max(0, 1 - 0) & &= 1 - 1 = 0 \\ M(2) &= 1 - \max(0, 1 - 2) & &= 1 - 0 = 1 \end{aligned}$$

$$\begin{aligned} \text{InputXGradient}(M, 0) &= \max(0, \text{sign}(1 - 0)) \cdot 0 = 1 \cdot 0 &= 0 \\ \text{InputXGradient}(M, 2) &= \max(0, \text{sign}(1 - 2)) \cdot 2 = 0 \cdot 2 &= 0 \end{aligned}$$

$$\text{IG}_i(M, 2, 0) = (2 - 0) \cdot \sum \begin{pmatrix} \max(0, \text{sign}(1 - 0.00) \\ \max(0, \text{sign}(1 - 0.02) \\ \max(0, \text{sign}(1 - 0.04) \\ \vdots \\ \max(0, \text{sign}(1 - 2.00) \end{pmatrix} \cdot \frac{1}{m} \approx 1$$

Feed-forward example

```
[1]: from collections import Counter
     from captum.attr import IntegratedGradients
     from nltk.corpus import stopwords
     from operator import itemgetter
     import os
     from sklearn.metrics import classification_report
     import torch
     from torch_shallow_neural_classifier import TorchShallowNeuralClassifier
     import sst

[2]: SST_HOME = os.path.join("data", "sentiment")

[3]: stopwords = set(stopwords.words('english'))

[4]: def phi(text):
         return Counter([w for w in text.lower().split() if w not in stopwords])

[5]: def fit_mlp(X, y):
         mod = TorchShallowNeuralClassifier(early_stopping=True)
         mod.fit(X, y)
         return mod

[6]: experiment = sst.experiment(
         sst.train_reader(SST_HOME), phi, fit_mlp, sst.dev_reader(SST_HOME))
```

```
Stopping after epoch 37. Validation score did not improve by tol=1e-05 for more
than 10 epochs. Final error is 0.7182262241840363

              precision    recall  f1-score   support

    negative      0.625     0.671     0.647       428
     neutral      0.246     0.127     0.167       229
    positive      0.634     0.748     0.686       444
```

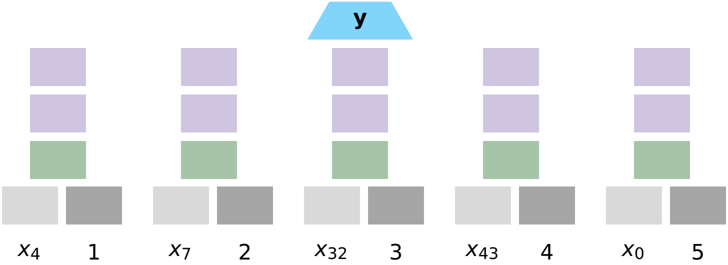
Feed-forward example

```
[7]: classifier = experiment['model']

[8]: classifier.classes_

[8]: ['negative', 'neutral', 'positive']

[9]: X_test = experiment['assess_datasets'][0]['X']
     y_test = [classifier.classes_.index(label)
               for label in experiment['assess_datasets'][0]['y']]
     preds = [classifier.classes_.index(label)
              for label in experiment['predictions'][0]]
     fnames = experiment['train_dataset']['vectorizer'].get_feature_names()

[10]: ig = IntegratedGradients(classifier.model)

[11]: baseline = torch.zeros(1, experiment['train_dataset']['X'].shape[1])

[12]: attrs = ig.attribute(
          torch.FloatTensor(X_test), baseline, target=torch.LongTensor(preds))
```

Feed-forward example

```
[13]: def error_analysis(gold=1, predicted=2):
          err_ind = [i for i, (g, p) in enumerate(zip(y_test, preds))
                     if g == gold and p == predicted]
          attr_lookup = create_attr_lookup(attrs[err_ind])
          return attr_lookup, err_ind

      def create_attr_lookup(attrs):
          mu = attrs.mean(axis=0).detach().numpy()
          return sorted(zip(fnames, mu), key=itemgetter(1), reverse=True)

[14]: attrs_lookup, err_ind = error_analysis(gold=1, predicted=2)

[15]: attrs_lookup[: 5]

[15]: [('.', 0.06881114692146112),
       ('film', 0.048555303175068946),
       ('fun', 0.04074530858858675),
       ('solid', 0.03245438354763919),
       (',', 0.028427555063823048)]

[16]: ex_ind = err_ind[0]

[17]: experiment['assess_datasets'][0]['raw_examples'][ex_ind]

[17]: 'No one goes unindicted here , which is probably for the best .'

[18]: ex_attr_lookup = create_attr_lookup(attrs[ex_ind:ex_ind+1])

[19]: [(f, a) for f, a in ex_attr_lookup if a != 0]

[19]: [('best', 0.7126857703976734),
       ('.', 0.07008059173159924),
       (',', 0.027381288326101944),
       ('one', -0.040591713271602575),
       ('goes', -0.21833576011067812),
       ('probably', -0.28605132775319597)]
```

BERT example



BERT example

```
[1]: import torch
     import torch.nn.functional as F
     from transformers import AutoModelForSequenceClassification, AutoTokenizer
     from captum.attr import LayerIntegratedGradients
     from captum.attr import visualization as viz

[2]: weights_name = 'cardiffnlp/twitter-roberta-base-sentiment'

[3]: tokenizer = AutoTokenizer.from_pretrained(weights_name)

[4]: model = AutoModelForSequenceClassification.from_pretrained(weights_name)

[5]: def predict_one_proba(text):
         input_ids = tokenizer.encode(
             text, add_special_tokens=True, return_tensors='pt')
         model.eval()
         with torch.no_grad():
             logits = model(input_ids)[0]
             preds = F.softmax(logits, dim=1)
         model.train()
         return preds.squeeze(0)
```

https://captum.ai/tutorials/Bert_SQUAD_Interpret

BERT example

[6]:
```
def ig_encodings(text):
    pad_id = tokenizer.pad_token_id
    cls_id = tokenizer.cls_token_id
    sep_id = tokenizer.sep_token_id
    input_ids = tokenizer.encode(text, add_special_tokens=False)
    base_ids = [pad_id] * len(input_ids)
    input_ids = [cls_id] + input_ids + [sep_id]
    base_ids = [cls_id] + base_ids + [sep_id]
    return torch.LongTensor([input_ids]), torch.LongTensor([base_ids])
```

[7]:
```
def ig_forward(inputs):
    return model(inputs).logits
```

BERT example

```
[8]:  #layer = model.roberta.encoder.layer[0]
      layer = model.roberta.embeddings
      ig = LayerIntegratedGradients(ig_forward, layer)

[9]:  text = "This is illuminating!"

[10]: true_class = 2  # positive

[11]: input_ids, base_ids = ig_encodings(text)

[12]: attrs, delta = ig.attribute(
          input_ids, base_ids, target=true_class, return_convergence_delta=True)

[13]: attrs.shape

[13]: torch.Size([1, 6, 768])

[14]: scores = attrs.sum(dim=-1)
      scores = (scores - scores.mean()) / scores.norm()

[15]: scores.shape

[15]: torch.Size([1, 6])
```

BERT example

[16]:
```
pred_probs = predict_one_proba(text)
```

[17]:
```
pred_class = pred_probs.argmax()
pred_class
```

[17]:
```
tensor(2)
```

[18]:
```
raw_input = tokenizer.convert_ids_to_tokens(input_ids.tolist()[0])
raw_input = [x.strip("Ġ") for x in raw_input]
```

[19]:
```
score_vis = viz.VisualizationDataRecord(
    word_attributions=scores.squeeze(0),
    pred_prob=pred_probs.max(),
    pred_class=pred_class,
    true_class=true_class,
    attr_class=None,
    attr_score=attrs.sum(),
    raw_input=raw_input,
    convergence_score=delta)
```

[20]:
```
_ = viz.visualize_text([score_vis])
```

BERT example

Legend: Negative Neutral Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
2	2 (0.93)	None	1.99	#s This is illuminating ! #/s

A small challenge test

Legend: Negative Neutral Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
2	2 (0.82)	None	2.79	#s They said it would be great , and they were right . #/s
0	0 (0.50)	None	2.09	#s They said it would be great , and they were wrong . #/s
2	2 (0.76)	None	1.38	#s They were right to say it would be great . #/s
0	0 (0.62)	None	2.62	#s They were wrong to say it would be great . #/s
2	2 (0.77)	None	1.21	#s They said it would be stellar , and they were correct . #/s
0	1 (0.47)	None	1.24	#s They said it would be stellar , and they were incorrect . #/s

References I

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