Complementary-Similarity Learning using Quadruplet Network

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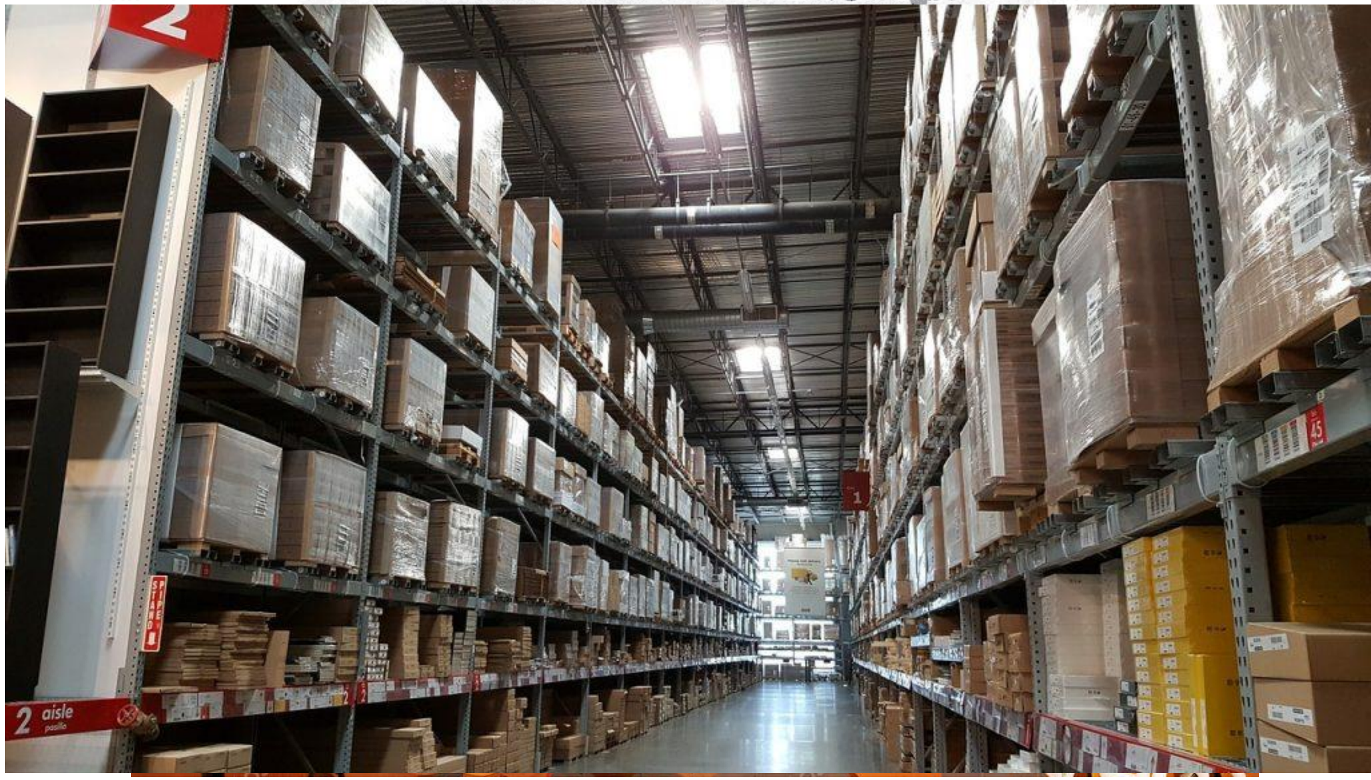
E-commerce Recommender Systems

Nancy

eCommerce Customer



Millions of items in eCommerce Catalog/ Warehouse

Item Relationships

- Similarity/ Substitutes
  - Show similar items during exploration phase

Item Relationships

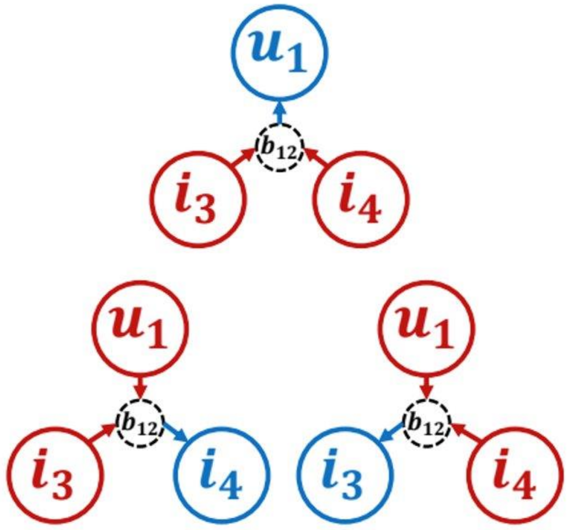
- Complementary
  - Show after purchase add example e.g. if someone has purchased dress, additional suggestions like sandals, purse etc

Challenges

- "Functional" or "Stylistic" Complementarity is different than "bought together"
- Lack of ground truth for complementary items
- Cold-start items
- Differentiation between similar and complementary items

Prior Work

- Triple2vec (Wan, CIKM 18)
  - Dual item embeddings
  - Maximize dot product between item pairs and user vectors
  - Challenges:
    - Solves co-purchasing more than "complementary"
    - Transitivity leads to similar items in recommendations
    - Does not handle cold-start items



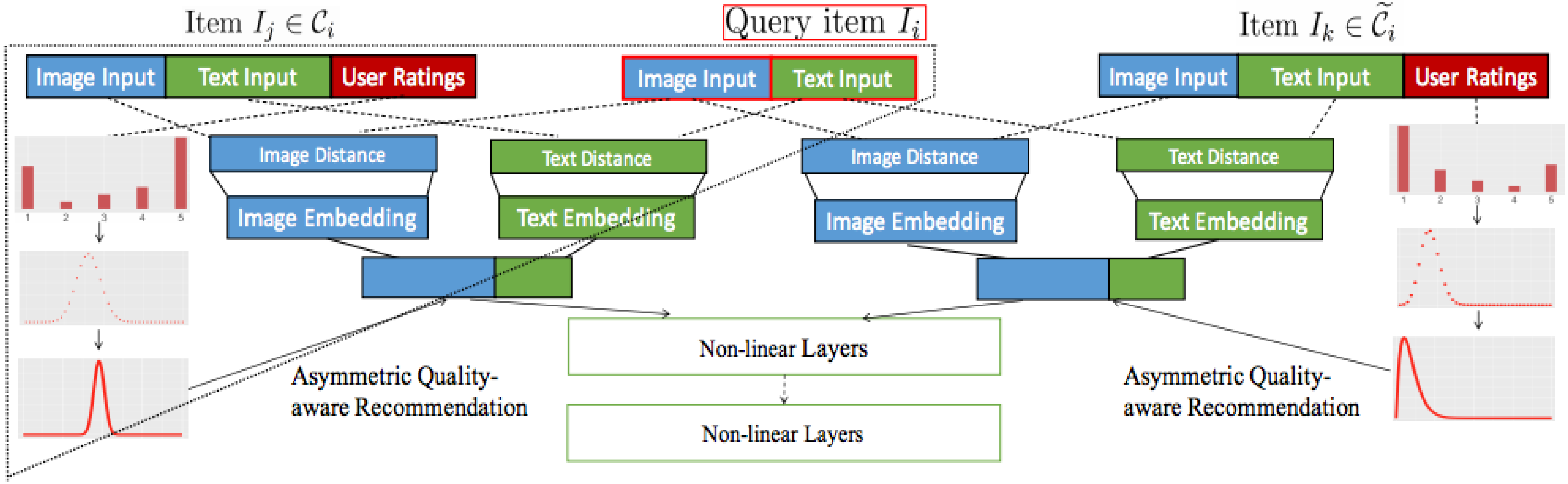
Prior Work

- Neural Complementary Recommender (ENCORE) - (Zhang, RecSys 18)

$$P_{comp} = \sigma\left(d\left(a_f, c_f\right)\right) = \frac{1}{1 + e^{d\left(a_f, c_f\right) - \eta}} \text{ [4]}$$

Challenges:

- Transitivity



Amazon Dataset

- Amazon Clothing, Shoes, and Jewelry data[2]
  - Category information and title
  - Complementary pairs: bought together by users from different categories
  - Similar pairs: items that lie in same category
  - Negative items: Randomly sample items which do not meet above criteria
  - Quads: anchor, complementary, similar, negative items
  - Train quads: 3.3M, Test quads:0.3M

https://github.com/mansimane/quadnet-comp-sim

Amazon Dataset Attribute Availability

Attribute	Coverage
Image	99.99
Description	5.68
Title	99.95
Price	38.29
Brand	6.25

Example Quadruplet

Anchor

Lee Dungarees Men’s Big, Tall Carpenter Jean

Complementary

Key Apparel Men's Big-Tall Short Sleeve Heavyweight Pocket Tee Shirt

Similar

Wrangler Men's Rugged Wear Relaxed Straight Fit Jean

Negative

Black and White Herringbone Wool Suiting Extra Long Tie

Motivation

- Why not just optimize for complementary items?

$$P_{comp} = \sigma\left(d\left(a_f, c_f\right)\right) = \frac{1}{1+e^{d\left(a_f, c_f\right)-\eta}}$$ [4]

a

Wonder Nation Twist-Front Graphic T-Shirt

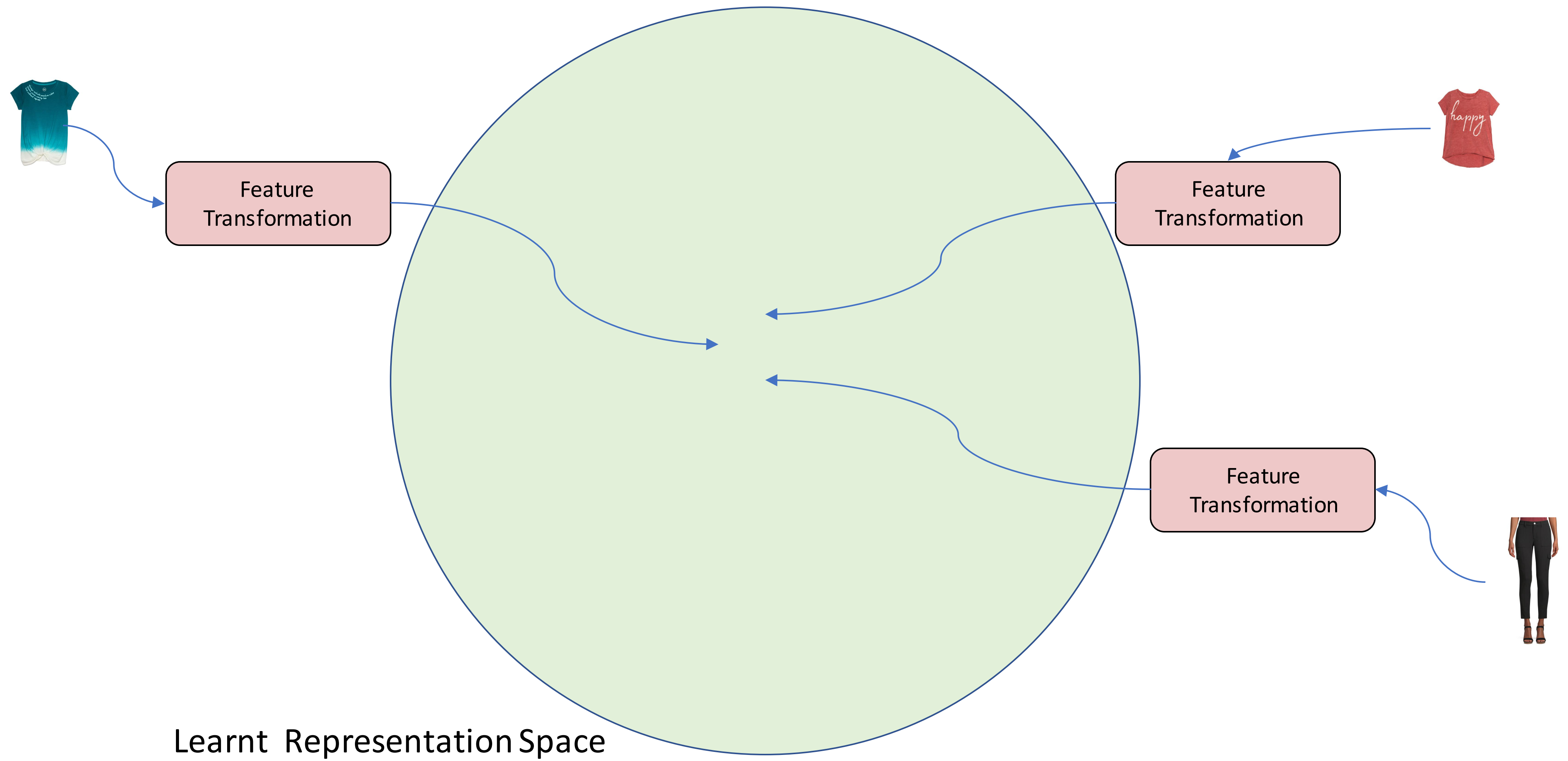
c

Women's Knit Skinny Cargo Pant

b

Wonder Nation Graphic Hi-Lo T-Shirt

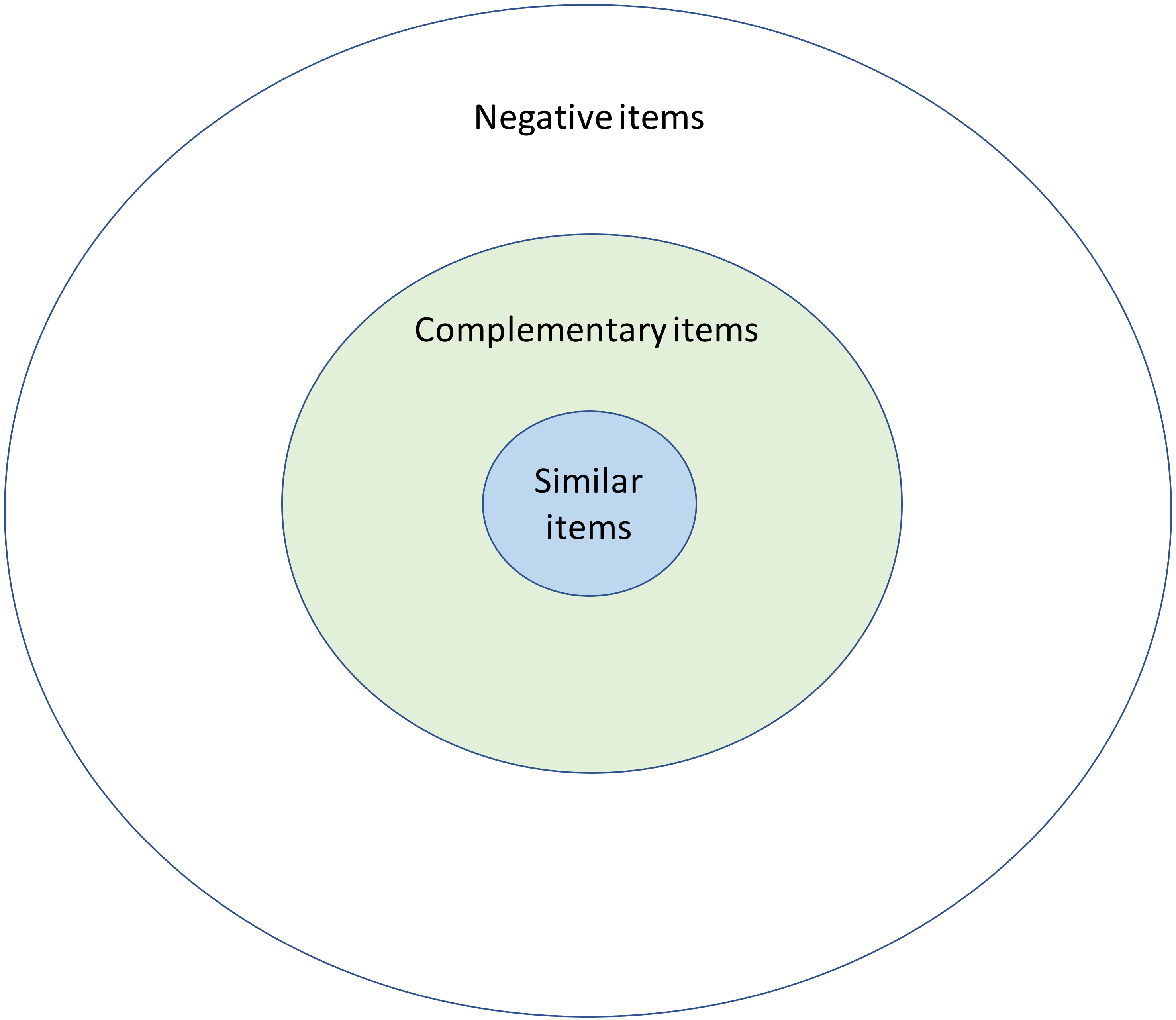
Motivation



Feature Transformation
Feature Transformation
Feature Transformation
Learnt Representation Space

Goal

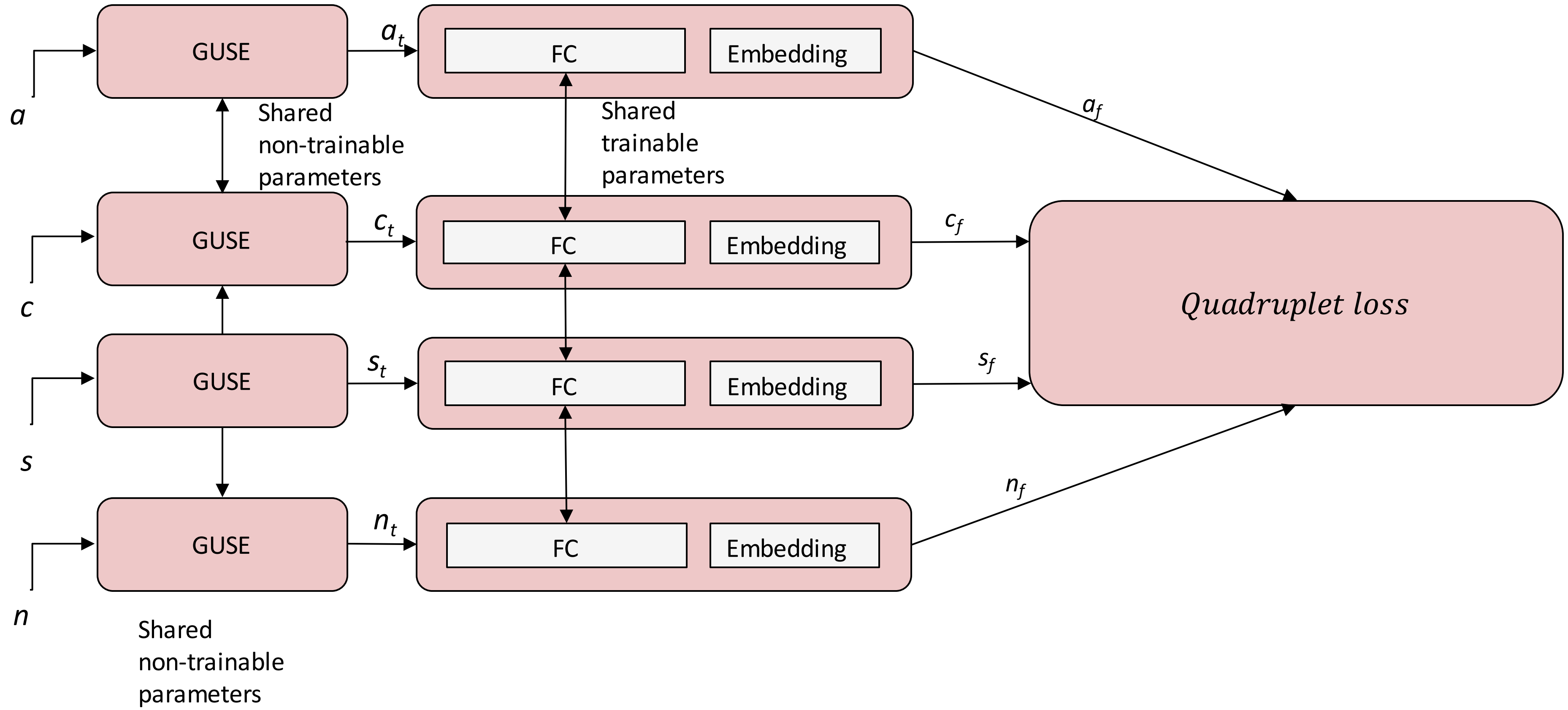
- Learn representation space which can differentiate between similar and complementary items



Problem Formulation

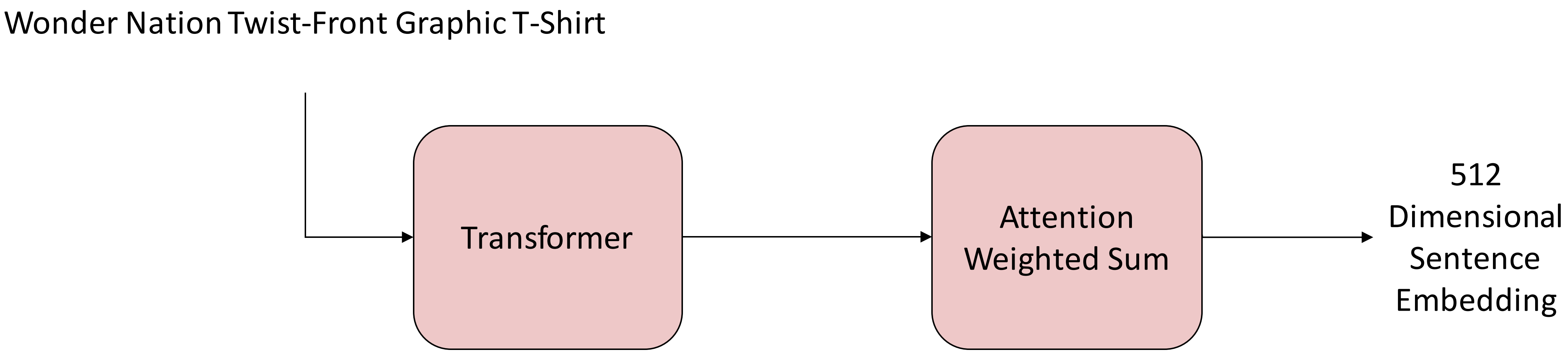
- a: Anchor item
- c: Complementary item to anchor item
- s: Similar item to anchor item
- n: Negative item to anchor item
- a_f' , c_f' , s_f' , n_f' : Normalized learnt feature representation for *a*, *c*, *s*, *n*

Network Architecture



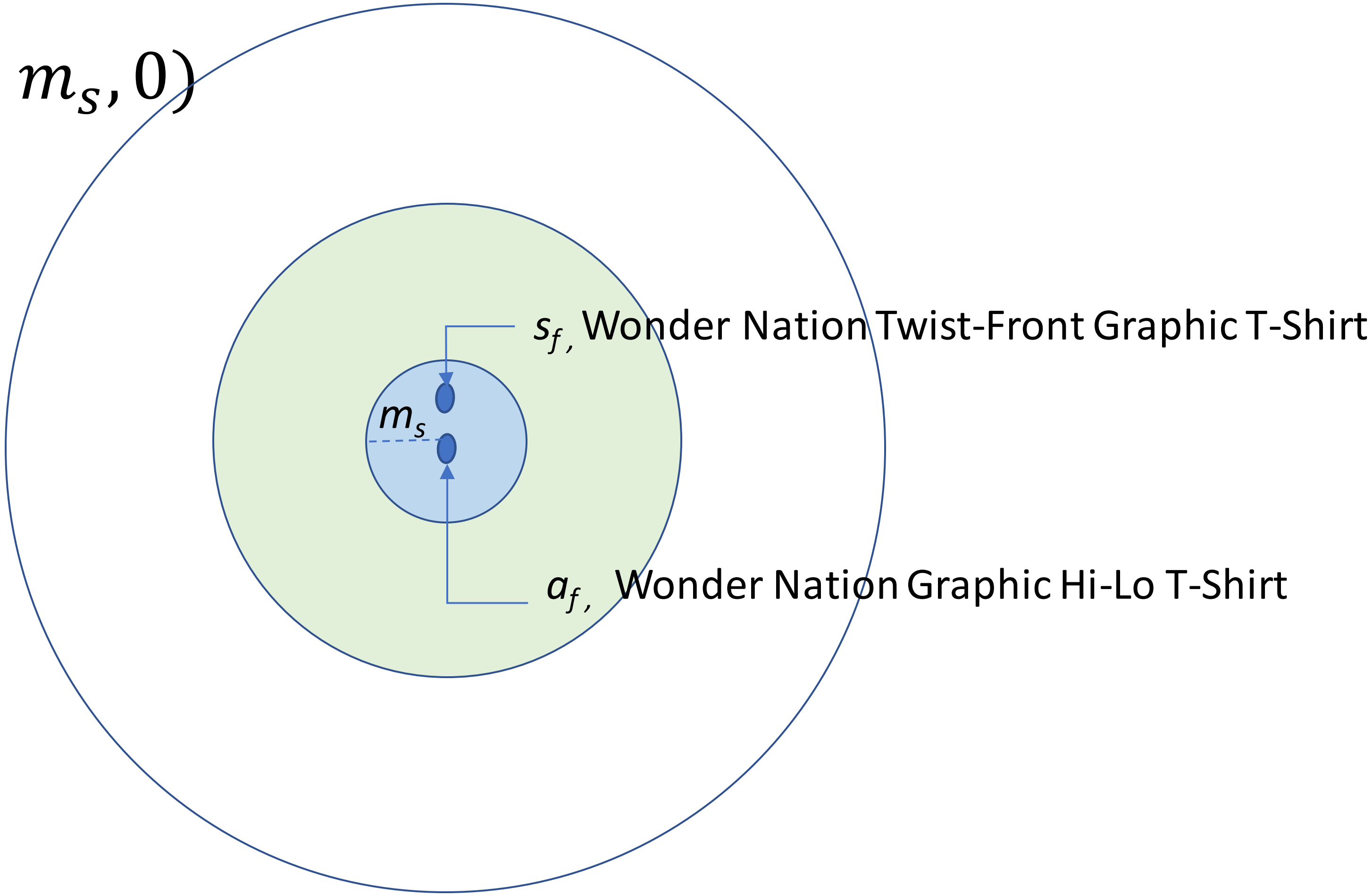
Feature Representation

- Universal Sentence Encoder [1]



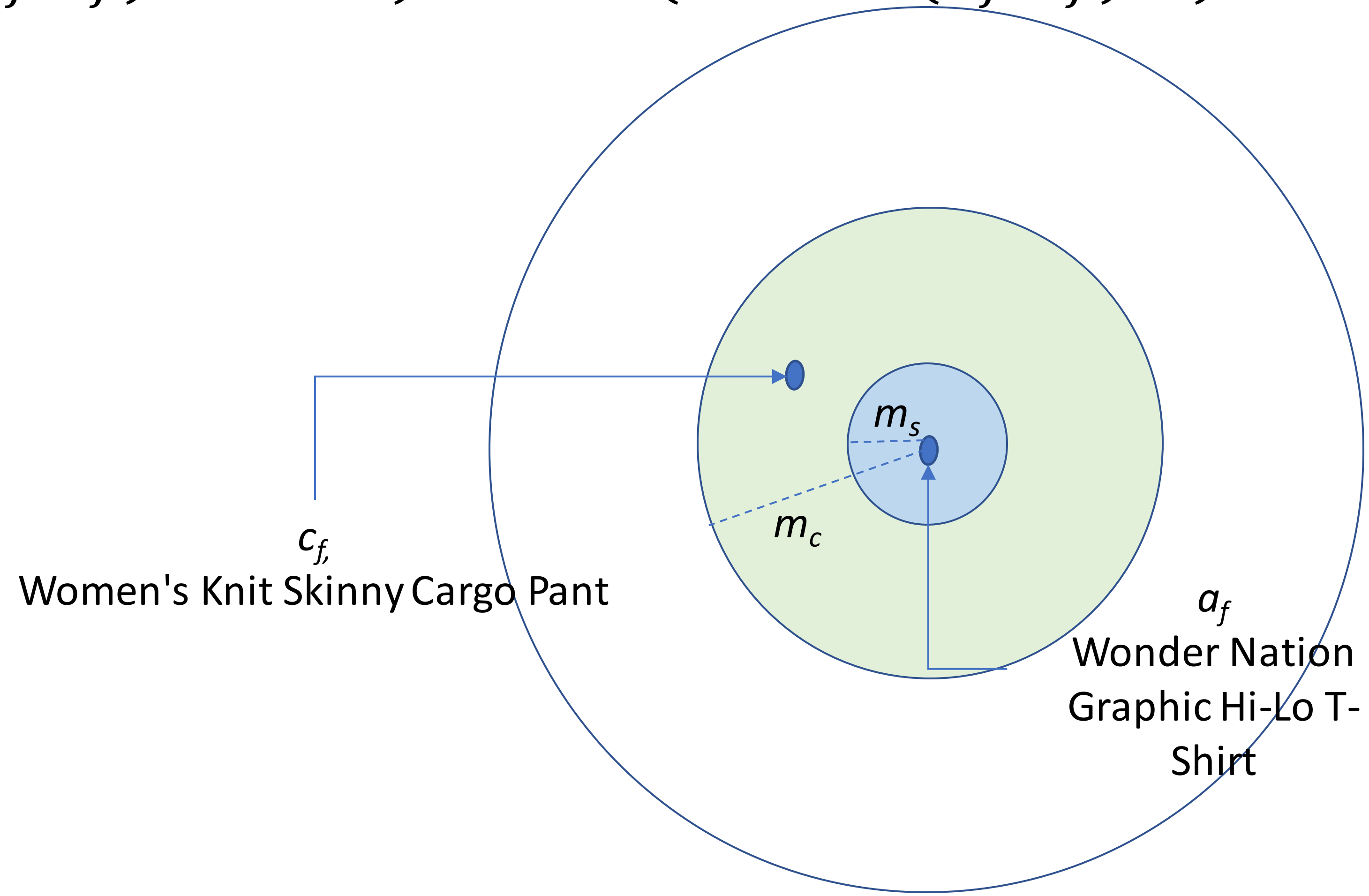
Similarity Loss

- $L_{sim} = \max(d(a_f' - s_f') - m_s, 0)$



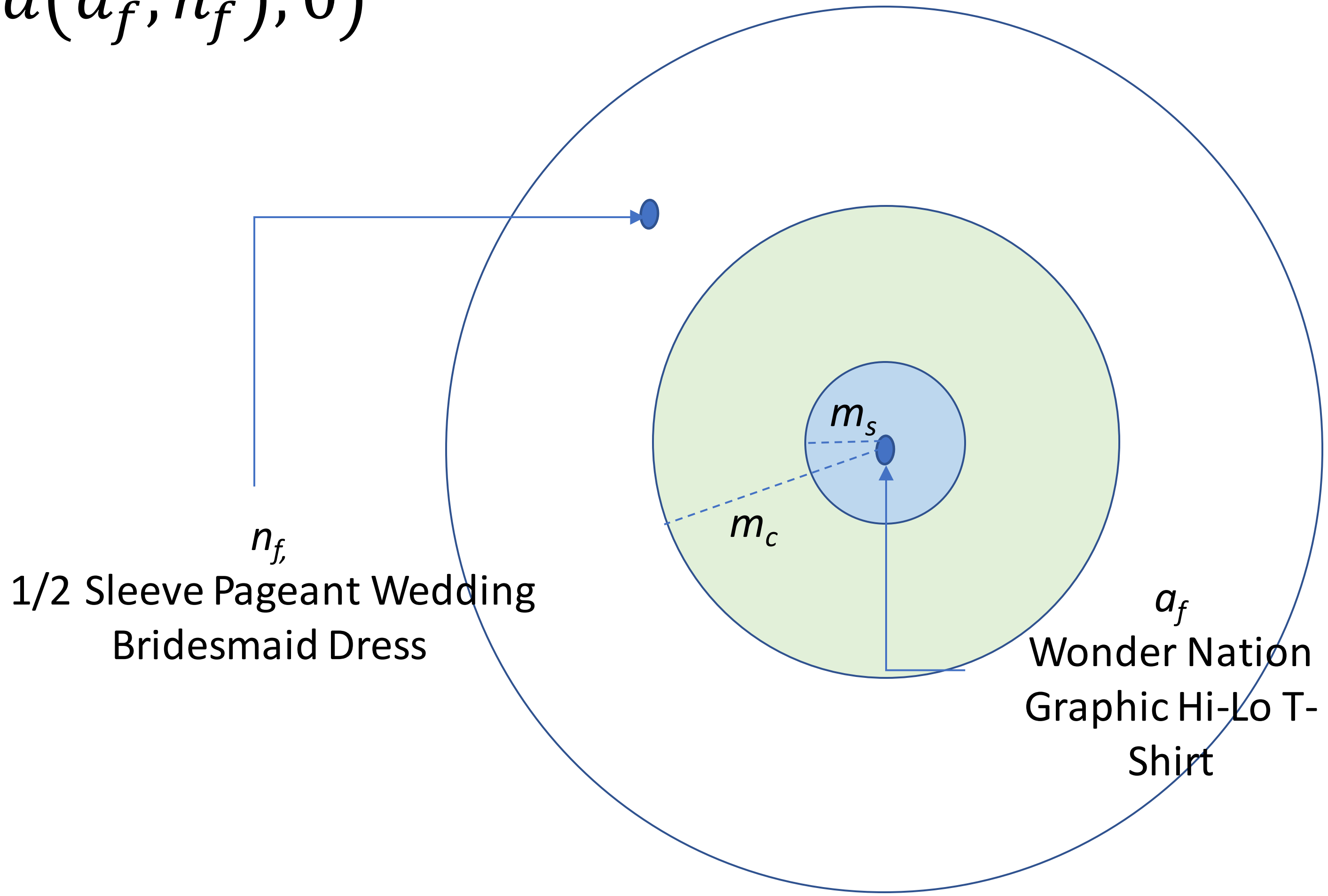
Complementary Loss

- $L_{comp} = \max\left(d\left(a_f', c_f'\right) - m_c, 0\right) + \max\left(m_s - d\left(a_f', c_f'\right), 0\right)$



Negative Loss

- $L_{neg} = \max(m_n - d(a_f', n_f'), 0)$



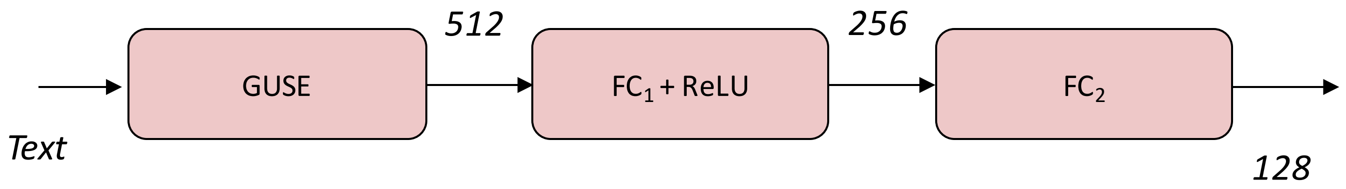
Quadruplet Loss

- $L_{sim} = \max(d\left(a_f' - s_f'\right) - m_s, 0)$
- $L_{comp} = \max\left(d\left(a_f', c_f'\right) - m_c, 0\right) + \max\left(m_s - d\left(a_f', c_f'\right), 0\right)$
- $L_{neg} = \max\left(m_n - d\left(a_f', n_f'\right), 0\right)$

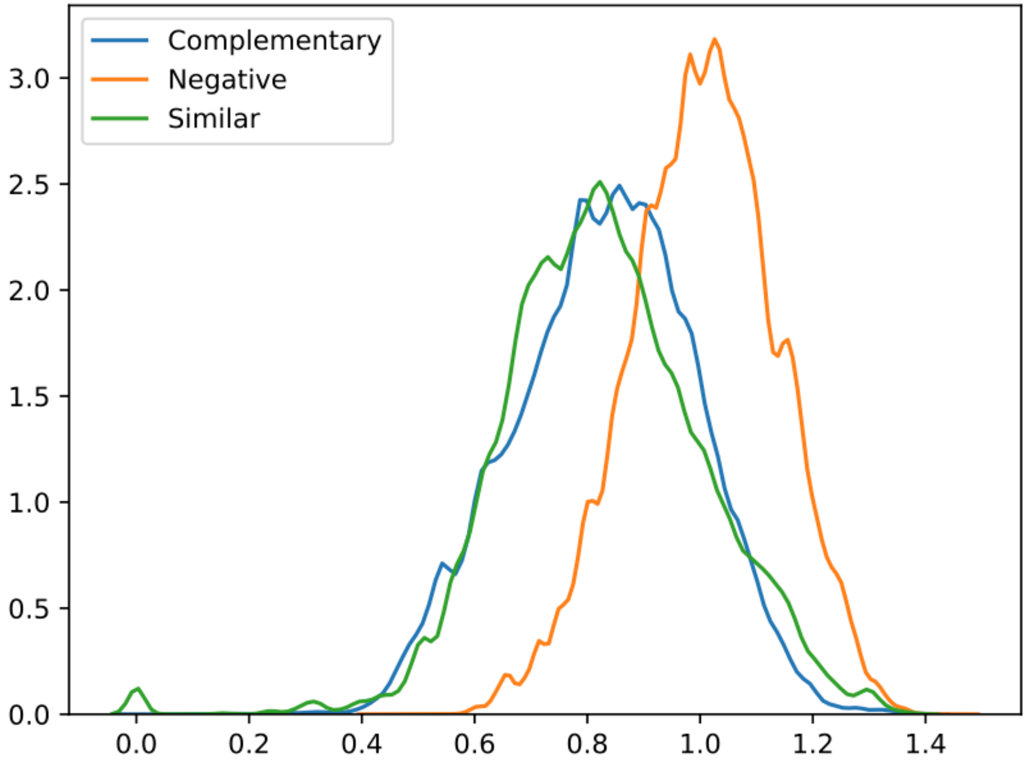
- $L_{quad} = L_{sim} + L_{comp} + L_{neg} + \lambda L_{l2}$

Hyperparameters

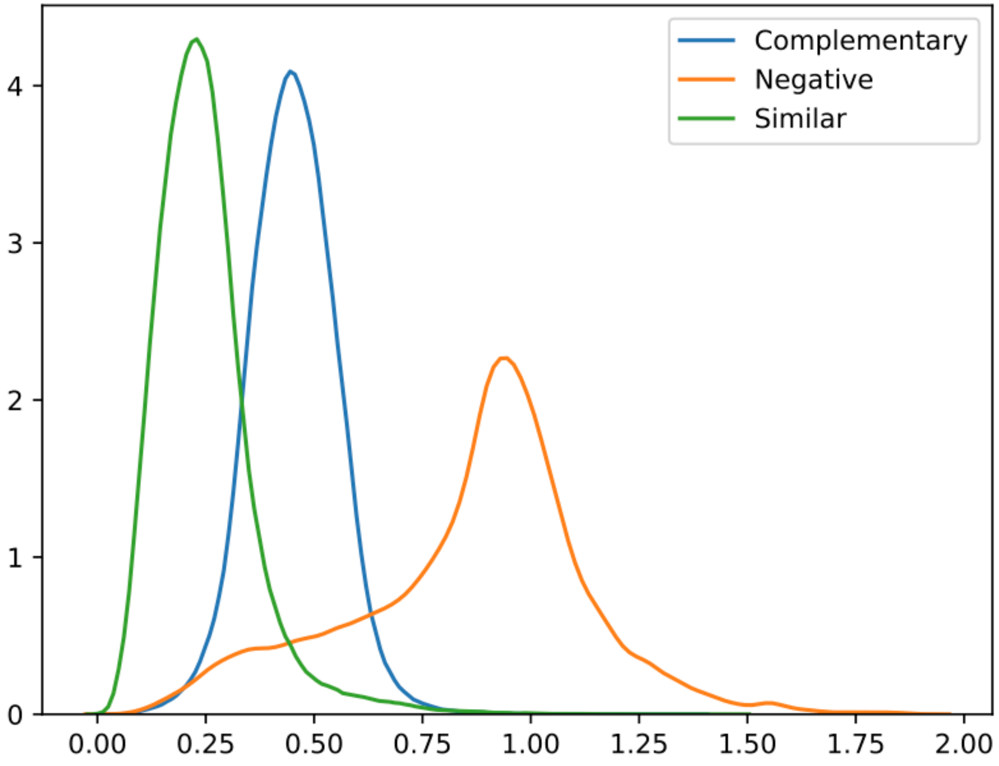
- Input feature dimension: 512
- Epochs: 50
- Weight Initialization: Xavier
- Learning rate: 0.001
- m_s : 0.1
- m_n: 0.4
- m_c :0.8
- Mapping function:



Experiments - Distance Distribution



Before Training



After Training

Experiments - Distance Distribution

	Similar		Complementary		Negative	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Train Data Before training	0.82119	0.17611	0.81975	0.15910	0.99804	0.13286
Test Data Before training	0.82752	0.17853	0.83086	0.15937	1.0037	0.12949
Train Data After training	0.24069	0.11226	0.45845	0.11485	0.86774	0.27724
Test Data After training	0.24772	0.11485	0.45181	0.09963	0.86023	0.27182

Experiments Accuracy

Method	Ranking Acc	Complementary Acc	Similarity Acc
Universal Sentence Encoder	37.68	-	-
Veit et al. [2]	14.92	91.05	56.45
Quadruplet Network	**67.15**	86.92	**68**

- Ranking accuracy is calculated as: $d_s < d_c < d_n$
- Complementary Accuracy: $margin_s < d_c < margin_c$
- Similarity Accuracy: $d_s < margin_s$

Inference (offline or RT)

- Use Approximate Nearest Neighbor (ANN) indices (FAISS, annoy, nmslib) to perform top-k embedding retrieval
- Divide all items into C disjoint groups (via taxonomy or clustering on embeddings)
- Create a set of ANN indices:
  - 1 global item index
  - 1 cluster centroid index
  - **C** separate cluster indices (of item embeddings associated with that cluster)

Inference (offline or RT)

- Given query item, obtain query embedding from quadruplet network
- Given a query embedding:
  - Top K similar items:
    - Nearest neighbor (NN) query on the item index
  - Top K complementary items:
    - Goal: Find K closest items whose distance is in range [$margin_c$, $margin_s$)
    - 1) NN query on the cluster index, consider the centroids in range
    - 2) For each in-range cluster, find the top K closest items. Merge the sets and retain the top K in range [$margin_c$, $margin_s$)

Future Work

- Modelling asymmetry between relationships
- Large scale experiments on the Amazon dataset (and others) with more evaluation metrics
- Clustering analysis on learnt embedding space

References

1. Cer, Daniel, et al. "Universal sentence encoder" *arXiv preprint arXiv:1803.11175* (2018).
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3. Veit, Andreas, et al. "Learning visual clothing style with heterogeneous dyadic co-occurrences" ICCV 2015.
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Thank You

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