Object Centric Abnormality Detection by Attribute Based Reasoning

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Motivation

How do you describe this object? What class is this object?

Car☑ Boat☑ Sofa☒ Airplane☒

Independent of its object category, it looks **Abnormal**!

We Argue that **Abnormalities** are among most important components that form what worth mentioning.

We are Proposing a method that **Recognize Abnormalities** in images and **Reports Weird Visual Attributes.**

Research Questions

I) What is Abnormality? A: There is NO clear answer for it!

II) What can make an image look weird? A: Large variety of sources!

III) Is it a simple Two-way classification (Normal vs. Abnormal)?

A: It is not a straightforward classification problem.

We can not use abnormal images for training the classifier mainly because:

1) Imbalanced number of Abnormal objects comparing to Normal objects.

2) People are able to judge Normality while they have not seen any Abnormal.

We only use Normal objects for learning a "Typicality Model" and represents Abnormality as meaningful deviation from Normality.

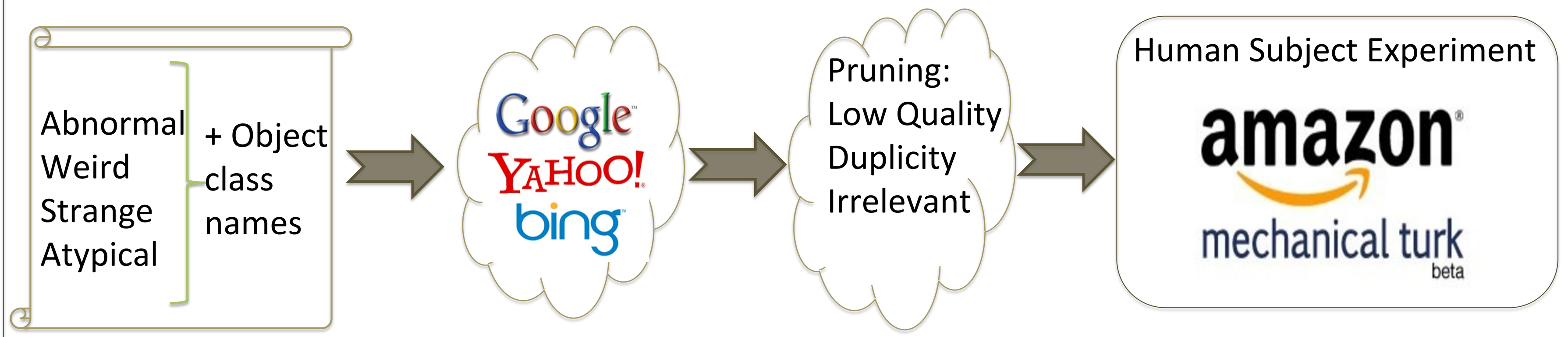
Dataset

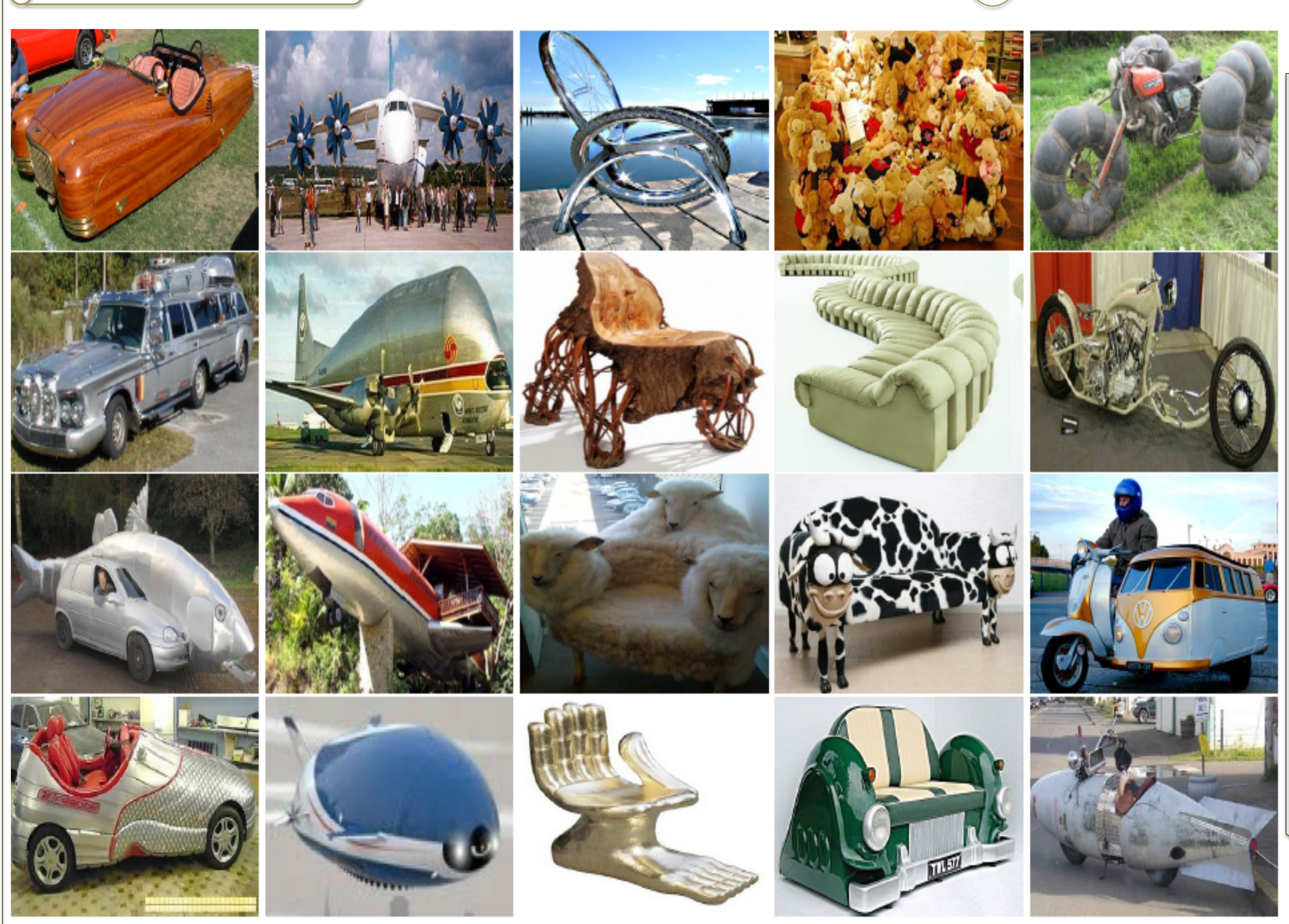
Cause of Abnormality: I) Abnormalities rooted in Object by itself (***Our Focus***)

II) Context related Abnormality

We present the **First Dataset** on **Abnormal Objects**. Along with a **Novel Human Subject Experiment** to acquire Ground truth annotation.

Data acquisition





1) Does this image look abnormal?
2) What is the reason? Object vs. Context
3) Categorize the object
4) Assuming its category membership, rate the abnormality cues:
 Shape / Color
 Texture / Pose

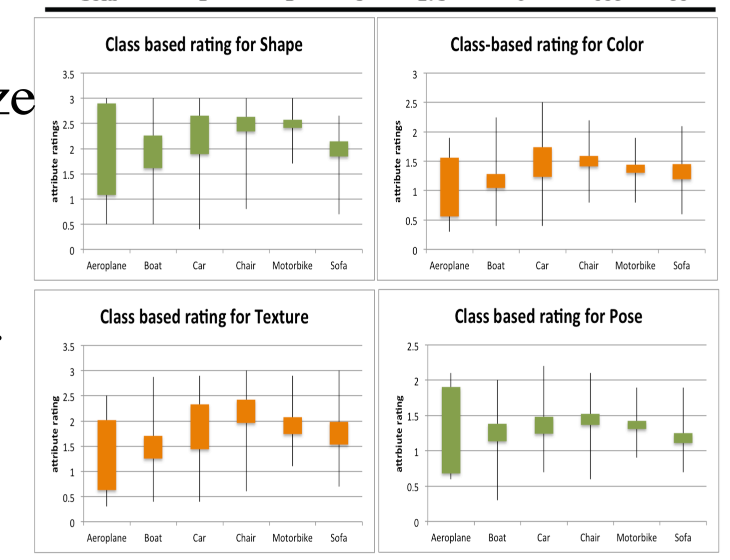
Human Subject Experiment

❖Ten human subject for each image

❖Outlier responders are removed

❖Averaging responses across users

	Aeroplane	Boat	Car	Chair	Motorbike	Sofa	None
Aeroplane	908	10	7	1	0	0	51
Boat	62	868	57	0	1	1	44
Car	7	9	1072	3	0	1	52
Chair	0	1	11	861	1	166	36
Motorbike	17	0	31	3	540	0	38
Sofa	1	1	3	273	0	666	86



Here are some insights:

§ It is even hard for Human to categorize Abnormal Objects

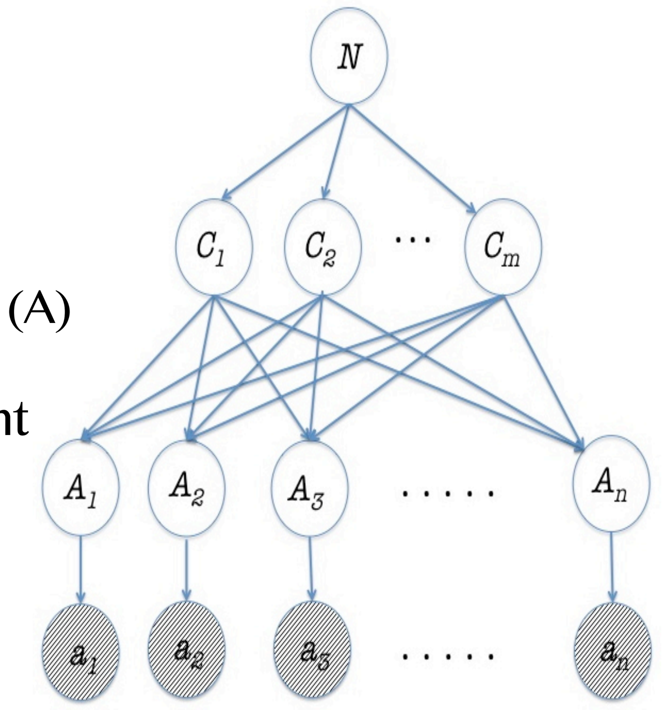
§ Across different cues, ***Shape*** is the most important reason for abnormality.

§ Except for Aeroplane people are sure about the cause of Abnormality.

Proposed Abnormality Model

Normality assumption (N) imposes a peaked distribution over Object Classes (C). As a result multimodal and uniform distributions over Categories suggests Abnormality.

Considering this point, Normality Model can be illustrated by this graphical model:



Conditioned on observed visual attributes (A) and without any assumption on the object class, Abnormality is the complement event of Normality:

$$P(\neg N|A) = 1 - P(N|A)$$

$$P(N|A) = P(A|N) * P(N)/P(A)$$

Estimating the joint attribute likelihood by marginalizing over object Classes: $P(A|N) = \sum_j P(A|C_j,N)P(C_j|N)$ and as given

An object class, attributes are independent:

$$P(A|N) = \sum_j \prod_{i=1}^{k} P(A_i|C_j,N)P(C_j|N)$$

For a given object class, each visual attribute has a different importance factor. We measured it by Conditional Entropy:

$$I(A_i = a|C_j,N) = -\log P(A_i = a|C_j,N)$$

As the learned attribute classifiers are not perfect we consider their accuracy during learning as a measure of their reliability:

$$surprise_{(A_i|C_j)}(a) = reliability(A_i) * I(A_i = a|C_j) * relevance(A_i|C_j)$$

$$signed\_surprise_{(A_i|C_j)}(a) = surprise_{(A_i|C_j)}(a) * (2*a-1)$$

Experimental Results

I) Abnormality Prediction

Method	AUC
One class SVM	0.5980
Two class SVM	0.8657
Graphical Model	0.8703
Our Model with surprise score	**0.9105**

* We use Normal images from Pascal dataset and Abnormal images from our dataset.

* Parameters are learned ***ONLY*** on Normal objects, which are represented by 64 Visual attributes.

* Our model has a better accuracy for Abnormality Detection (we are not using any abnormal images – during training). Second row shows the result for the case of using Abnormal images during training a classifier.

* Using surprise score, we are able to rank images based on how abnormal they look :

Less Abnormal High Abnormal

II) Abnormal Attribute Reporting

* Given an abnormal instance from an object class, we can Determine Missing (M) and Unexpected (U) attributes.

* For quantitative results, we made the baseline based on: *Farhadi et al (CVPR 2009)* which assumes a Gaussian Distribution over attributes for normal objects.

*To be comparable with human responses we have grouped Visual attributes into disjoint lists, representing : *Shape, Pose, Color* and *Texture.*

Aeroplane(U):Wheel,Clear (M):Tail,JetEngine,RowWin**Car** : (U): Skin, Clear ,Propeller, Wing (M) : Handlebars

Aeroplane: (M): Label,Taillight (U): Mast **Boat** : (U): Propeller, Glass ,Wheel (M) : Mast, Wood

Aeroplane : (U):Round,Leather(M):Glass,,Engine ,Tail,Text**Sofa**: (M)Round, Cloth (U) : Metal,Taillight, Window

Boat:(U) :Skin, Engine, Wheel (M) : Mast, Text **Aeroplane** :(M): Label, Clear, Tail (U) : Engine, Skin

{Numbers are KL-Divergence}

Method	Airplane	Boat	Car	Chair	Motorbike	Sofa	Average
Baseline I	0.0796	0.0801	0.0775	0.1035	0.0944	0.064	0.0832
Baseline II	0.0826	0.0768	0.0809	0.0956	0.0892	**0.0565**	0.0803
Our Model	**0.0567**	**0.0369**	**0.0758**	**0.0631**	**0.0635**	0.0695	**0.0609**

III) Abnormality Detection helps Object Categorization

*By knowing an object is an abnormal instance of a given class, we will have a list of attributes which made this object look weird.

*Adjusting these abnormal attributes with what is expected from a normal instance, will improve the object categorization task.

* We Measure KL-Divergence between Distribution over object categories using TURK vs. our Model

	KL-Divergence
SVM classification ***before*** Abnormality detection	47.2502
SVM classification ***after*** Abnormality detection	38.5203