# Spontaneous Analogy by Piggybacking on a Perceptual System


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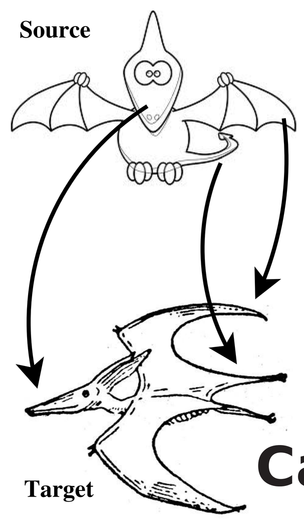
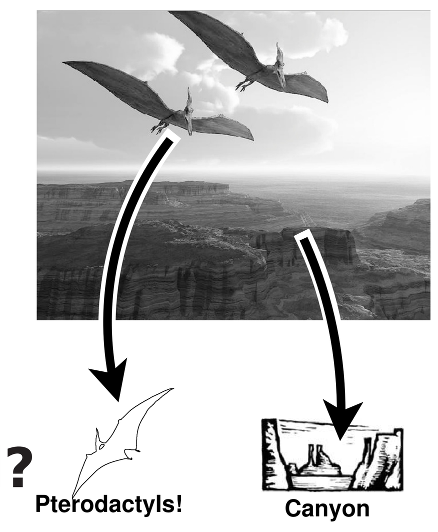
## How are analogs retrieved spontaneously?



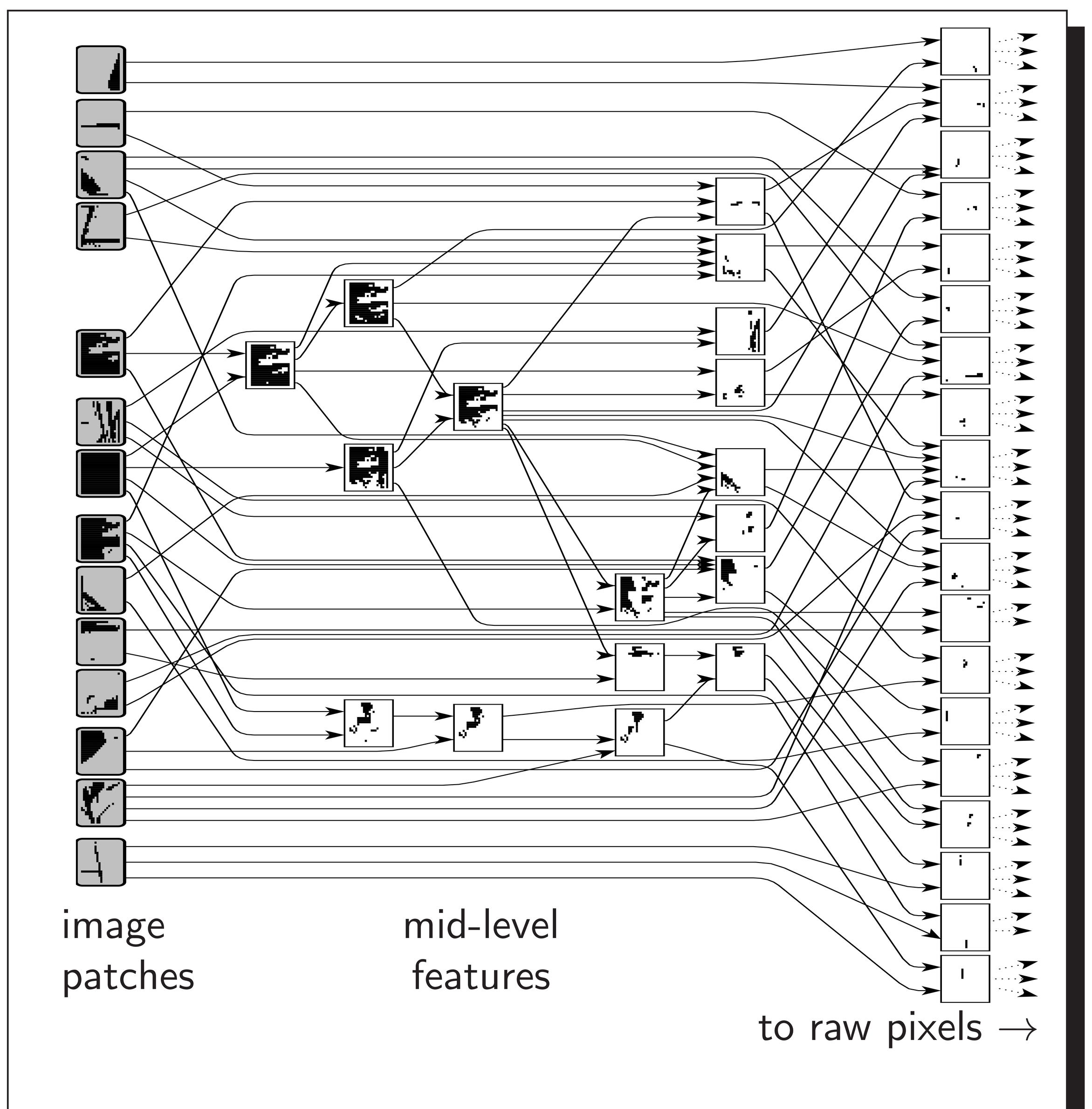

**"Classic" analog retrieval**
- Is given *delineated* target
- Searches through *all* stored cases
- Mapping *after* retrieval

**Spontaneous analog retrieval**
- Is given *unsegmented* target
- Searches through *fraction* of cases
- Mapping *concurrent with* retrieval




**Can analog retrieval be more like perceptual retrieval?**
(Hint: Use "perceptual" methods.)

## A System for Learning from Perceptual Data



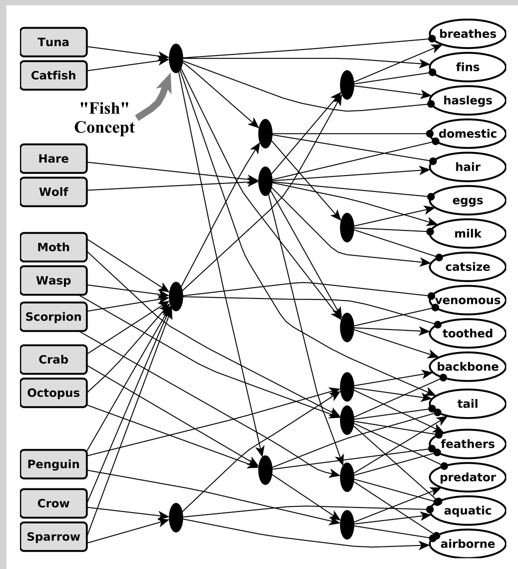

**Hierarchy Learned from Visual Data** (partial view)

**Given set of uninterpreted feature-bags, system:**

- **learns** feature hierarchy (using chunking)
- **parses** new instances using learned features (characterizes instance in terms of higher features)
- **predicts** missing elements using top-down inference

### Not just for perceptual data

The system learns from any dataset described using feature-bags, (e.g., animals described as sets of attributes). Individual animals are at left. Base features are at right. Black nodes correspond to higher-level features. Note the "fish" concept at upper-left.




**Learned "Zoo" Hierarchy**

**But... system requires input to be feature-bags (not relational structures).**

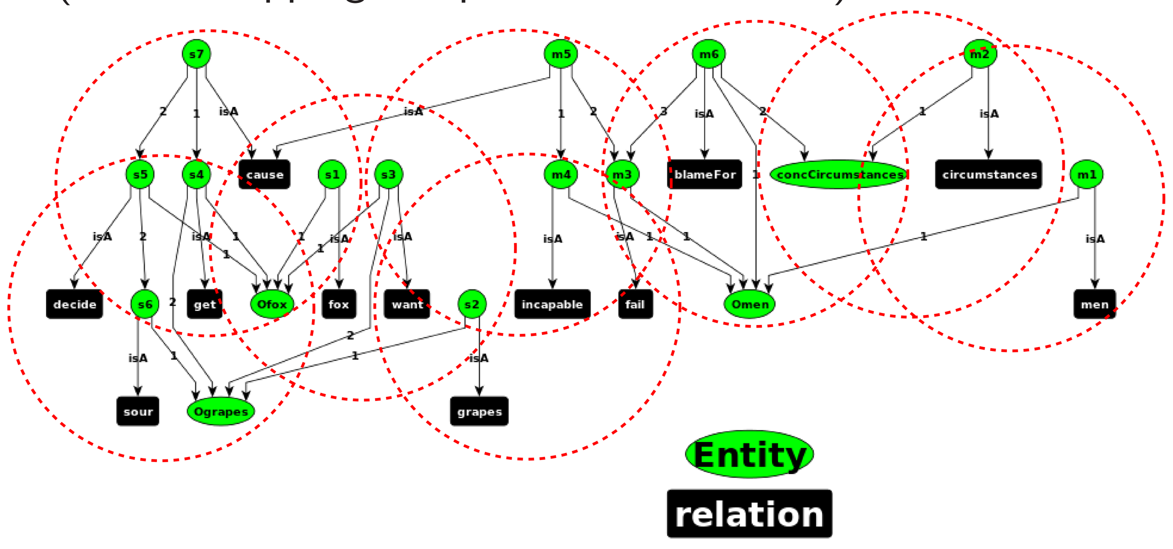
## Transforming Relational Structures into Feature-bags

**How to transform relational structures into feature-bags** such that *surface overlap* in bags corresponds to *analogical overlap* in original structures

1. **Given** relational structure (in predicate logic)...

```
fox OFox        cause s1 s2               sameAs s3 (sour OGrapes)
false s3        grapes OGrapes            sameAs s5 (decide OFox s3)
cause s4 s5     incapable OMen            sameAs s4 (get OFox OGrapes)
false s4        decide OFox s3            sameAs s1 (incapable OMen)
men OMen        sameAs s2 (fail OMen)     blameFor OMen concCircum s2
fail OMen       want OFox OGrapes         circumstances concCircum
```

2. **Grab** many overlapping connected "windows" (like overlapping receptive fields in vision)




3. **Transform** each window into feature bag by *chaining* roles and fillers:

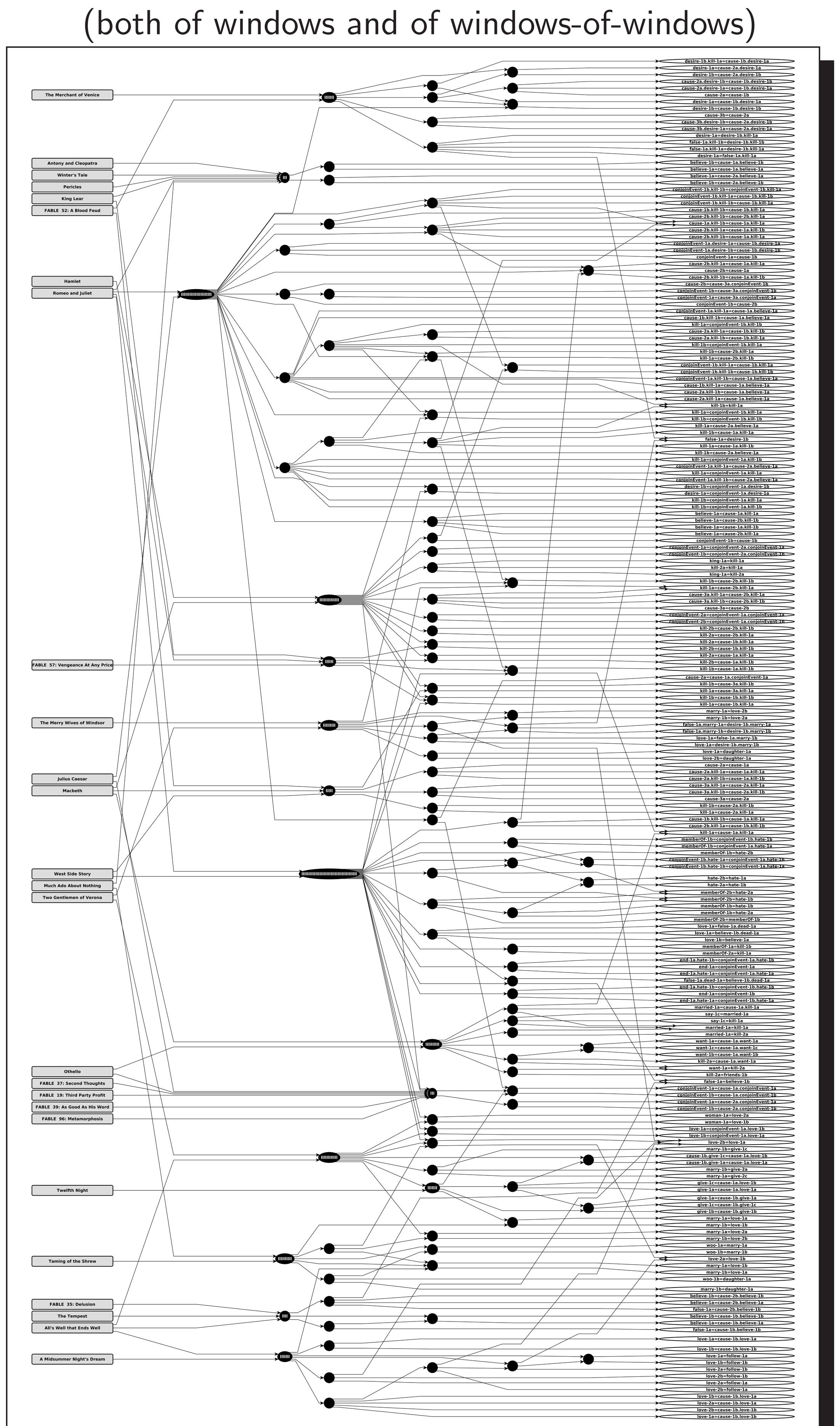
```
blameFor OMen concCircum s2           blameFor1=blameFor3.fail1
sameAs s2 (fail OMen)                 circumstances1=blameFor2
fail OMen                             fail1=blameFor3.fail1
circumstances concCircum      T       fail1=blameFor1
men OMen                     ==>      incapable1=blameFor3.fail1
incapable OMen                        incapable1=blameFor1
                                      incapable1=fail1
                                      men1=blameFor3.fail1
                                      men1=blameFor1
                                      men1=fail1
                                      men1=incapable1
```

4. **Represent** each structure as *bag* of feature-bags

```
blameFor1=blameFor3.fail1      cause2.fail1=blameFor3.fail1    blameFor1=blameFor3.fail1
circumstances1=blameFor2       blameFor1=blameFor3.fail1       fail1=blameFor3.fail1
fail1=blameFor3.fail1          blameFor1=cause2.fail1          fail1=blameFor1
fail1=blameFor1                cause2=blameFor3                incapable1=blameFor3.fail1
incapable1=blameFor3.fail1     fail1=blameFor3.fail1           incapable1=blameFor1
incapable1=blameFor1           fail1=cause2.fail1              incapable1=fail1
incapable1=fail1               fail1=blameFor1                 men1=blameFor3.fail1
men1=blameFor3.fail1           men1=blameFor3.fail1            men1=blameFor1
men1=blameFor1                 men1=cause2.fail1               men1=fail1
men1=fail1                     men1=blameFor1                  men1=incapable1
men1=incapable1                men1=fail1
```

(Etc...)

**Given many transformed structures, learn hierarchy**
(both of windows and of windows-of-windows)




**Hierarchy Learned from Story Data** (partial view)

**Now we can apply "perceptual" methods to relational structures!**

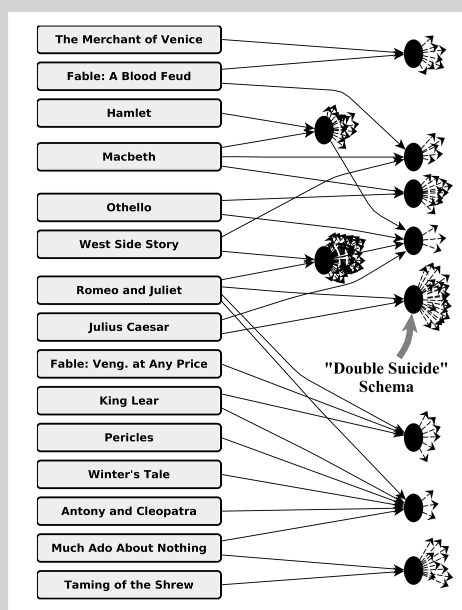
## Learning Analogical Schema Hierarchies

**How to quickly retrieve analogs:**
- Learn hierarchy using "perceptual" system on set of transformed structures
- Given new structure:
  - **transform** structure into feature-bags
  - **parse** structure using hierarchy

**Analog Retrieval Comparison:**
- Hierarchy acts as "index" for *fast* $O(\log n)$ retrieval (compared to $O(n)$ for earlier methods)
- Extracts relevant shared sub-structures during retrieval
- Slight accuracy cost, but significant speedup

| | Accuracy | Avg. # Comparisons |
|---|---|---|
| MAC/FAC | 100.00% ± .00% | 100.00 ± .00 |
| Ours | 95.45% ± .62% | 15.43 ± .20 |

### A Hierarchy of Plot Devices

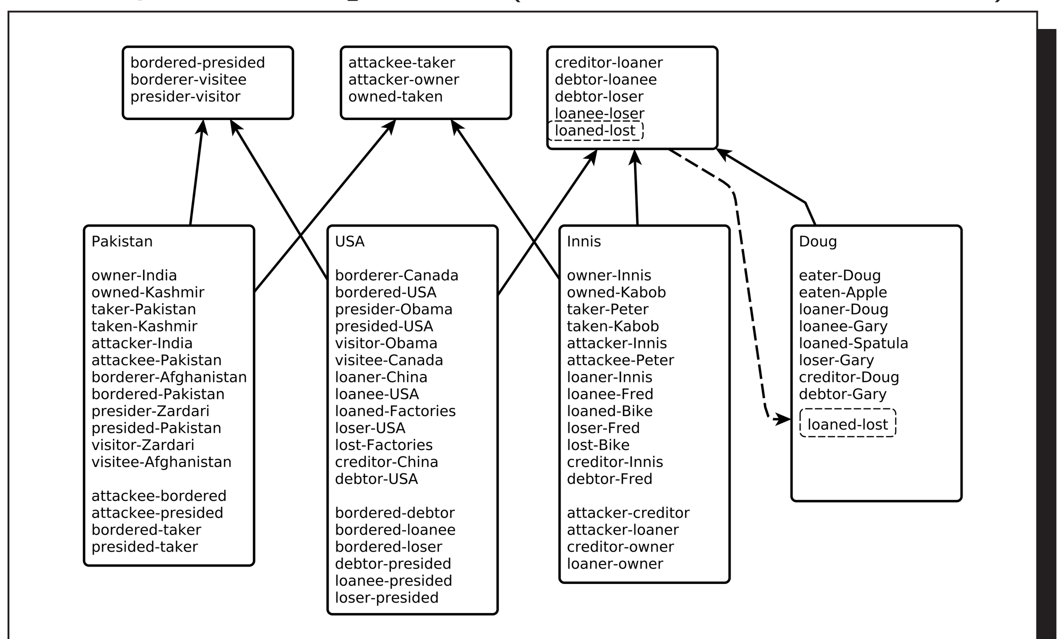



**Story Hierarchy** (detail)

Using the "perceptual" learning algorithm, on (transformed) story data, we get hierarchy of analogical schemas (detail at left). Higher-level features correspond to plot devices. E.g., *Double Suicide* schema: "$A$ thinks $B$ is dead, so kills self. $B$ (alive) finds $A$ dead so kills self." where $A$ = `Romeo/Cassius` and $B$ = `Juliet/Titinius`.

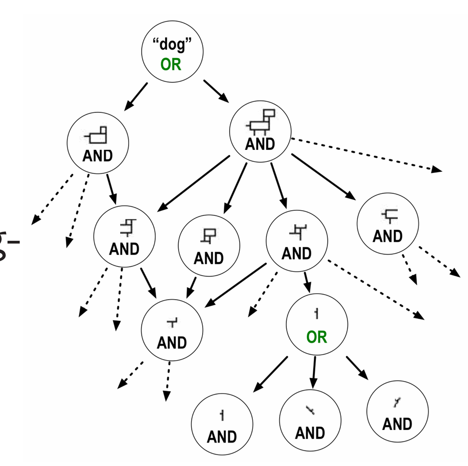
## Current and Future Work

**Analogical Inference Using "Perceptual" Methods:**
- **parse** "Doug" story (to inherit from top-right node)
- **predict** (top-down) `loaned-lost` feature
- **chain** `loaned-lost` with `loaned-Spatula` to get `lost-Spatula` (i.e., the Spatula was lost)

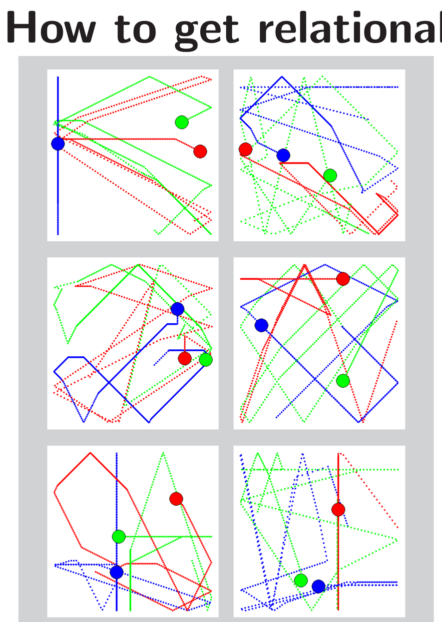



**Toy Example for Analogical Inference**

**Merging to get Disjuncts/Pooling-Nodes:**
- pooling-nodes to represent **invariant features** (For images: translation, rotation, scale, etc.)
- **prediction:** for stories merging will recognize similarities between "likes" and "loves"




**How to get relational structures from sensor data?**



- How to infer relations from not-explicitly-relational data?
- E.g., given many (pixel-level) still images like those on left, how might system develop concept for `hit(ball1, ball2)`?

## References


[1] M. Pickett, D.W. Aha Spontaneous Analogy by Piggybacking on a Perceptual System In *Proc. of 35th Conf. of Cog. Sci. Soc.*, 2013.

[2] M. Pickett, D.W. Aha Using Cortically-Inspired Algorithms for Analogical Learning and Reasoning In *Bio. Inspired Cog. Archs.*, 2013.