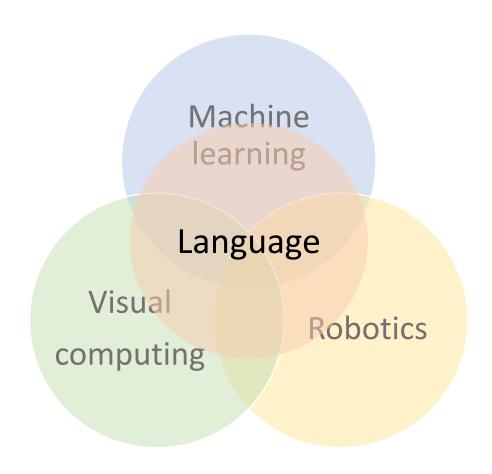
CMPT 983

Grounded Natural Language Understanding

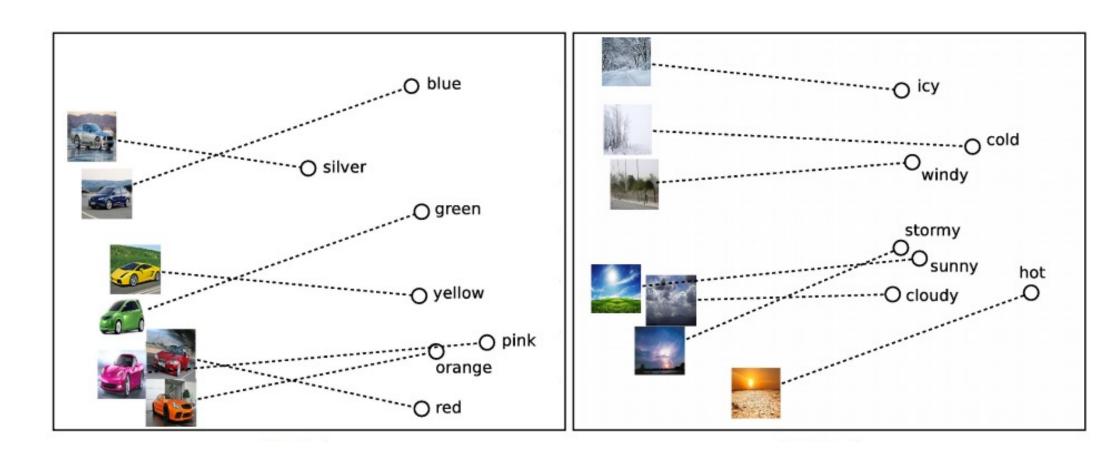
April 15, 2021 Conclusion

Grounded natural language understanding

• Lightening tour of topics at the intersection of language and machine learning, visual computing and robotics



Multimodal Embeddings

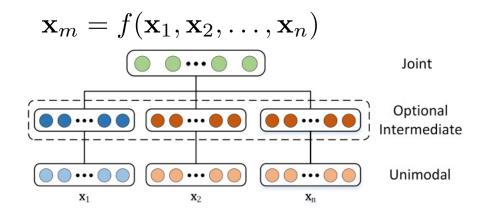


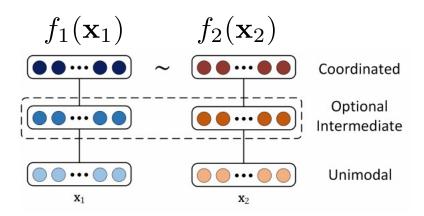
"Unifying Visual-Semantic Embeddings with Multimodal Neural Language Models" [Kiros, Salakhutdinov, Zemel TACL 2015]

Multimodal representations

- Joint vs Coordinated representations
 - Joint: Autoencoder + Fusion (e.g. concat)
 - Coordinated: CCA, joint embeddings

$$\mathcal{L}_C(\mathbf{W}, \mathbf{U}, I_i, y_i) = \sum \max\{0, \alpha - D(\Psi(I_i), \mathbf{u}_{y_i}) + D(\Psi(I_i), \mathbf{u}_{y_c})\}$$





• Useful for retrieval, translation

Attention

Not every part of the input given the task context

Exit the bathroom. Turn left and exit the room using the door on the left. Wait there.



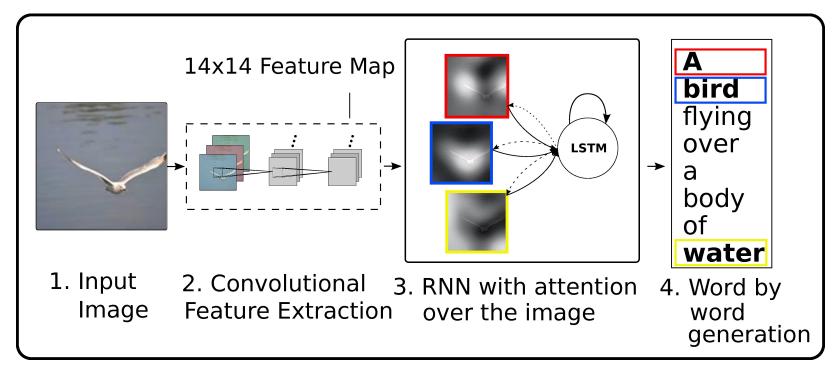




Slide credit: Stefan Lee

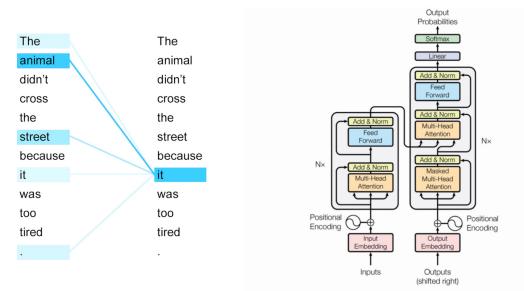
Attention

- Used for many vision and language tasks
- Including captioning and understanding referring expressions
- Representation that weighs different parts of the input differently



Attention

- Mathematically: weighted sum $\hat{\boldsymbol{v}} = \sum_{i=1}^k \alpha_i \, \boldsymbol{v_i}$
- Types of attention
 - Different ways to compute weight / similarity
 - Hard vs Soft
- Query-key-value view of attention
- Self-attention and transformers



Attention function,
$$f$$

$$a_i = g(\mathbf{k}_i, \mathbf{q})$$

$$\alpha = \operatorname{softmax}(\mathbf{a})$$

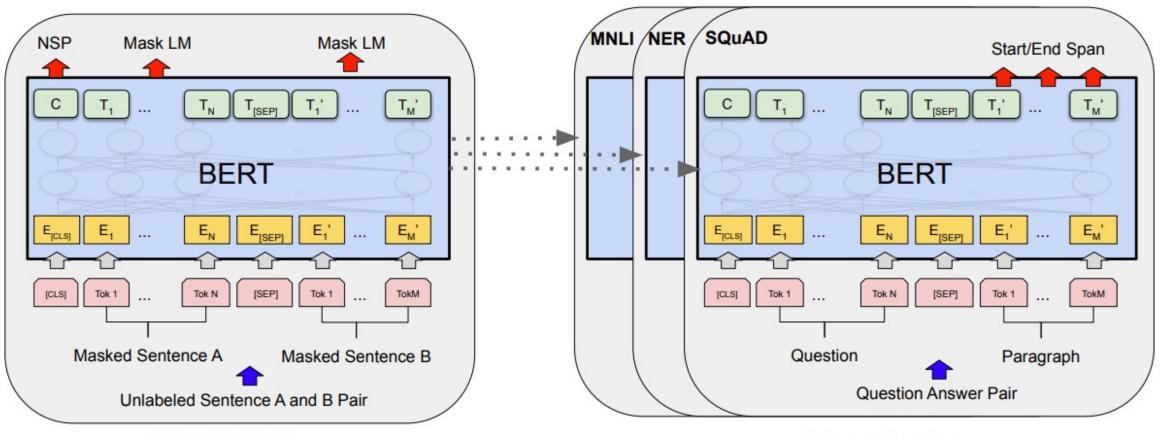
$$\hat{\mathbf{c}} = \sum_{i=1}^k \alpha_i \ \mathbf{v}_i$$

Scaled dot-product attention:

$$g(\mathbf{c}_i, z) = z^{\top} \mathbf{c}_i / \sqrt{d}$$

Pretraining

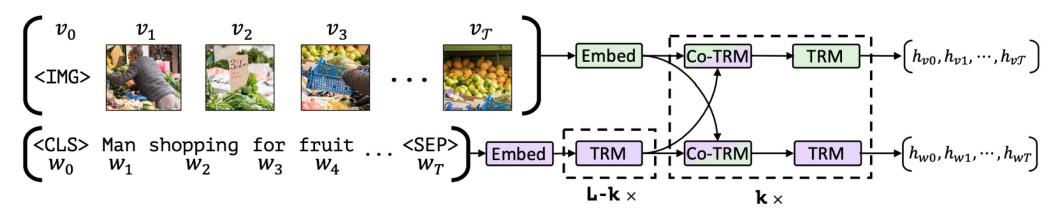
Big pile of unannotated data! Lots of resources to train! Task specific
Small amount of annotated data
Start with pre-trained model



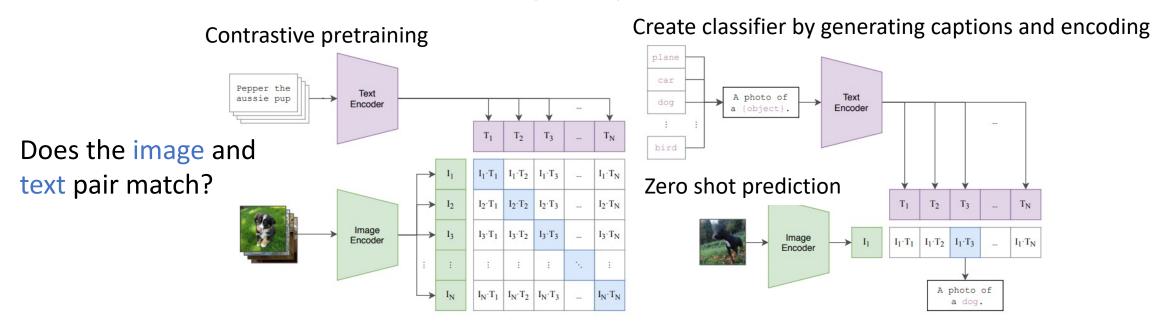
Pre-training

Fine-Tuning

Pretraining and masked multimodal models



VilBERT, Lu et al, NeurIPS 2019

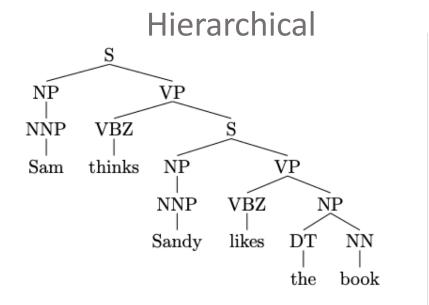


CLIP, Radford et al, 2021

Structure and compositionality

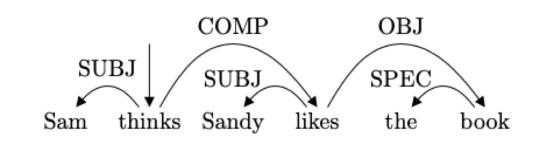
Structured representations for compositionality

Constituency Parse Tree



Dependency Parse

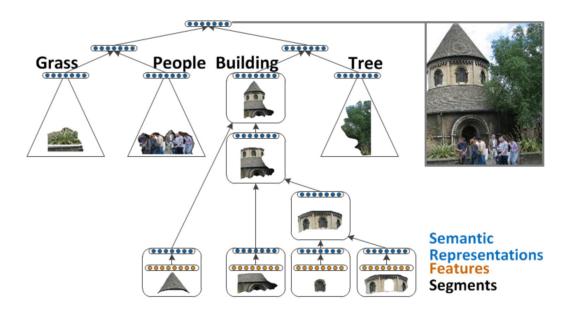
Relational



Structured representation of images

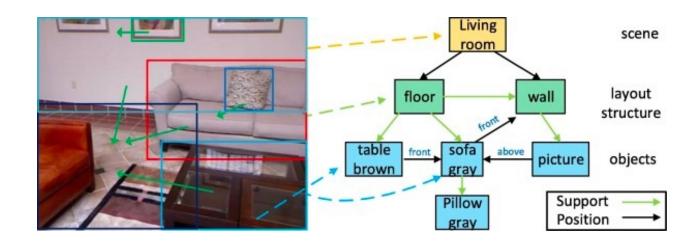
Scene Parse Tree

Hierarchical



Scene Graph

Relational



Socher, Lin, Ng, and Manning, "Parsing Natural Scenes and Natural Language with Recursive Neural Networks", ICML 2011

Yang, Liao, Ackermann, and Rosenhahn, "On support relations and semantic scene graphs", ISPRS Journal of Photogrammetry and Remote Sensing, 2017

Semantic parsing

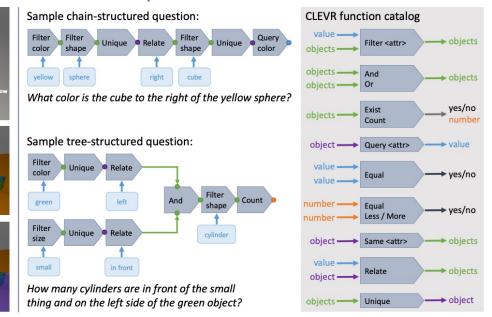
- Parse natural language into programs
- Use in VQA

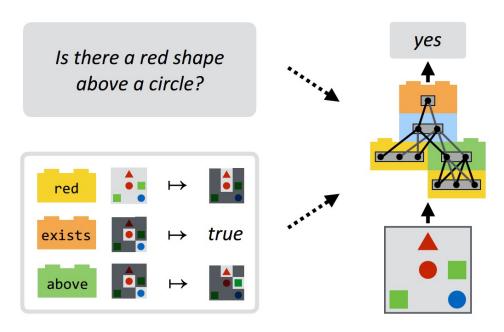
Shape and attributes

Left vs. right

In front vs. behind

Programs: formed from composable modules





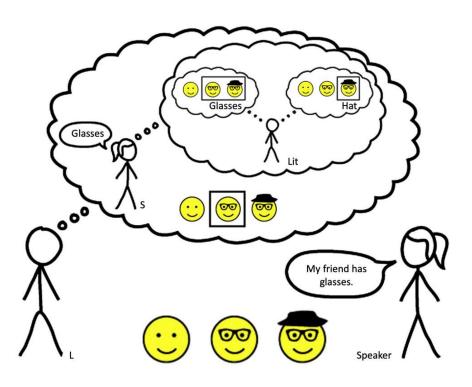
Relations

Generated language

Neural module networks, Andreas et al, CVPR 2016

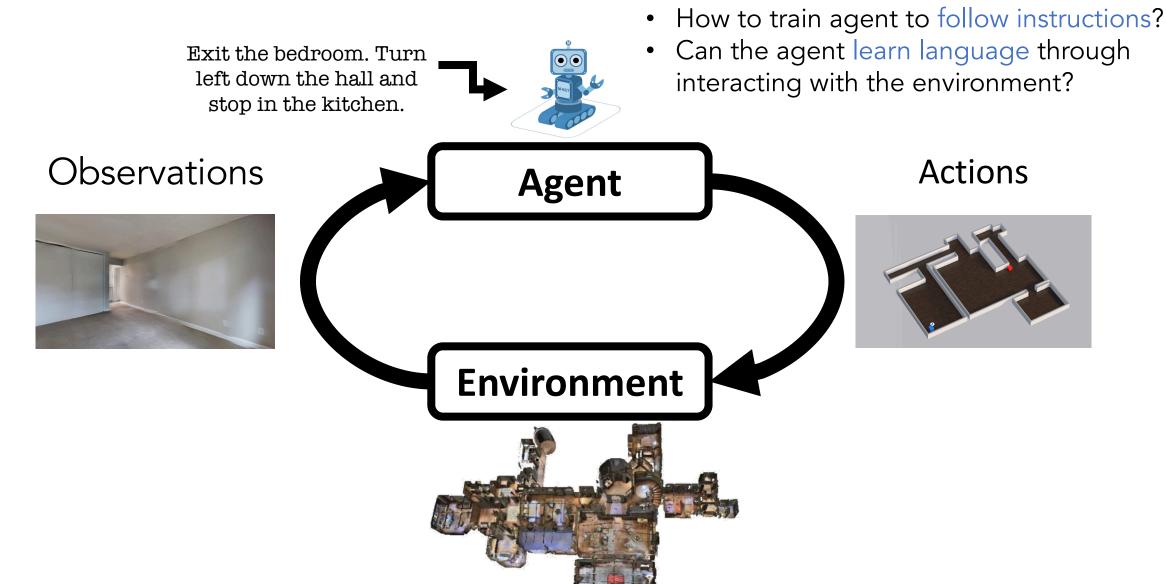
Speaker-listener models

- Need to model other party
- Rational Speech Acts (RSA)
- Used in referring expression generation + comprehension
- Looked at ShapeGlot and emergent communications



Goodman and Frank, 2016

Instruction following



Instruction following (RoboNLP)

- Quick review of imitation learning and reinforcement learning
- Visual language navigation
- Instruction following with manipulation and interaction



ALFRED, Shridhar et al, CVPR 2020

- Lots of challenges:
 - Data, task specification, accurate simulation

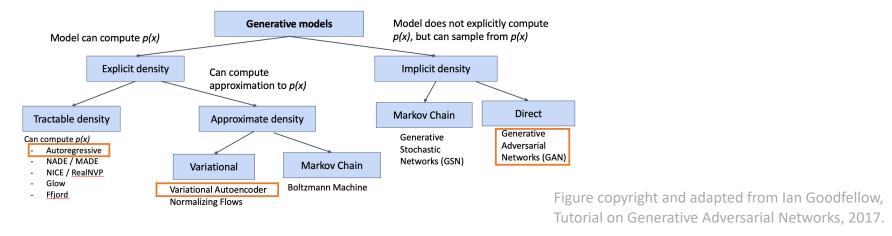
Interactive language learning

- Language learning with feedback
 - Human or the environment
- Model weights are adjusted based on feedback



Text conditioned content generation

Review of generative models



- Examples of text-to-image generation with
 - GANs (GAN+CLS+INT, StackGAN++)
 - VAE+Autoregressive (DALL-E like VQ-VAE but text conditioned)
- Text to 3D is underexplored

Thank you!

