



CS4650 Final Presentation

Interpret, visualize BERT

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Goal

- Understand BERT
 - whether BERT create reasonable embeddings
 - explore each layer's necessity
- Find out possible improvement to solve “anistropy” problem

Method

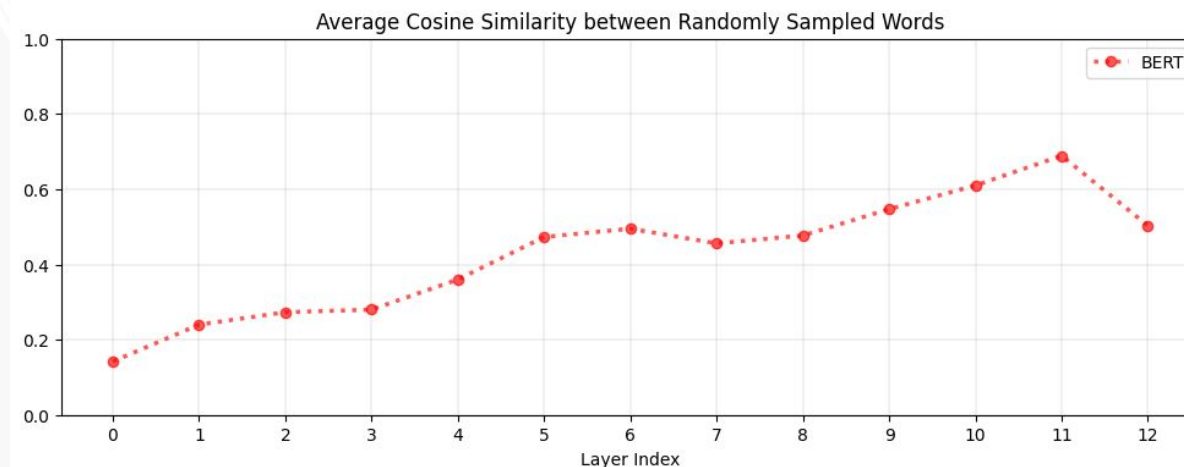
- Remove Layer 12 in BERT
- Biased Dataset Analysis
- Contrastive Learning

Data

- Stanford Natural Language Inference (SNLI) Corpus
 - <https://nlp.stanford.edu/projects/snli/>

Text	Judgments	Hypothesis
A man inspects the uniform of a figure in some East Asian country.	contradiction C C C C C	The man is sleeping
An older and younger man smiling.	neutral N N E N N	Two men are smiling and laughing at the cats playing on the floor.
A black race car starts up in front of a crowd of people.	contradiction C C C C C	A man is driving down a lonely road.
A soccer game with multiple males playing.	entailment E E E E E	Some men are playing a sport.
A smiling costumed woman is holding an umbrella.	neutral N N E C N	A happy woman in a fairy costume holds an umbrella.

Anisotropy



We randomly select 2 words and calculate the cosine similarity, and find that as layer goes deeper, any words cosine similarity grows □

Any 2 random words have similar representation, which means, the whole vector space tend to be a cone instead of ball.

- How to adjust for it?
 - Use anisotropy baseline

$$\text{Baseline}(f_\ell) = \mathbb{E}_{x,y \sim U(\mathcal{O})} [\cos(f_\ell(x), f_\ell(y))]$$

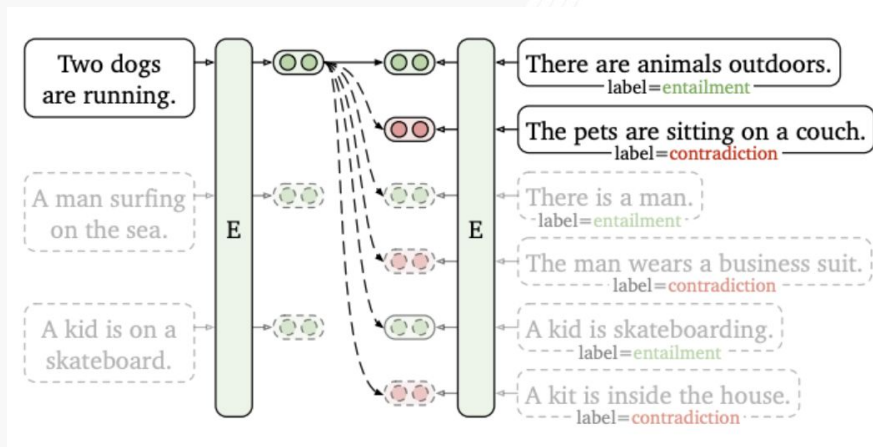
$$\text{SelfSim}_\ell^*(w) = \text{SelfSim}_\ell(w) - \text{Baseline}(f_\ell)$$

Contrastive Learning

- Loss Function

$$\mathcal{L} = - \sum_{i,j=1}^b t_{i,j} \log p_{i,j} = - \sum_{i,j=1}^b t_{i,j} \log \frac{e^{s_{i,j}}}{\sum_j e^{s_{i,j}}} = - \sum_{i,j=1}^b t_{i,j} s_{i,j}$$

b is batch size, $t_{i,j}$ is the label, - one hot matrix. $s_{i,j}$ is the similarity score between sample i and j

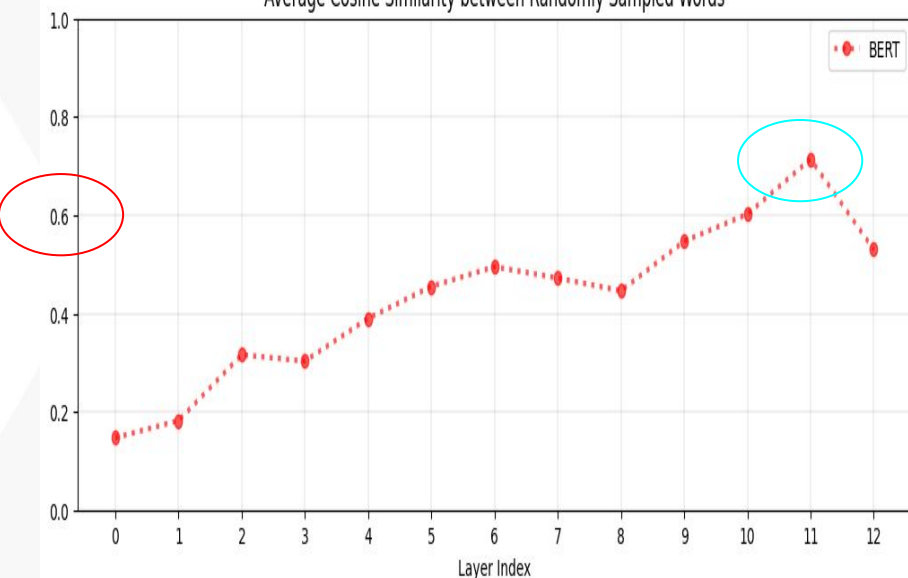


Use **cross entropy loss** of negative samples with in a batch.
 Make the feature of x more similar to the positive sample and less similar to the feature of the negative sample

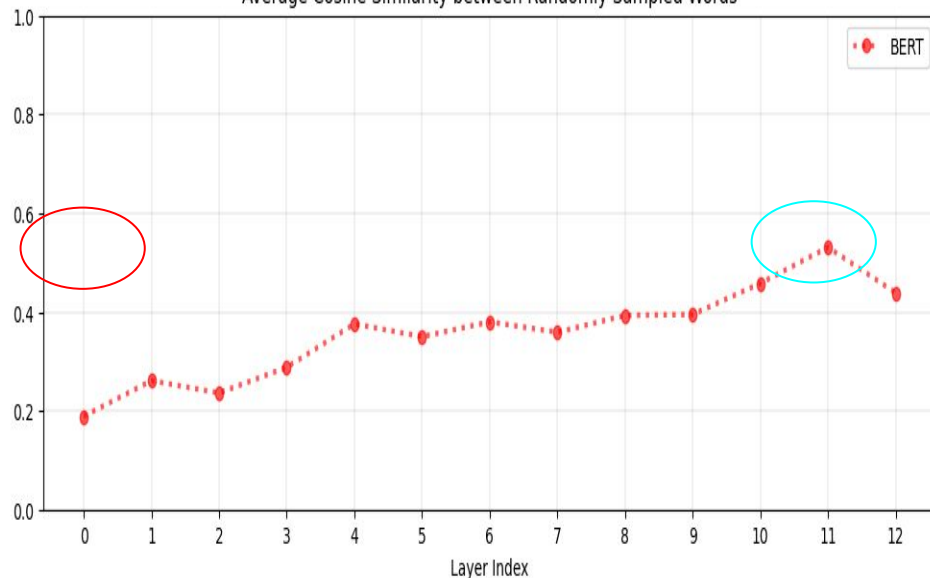
Results

- Contrastive Learning

Average Cosine Similarity between Randomly Sampled Words



Average Cosine Similarity between Randomly Sampled Words



As the layer goes deeper, contrastive-learning BERT model's any words cosine similarity grows **slower** than the original BERT.
Anisotropy issue **alleviate**

Remove Layer 12 Experiment

Experiment

Experiment 1:

Use SNLI to do **classification**:

length of train loader: 17168

length of val loader: 308

whether premise can infer hypothesis, if so, label is entailment. if not, label is contradiction. If not sure, label is neutral.

Premise: A man inspects the uniform of a figure in some East Asian country.

Hypothesis: The man is sleeping.

Label: *contradiction*

Original BERT

```
(11): BertLayer(
  (attention): BertAttention(
    (self): BertSelfAttention(
      (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)
  )
  (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=3, bias=True)
)
```

BERT w/o Layer12

```
(10): BertLayer(
  (attention): BertAttention(
    (self): BertSelfAttention(
      (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)
  )
  (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()
)
(classifier): Sequential(
  (0): Linear(in_features=768, out_features=50, bias=True)
  (1): ReLU()
  (2): Linear(in_features=50, out_features=3, bias=True)
)
)
```


Remove Layer 12 Experiment

Experiment

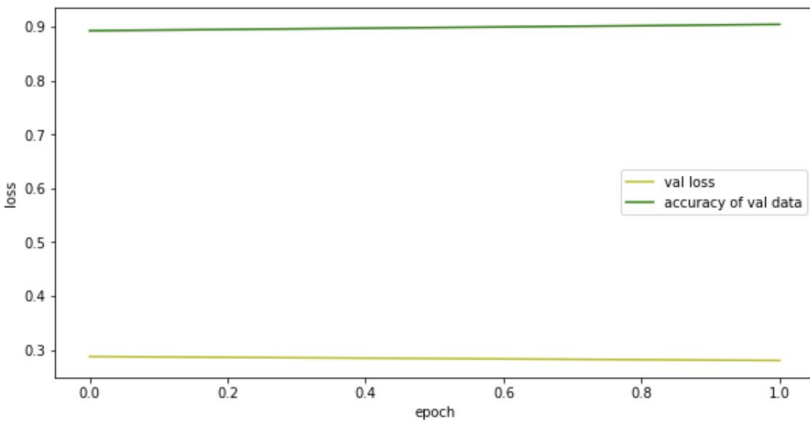
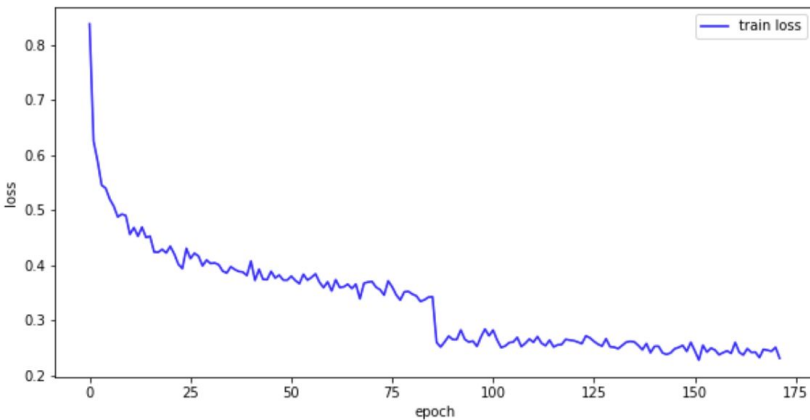
During fine-tuning, I set all parameters as the same

`epochs = 2`

`optimizer = AdamW(model.parameters(), lr=5e-5, eps=1e-8)`

`loss_fn = nn.CrossEntropyLoss()`

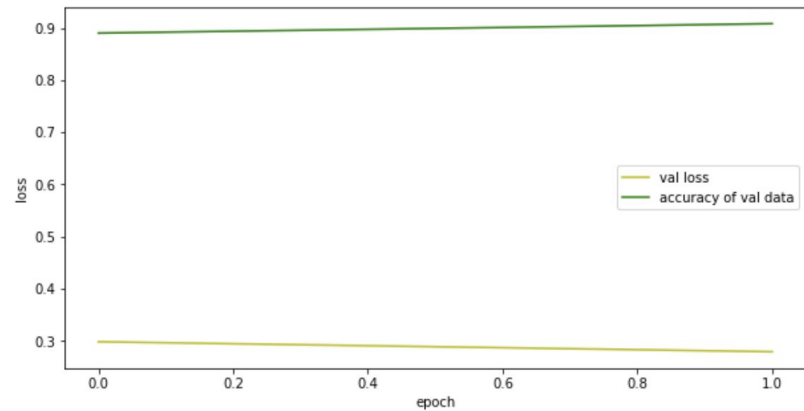
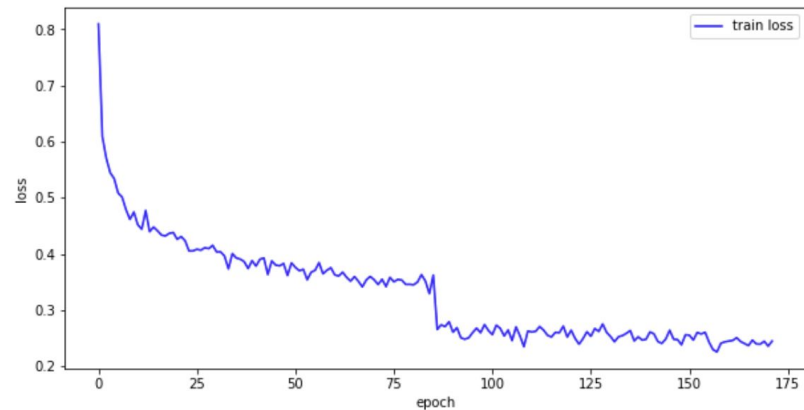
Original BERT



Accuracy on test dataset: 90.45195439739413

total time: 6140.41s

BERT w/o Layer 12



Accuracy on test dataset: 90.32980456026058

total time: 5623.56s

Remove Layer 12 Experiment

Experiment

Experiment 2:

Use **MedWeb** to do **classification**: length of train loader: 7021
length of val loader: 1505

Reviews to predict satisfaction level (1,2,3,4,5,6) for drugs

	Age	Condition	Date	Drug	DrugId	EaseofUse	Effectivene	Reviews	Satisfaction	Sex	Sides	UsefulCount
1	75 or over	Stuffy Nose	#####	25dph-7.5p	146724	5	5	I'm a retire	5	Male	Drowsiness	0

Original BERT

```
(11): BertLayer(
  (attention): BertAttention(
    (self): BertSelfAttention(
      (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)
  )
  (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=3, bias=True)
```

BERT w/o Layer12

```
(10): BertLayer(
  (attention): BertAttention(
    (self): BertSelfAttention(
      (query): Linear(in_features=768, out_features=768, bias=True)
      (key): Linear(in_features=768, out_features=768, bias=True)
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  )
  (output): BertOutput(
    (dense): Linear(in_features=3072, out_features=768, bias=True)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
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(classifier): Sequential(
  (0): Linear(in_features=768, out_features=50, bias=True)
  (1): ReLU()
  (2): Linear(in_features=50, out_features=3, bias=True)
```

Remove Layer 12 Experiment

Experiment

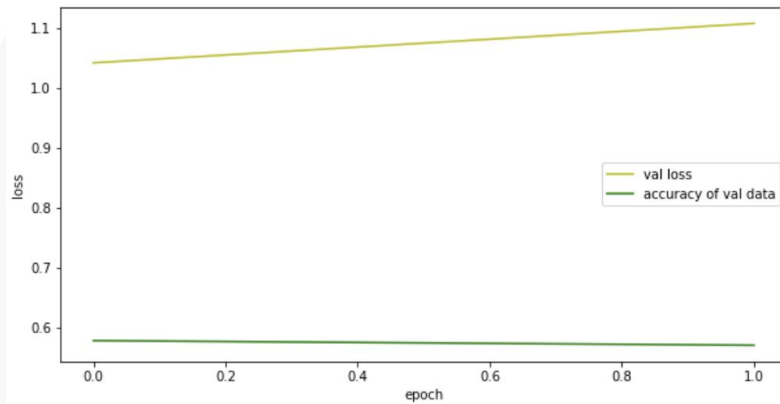
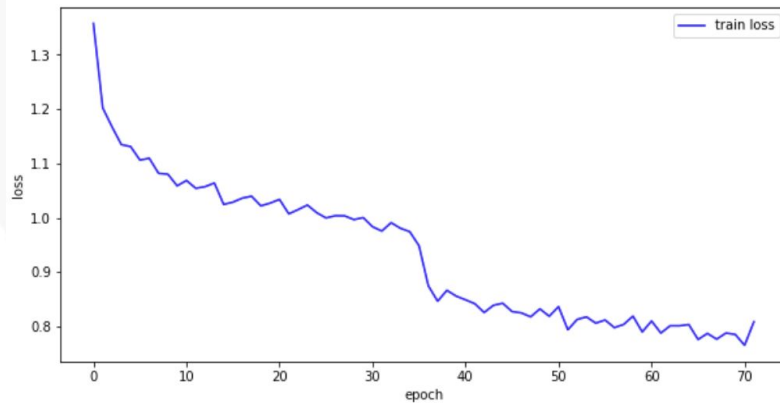
During fine-tuning, I set all parameters as the same

epochs = 2

optimizer = *AdamW(model.parameters(), lr=5e-5, eps=1e-8)*

loss_fn = *nn.CrossEntropyLoss()*

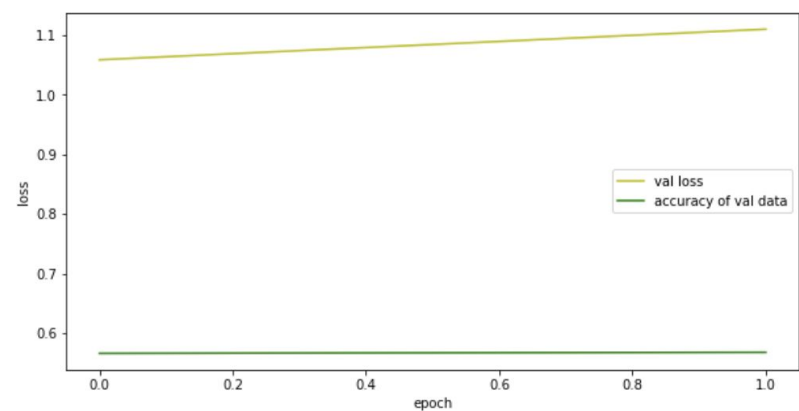
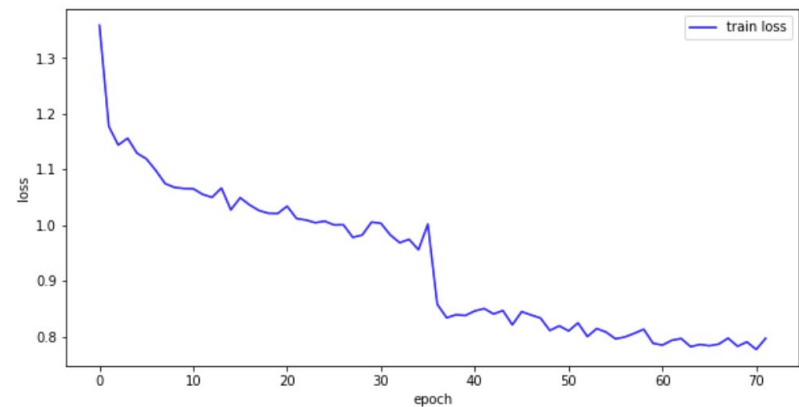
Original BERT



Accuracy on test dataset: 58.90691741813004

total time: 2652.56s

BERT w/o Layer 12



Accuracy on test dataset: 58.66961319411485

total time: 2447.34s

Biased Dataset Experiment

Experiment

Experiment:

Use **SNLI** to do **classification**:

we remove sentences which contains words related to “female” in training dataset but keep original validation and test dataset.

```
forbidden_words = ['women', 'woman', 'girl', 'girls', 'mother', 'wife', 'female']
```

Biased SNLI

```
length of train loader: 13197  
length of val loader: 308
```

```
Accuracy on test dataset: 59.46661237785016
```

Original SNLI

```
length of train loader: 17168  
length of val loader: 308
```

```
Accuracy on test dataset: 90.45195439739413
```

Conclusion:

BERT may not perform well in biased dataset, we should make sure dataset is unbiased.

Conclusion

- Data-biased
 - BERT may not perform well in biased dataset, we should make sure dataset is unbiased.
- Structure
 - We used Hugging Face to freeze layer 12 and found out there is no much difference compare to the original BERT but the process is much faster
- Anisotropy
 - Contrastive learning could alleviate anisotropy by make feature more similar to it's positive sample and less similar to it's negative sample