Multimodal Deep Learning
lenify multimodal signals into a single vector
space and thereby enable cross-modulity
Signal processing."
rapresentation learning
lo .
Multimodel Vepresentation
Visual Representation: image embeddings
Larguage Representation: Text embeddings
Vector arithmetic
for word and image word embeddings embeddings
This was a second of the secon
Syntactic / semantic vastilais Line

4. Speak Representation: 2-Vector approach Multimodal Representation: joint embeddings to beverage the complementarity of multimodal data to represent such concepts more accurately D Unsupervised Training Methods: deep Boltzmann machines auto encoders deep multimodal similarity model (DMSM) / generate fine-grained multimodal embeddings deep attentional nultimodal sinilarity

Model (DAMSM) I measure the similarity between image

Sub-regions and words as an additional boss function for text - to-image generation" 2) Supervised Training Methods. improve the learning of multimodal representation Discriminative Intra-modality generative factors (Supervised training) (Unsupervised training) 3) Methods for zero-shot Learning "Cartain representations may require pairwise data from different modalities

Simultaneously."
4 Transformer-based Methods:
Fusion of Multimodal Signals
integrate information extrated from different
Unimodal dorta sources into a single
compact multimodal representation"
D Simple Operation - based Fusion
3) Attention—based Fusion
3) Bilinear Pooling - based Fusion
(Factoritation for Bilinear Pouling Bilinear Pouling and Attention Mechanisms

Applications		
Image Captioning		
Text-to-Image Generation		
D GAN-based Methods		
2 Generating High-quality Generating Serentically Consis	inajes	
Geneveting Serantically Consig	tent	mage
Squartic legat control for co.	mplex	Scen
Visual Question Answering		
Visual Recsoning		