




## Scalability of Object Class Recognition

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thanks to: Micha Andriukha, Sandra Ebert, Mario Fritz,  
 Peter Gehler, Michael Goesele, Leonid Pischchulin,  
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 Bojan Peplik, Michael Stark, Christian Wojek



## DAGM Workshop on ~~Pattern~~ Recognition

### Unsolved Problems in ~~Pattern~~ Recognition

## Motivation for Part-Based Models

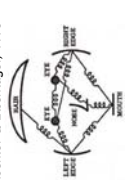
[slide from Pietro Perona]





 Scalability of Object Class Recognition

## Model of Parts & Structure: Part-Based Models...

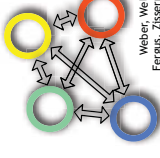
Fischer & Elschlager, 1973




Constellation Model:  
Fully connected shape model



Implicit Shape Model or Deformable Part Model:  
Star-Model w.r.t. Reference Point



Leibe, Schiele '03  
 Leibe, Leonardis, Schiele '04  
 Felzenszwalb, McAllester, Ramanan '08  
 Weber, Welling, Perona '00  
 Fergus, Zisserman, Perona '03



 Scalability of Object Class Recognition

## Object Models

### State-of-the-Art in Computer Vision


- Bag of Words Models (BoW)**
  - object model = histogram of local features
  - e.g. local feature around interest points
- Global Object Models**
  - object model = global feature object feature
  - e.g. HOG (Histograms of Oriented Gradients)
- Part-Based Object Models**
  - object model = models of parts & spatial topology model
  - e.g. DPM & ISM & constellation model

low: no spatial relationships  
 e.g. HOG: fixed spatial relationships  
 e.g. DPM, ISM or constellation model: flexible spatial relationships


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## Object Class Recognition

- State-of-the-Art in 2011
  - Computer Vision
    - recognition of few 100s, maybe 1,000s of object classes "possible"
  - Human Vision
    - recognition of several 10,000s of object classes
- Open Research Question for Computer Vision:
  - how to scale to recognize 1,000s or 10,000s of object classes?**


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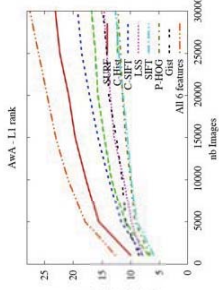
## Scalability of Object Class Recognition Different Thoughts for Discussion...

- 1. Rethinking our Object Representations
  - current models don't seem powerful enough
  - we heavily rely on machine learning to make our models "work"
- 2. Labels for Most Object Classes are Sparse
  - we need to reuse and transfer learned knowledge
- 3. Reformulation of Recognition Problem
  - are basic level categories the "right" problem to work on ?
  - what about new ways of addressing recognition ?
- 4. ??

## 1. Rethinking our Object Representations

- AwA (Animals with Attributes)

- 50 animals classes



- Observations of Nearest Neighbor Quality

- more features & combining features is better
- more images are better !
- but: today's representation are not good enough !

## 1. Rethinking our Object Representations

- ImageNet Challenge 2010
  - 1,000 object classes, about 1,000 images per class total of 1.2 Million images
- Some Results...

Model	Descriptor	Learning method	Total dim.	Err. top 5	Err. top 1
BoW [2]	Sift	LibLinear	1,000	80	91
BoW	Sift	MeanSGD	1,000	72	86
BoW + SPM	rgSift	MeanSGD	8,000	59	76
LLC + SPM	rgSift	MeanSGD	21,000	50	69
Fisher vector	rgSift	MeanSGD	32,768	43	61
LLC+SPM, Fisher	rgSift	MeanSGD	53,768	38	57
Fisher+SPM [25]	Sift_Color	SGD	262,144	34	47
LLC+SVC+SPM [16]	Hog_Lbp	ASGD	1,179,648	28	47

- best published result: 47% error !
- the higher the dimensionality - the better the performance !!
- this suggests: our "object models" are not good enough !!!

## Discussion 1. Rethinking our Object Representations

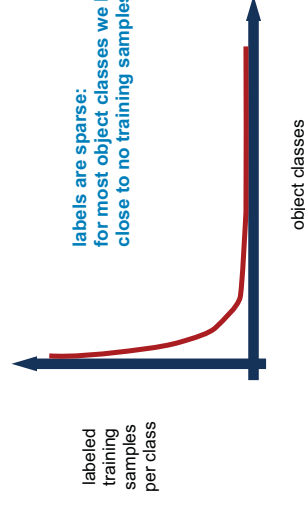
- Pros of our current approaches:
  - nice scientific problem (learning object models from large databases with or without noisy labels)
  - have shown to work for "small scale" problem
- Cons & Pitfalls:
  - our object representations do not seem to be powerful enough (yet?)
  - powerful machine learning seems to be "key to success"
  - we never seem to have (or at least make use of) enough data
  - majority of work tries to recognize "basic level categories"
    - is that the right problem to work on?

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## 2. Labels for Most Object Classes are Sparse

labels are sparse:  
for most object classes we have close to no training samples

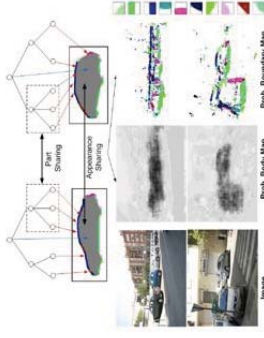


## 2. Labels for Most Object Classes are Sparse Potential of Knowledge Transfer

- Assumptions (Observations)
  - different object classes share **properties** & **features** (texture, color, ...) or **share parts** (wheels, head, legs, ...) or ...
  - i.e. one should transfer knowledge
- Large Variety of Approaches:
  - distance metric learning** (e.g. [Fink@nips04], [Bart&Ullmann@bmvc05], [Thrun@nips06])
  - joint learning of multiple object classes** (e.g. [Torralba&al@cvpr04], [Amit&al@icml07], [Zhu&al@cvpr10])
  - use of prior information** (e.g. [Levi&al-04], [Bart&Ullmann@cvpr05], [Fei-Fei@icml06], [Zweig&Weinshall@iccv07], [Stark, Goesele, Schiele@iccv09], [Rodner&Denzler@dagm10])

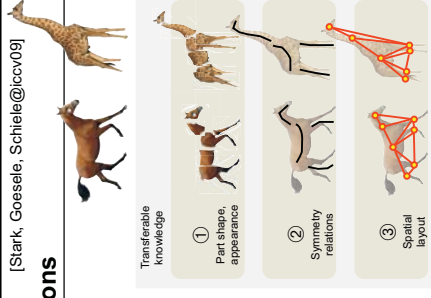
## 2. Knowledge Transfer Some Approaches

- Part and Appearance Sharing; Recursive Compositional Models for Multi-View Multi-Object Detection
  - [Zhu,Chen,Torralba,Freeman,Yuille@cvpr10]



## Motivation and Contributions

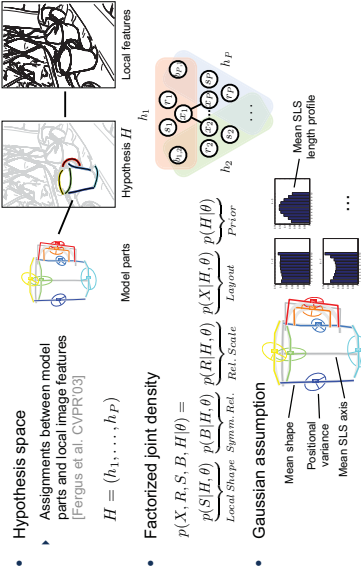
- Motivation
  - Scaling recognition to large numbers of object classes suffers from high amount of needed training data
  - Knowledge transfer from existing models may reduce number of required training examples
- Contributions
  - Novel shape-based object class model for explicit knowledge transfer (①, ②, ③)
  - Effective incorporation of symmetries
  - Competitive shape-based object recognition results



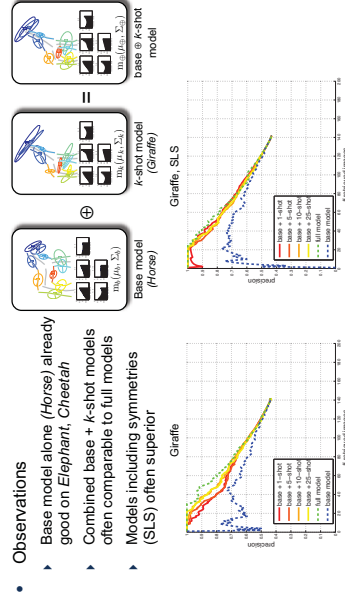
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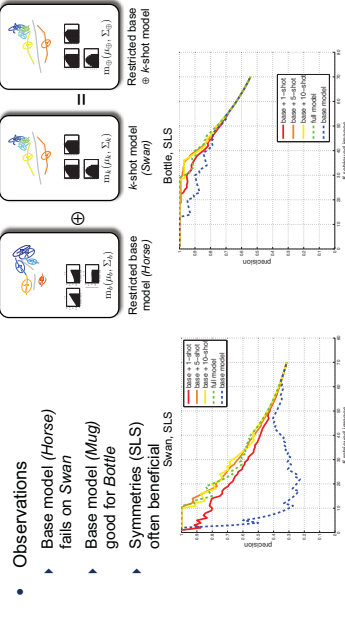
## Probabilistic Formulation



## Experiments - Full Model Transfer



## Experiments - Partial Model Transfer









## 2. Knowledge Transfer Discussion

- Pros:
  - ▶ intuitive approach
  - ▶ typical object-centric representation and transfer
- Cons:
  - ▶ approaches still in their infancy
  - ▶ many open questions
    - which knowledge to transfer
    - how to transfer knowledge
    - how to identify knowledge to transfer
- Note: Knowledge Transfer is just one way to deal with the problem that labels are sparse for most object classes

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## 3. Reformulate Problem Example 1: Attribute-Based...

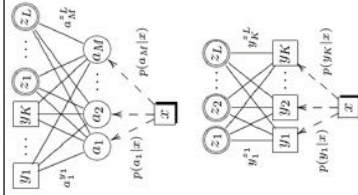
- Describing objects by their attributes [Farhadi&al@cvpr09]
  - ▶ "Shift goal of recognition from naming to describing"
    - ▶ Naming:  Aeroplane
    - ▶ Description:  Unknown Has Wheel Has Wood
    - ▶ Unusual attributes:  Bird No Head No Beak
    - ▶ Unexpected attributes:  Motorbike Has Cloth
    - ▶ Textual description:  Has Horn Has Leg Has Head Has Wool
  - ▶ zero-shot recognition from textual description: 

## 3. Reformulate Problem Example 1: Attribute-Based...

- Assumption:
  - ▶ assume large enough databases and efficient enough indexing algorithms
  - ▶ direct matching might solve a large portion of the recognition problem...
- Examples
  - ▶ [Russell&al@nips07] - Object recognition by scene alignment
  - ▶ [Torralba&al@pami08] - 80 million tiny images: a large dataset for non-parametric object and scene recognition
  - ▶ [Malisiewicz&Efros@cvpr08,nips09] - Recognition by associations, Visual Memex

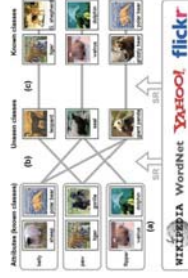
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- [Lampert&al@cvpr09]
  - ▶ attribute classifiers trained on known classes
    - a: attributes
    - y: known classes
  - ▶ transfer to unknown classes
    - known associations between a and z: unknown classes
  - ▶ second approach: direct similarity (similar to Bart&Ullmann-05)
    - y: known classes
    - known associations between y and z: unknown classes



## 3. Reformulate Problem Example 1: Attribute-Based...

- [Rohrbach, Stark, Szarvas, Gurevych, Schiele@cvpr10]:
  - ▶ question addressed: how to automatically decide which information to transfer across object classes (setting: zero-shot-learning)
  - ▶ using NLP (natural language processing)
    - 1. different language sources (Wikipedia, WordNet, Yahoo!, Flickr, Yahoo! Img Search, ...)
    - 2. different semantic relatedness measures (frequent, path-length, vector-based, ...)
  - ▶ main results:
    - manual supervision of attribute-object-class associations can be fully replaced (in principle) by tapping into language sources
    - Yahoo! Img Search & Wikipedia much better suited than e.g. WordNet...



### Realtime 3D Object Detection

- Approach
  - ▶ Represent Object by a Stack of Templates (no machine learning ;-)
  - ▶ Real-Time Template Matching
    - Dominant Orientation Template matching (inspired by HOG)
    - Template Clustering & Branch-and-Bound
    - etc.



### 3. Reformulate Problem Discussion

- Pros:
  - ▶ promising ideas & new formulations offer new insights
  - ▶ more new ideas are needed !
- Cons:
  - ▶ approaches clearly in their infancy
  - ▶ open questions:
    - how scalable are those approaches really
    - do we need other / new representations for direct matching/attributes/...
    - ...
- Important Note:
  - ▶ these approaches fundamentally challenge the assumption that basic level categories is the "right" level to address object recognition

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  - ▶ Larger Datasets: LabelMe, ImageNet, SUN Dataset, ...
  - ▶ Exploiting Context, Hierarchical Context, ...
  - ▶ ...???




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