# Understanding Visual Scences

## Dependency Graphs, Word Senses, and Multimodal Embeddings

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# Structure in Multimodal Processing

Lots of recent in work on multimodal processing:

- image description generation;
- visual question answering;
- multimodal machine translation;
- video summarization.

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Who does what to whom?

Understanding requires structure, not just an unordered set of labels:

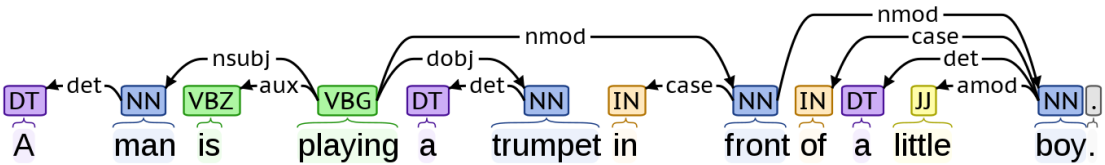
- linguistic structure;
- image structure.

# Structure in Multimodal Processing

A man is playing a trumpet in front of a little boy.

# Linguistic Structure

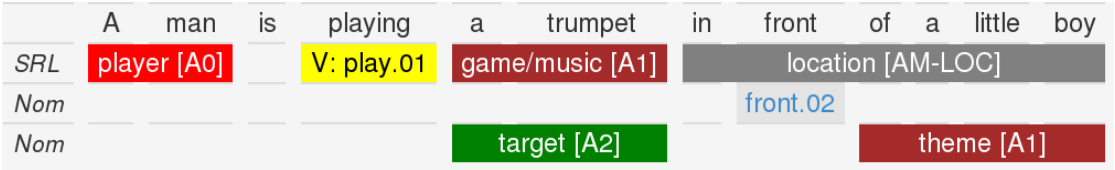
Output of dependency parser (with PoS labels):




http://nlp.stanford.edu:8080/corenlp/process

# Linguistic Structure

Output of a semantic role labeler (with word senses):




http://cogcomp.cs.illinois.edu/page/demo_view/srl

# Structure in Multimodal Processing

Linguistic structure:

- discrete base units (words), ordered in 1D;
- span-based labels (e.g., PoS, phrases);
- tree-based hierarchies;
- clear distinction between syntax and semantics;
- canonical representations defined by linguistic theory.

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Now let's compare this to image structure.

# Image Structure

Output of an image labeler:

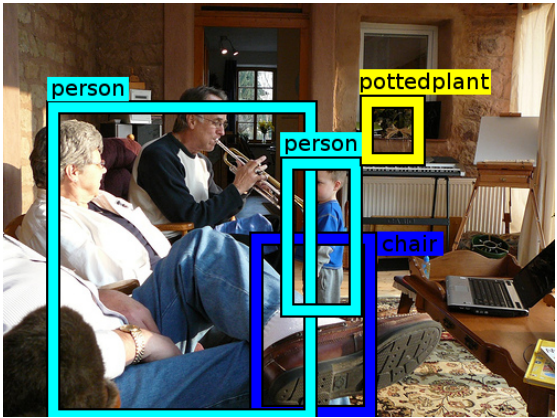
people
man
furniture
room
adult
group
child
indoors
woman
seat
family
music
education
sit

https://www.clarifai.com/demo

We could also label: attributes, scene type, colors, textures, etc.

# Image Structure

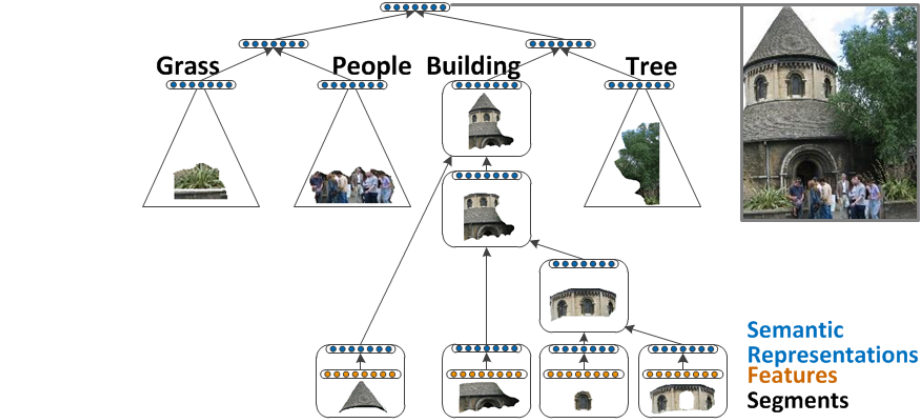
Output of an object recognizer:




Output of FastRCNN model with AlexNet architecture trained on PASCAL VOC 2007.

# Image Structure

Hierarchical segmentation (indicates part-whole relationships):




http://www.socher.org/index.php/Main/ParsingNaturalScenesAndNaturalLanguageWithRecursiveNeuralNetworks

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Image structure:

- continuous base units (pixels), ordered in 2D;
- region-based labels (e.g., objects, attributes);
- part–whole structure;
- no clear distinction between syntax and semantics;
- no “correct” canonical representations.

# Representational Divergence

Representational divergence: for multimodal processing, we need to fuse linguistic and image structures, but they are very different.

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Hypothesis: We need to align visual representations.

Two examples in this talk:

- visual dependency representations;
- visual sense disambiguation.

# Spatial Relations

We need a grammar that defines the relations between the objects in an image: Visual Dependency Grammar (Elliott & Keller 2013).

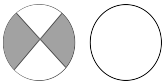
It assumes eight relations that can hold between pairs of objects, based on three geometric properties:

- pixel overlap;
- angle between objects;
- distance between objects.

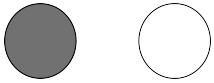
# Spatial Relations

X *on* Y

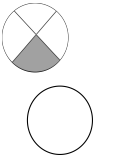
X *surrounds* Y



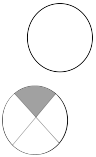
X *beside* Y



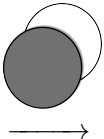
X *opposite* Y



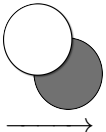
X *above* Y



X *below* Y



X *infront* Y



X *behind* Y

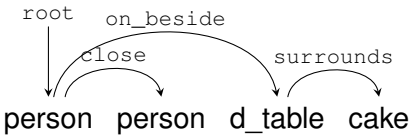
# Visual Tuples

An image represented a bag of VDR tuples (Ortiz et al., 2015).

person `close` person
person `on_beside` d_table
d_table `surrounds` cake
person `near` cake
person `close` d_table
person `above_close` cake

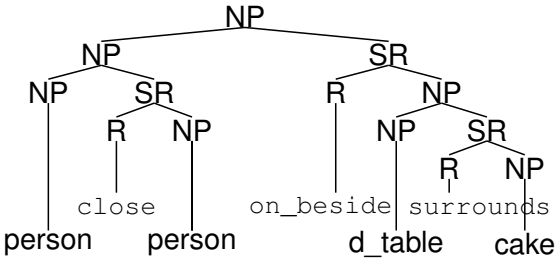
# Visual Dependency Representations

An image is represented as a dependency tree (Silberer et al., 2017).

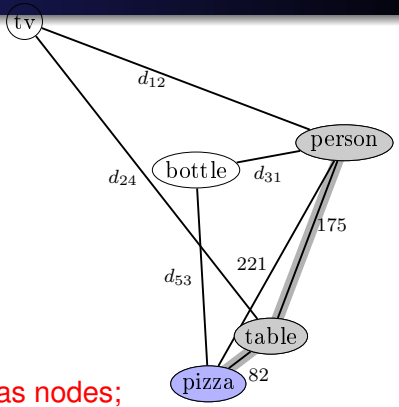


# Visual Constituency Representations

An image is represented as a constituency tree (Silberer et al., 2017).



# Tree Construction




- Build a fully connected graph with all objects as nodes;
- edge weights correspond to spatial distance;
- minimum spanning tree (MST): visual dependency representation;
- use grammar to generate visual constituency representation.

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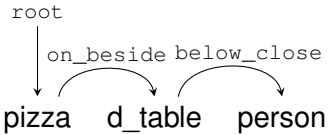


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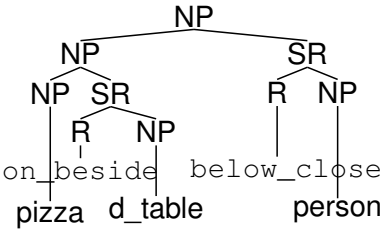


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- Repurpose existing NLP technology to construct visual representations;
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  **create parallel corpus of trees with multiple descriptions;**
- translation is loose: not all visual objects are verbalized; multiple descriptions can focus different aspects of a scene:
  **generation model performs content selection.**

# Parallel Corpus Creation

**Step 1: Grounding objects to linguistic expressions.**

person
d_table
person
cake
plate
cup

*Little kids sitting around a table that has a birthday cake on it.*
*A group of young children standing around a cake.*

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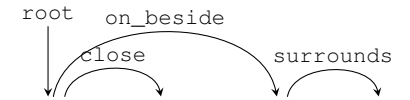
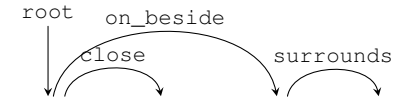
# Parallel Corpus Creation

**Step 2: Render scenes as trees and generate corpus.**



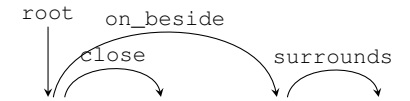

Kids sitting around a table.

---




A table that has a birthday cake.

---




Children standing around a cake.

# MT Model: Surface Realization

We train a translation model on our parallel corpus using the MT framework implemented in Moses (Koehn et al., 2007):

$$t^* = \arg\max_t P(t|s)$$

$$P(t|s) = \arg\max_d \left( \sum_{k=1}^{K} \lambda_k h_k(d) \right)$$

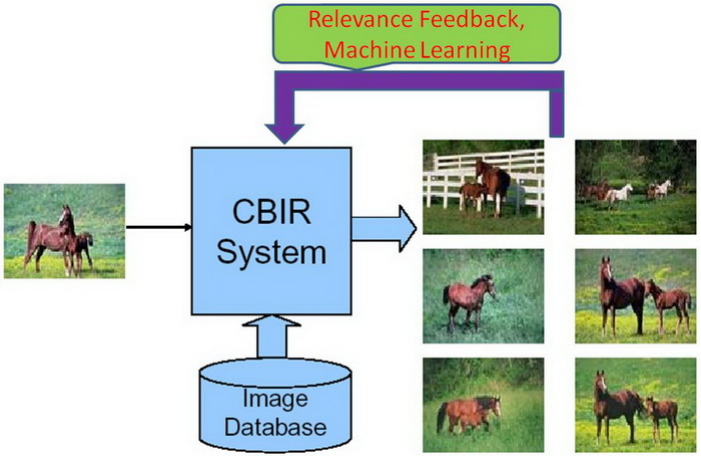
- $d \in D(s,t)$ are derivations in a synchronous grammar;
- $h_k$ feature functions (language model, translation table, word penalty model);
- constants $\lambda_k$ scale different models, tuned during training.

# MT Model: Content Selection

At test time we must decide which objects to talk about:

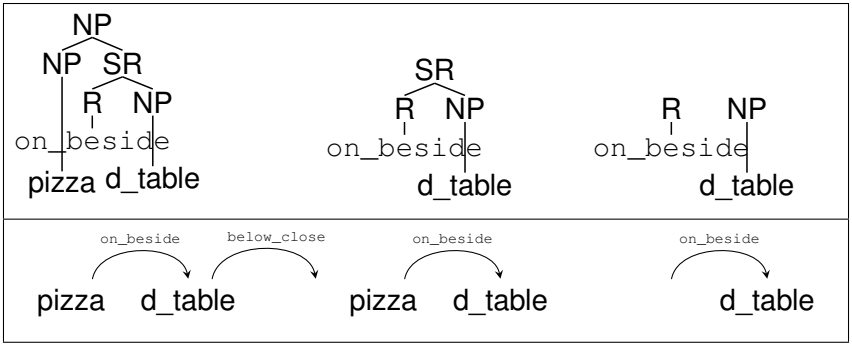
- predict whether a detected object is relevant for scene;
- we use logistic regression with $l_2$ regularization;
- trained on positive and negative instances;
- positives: objects aligned to SRL arguments;
- negatives: unaligned objects;
- features: object detection score, relative size, relative distance between two objects, object occurrences, spatial features.

# Query-by-Example Image Retrieval

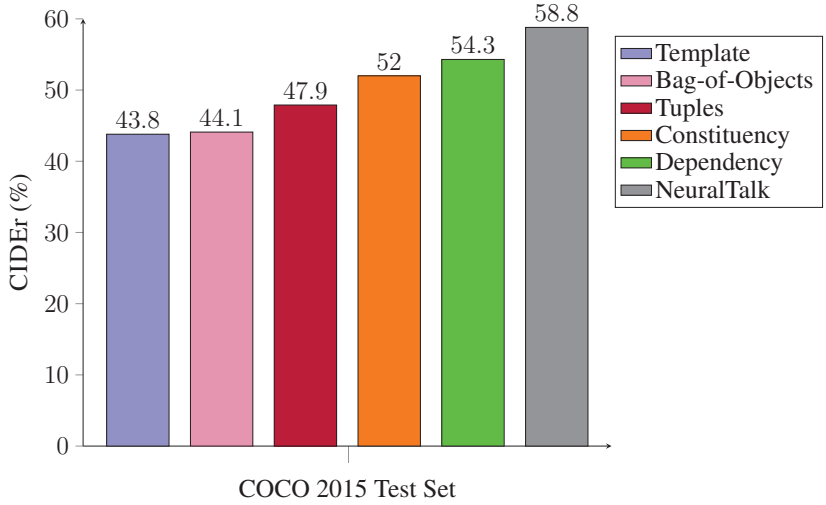


# Query-by-Example Image Retrieval

- Let $\mathcal{I}$ denote an image collection;
- for every image $q$ produce a ranking in order of similarity to $q$;
- subtree kernels measure similarity of constituent trees;
- partial tree kernels measure similarly of dependency trees.



# Results: Image Description Generation



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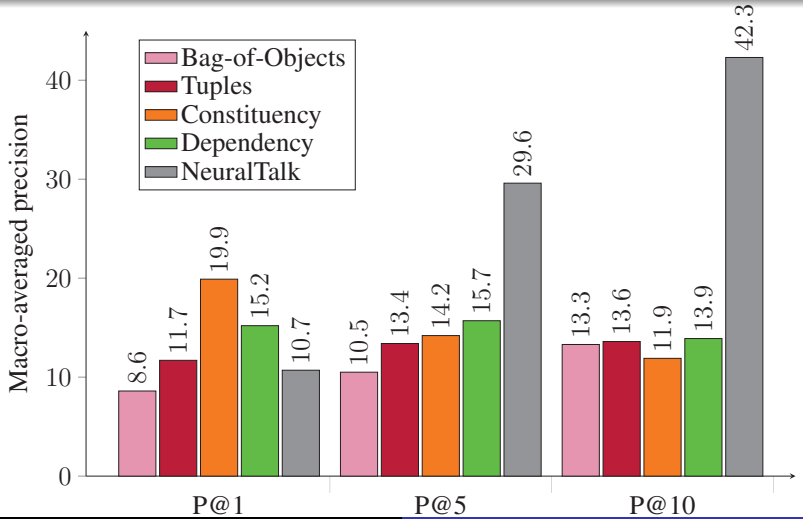

# Example Output

| | | |
|---|---|---|
| Template | 5) a couch has a couch | 2) an airplane is near a car |
| Tuples | 4) the room has a couch | 5) a airplane sitting on a street |
| Dependency | 1) a dog sitting on a couch | 3) a airplane parked next to a car |
| Constituency | 2) dog laying on a couch | 4) a airplane parked next to a car |
| Human | 3) a dog is looking at something | 1) a large plane with a red tail |

# Aligning Actions and Verbs

So far, we have looked at syntactic structure only: how do the objects in an image relate to each other.

To really understand the content of an image, we need semantics: represent the event depicted, its participants, and the roles they play.

We can achieve this using verb senses:

- well established in linguistics (e.g., WordNet);
- more general that the action labels used in computer vision;
- can be aligned with both sentences and images.

# Word Sense Disambiguation

Word sense disambiguation is a standard NLP task:

(1) A man is **playing** a guitar.

(2) The children are **playing** across the street.

(3) Two men **playing** doubles tennis on a grass court.

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New task: visual sense disambiguation (VSD, Gella et al. 2016).

# Existing Action Recognition Datasets

| Dataset | Actions |
|---|---|
| PPMI (Yao & Fei-Fei 2010) | 24 |
| Stanford 40 (Yao et al. 2011) | 40 |
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| Dataset | **Verbs** | Actions | Sense |
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| TUHOI (Le et al. 2014) | **–** | 2974 | N |

- Actions: verb phrases or verb-object pairs;
- verb senses are more general than actions;
- no existing datasets with verb sense annotation.

# Dataset for Visual Verb Sense Disambiguation

Design a new dataset using images from:

- MSCOCO: 123k images with object labels, image descriptions:
  - not designed for action recognition;
  - use verbs in descriptions as labels.
- TUHOI: 10,805 images with object labels:
  - labeled with actions (verb-object pairs);
  - use verbs as labels.

# Dataset for Visual Verb Sense Disambiguation

We use the OntoNotes inventory of verb senses (less fine-grained than WordNet).
But: not all verb senses are visual.

Visual:

- S: (v) **play** (perform music on (a musical instrument)) *"He plays the flute"; "Can you play on this old recorder?"*

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Non-Visual:

- S: (v) **play** (use to one's advantage) *"She plays on her clients' emotions"*
- S: (v) dally, trifle, **play** (consider not very seriously) *"He is trifling with her"; "She plays with the thought of moving to Tasmania"*

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Solution: annotate only the visual senses:

- annotators decide which senses are visual (about 50% in MSCOCO);
- new annotators select correct visual sense for each image.

# Annotating Image and Verb with Visual Sense

- **Verb: play**
  - engage in or make moves related to competition or sport They played cards far into the night. more examples
  - engage in a fun or recreational (childlike) activity The children are playing across the street. more examples
  - perform or transmit music The band played all night long. more examples
  - perform/act a role, pretend He usually plays a villain in films. more examples
  - FISHING-exhaust by allowing to pull on the line John knows how to play a hooked fish.
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# VerSe Dataset

Comparison of VerSe with existing action recognition datasets:

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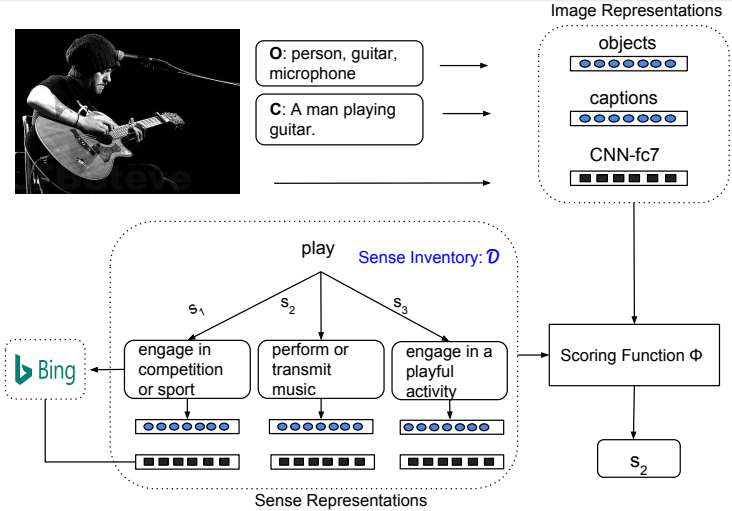
| TUHOI (Le et al. 2014) | – | 2974 | N |
| **VerSe** (our dataset) | **90** | – | **Y** (163) |

# VerSe Dataset

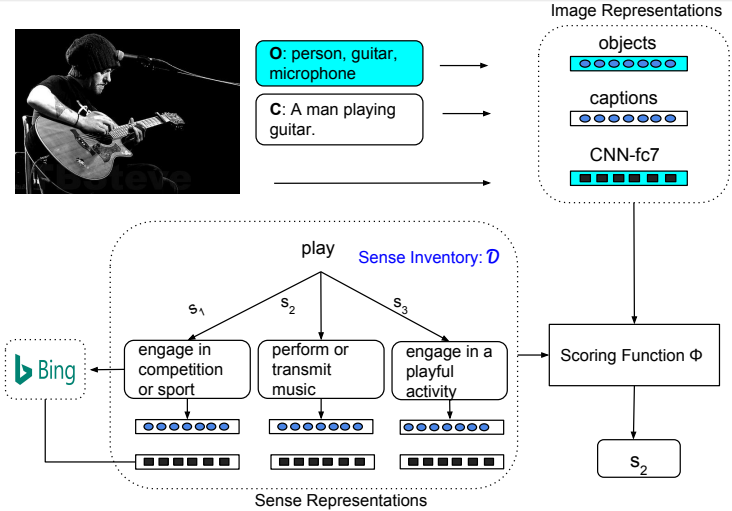
VerSe dataset divided into motion and non-motion verbs:

| Verb type | Verbs | Images | Senses | Examples |
|---|---|---|---|---|
| Motion | 39 | 1812 | 5.79 | run, walk, jump, swing, hit, kick |
| Non-motion | 51 | 1698 | 4.86 | sleep, sit, lean, read, write, look |

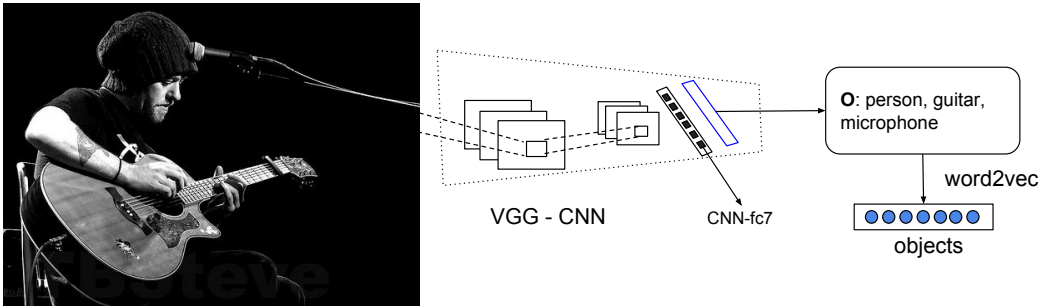
# Unsupervised Model for VSD



# Unsupervised Model for VSD

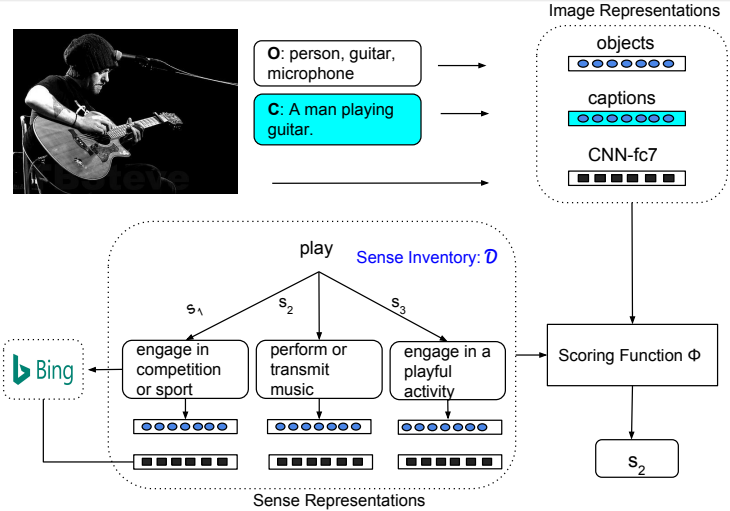


# Unsupervised Model for VSD




Object labels obtained using VGG (Simonyan & Zisserman 2014).

# Unsupervised Model for VSD



# Unsupervised Model for VSD

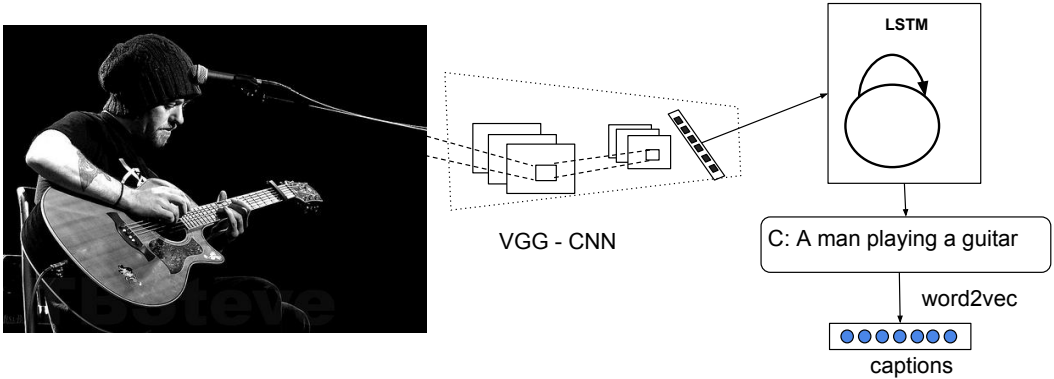
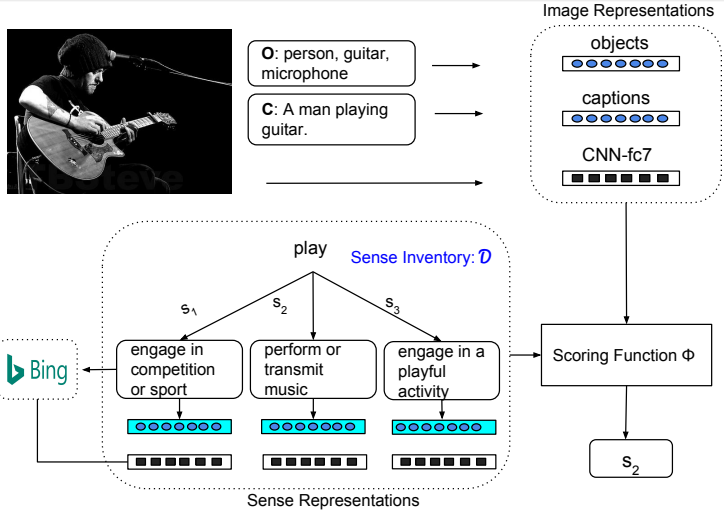



Image descriptions from Show and Tell (Vinyals et al. 2015).

# Unsupervised Model for VSD



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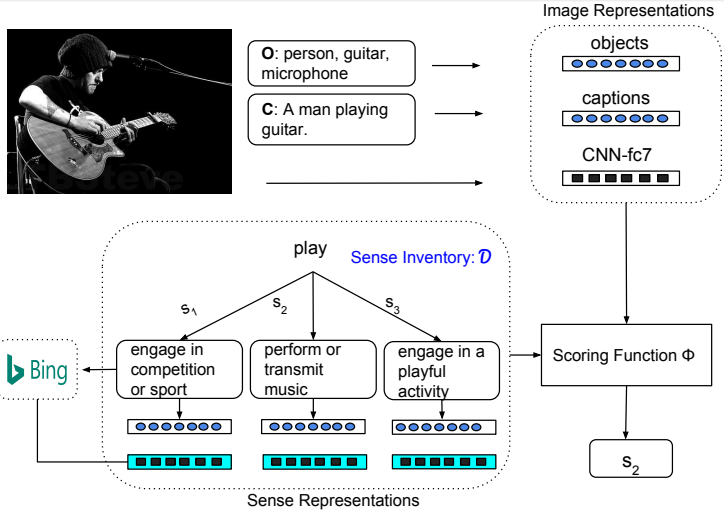
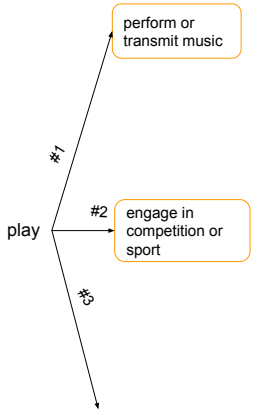


# Visual Representation for Senses



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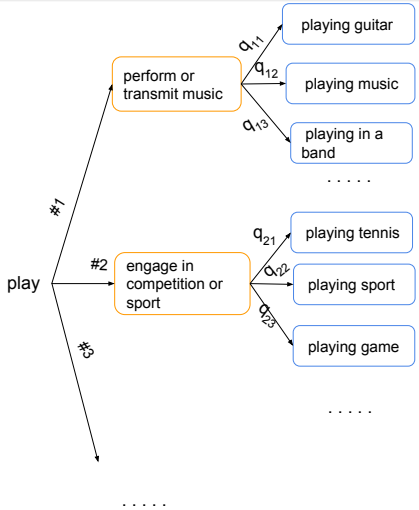

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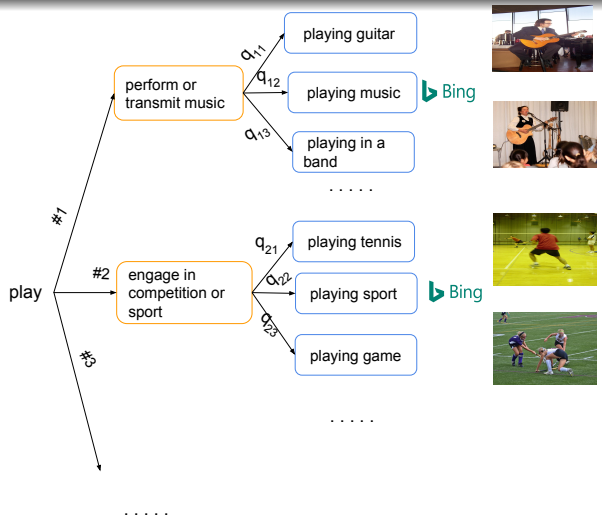

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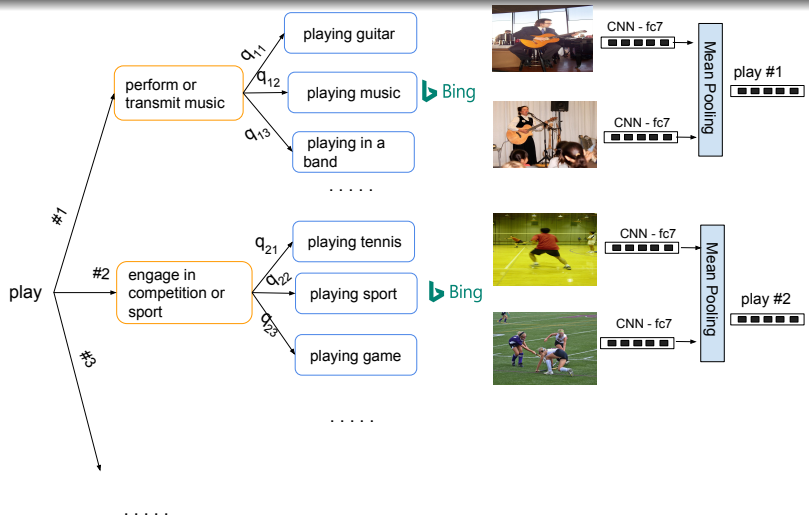
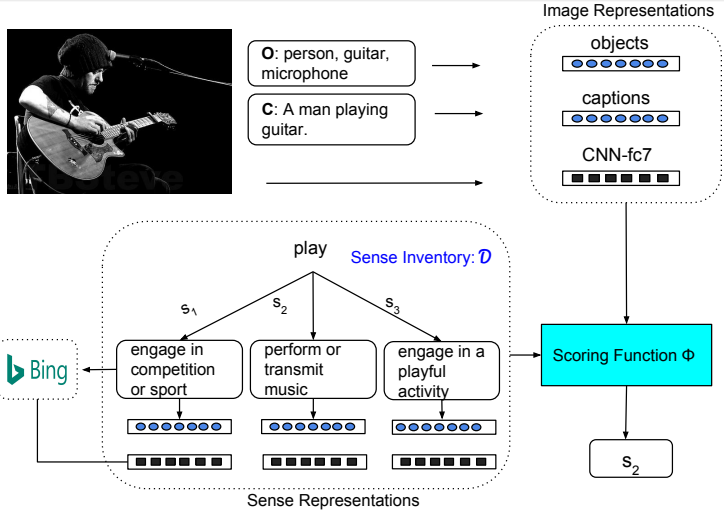


# Unsupervised Model for VSD



# Scoring Function

Use vector similarity (cosine) as scoring function:

$$\hat{s} = \arg\max_{s \in S(v)} \Phi(s, i, v, D)$$

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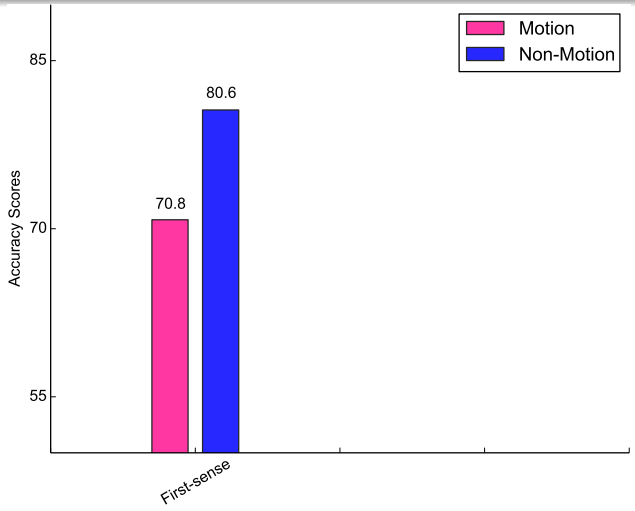
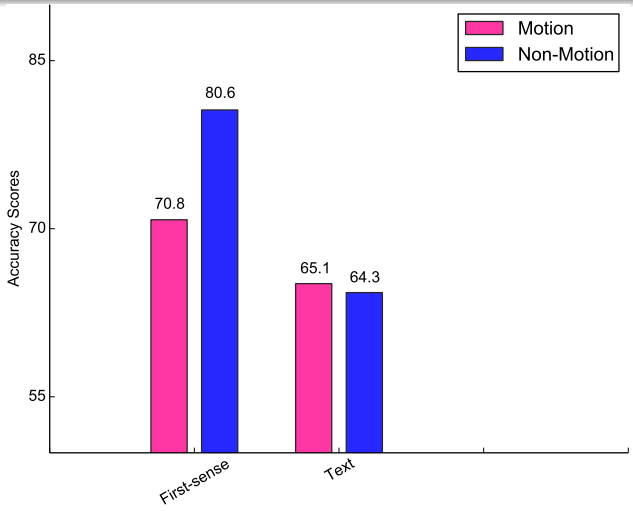
Representations:

- textual: O, C embeddings;
- visual: CNN features;
- multi-modal: fused textual and visual features using Canonical Correlation Analysis.

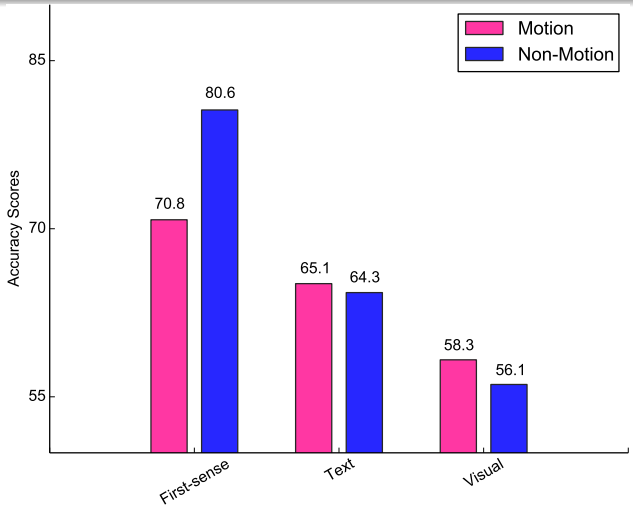
# Results


Motion
Non-Motion
85
70
55
Accuracy Scores
80.6
70.8
First-sense

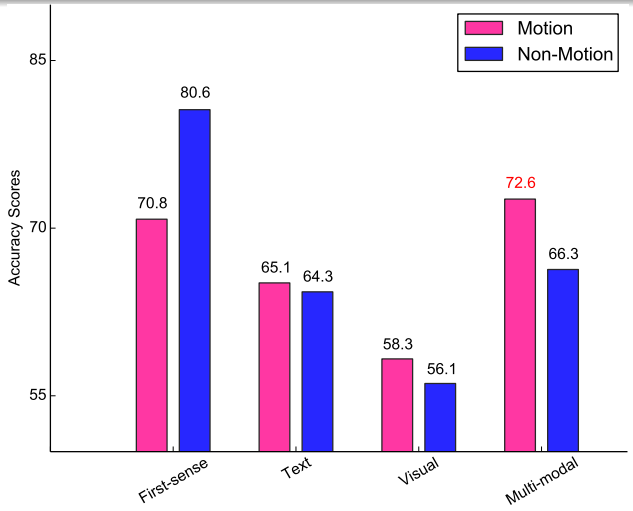
# Results


Motion
Non-Motion
Accuracy Scores
85
70
55
80.6
70.8
65.1
64.3
First-sense
Text

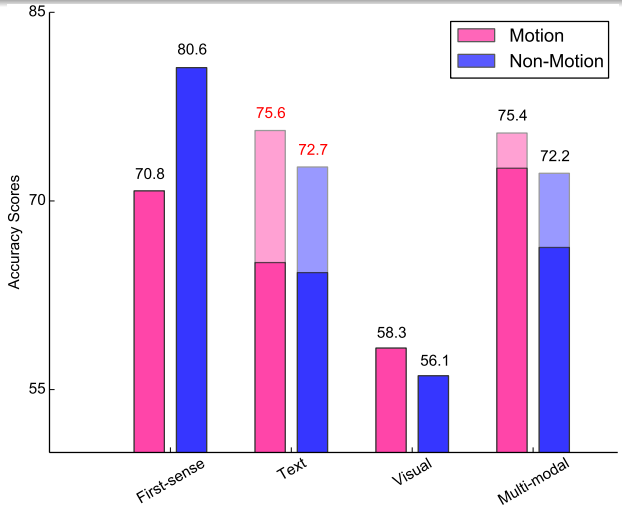
# Results


Motion
Non-Motion
Accuracy Scores
85
70
55
80.6
70.8
65.1
64.3
58.3
56.1
First-sense
Text
Visual

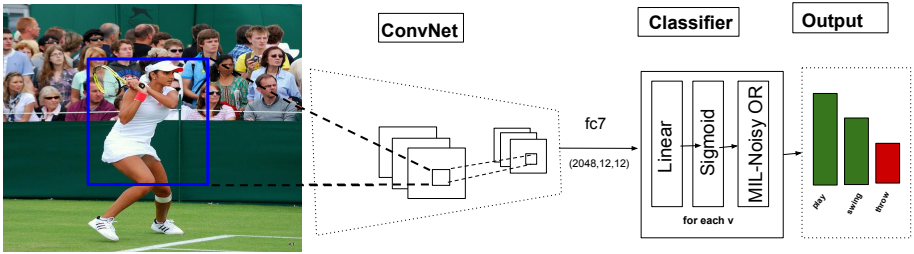
# Results


Motion
Non-Motion
Accuracy Scores
85
70
55
80.6
70.8
65.1
64.3
58.3
56.1
72.6
66.3
First-sense
Text
Visual
Multi-modal

# Results: Gold Standard Image Descriptions



# Verb Prediction




- detect the verbs that are present in an image (250 classes);
- use multiple instance learning (we do not know which bounding boxes correspond to which verbs).

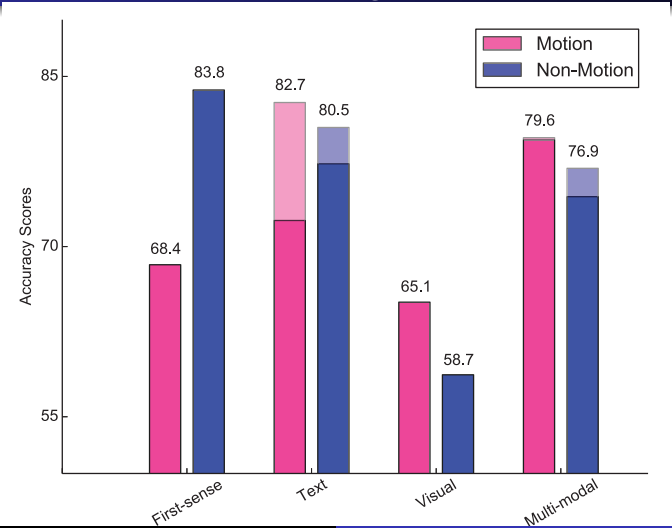
# Examples: Verb Prediction

play, perform

hit, swing, play

hold, sit, use

# Verb Prediction and Sense Disambiguation



# Conclusions

- Image understanding (like text understanding) requires structured representations;
- for multimodal tasks, we need to align linguistic and image structure;
- syntactic example: visual dependency representations align geometric structure of an image with syntactic structure of a sentence;
- application in image description and image retrieval;
- semantic example: visual word senses align event depicted in an image with event described in a sentence;
- unsupervised VSD model using multimodal embeddings.

# Other Approaches to Image Structure

Other approaches that align linguistic structure and image structure:

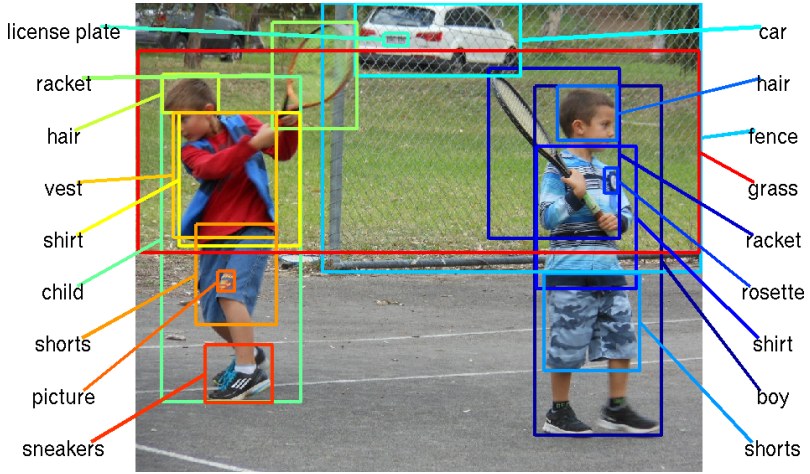
Scene (description) graphs (Johnson et al. 2015; Aditya et al. 2015):

- triples of object, attribute, relation;
- aligned with image regions and region descriptions;
- no explicit alignment with linguistic structure (but could be derived).

Visual semantic roles (Yatskar et al. 2016):

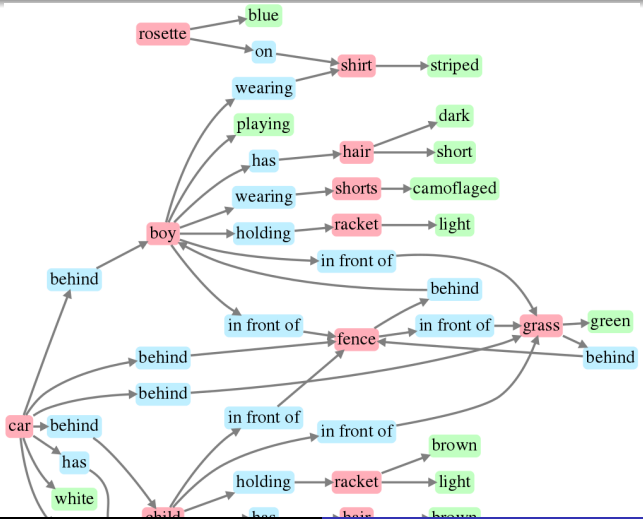
- uses semantic frames from FrameNet;
- annotates images with frames, participants, and roles;
- not aligned with regions or image descriptions; no verb senses.

# Scene Graphs




http://cs.stanford.edu/people/jcjohns/cvpr15_supp/

# Scene Graphs



# Visual Semantic Roles

| practicing | | | |
|---|---|---|---|
| agent | skill | tool | place |
| man | music | violin | room |

http://imsitu.org/demo/

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