Multimodal representation and learning

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Outline

- Motivation
- Cross modal retrieval - text and image
  - Semantic text encoding
- Cross modal verification - audio and image
  - Test protocols
- Future research directions

Motivation

- Deep learning has remarkably improved the state-of-the-art in speech recognition, visual object recognition, object detection, and text processing
- Majority of these techniques focused on unimodality
- Real-world scenario presents data in a multimodal fashion
  - We see objects, listen sounds, feel texture, smell odors, and taste flavor
- Therefore, it is important to perform multimodal learning to understand the web and the world around us

Multimodal Examples

(a) Useful accessory for those who ride a **bike**. Size 46-52.

(b) The First **Bike** Pink Arrow dedicated to little girls.

(c) Telescopic **ladder** to partial or total opening. Ideal for any external intervention.

(d) Custom multifunction dynamic construction **scaffolding**, simple for decoration.

- In the top row, an example of ambiguous text descriptions that can be disambiguated with the analysis of the accompanying images
- In the bottom row, an examples of ambiguous images that can be disambiguated with the analysis of the associated text descriptions

Ignazio Gallo, Alessandro Calefati, **Shah Nawaz**. “Multimodal Classification Fusion in Real-World Scenarios”. ICDAR 2017

Multimodal Examples

- An example of multimodal tweets. In this tweet, "**Rocky**" is the name of the dog

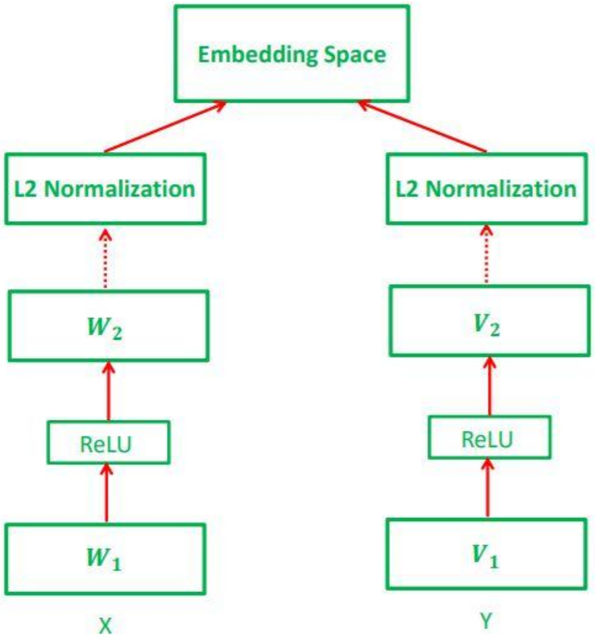
Representation - Feature Extraction

- Traditional representation or feature extraction
  - Histogram of oriented gradients
  - Scale-invariant feature transform
- Convolutional Neural Network
  - Produce state-of-the-art features

Multimodal Applications

- Numerous applications
  - **Cross-modal retrieval**
  - **Cross-modal verification**
  - **Classification**
  - Visual question answer
  - Semantic relatedness
  - Multimodal named entity recognition

Cross Modal Retrieval (Image-Text)

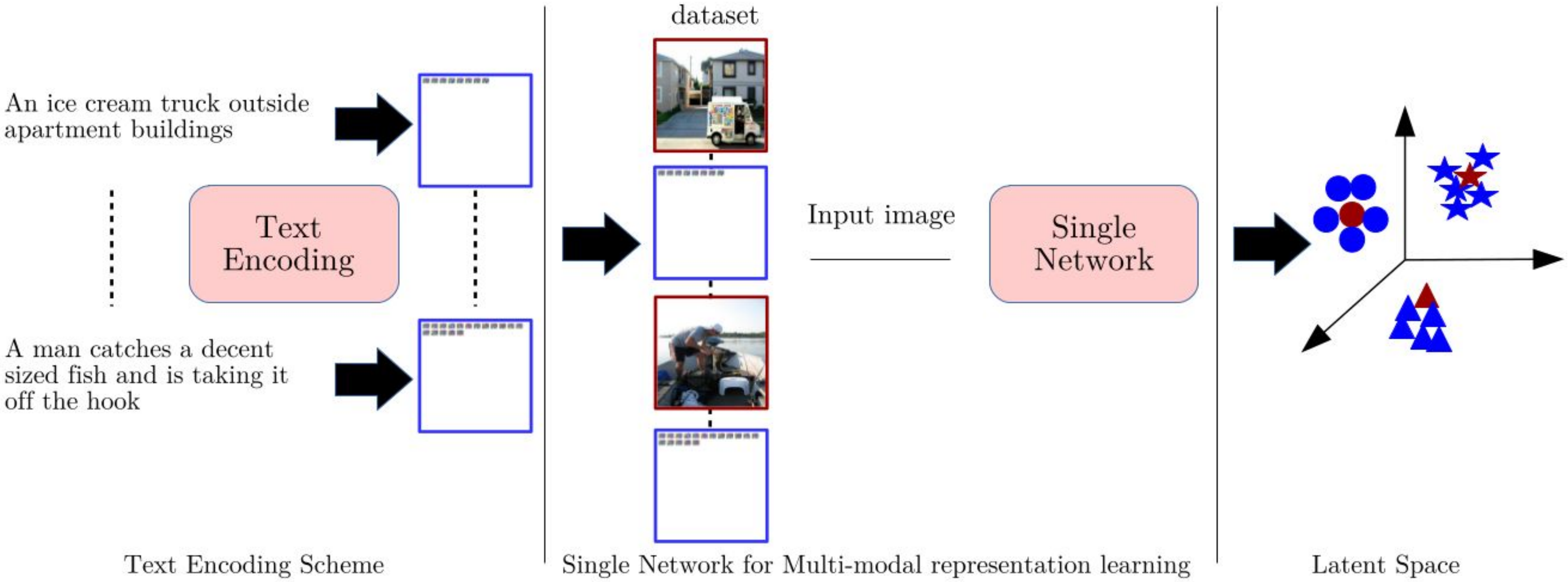


Two Branch Network

- Two modalities are often encoded separately
  - Image branch
  - Text branch
- A loss function minimizes the gap between image and text descriptions
- Evaluation on Recall-at-K(R@K)

Liwei Wang, Yin Li and Svetlana Lazebnik. “Learning Deep Structure-Preserving Image-Text Embeddings”. CVPR 2016

Cross Modal Retrieval (Image-Text)



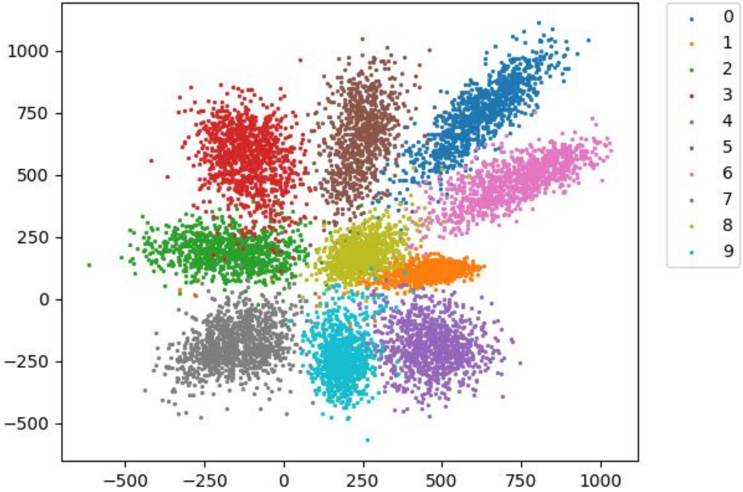
Shah Nawaz, Muhammad Kamran Janjua, Alessandro Calefati, Ignazio Gallo, Arif Mahmood and Faisal Shafait. "Do Cross Modal Systems Leverage Semantic Relationships?". **Submitted:** ACMM- 2019

Cross Modal Retrieval - Mod Center Loss

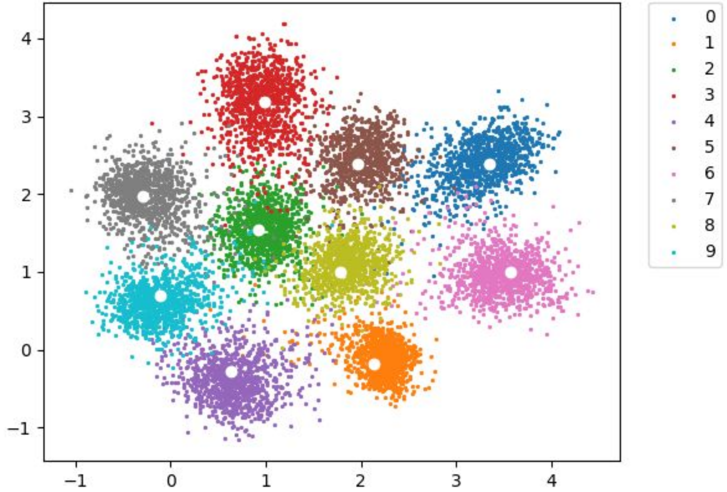
$$\mathcal{L}_S = -\sum_{i=1}^{m} \log \frac{e^{W_{y_i}^T \boldsymbol{x}_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_j^T \boldsymbol{x}_i + b_j}}$$

$$-\sum_{i=1}^{m} \log \frac{e^{W_{y_i}^T \boldsymbol{x}_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_j^T \boldsymbol{x}_i + b_j}} + \frac{\lambda}{2} \sum_{i=1}^{m} \|\boldsymbol{x}_i - \boldsymbol{c}_{y_i}\|_2^2$$

Softmax Loss



Softmax Loss + Center Loss



Cross Modal Retrieval (Image-Text)

	MSCOCO						Flickr30K					
Model	Image-to-Text			Text-to-Image			Image-to-Text			Text-to-Image		
	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
DVSA (2015)	38.4	69.9	80.5	27.4	60.2	74.8	–	–	–	–	–	–
HM-LSTM (2017)	43.9	-	87.8	36.1	-	86.7	–	–	–	–	–	–
m-RNN-vgg (2015)	41.0	73.0	83.5	29.0	42.2	77.0	35.4	63.8	73.7	22.8	50.7	63.1
Order-embedding (2015)	46.7	-	88.9	37.9	-	85.9	–	–	–	–	–	–
m-CNN(ensemble) (2015)	42.8	73.1	84.1	32.6	68.6	82.8	33.6	64.1	74.9	26.2	56.3	69.6
Str. Pres. (2016)	50.1	79.7	89.2	39.6	75.2	86.9	40.3	68.9	79.9	29.7	60.1	72.1
Two-Way (2017)	–	–	–	–	–	–	49.8	67.5	-	36.0	55.6	-
TextCNN (2016)	13.6	39.6	54.6	10.3	35.5	55.5	–	–	–	–	–	–
FV-HGLMM (2016)	14.3	40.5	55.8	12.7	39.0	57.2	–	–	–	–	–	–
Our Work (*cfg-std*)	13.2	30.4	41.9	12.2	33.0	46.7	10.5	26.2	36.8	8.2	22.82	32.0
Our Work (*cfg-2*)	13.0	32.9	46.0	12.94	36.62	49.94	21.2	40.7	50.4	19.36	38.12	47.34
Our Work (*cfg-3*)	32.9	58.5	70.2	26.22	56.7	69.96	–	–	–	–	–	–

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Cross Modal Retrieval (Image-Text)

- R@K inadanacy

Query Image	Retrieved Text	λ
	– A man riding a skateboard at a skatepark	0.82
	– A man riding a skateboard down a ramp	0.81
	– A person riding a skateboard at a skatepark	0.78
	– A skateboarder trying to get up a ramp	0.78
	– A man riding a skateboard over an obstacle	0.77

Query Text: A man is playing tennis on the tennis court.

0.82 0.75 0.69 0.68 0.64

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Cross Modal Retrieval (Image-Text)

- Similarity Index

$$\lambda(X_l, Y_m) = \frac{\sum_{i=1}^{n} x_i^l y_i^m}{\sqrt{\sum_{i=1}^{n} (x_i^l)^2} \sqrt{\sum_{i=1}^{n} (y_i^m)^2}}; \forall X_l, Y_m$$

$X_l = (x_1^l, x_2^l, x_3^l, ..., x_n^l) \in \mathcal{R}^n$ belonging to l^{th} class of images

$Y_m = (y_1^m, y_2^m, y_3^m, ..., y_n^m) \in \mathcal{R}^n$ belonging to m^{th} class of text descriptions

- Semantic Map

$$\lambda@K = \frac{1}{N \cdot K} \sum_{l=1}^{c} \sum_{m=1}^{K} \lambda(X_l, Y_m)$$

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Cross Modal Retrieval (Image-Text)

	MSCOCO						Flickr30K					
Model	Image-to-Text			Text-to-Image			Image-to-Text			Text-to-Image		
	$\lambda@1$	$\lambda@5$	$\lambda@10$	$\lambda@1$	$\lambda@5$	$\lambda@10$	$\lambda@1$	$\lambda@5$	$\lambda@10$	$\lambda@1$	$\lambda@5$	$\lambda@10$
Str. Pres.	67.24	64.63	62.74	64.07	59.29	56.30	62.30	59.59	57.79	59.05	54.60	51.97
Our Work	68.67	65.25	62.86	66.70	59.42	54.45	49.13	45.52	43.33	43.97	39.22	36.43

Model	Image-to-Text			Text-to-Image		
	$\lambda@1$	$\lambda@5$	$\lambda@10$	$\lambda@1$	$\lambda@5$	$\lambda@10$
Str. Pres.	60.68	58.16	56.54	57.53	53.66	51.28
Our Work	**67.57**	**64.17**	**61.81**	**65.42**	**58.36**	**53.55**

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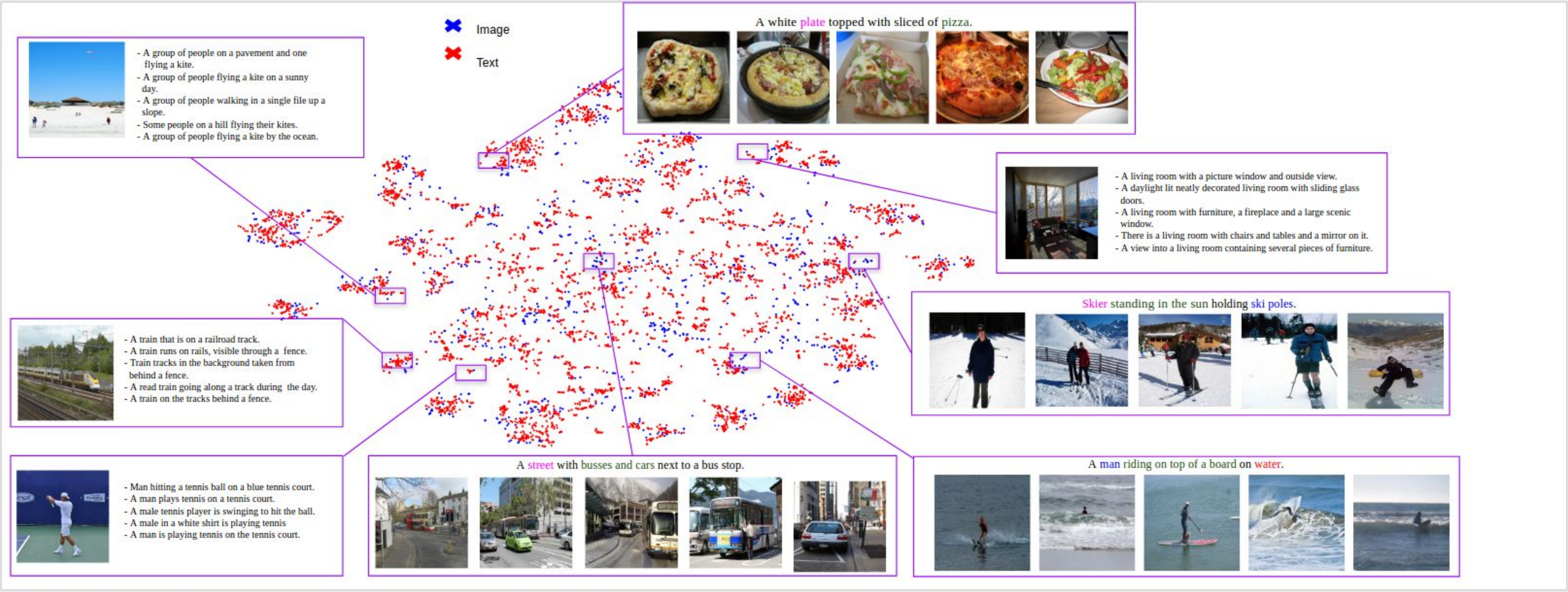
Cross Modal Retrieval (Image-Text)



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Semantically Reasonable Results

Human Experts	Image-to-Sentence
Expert # 1	85.40
Expert # 2	85.00
Expert # 3	83.40
$R@K$	84.6

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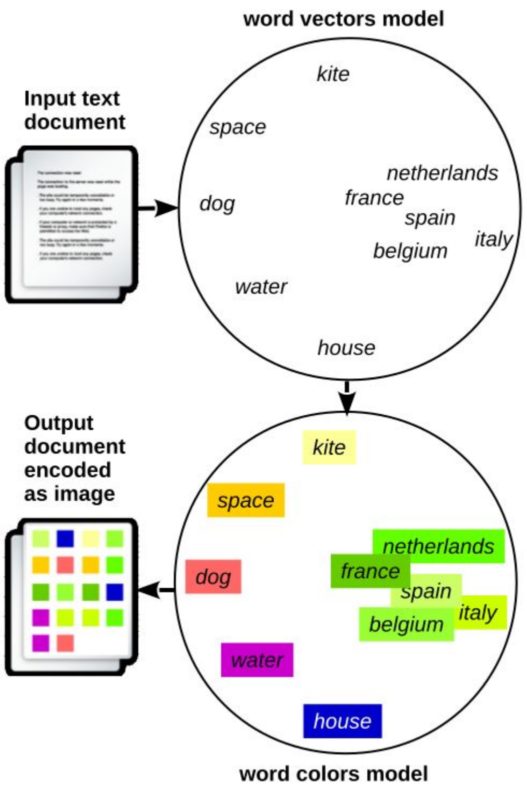
Semantic Text Encoding

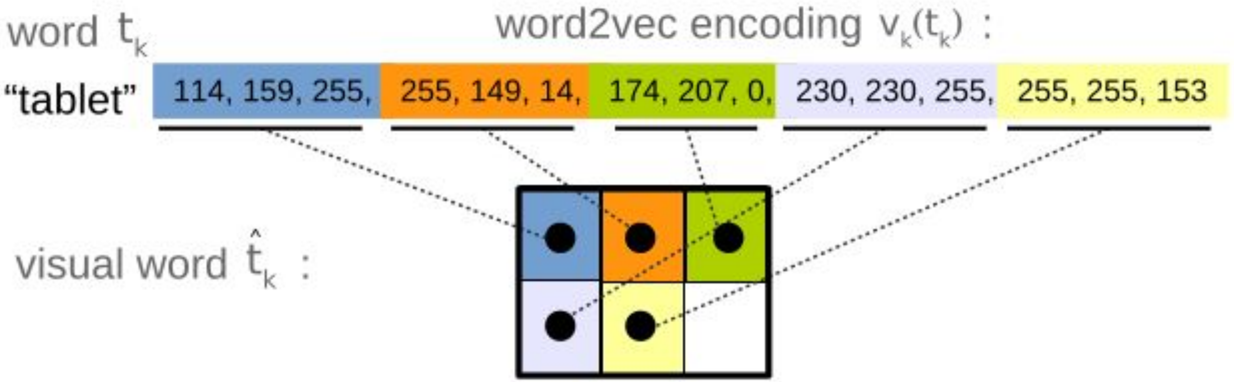
- ❑ Transform text embedding into an encoded image
- ❑ Based on **Word2Vec word embedding**
- ❑ Words that occur in **similar contexts** have **similar word embeddings**
- ❑ Intuitively, **similar words** will have **similar color encodings**



Ignazio Gallo, **Shah Nawaz**, Alessandro Calefati. "Semantic Text Encoding for Text Classification using Convolutional Neural Networks". ICDAR 2017.
Shah Nawaz, Alessandro Calefati, Muhammad Kamran Janjua, Ignazio Gallo. "Visual Word Embedding for Text Classification". **Submitted:** MVA 2019.

Semantic Text Encoding

- Toy example



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Semantic Text Encoding

- Comparison with state-of-the-art text classification methods

Model	AG	Sogou	DBP.	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. P.
Xiao *et al.*	8.64	4.83	1.43	5.51	38.18	28.26	40.77	5.87
Zhang *et al.*	**7.64**	**2.81**	1.31	4.36	37.95	28.80	40.43	4.93
Conneau *et al.*	8.67	3.18	1.29	**4.28**	**35.28**	26.57	**37.00**	4.28
Encoding scheme + AlexNet	9.19	8.02	1.36	11.55	49.00	25.00	43.75	3.12
Encoding scheme + GoogleNet	7.98	6.12	**1.07**	9.55	43.55	**24.10**	40.35	**3.01**

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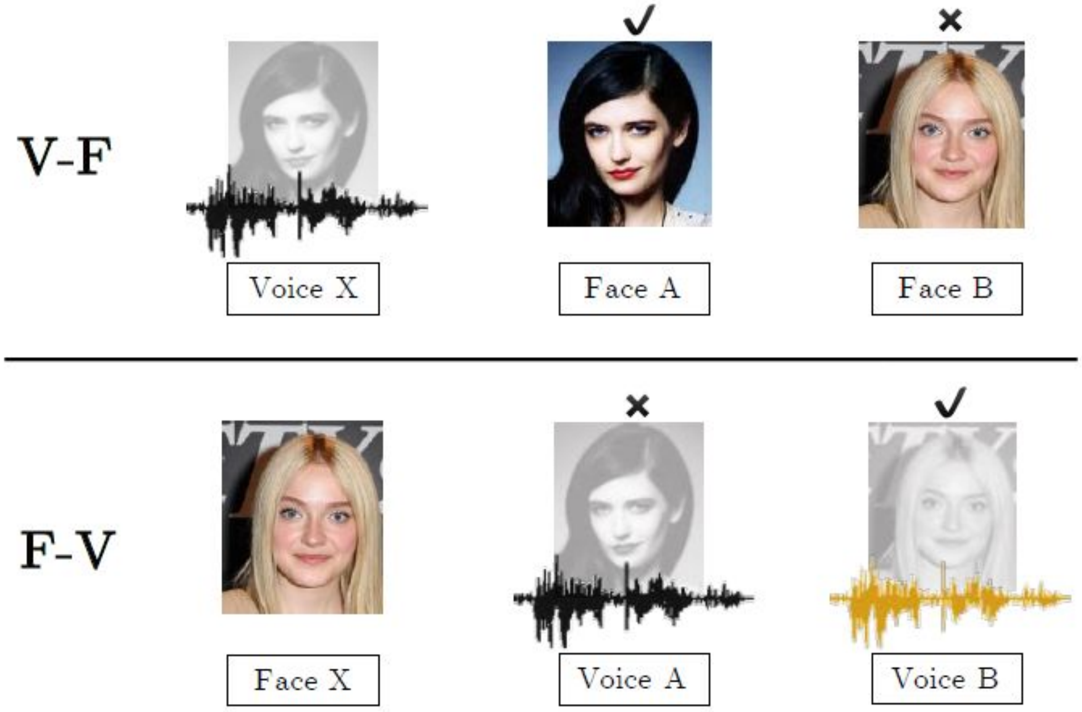
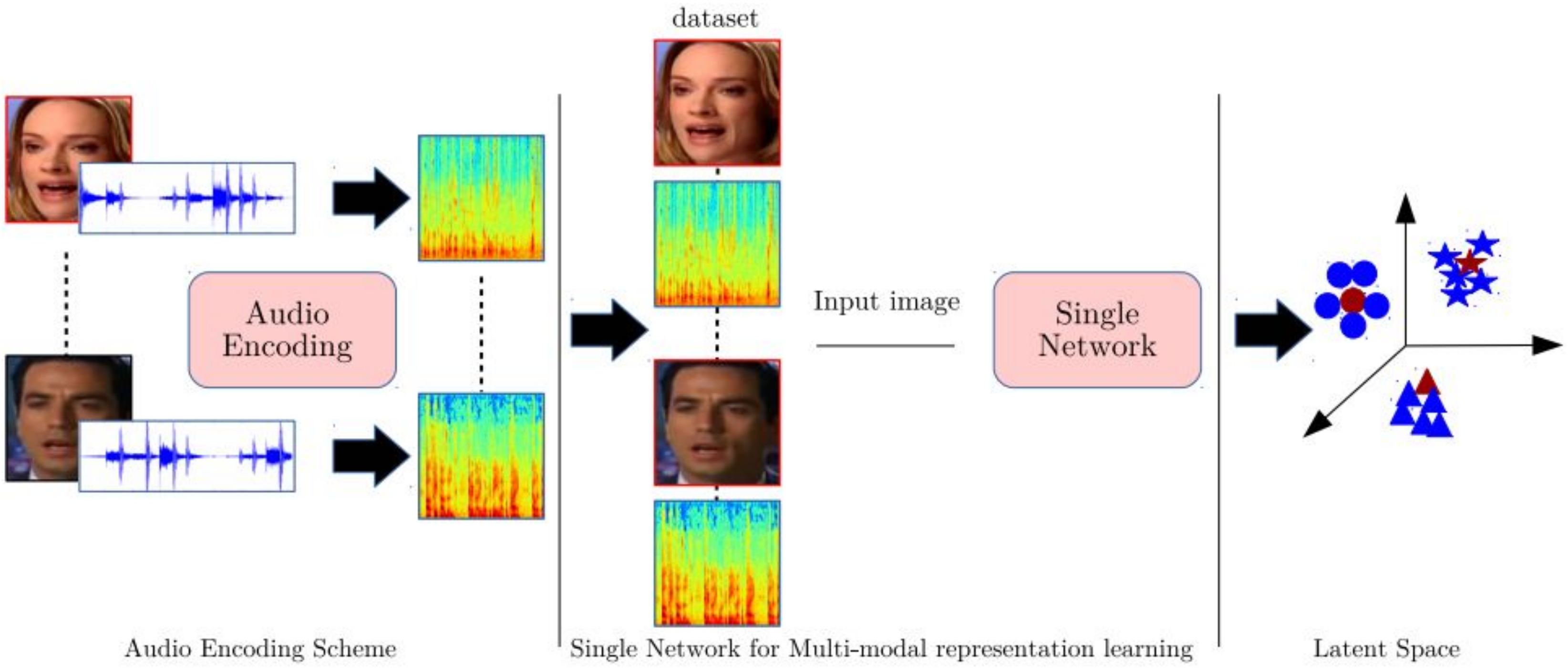
Shah Nawaz, Alessandro Calefati, Muhammad Kamran Janjua, Ignazio Gallo. “Visual Word Embedding for Text Classification”. **Submitted:** MVA 2019.

Cross Modal (Audio - Image)



Arsha Nagrani, Samuel Albanie, Andrew Zisserman. “Seeing Voices and Hearing Faces: Cross-modal biometric matching”. CVPR 2018.

Cross Modal (Audio - Image)



Shah Nawaz, Muhammad Kamran Janjua, Ignazio Gallo, Arif Mahmood and Alessandro Calefati, "Deep Latent Space for Cross Modal Mappings of Audio and Visual Signals". **Submitted:** BMVC 2019.

Cross Modal (Audio - Image)

- Two test protocols
  - Seen - Heard
  - Unseen - Unheard
- Verification
  - Gender, Age and Nationality
- Force Matching

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Cross Modal (Audio - Image)

- Cross Modal Verification

	AUC %	EER %
	Seen-Heard	
Learnable Pins	73.8	34.1
SSNet	**89.2**	**19.0**
	Un-seen-Un-heard	
Learnable Pins	63.5	39.2
SSNet	**71.8**	**34.2**

Shah Nawaz, Muhammad Kamran Janjua, Ignazio Gallo, Arif Mahmood and Alessandro Calefati, "Deep Latent Space for Cross Modal Mappings of Audio and Visual Signals". **Submitted:** BMVC 2019.

Cross Modal (Audio - Image)

- Demographic Criteria - Gender, Age, Nationality

Demographic Criteria	Random	G	N	A	GNA
	Seen-Heard (AUC %)				
Learnable Pins-[Scratch]	73.8	-	-	-	-
Learnable Pin-[Pre-train]	87.0	74.2	85.9	86.6	74.0
SSNet-[Scratch]	**89.2**	**82.7**	**88.6**	**89.2**	**82.4**
	Unseen-Unheard (AUC %)				
Learnable Pins-[Scratch]	63.5	-	-	-	-
Learnable Pins-[Pre-train]	**78.5**	61.1	**77.2**	**74.9**	**58.8**
SSNet-[Scratch]	71.8	**61.9**	51.9	69.5	52.1

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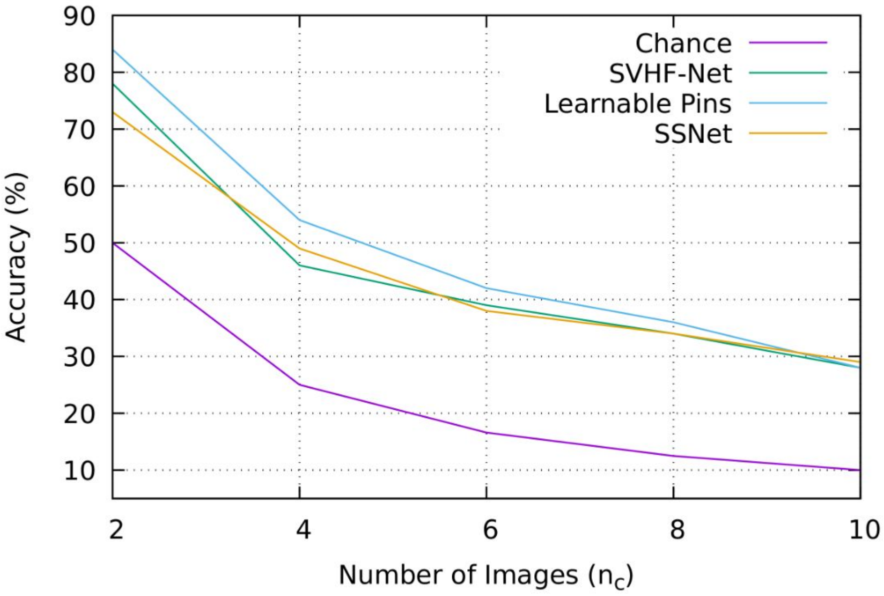
Cross Modal (Audio - Image)

- Force matching



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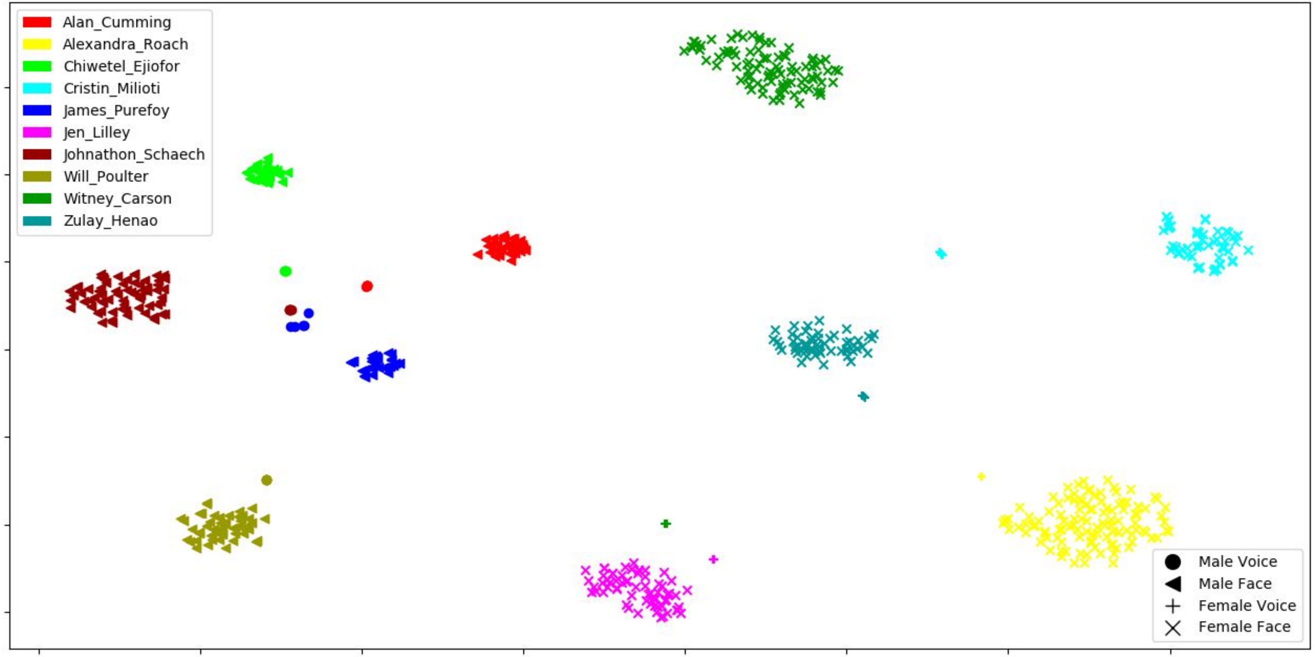
Cross Modal (Audio - Image)

- T-sne Visualization - Seen - Heard



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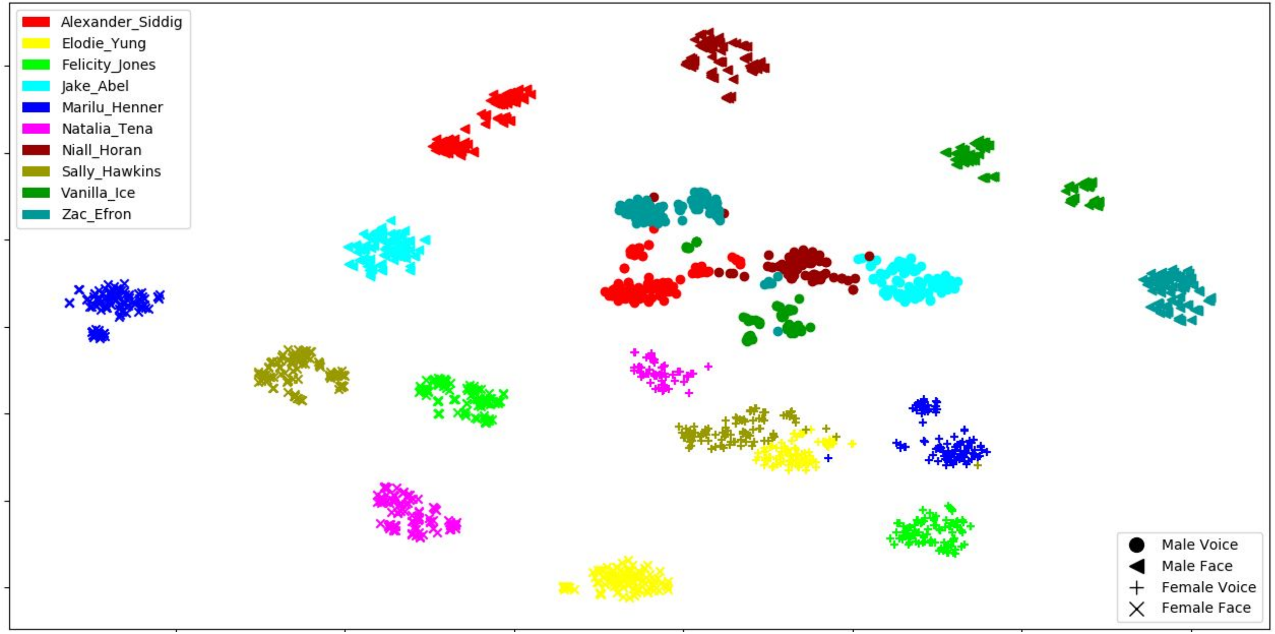
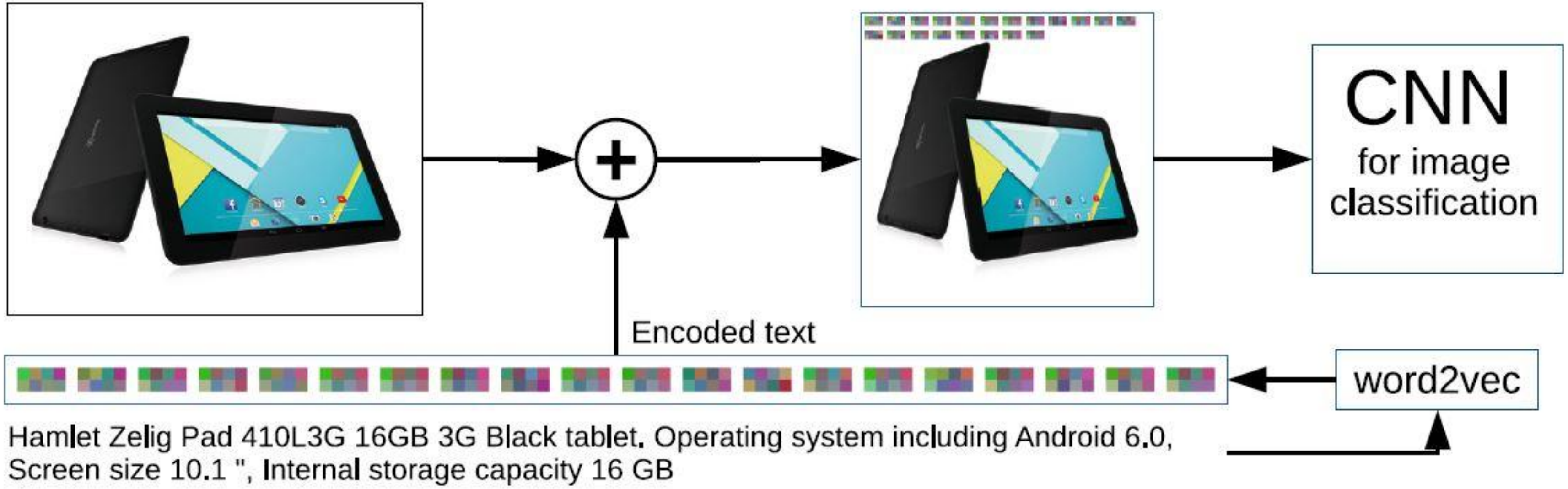
Cross Modal (Audio - Image)

❑ T-sne Visualization - Unseen - Unheard



Shah Nawaz, Muhammad Kamran Janjua, Ignazio Gallo, Arif Mahmood and Alessandro Calefati, "Deep Latent Space for Cross Modal Mappings of Audio and Visual Signals". **Submitted:** BMVC 2019.

Fused Representation for Classification



Shah Nawaz, Alessandro Calefati, Muhammad Kamran Janjua, Muhammad Umer An-waar, Ignazio Gallo. Learning Fused Representations for Large Scale Multimodal Classification. Accepted: IEEE Sensors Letters 2018.

Fused Representation for Classification

Image | Encoded Text | Fused representation

- ❑ Image only - 77.42% **Baby**, 11.16% **Home and Kitchen**, ...
- ❑ Fused representation - 100 **Baby**

Shah Nawaz, Alessandro Calefati, Muhammad Kamran Janjua, Muhammad Umer An-waar, Ignazio Gallo. Learning Fused Representations for Large Scale Multimodal Classification. Accepted: IEEE Sensors Letters 2018.

Fused Representation for Classification

	Model	Ferramenta	UPMC Food-101	Amazon Product Data
	Wang et al	–	85.10	–
Previous work	Kiela et al	–	**90.8±0.1**	–
	Gallo et al	94.42	60.63	–
Baseline	Image	92.47	55.65	51.42
	Text	84.50	56.75	64.37
Ours	Proposed	**95.87**	85.69	**78.26**

Shah Nawaz, Alessandro Calefati, Muhammad Kamran Janjua, Muhammad Umer An-waar, Ignazio Gallo. Learning Fused Representations for Large Scale Multimodal Classification. Accepted: IEEE Sensors Letters 2018.

Current Research Directions

- Multimodal Named Entity Recognition

My daughter got 1 place in [Apple valley **LOC**] Tags gymnastics

[Apple **ORG**] 's latest [iOS **OTHERS**] update is bad for advertisers

Questions

Multimodal Representation

- ❑ Unimodal representation
  - ❑ Images, text, audio etc.
- ❑ Joint representation
- ❑ Challenges
  - ❑ Different representation of each modality
  - ❑ Different correlation structure
- ❑ State-of-the-art representation