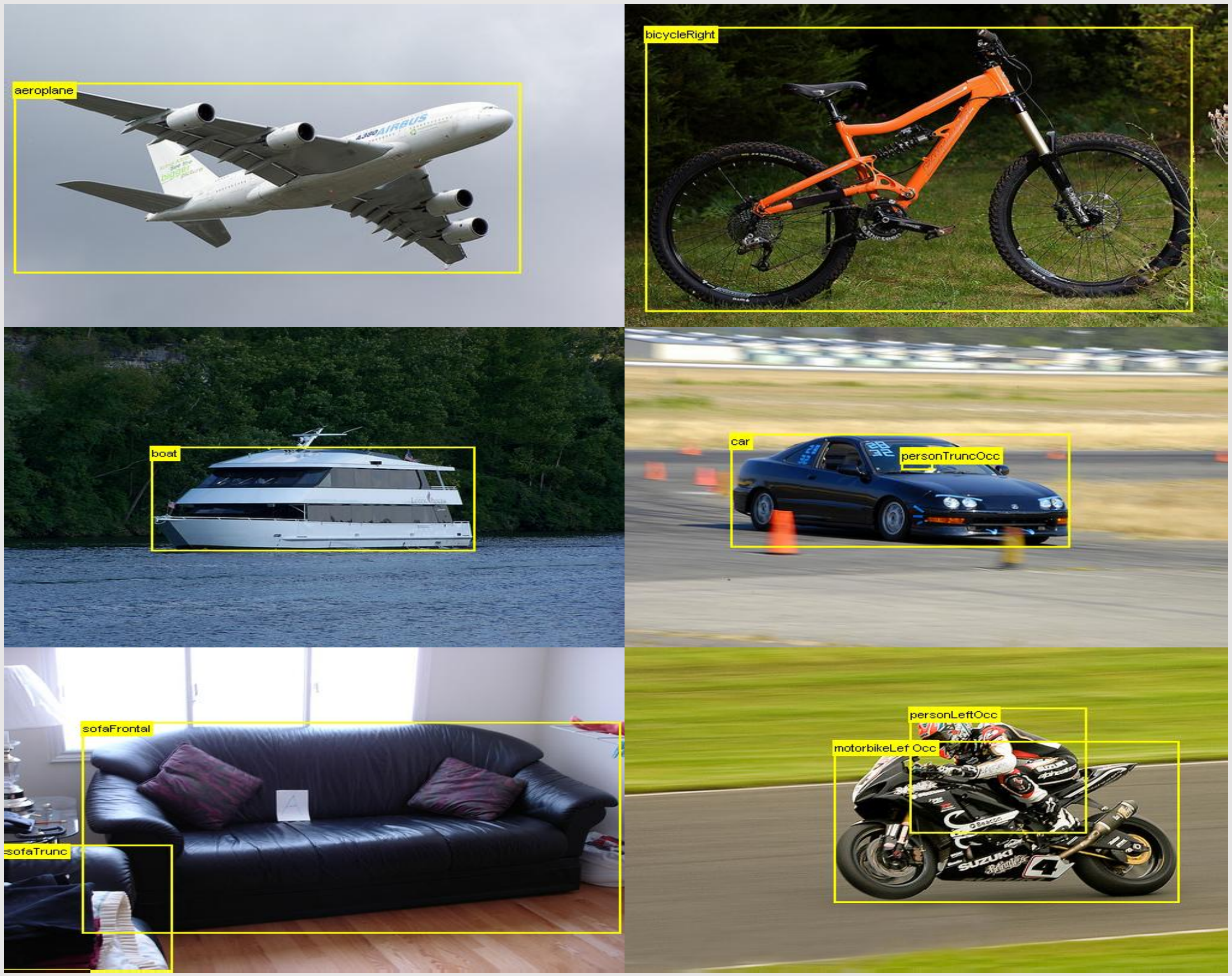
The Role of Typicality in Object Classification

Babak Saleh

Outline

- Motivation
- Related Work
- Problem Definition
- Estimating Typicality of objects/images
    - Data Collection
    - Computational Models
        - Abnormal Object Detection
        - Taxonomy of Abnormalities in Images

Motivation


aeroplane
AIRBUS
bicycleRight
boat
car
personTruncOcc
sofaFrontal
sofaTrunc
personLeftOcc
motorbikeLef Occ
SUZUKI

Motivation

Motivation

Despite human vision, CNN models categorize abnormal objects with a high confidence.

It looks weird!!

It looks weird!!
However it looks like a Car and a Boat

It looks weird!!
However it looks like a Car and a Boat
Boat with a wheel??
Car with a bow?

Motivation

- State-of-the-art (CNN based models) fail drastically to recognize abnormal objects.

Method	Top-1 error (%)			Top-5 error (%)		
	Train	Test-T	Test-A	Train	Test-T	Test-A
AlexNet [Krizhevsky *et al.*, 2012]	38.1	49.5	74.96	15.32	24.01	47.07
OverFeat [Sermanet *et al.*, 2013]	35.1	45.36	75.62	14.2	22.27	46.73
Caffe [Jia *et al.*, 2014]	39.4	51.88	77.12	16.6	24.74	46.86
VGG-16 [Simonyan and Zisserman, 2015]	30.9	44.04	77.82	15.3	26.31	47.49
VGG-19 [Simonyan and Zisserman, 2015]	30.5	43.72	76.35	15.2	26.85	45.99

Normal

Abnormal

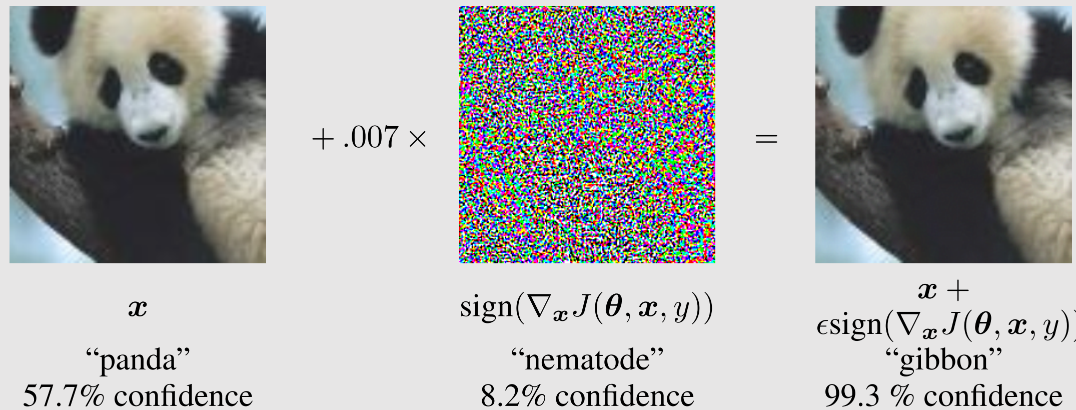
Normal

Abnormal

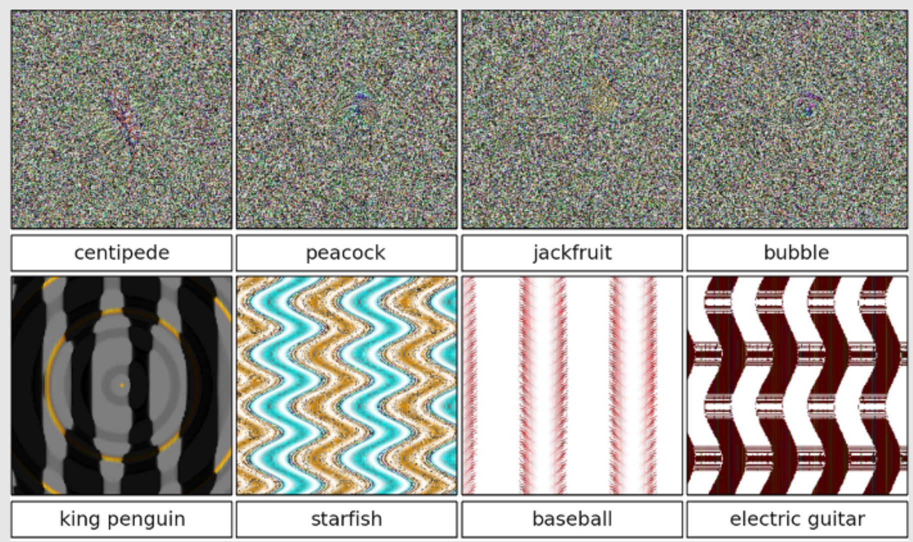
Related Work

- Analysis of failure modes for CNN

- [Goodfellow et al.'15]



- [Nguyen et al.'15]



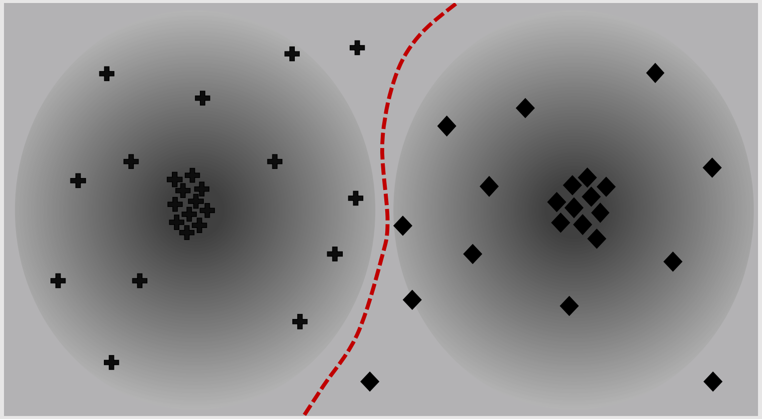
Related Work

Training strategies for learning:

- Technical specifications
  - Learning rate
  - Batch size

- Curriculum learning
  - Order of the training samples are important.
  - Better classifiers are trained with seeing better examples first

- Discriminative Models
  - Boundary examples
- Generative Models
  - Center of density
- Hybrid Models
  - Using generative hints in training discriminative models. Best of both worlds.
  - Not all abnormal samples are boundary examples.



Problem Definition

- Improving generalization capacity of discriminative classifiers using signals from a generative model that focuses on representativeness of samples.

- In this work, we take most normal/typical examples as most representative samples.

What makes an object abnormal?

- **<u>What</u>** is abnormal object/image?
  - Not a well-agreed answer.
- **<u>What</u>** makes an object/image look strange?
  - Shape, parts, texture.
- **<u>Why</u>** abnormality happens?
  - Unexpected context, relative size, strange location.

Data Collection

Abnormal
Weird
Strange
Atypical

Object class +names from Pascal

Weird Car, Strange Sofa, etc.

Google
YAHOO!
bing

Pruning:
Low Quality
Duplicity
Irrelevant

Human Subject Experiment

amazon mechanical turk beta

Abnormal Image Dataset

Human Subject Exp. I

- The goal of the first round of our human subject experiment is manifold:
    1. Verifying that our image collection is abnormal.
    2. Abnormality rating for objects as a graded concept.
    3. Delving into reasons that cause abnormality in objects.
    4. Rich set of annotation in terms of object categories and abnormality reasons.

HIT Preview

amazon mechanical turk beta

1. Do the objects in the image seem normal or abnormal (i.e. strange) to you?: (select only ONE of the following)

- ○ Normal
- ○ Abnormal

2. Which of the following categories best describe the object? (select all that apply):

- ☐ Aeroplane
- ☐ Boat
- ☐ Car
- ☐ Chair
- ☐ Motorbike
- ☐ Sofa
- ☐ None of them

Showing HIT 1 of 1000 [Next HIT]

[Cancel] [Next]

HIT Preview

3. Why do you think the object in the image is abnormal? (select all that apply)

- ☐ Object by itself
- ☐ Object in relation to the other scene parameter

If you selected "Object by itself" for abnormality in question 3: (If this part doesn't apply to this image, please select "Doesn't apply")

4. Please rate importance of each of these following attributes in affecting your decision that this object is Abnormal. You are allowed to assign the same rating to more than one attribute.

Attribute name	Normal(rate 1)	somehow Abnormal or Strange (rate 2)	Abnormal or Unusual (rate 3)	Doesn't apply
Color	☐	☐	☐	☐
Shape (including Object size, parts configuration)	☐	☐	☐	☐
Texture / Material	☐	☐	☐	☐
Object pose / Viewing direction	☐	☐	☐	☐

Showing HIT 1 of 1000 Next HIT

Cancel Next

If the abnormality comes from "Object in relation to the scene parameter" (in question 3) or in case that you think abnormality is a result of something that is missing in questions above:

5. Please describe why you think this image is Abnormal by characterizing the Abnormality aspects:

some of Abnormality aspects are:

1) Geometrical relationships with other objects in the scene. (for example: a train on top of a car)

2) Semantically inappropriate. (for example: an elephant inside the living room)

3) Size of the objects with respect to other objects on the scene

Submit

amazon mechanical turk beta

Showing HIT 1 of 1000 Next HIT

Cancel Next

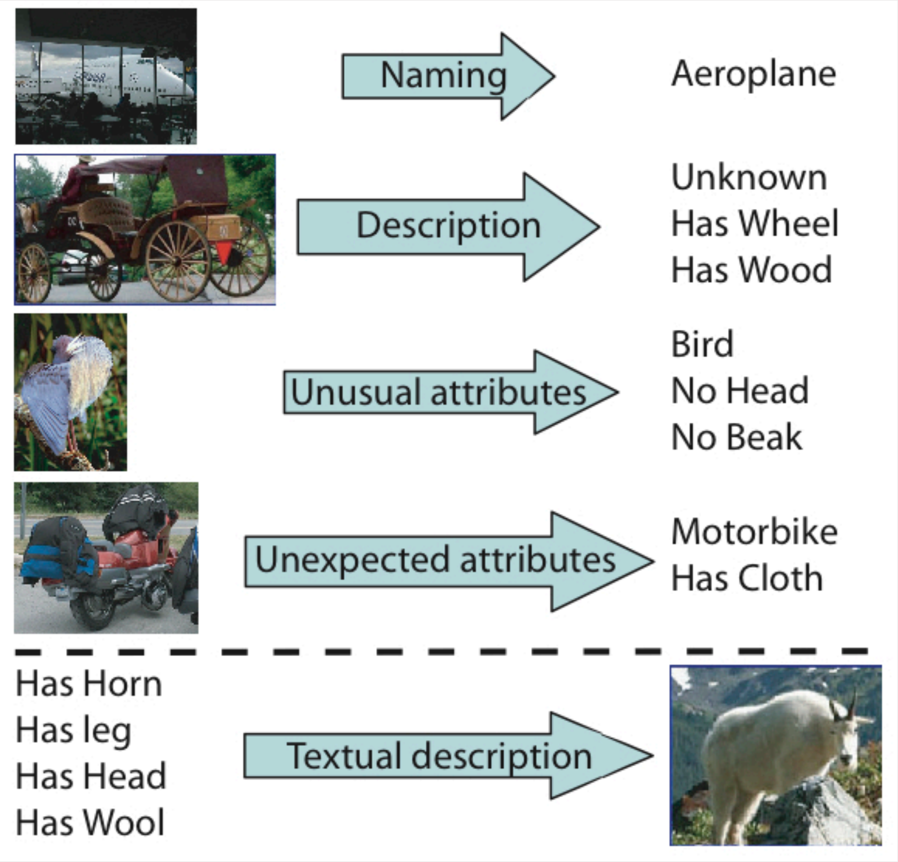
Abnormal **Object** Detection

- We should NOT learn on top of abnormal samples
  - It is not a two way classification problem.
    - ➢ Imbalanced data
    - ➢ Uncontrolled variations in the visual space
    - ➢ Human-like vision
- We just learn the model based on normal samples and define:

"Abnormality is <u>Meaningful Deviation</u> from Normality"

Visual Attribute

- Semantically meaningful visual characteristics. [Farhadi et al.'09]
- Pre-defined list of attributes, usually require expert knowledge.
- Visual classifiers for each attribute, trained on low-level visual features (HoG, SIFT, etc.)
- Shareable between object categories. Normal and Abnormal objects.



Abnormal Object Detection

Graphical Model for Normality (N)

C: object **C**ategory, **A**: visual **A**ttributes

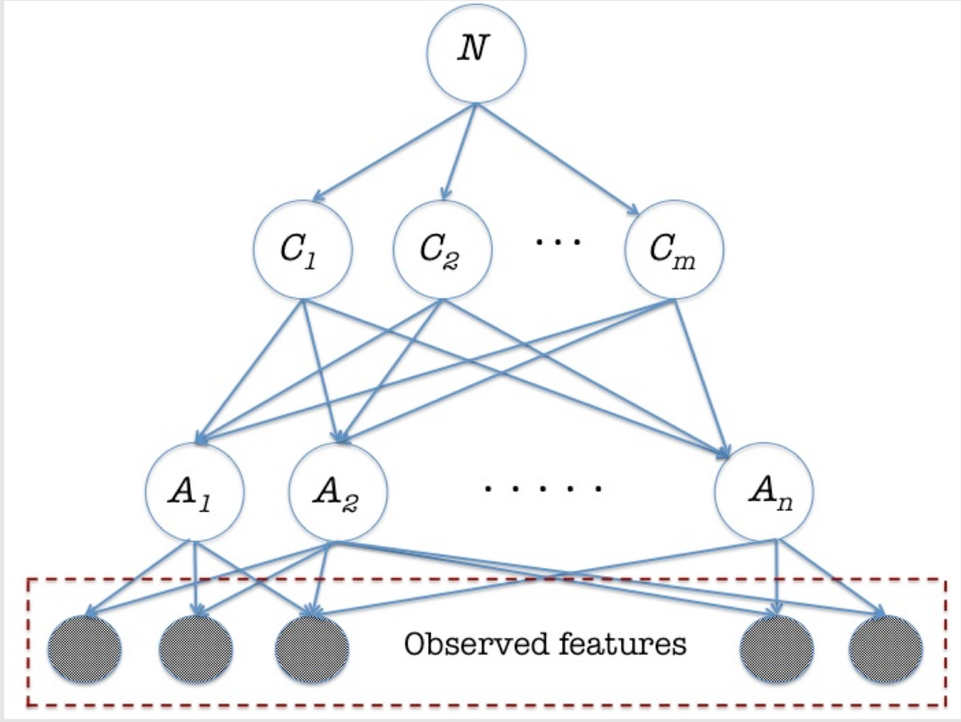
$$P(\neg N|A) \;=\; 1 - \; P(N|A)$$

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

$$P(A|N) = \textstyle\sum_j P(A|C_j, N)P(C_j|N)$$

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

$$P(A_i|C_j) \;\sim \mathcal{N}(\mu_{ij}, {\sigma_{ij}}^2)$$



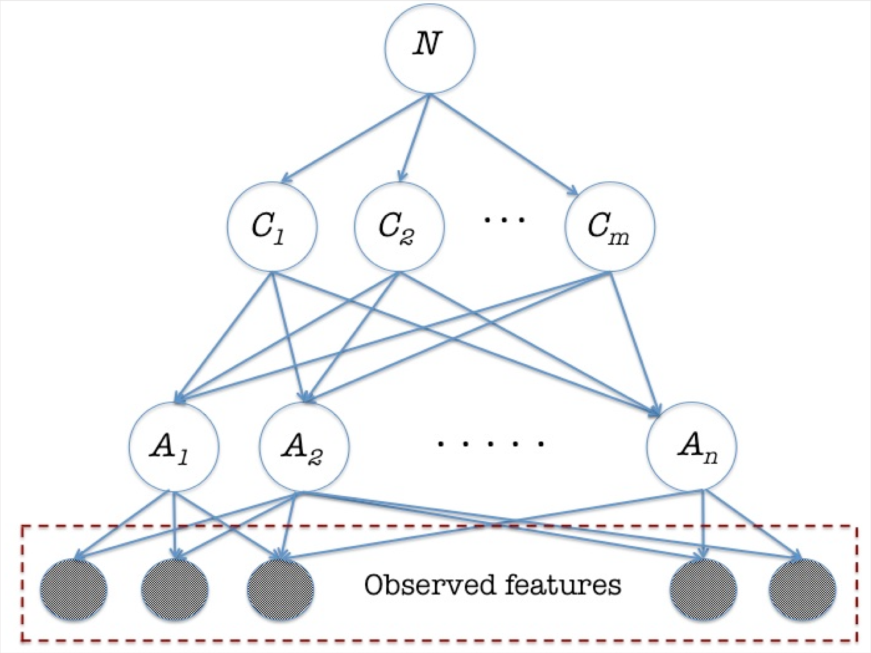
Abnormal Object Detection

Surprise Score for Abnormality

- The amount of information produced by an attribute is different from one category to another.
- ➢ We measure it via information theory

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

- Attribute classifiers are noisy!
- ➢ Measure reliability of attributes as its accuracy over validation set.



Abnormal Object Detection

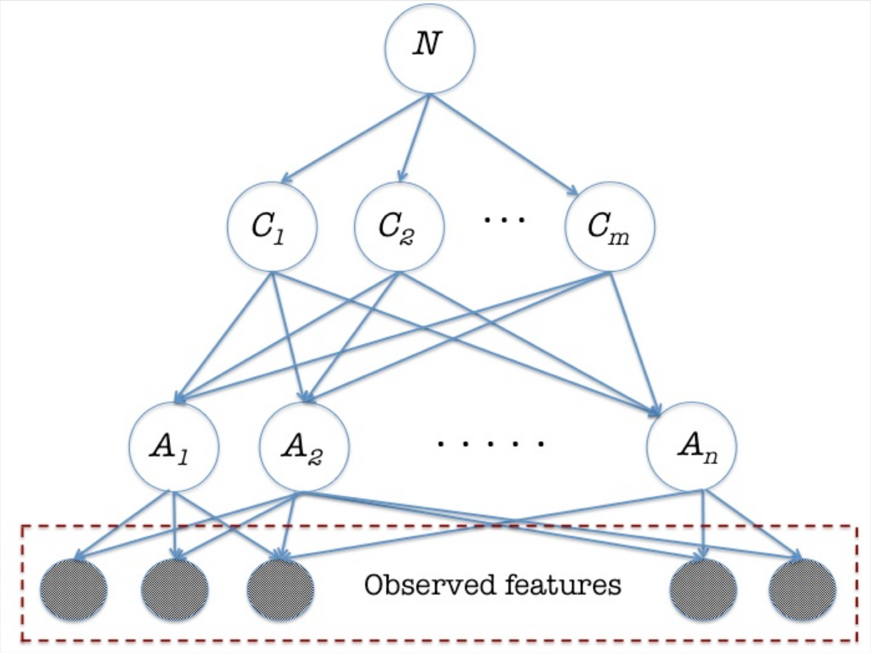
Surprise Score for Abnormality

- Importance of visual attributes is dependent on the object category.
- ➢ Compute relevance of an attribute over training set once.

$$relevance(A_i|C_j) = 1/H(A_i|C_j)$$

- Surprise score is aggregation over all attributes and object categories.

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



Abnormality beyond Objects

- Comprehensive understanding of what can cause abnormality? Going beyond abnormal objects

- However, the taxonomy of possible reasons for abnormality in images is not defined

- Still, this is Not a two-way classification

- We use Information theoretic approaches, because it mimics human reasoning about these images

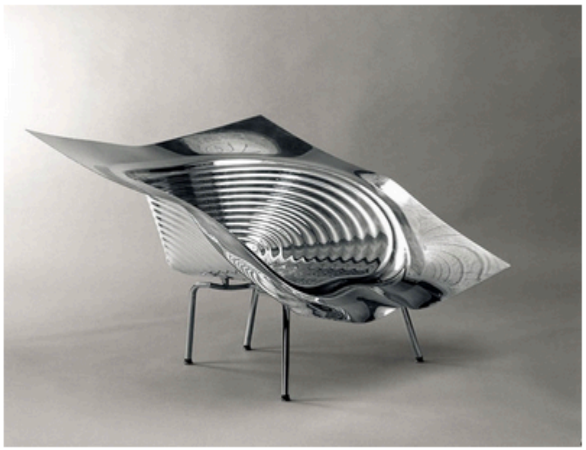
Human Subject Exp. II

- Investigating human thinking about abnormality
- Proposing a taxonomy of reasons that can make an image look abnormal.

amazon mechanical turk beta

*Nothing abnormal about this image
*Strange contour (boundary) for typical objects of that category
*Object in the shape of another object
*Object is not complete

HIT Preview



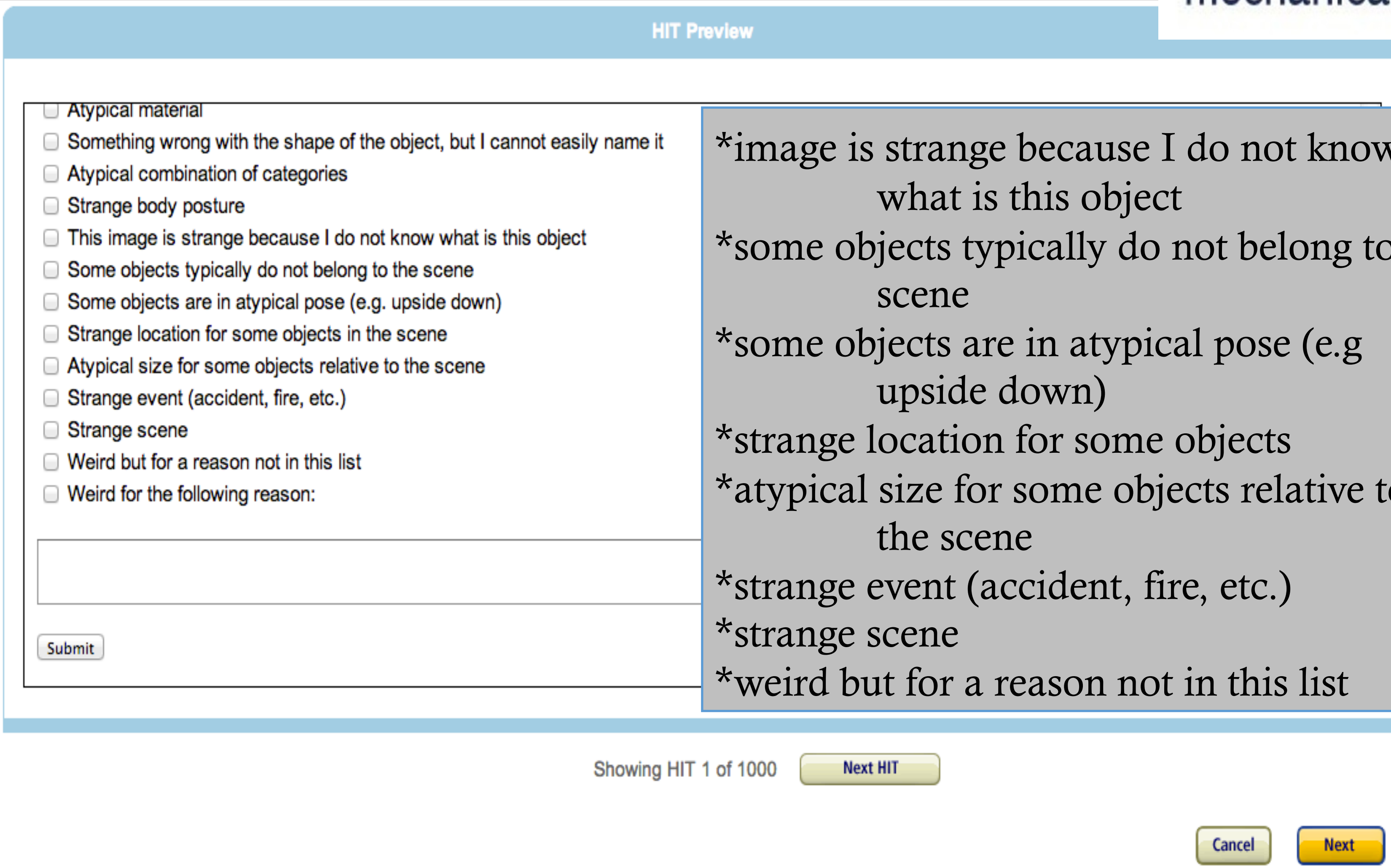
After looking at this image tell us if you think this image looks typical to you or not by sel

- Nothing abnormal about this image
- Strange contour (boundary) for typical objects of that category

*object is not complete
*missing specific part(s)
*misplaced part(s)
*weird-shaped part(s)
*unexpected parts, extra parts
*strange texture
*strange color
*strange pattern
*atypical material
*something wrong with the shape of the object, but I cannot easily name it
*atypical combination of categories
*strange body posture

Showing HIT 1 of 1000 Next HIT

Cancel Next



amazon mechanical turk beta

*image is strange because I do not know what is this object

*some objects typically do not belong to the scene

*some objects are in atypical pose (e.g upside down)

*strange location for some objects

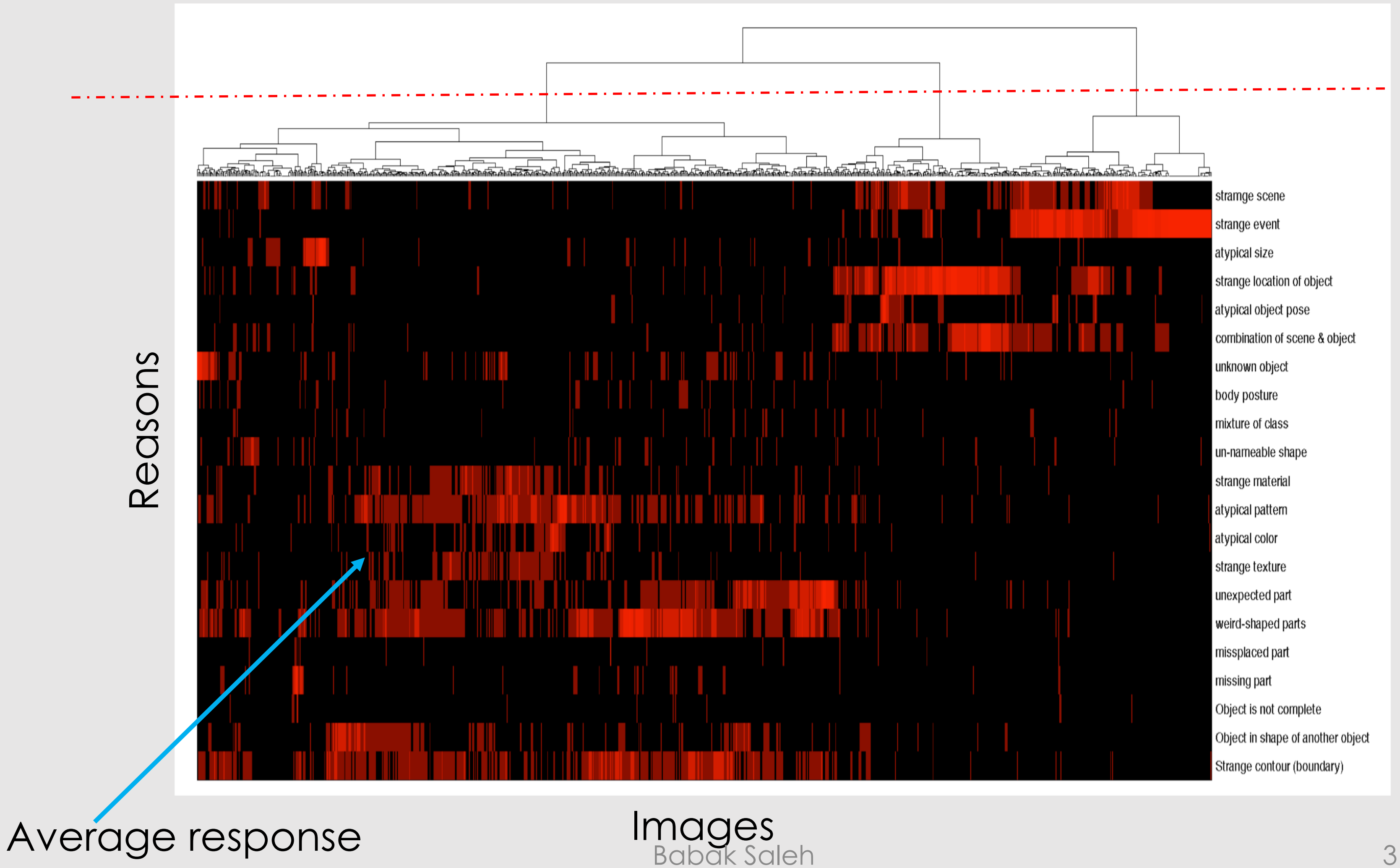
*atypical size for some objects relative to the scene

*strange event (accident, fire, etc.)

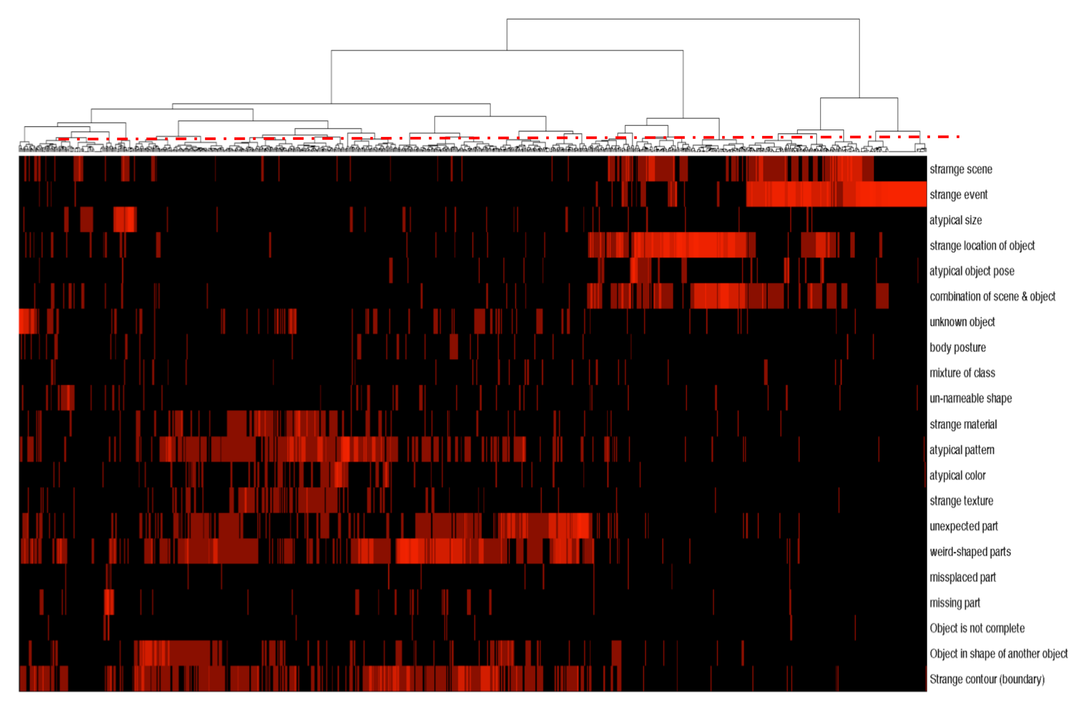
*strange scene

*weird but for a reason not in this list

- For all images, average responses of 10 users
- bottom-up agglomerative clustering
- Ward's minimum variance criteria as the Linkage function
- Three main branches on top



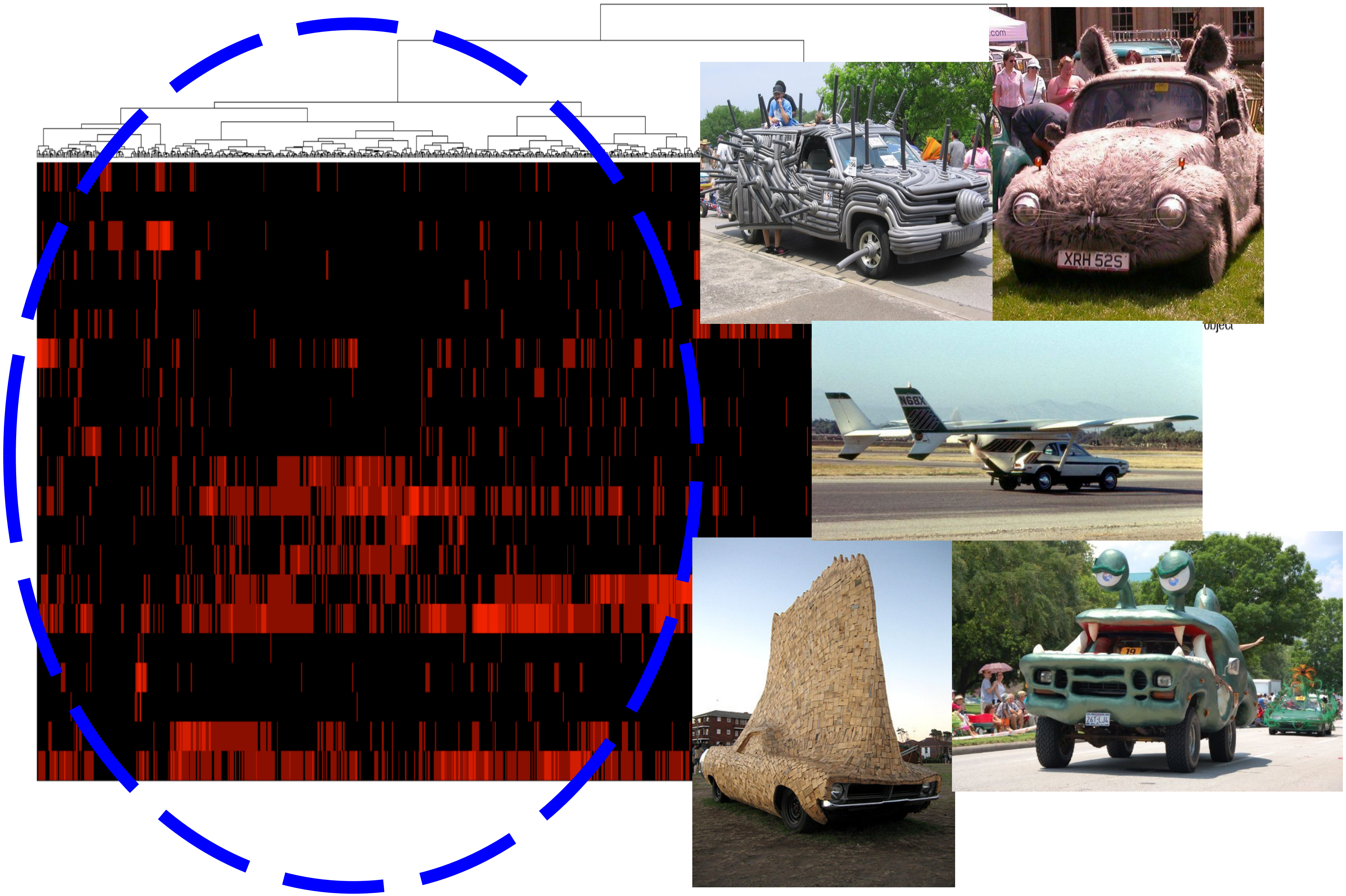
Main Category	Detailed Reasons in Amazon Mechanical Turk Experiment
Scene-centric	Strange event happening in the scene(21); Strange scene(20)
Contextual	Atypical object size(19); Strange location of the object(18); Atypical object pose(17); Weird combination of objects and scene(16)
Object-centric	Unexpected part(7); Weird shaped part(6); Misplaced part(5); Missing part(4); Body posture(14); Mixture of object classes(13); Un-nameable shape(12); Object is not complete(3); Unknown object(15); Object in the shape of another object(2); Atypical pattern(10), Weird color(9), Strange material(11), Weird texture(8); Strange object contour(1)



Scene-centric Abnormality

Contextual Abnormality

Object-centric Abnormality



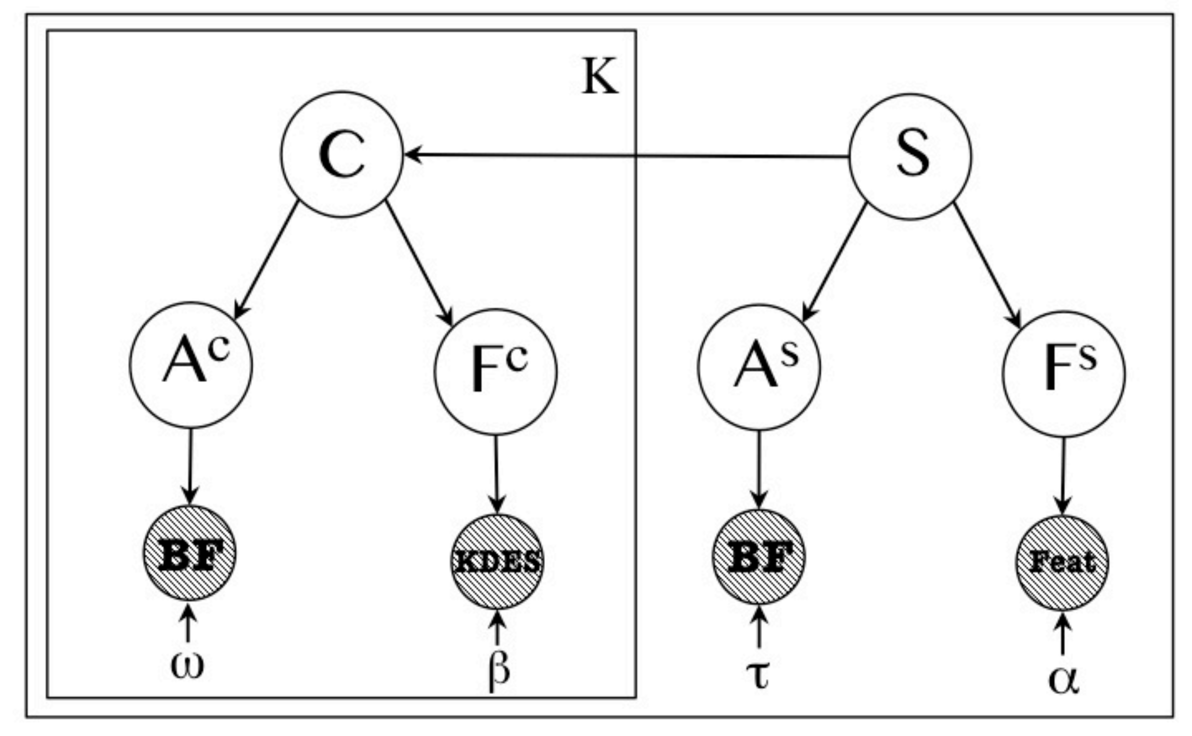
- Following the inferred taxonomy of abnormality, we build three computational models to measure how surprising is an image:
    - Object-centric surprise score
    - Scene-centric surprise score
    - Contextual surprise score

Modeling Normal Images

S: Scene category
C: Object category

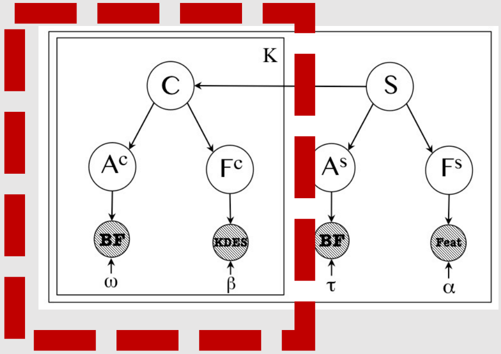
F^S F^C : Vis. Feat for Scene/Object categorization

A^S A^C : Vis. Attributes for Scene/Object



This model is able to find three main reasons of abnormality

Object-centric Surprise



$$\sum_k P(O_k) * (\sum_i I(A_i^o|O_k) * \Upsilon(A_i^o) * \Omega(A_i^o, O_k))$$

Object category

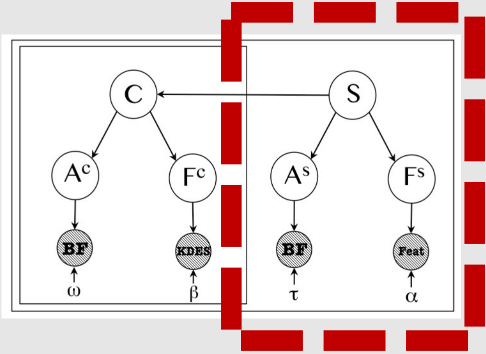
$-log(P(A_i^o|O_k))$

Amount of surprise by observing i-th attribute for the given object category

Attribute reliability

Importance of i-th attribute for the given object category

Scene-centric Surprise



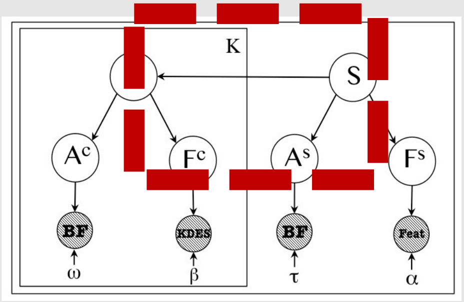
$$\sum_i I(A_i^s | S_j)\Upsilon(A_i^s)\Omega(A_i^s, S_j)$$

Attribute reliability

Amount of information by observing i-th attribute for the given scene category

Importance of i-th attribute for the given scene category

Contextual Surprise



$$\sum_k \sum_j \Lambda(O_k)[\hat{I}(O_k|S_j) + I(L_k|O_k)]$$

Relative size of the object
Modeled by Gamma Dist.

Amount of information
that location of the
object reveals

$$\hat{I}(O_k|S_j) = P(S_j)P(O_k)I(O_k|S_j)$$

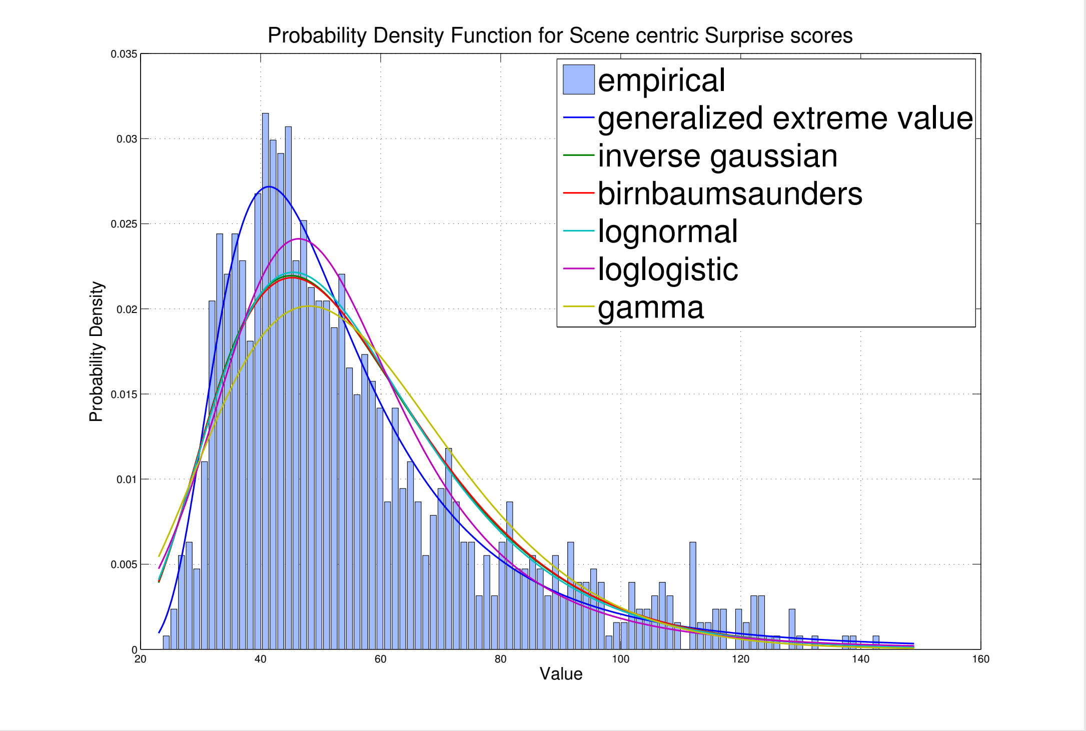
Surprise rooted in the co-occurrence
of object categories and scene

Abnormality Scores

$$\underset{o,s,c}{\operatorname{argmax}}(\phi_o(Surprise_O),\phi_s(Surprise_S),\phi_c(Surprise_C))$$

- $\phi_o(\cdot)$,$\phi_s(\cdot)$,$\phi_c(\cdot)$ are Inverse Gaussian CDF for Object, Scene, and context surprise.

- Taking the maximum among the complimentary probability values for these reasons, indicates the most influential reason behind the atypicality of the image.

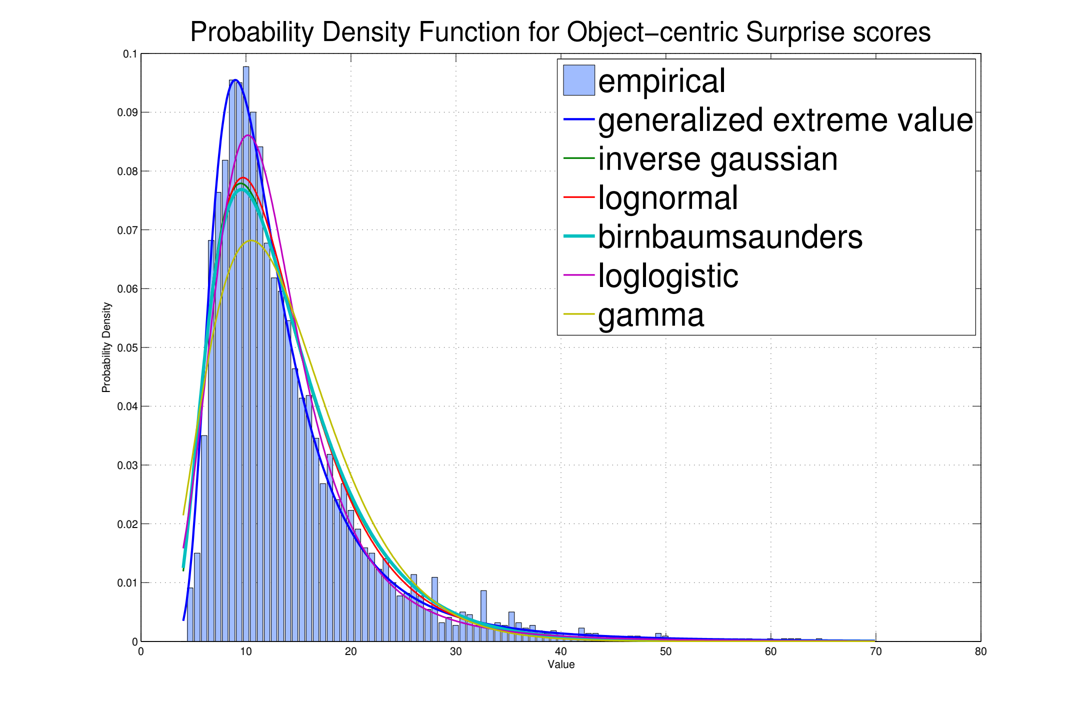


Surprise scores(scene centric) for normal images

Abnormality Scores

- Raw surprise score are not comparable, and cannot be used to judge abnormality of an image.

- However, raw surprise scores follow exponential distributions when we plot the histogram of values for normal images.



Surprise scores (object centric) for normal images

Dataset

- Abnormal images:
  1. Continues abnormality score [0,1]
  2. Main reason of abnormality [cluster index in the inferred dendrogram]
  3. Rating of fine-grained reasons of abnormality.
- Normal images:
  1. Standard dataset for image categorization (PASCAL)

Experimental Setting

- Object Representation:
  - 64 Visual attributes.
  - Low-level features for categorization:
    - Kernel Descriptors [Bo et al, NIPS 2010]
- Scene Representation:
  - 102 Visual attributes [Patterson et al, CVPR 2012]
  - Scene categorization [Juneja et al, CVPR 2013]

Abnormality Detection – Prior Art

Experiment Number	Method	Accuracy
I	Object-centric baseline (Saleh, Farhadi, and Elgammal 2013)	0.9125
	Our Model - Object-centric	**0.9311**
II	Context-centric baseline (Park, Kim, and Lee 2012)	0.8518
	Our Model - Context-centric	**0.8943**

- Prior art in object-centric abnormality detection suffer from poor object classifiers (attribute-based). Our model also benefits from a richer set of visual features used for learning attribute classifiers.

- Similar to our work, Park et al. built their models only based on normal images. However, our reasoning based on information theoretic terms outperforms their CRF-based model of supporting context and objects.

Abnormality Detection - Baselines

Experiment Number	Method	Accuracy
III	One Class SVM - based on Attributes	0.5361
	Two Class SVM - based on Attributes	0.7855
	One class SVM - based on Deep features (fc6)	0.5969
	Two class SVM - based on Deep features (fc6)	0.8524
IV	Our Model - No Object-centric score	0.8004
	Our Model - No Context-centric score	0.8863
	Our Model - No Scene-centric score	0.8635
	Our Model - All three reasons	**0.8914**

- Our model is learned using only normal images, but outperforms two-way classifiers. Either trained via attributes or vanilla deep features.

- We relate this to the complexity of visual world, which makes it hard to find support vectors. Also, training SVM classifiers suffer from imbalanced data very much.

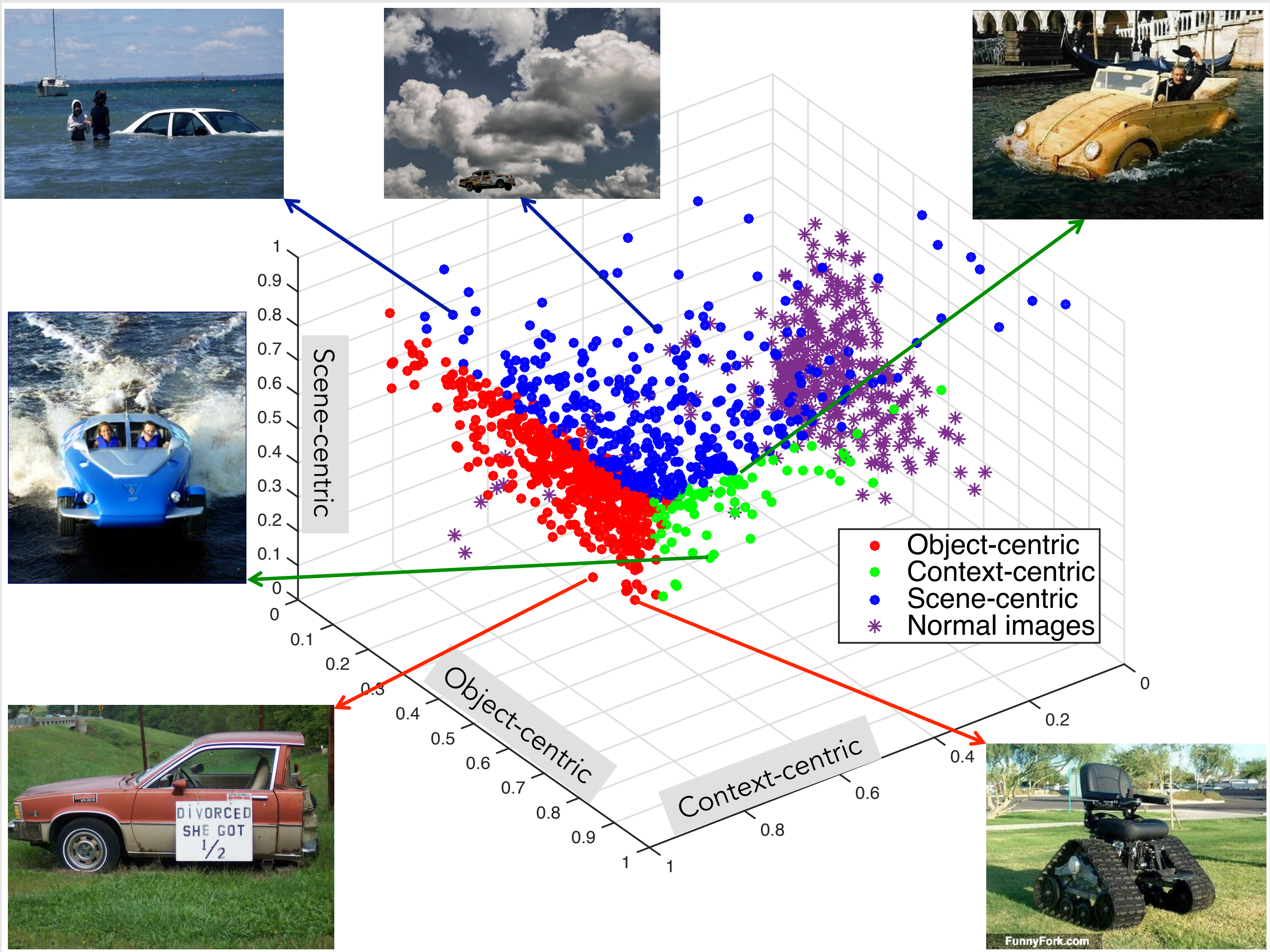
Abnormality Detection–Ablation Exp.

Experiment Number	Method	Accuracy
IV	Our Model - No Object-centric score	0.8004
	Our Model - No Context-centric score	0.8863
	Our Model - No Scene-centric score	0.8635
	Our Model - All three reasons	**0.8914**

- This ablation experiment shows the importance of each component of our final mode, where we held out one reason at a time.
- Clearly, the object-centric is the most important component of our performance in abnormality recognition in images.
- We relate this to the the fact that majority of images in our dataset are atypical due to having abnormal object(s).

Abnormality Ranking

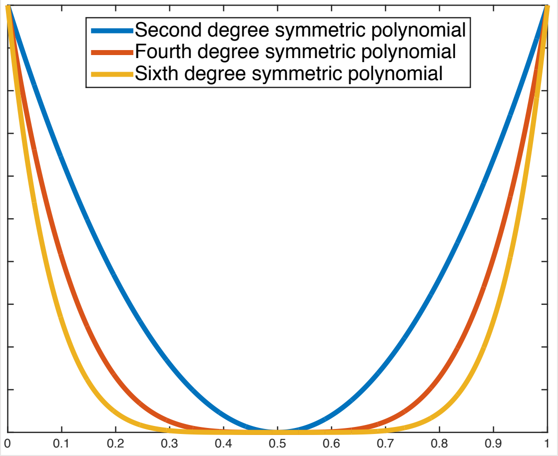
Abnormality in Perspective



Approach - Weighting Samples

- We propose a new training strategy for CNN:
  - Same training data (ImageNet), and same optimization (SGD)
  - Not all training examples are equally important
  - Modeling the importance of each training image based on how typical/normal it looks like
  - Weighting training sample during training as a function of their typicality.
  - At inference/test time, <u>no need</u> to measure the typicality of image

- Even-degree Polynomials
  - To emphasize on both normal and abnormal samples
  - Suitable for hybrid model, where typicality is as important as atypicality (discriminative)



Alternative Weighting function

- Internal scores of typicality
  - Entropy of the output of the layers of CNN resembles human's opinions about the typicality [Lake et al'15]
  - We used these scores to re-train the same CNN
  - This approach predicts the typicality of test images as well

Experiments

Weighting Function used in Fine-Tuning	Mean Accuracy (%)			
	Test Atypical		Test Typical	
	Epoch 1	Epoch 10	Epoch 1	Epoch 10
No weight	56.39	65.18	78.15	83.51
Random	57.15	66.45	73.60	83.84
Typicality	64.53	68.58	69.22	79.90
Atypicality	66.61	70.65	75.82	84.07
Cls-Typ	67.25	70.84	77	81.88
Cls-Atyp	63.26	68.46	76.96	83.40
Log-Typ	64.38	68.28	78.80	83.67
Log Cls-Atyp	64.21	67.80	76.13	83.24
Memorability	64.69	68.33	76.31	83.96
Poly Deg-2	59.13	69.49	80.03	84.42
Poly Deg-4	60.22	71.52	77.74	83.45
Poly Deg-6	60.86	70.31	77.66	84.22
In-Probability	65.97	69.53	80.71	85.82
In-Entropy	60.54	68.05	79.44	82.29
In-Prob + Atyp	62.94	68.21	75.82	83.09

Summary

1. There is a big gap between humans and computer vision, when it comes to atypical images.
2. Similar to human learning, we built algorithms that understand atypical images, without seeing them before.
3. We used information theory and visual attributes to show that computational reasoning correlates with human reasoning about abnormality.
4. Proposed a taxonomy for abnormality that has three main branches: Object, Context and Scene.
5. Incorporating typicality estimation in learning discriminative object classifiers improves the performance on both normal and abnormal objects.

Thank you!

Ahmed Elgammal
Rutgers

Jacob Feldman
Rutgers

Ali Farhadi
Apple
UW

Kostas Bekris
Amazon
Rutgers

Devi Parikh
Facebook AI Research
Georgia Tech

Dataset Statistics: Category Membership

- Categorization of abnormal objects are harder than regular objects.
  - Even humans are not in a total agreement about the category membership of abnormal objects.

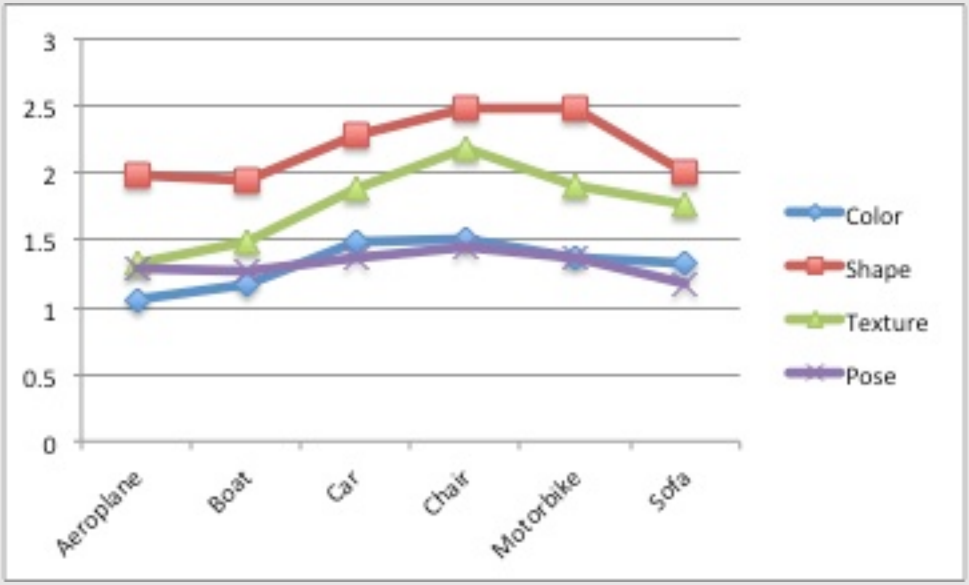
	Aeroplane	Boat	Car	Chair	Motorbike	Sofa	None
Aeroplane	908	10	7	1	0	0	51
Boat	62	868	57	0	1	1	44
Car	7	9	1072	3	0	1	52
Chair	0	1	11	861	1	166	36
Motorbike	17	0	31	3	540	0	38
Sofa	1	1	3	273	0	666	86

Confusion Matrix - Object Categorization – Abnormal Objects

Dataset Statistics: Abnormality Reasons

- Human subject scores averaged for each one of four reasons.

- Independent of the object category, **Shape** is the 1st reason for making an object abnormal. Followed by **Texture**, **Color** and **Pose**.



Dataset Statistics: Abnormality Reasons

- Confidence of reasoning about abnormality varies from one category to another.

Computational Models:

I. Abnormal Object Detection

- "*Object-Centric Anomaly Detection by Attribute-Based Reasoning*"; B. Saleh, A. Farhadi, A. Elgammal. **CVPR 2013**
- "*Detecting Strange Object via Visual Attributes*"; B. Saleh, A. Elgammal, A. Farhadi. **ECCVW 2014**
- "*Recognition of Abnormal Images and Reasoning about Strange Objects via Visual Attributes*"; B. Saleh, A. Farhadi, A. Elgammal. Under Submission. In preparation **TPAMI 2016**

Abnormal Object Detection

- Based on Abnormality Score from the Normality model, we can classify an object as Normal vs. Abnormal.

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

Abnormal Object Ranking

- Based on surprise scores we are able to rank images, showing how strange they look like.

Less Abnormal → Highly Abnormal

Abnormality Reasoning

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

$$surprise_{(A_i|C_j)} : [0,1] \rightarrow [0,\infty)$$

1. Given the object category, one can measure the surprise score of the observed value of an attribute.
2. Grouping attributes into Shape, Color, Texture and Pose. Consequently average corresponding surprise scores to compare them with human response.

Abnormal Object Reasoning Via Visual Attributes

KL Divergence between two distribution [1) Model 2) Human Sub. Exp.]

Method	Airplane	Boat	Car	Chair	Motorbike	Sofa	Average
Baseline I*	.0796	.0801	.0775	.1035	.0944	.064	.0832
Baseline II*	.0826	.0768	.0809	.0956	.0892	.0565	.0803
Our Model	.0567	.0369	.0758	.0631	.0635	.0695	.0609

***"*Describing objects by their attributes*", Farhadi et al. CVPR'09

Abnormality Reasoning

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

$$signed\_surprise_{(A_i|C_j)} : [0,1] \rightarrow (-\infty, \infty)$$

- Compute signed surprise score in order to report missing (negative surprise), or unexpected (positive surprise) attributes.

Abnormal Object Reasoning Via Visual Attributes

Aeroplane: (M) RowWind, Engine, Propeller, Tail, JetEngine (U): Sail **Boat** : (M): Sail (U):Clear,Handlebars , Skin

Sofa : (U):Wing, Exhaust, Wool, Round,(M): Text, Feather **Aeroplane** : (M)Engine,Propeller (U) :Sail, Label, Handlebars

Aeroplane: (U):Round,Taillight, 3DBoxy (M):Text, Glass **Sofa**: (U)Round, Metal, Headlight (M)Text ,Wool

Sofa:(M):Round, Wool (U):Handlebars,Wheel, SideMirror **Aeroplane**: (M): Engine, Wheel, Text (U): Round, Handlebars, Sail

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

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

Sofa:(M):Cloth, Leather,Wool (U):Skin, Propeller **Aeroplane**: (M):Propeller, JetEngine, (U):Sail,Skinow

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

Computational Models:

II. Taxonomy of Abnormalities in Images

- *"Toward a Taxonomy and Computational Models of Abnormalities in Images"*; B. Saleh, A. Elgammal, J. Feldman, A. Farhadi. ***Best Paper Award*** **AAAI 2016**
- "A Comprehensive Study of Abnormality Reasons in Images"; B. Saleh, A. Elgammal, J. Feldman, A. Farhadi. In preparation ***JAIR 2016.***
- *"Wow! That looks strange: computational models for detection and reasoning about abnormality in images"* ***ACM AI Matters 2016.***

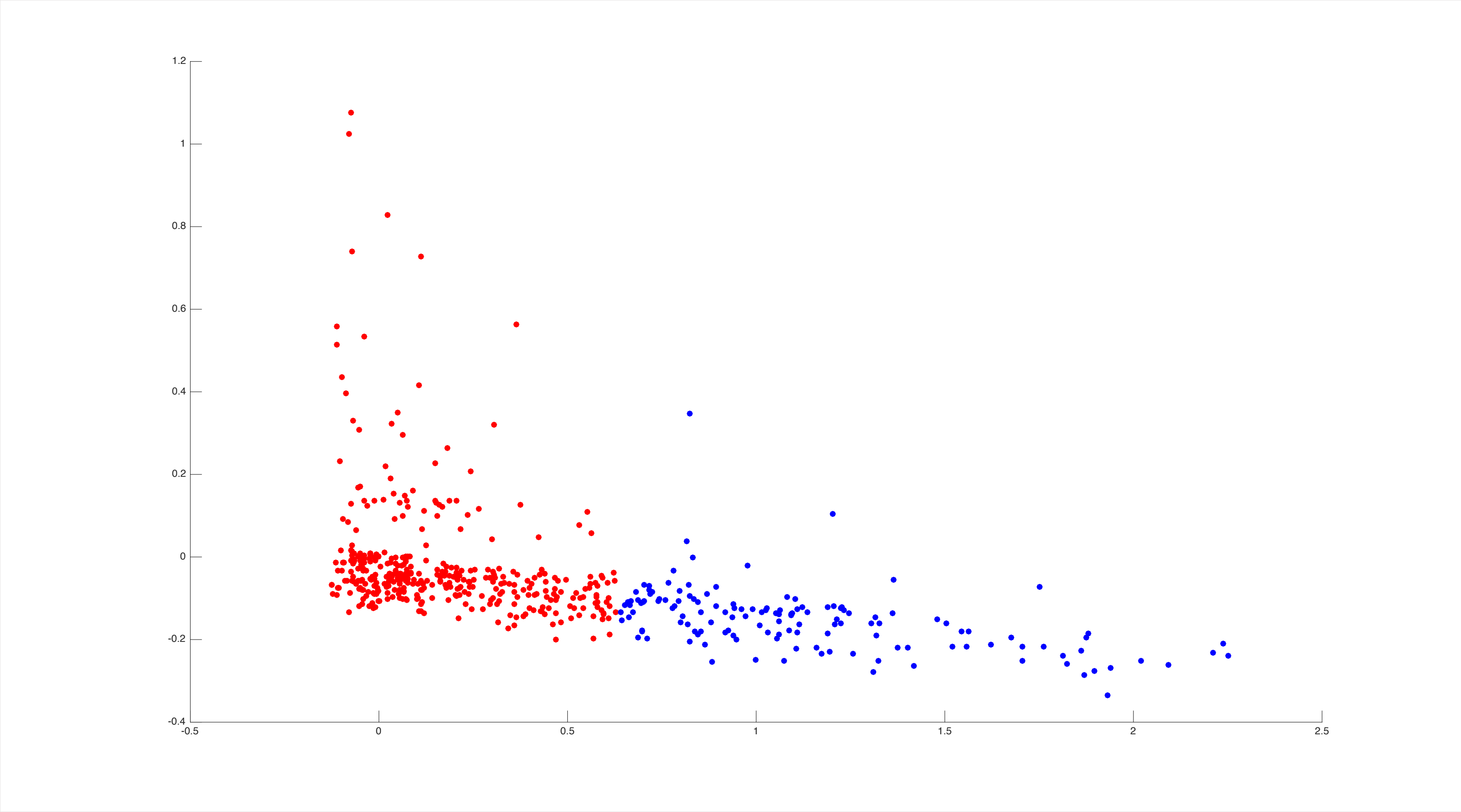
Further analysis of “Object—centric abnormality” cluster

- Deeper (lower) hierarchical clusters do not provide informative grouping of reasons.
- We hypothesize that :
  - Although variety of reasons provide helpful information, but might confuse human subjects in expressing their opinions.
  - Subjects refer to same visual concepts/reasons, but expressing it via different wording.
- We used exploratory factor analysis to learn hidden factors that can explain all fine-grained reasons of abnormality in objects.
- We use statistical significance measure to determine the minimum number of factors that are needed to explain the data. (common/principal factor analysis)

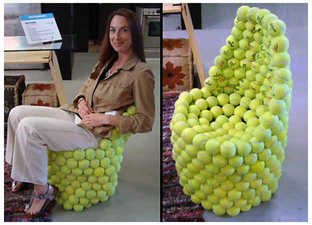
Two Inferred Factors in Object-centric Abnormality Reasons

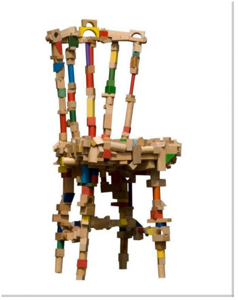
First Factor	0.891447558743145 0.748373028770638 0.694005373675896 0.644901858617892 0.0790435014872081	'strange texture' 'strange material' 'atypical pattern' 'atypical color' 'Object in shape of another object'
Second Factor	0.958508457108101 0.535534222059008 0.331676465239351 0.0531447346520316 0.0322912279988133	'missing part' 'Object is not complete' 'misplaced part' 'body posture' 'un-nameable shape'

- Running K-means clustering on images, after projecting the human responses by using factor matrices.



Sample images taken from the first cluster





Sample images taken from the first cluster

Sample images taken from the second cluster



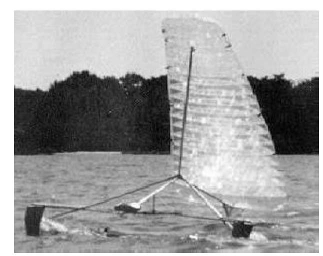




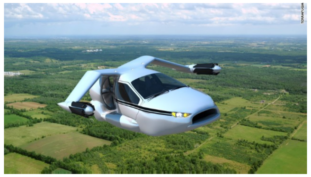


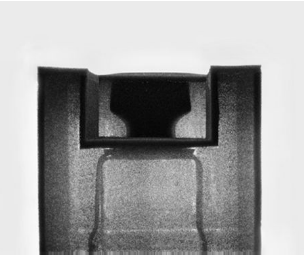







Sample images taken from the second cluster



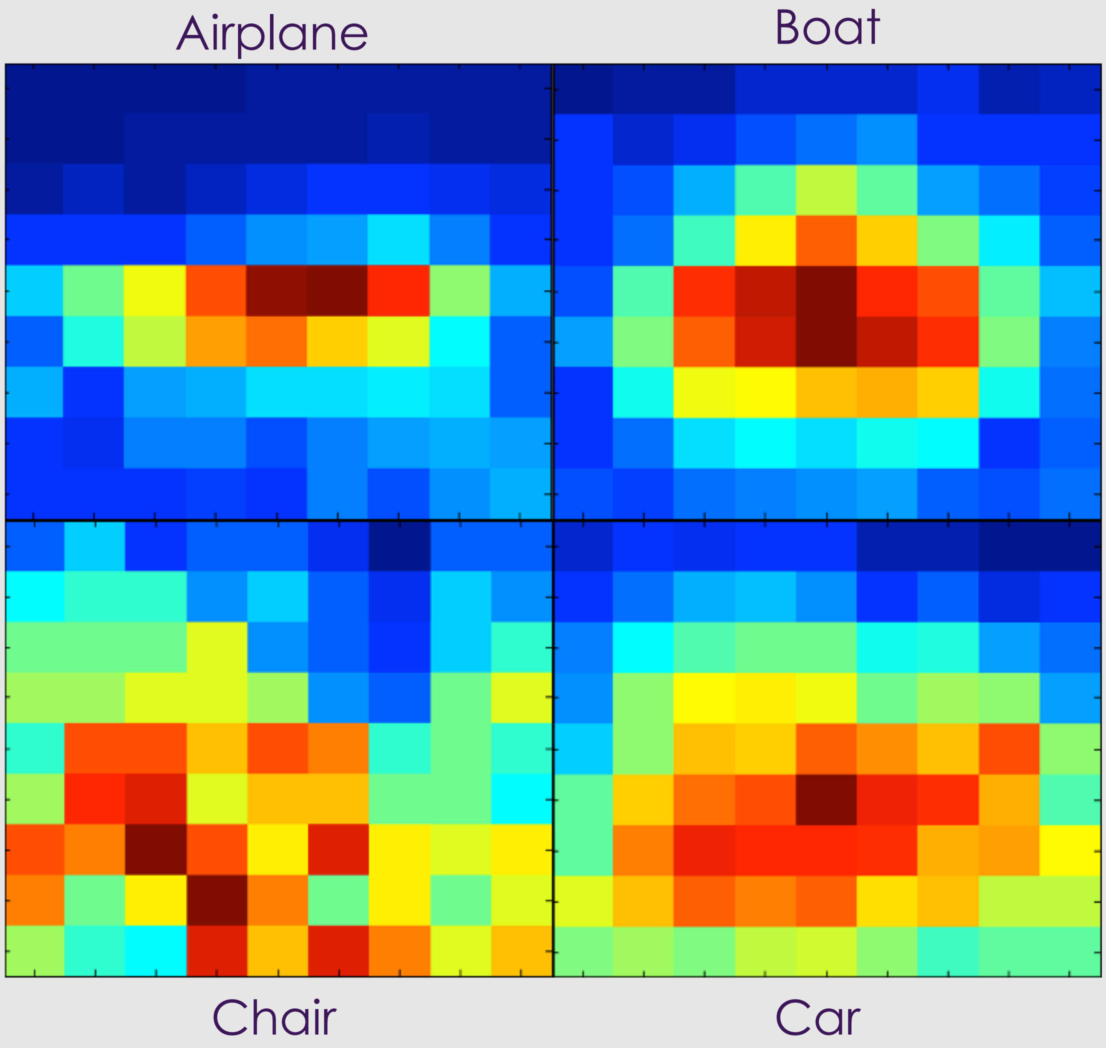


K-Means Clustering of Abnormal Objects Based on Projected Responses

First cluster	Second cluster
'atypical pattern' 'strange material' 'strange texture' 'atypical color' 'Strange contour (boundary)' 'unexpected part' 'Object in shape of another object'	'weird-shaped parts' 'Strange contour (boundary)' 'unexpected part' 'atypical pattern' 'Object in shape of another object'

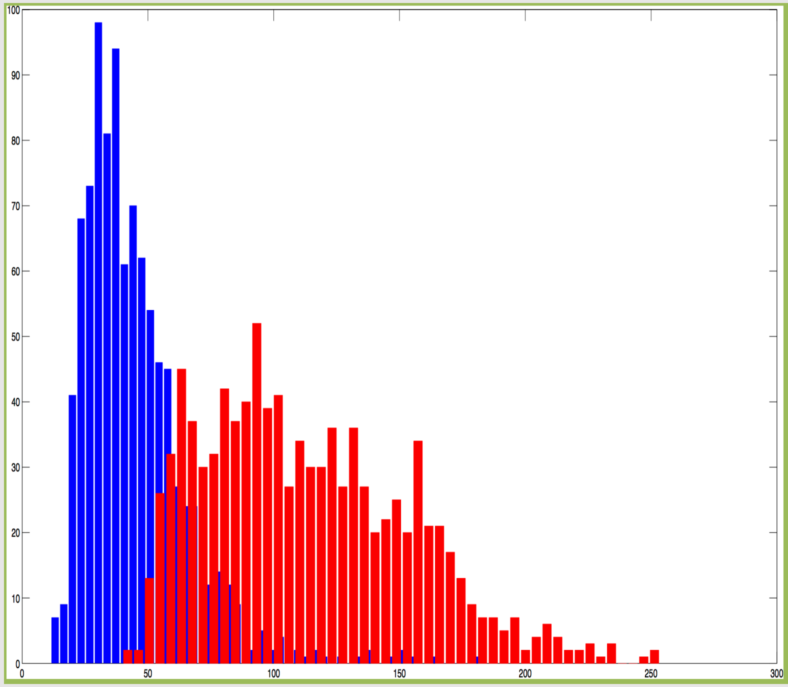
Contextual Surprise

- Heat map showing location of object categories in normal images.
- Learn distribution of pixel assignments in normal images, and use it for finding abnormal location of a given object.

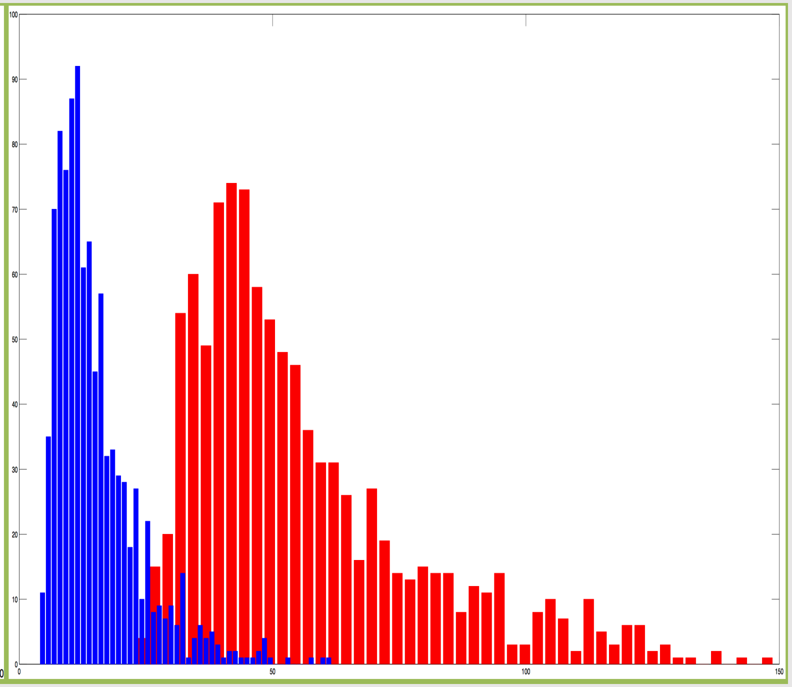


Normal images : Blue
Abnormal Images : Red

Scene-centric



Object-centric



Approach - Loss functions

- Inspired by human-learning, typicality of training samples is very important.
- Sample-based weighting of training samples during the training, to incorporate how typical each sample is.
- We tried two loss functions:

1. Softmax log-loss

$$\mathcal{L} = \sum_n -\tau(\mathcal{X}_n) * \log(\sigma_i(\mathcal{X}_n)) \quad (n = 1, ..., N)$$

$$\sigma_i(\mathcal{X}_n) = \exp(z_i(\mathcal{X}_n)) / \sum_j \exp(z_j(\mathcal{X}_n)), (i, j = 1, ..., \mathcal{C}).$$

Approach – Loss functions

- Although Softmax loss is widely used in state-of-the-art object classifiers, there are better options for our setting.
- Multi-class Hinge Loss, takes into account abnormality of a sample as it is captured by its fuzzy category membership.

2. Multi-class structured hinge loss

$$\mathcal{L} = \sum_{n} \tau(\mathcal{X}_n) * \max(0, 1 - \phi_i(\mathcal{X}_n))$$

$$\phi_i(\mathcal{X}_n) = z_i(\mathcal{X}_n) - max_{i \neq j}(z_j(\mathcal{X}_n)).$$

Experiments

- Typicality estimation is based on a model that is trained via images in PASCAL dataset

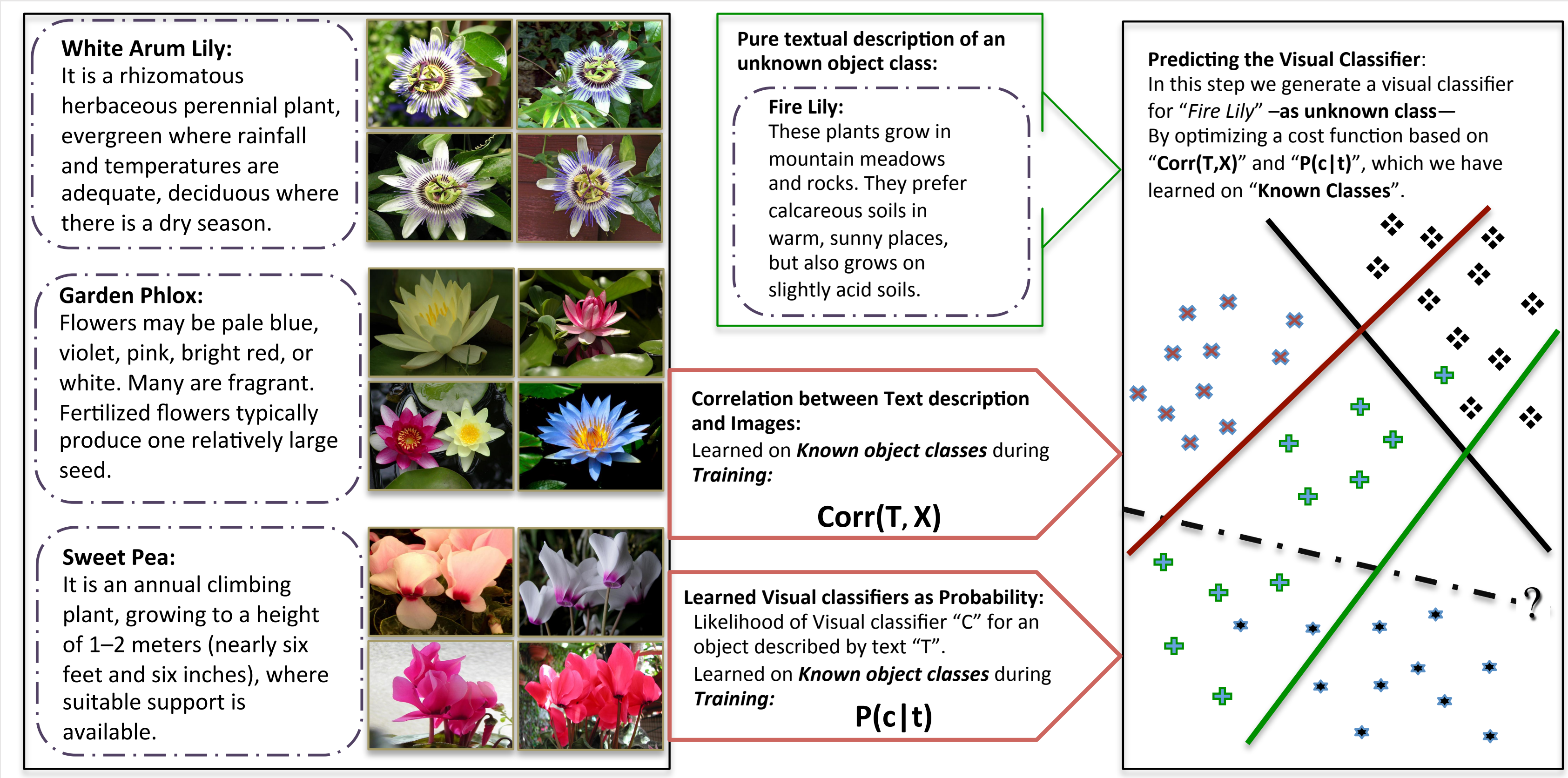
- For learning CNN, **Train set** is ImageNet train set (Normal), and **Test set I** consists of Abnormal (our dataset) and Normal images (ImageNet test set).
- **Test set II** is consisting of Abnormal images (our dataset) and Normal images (PASCAL dataset).

Experiments

- Evaluation of different loss functions

Loss	Test set	Typ	Atyp	Cls-Typ	Cls-Atyp
MS-Hinge	Atypical	68.58	70.64	70.84	68.47
Softmax	Atypical	63.69	66.82	65.81	66.48
MS-Hinge	Typical	79.90	84.07	82.88	83.40
Softmax	Typical	77.11	80.42	83.40	82.96

Typ : Raw Typicality scores
Atyp: Raw Atypicality scores
Cls-Typ : Class-specific Raw Typicality scores
Cls-Atyp: Class-specific Raw Atypicality scores



$$
\begin{aligned}
\hat{c}(\mathbf{t}_*) = & \operatorname*{argmin}_{\mathbf{c},\zeta_i} [\mathbf{c}^\mathsf{T}\mathbf{c} - \alpha \mathbf{t}_*{}^\mathsf{T}\mathbf{W}\mathbf{c} - \beta \ln(p_{reg}(\mathbf{c}|\mathbf{t}_*)) \\
& + \gamma \sum \zeta_i] \\
& s.t. : -(\mathbf{c}^\mathsf{T}\mathbf{x}_i) \geq \zeta_i, \quad \zeta_i \geq 0, \quad i = 1 \cdots N \\
& \mathbf{t}_*{}^\mathsf{T}\mathbf{W}\mathbf{c} \geq l \\
& \alpha, \beta, \gamma, l : \text{hyperparameters}
\end{aligned}
$$