

# Classifier Incongruence Detection for Anomaly Flagging in Machine Perception

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# Outline

- Introduction to anomaly detection
- Prior art
- Critique of conventional anomaly detection
- Proposed anomaly detection system
- Applications
  - new object class detection
  - number of players anomaly
  - out-of-play anomaly in tennis video annotation
- Conclusions

# Introduction to anomaly

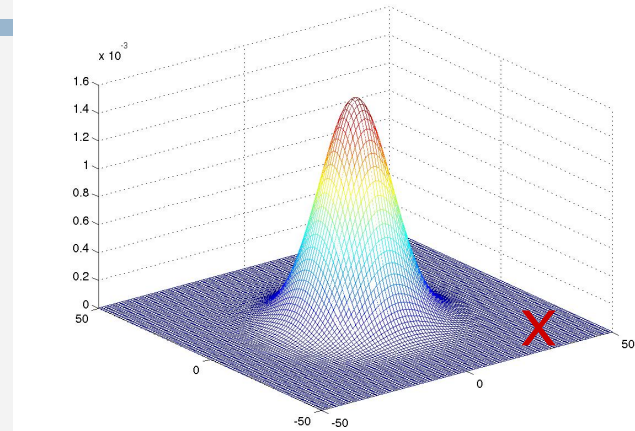
- *Anomaly* –
  - an important notion in human understanding of the environment
  - deviation from normal order or rule
  - failure to relate sensor data to a meaning
  - manifest in weak or no support for domain specific hypotheses
- *Many synonyms signifying different nuances*
  - rarity, irregularity, incongruence, abnormality, unexpected event, novelty, innovation, outlier

# Diverse applications

- Many applications formulated as anomaly detection problems
  - surveillance
  - novel object detection
  - abnormal communication network activity
  - medical diagnostics
  - video segmentation
  - suspicious behaviour

# Classical anomaly model

- *In science/engineering*
  - prove disprove hypothesis
  - fault detection
  - outdated model requires adaptation
- *Conventional mathematical model*
  - outlier of a distribution
  - empirical distribution deviates from the model distribution

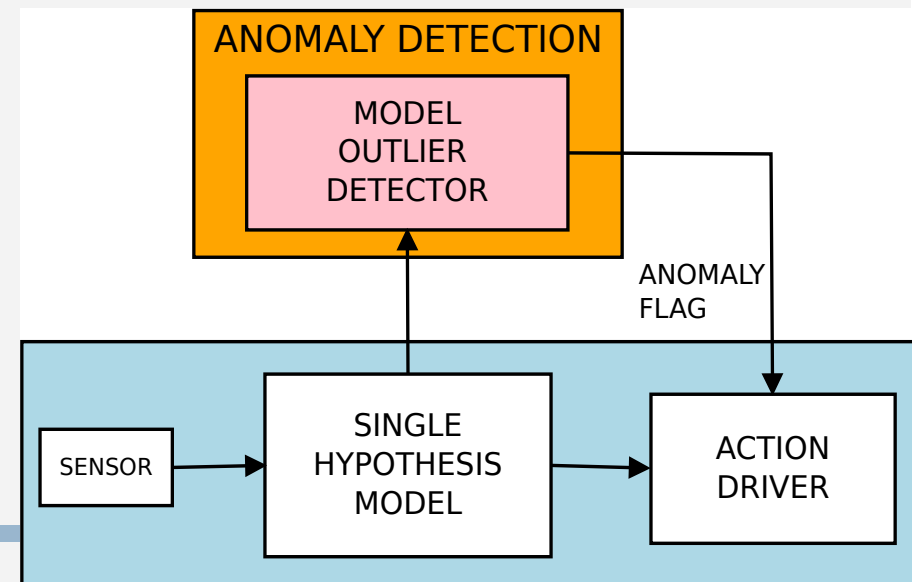
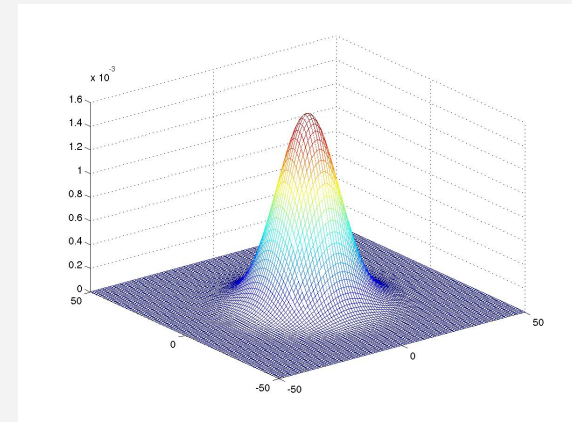


# Prior art in anomaly detection

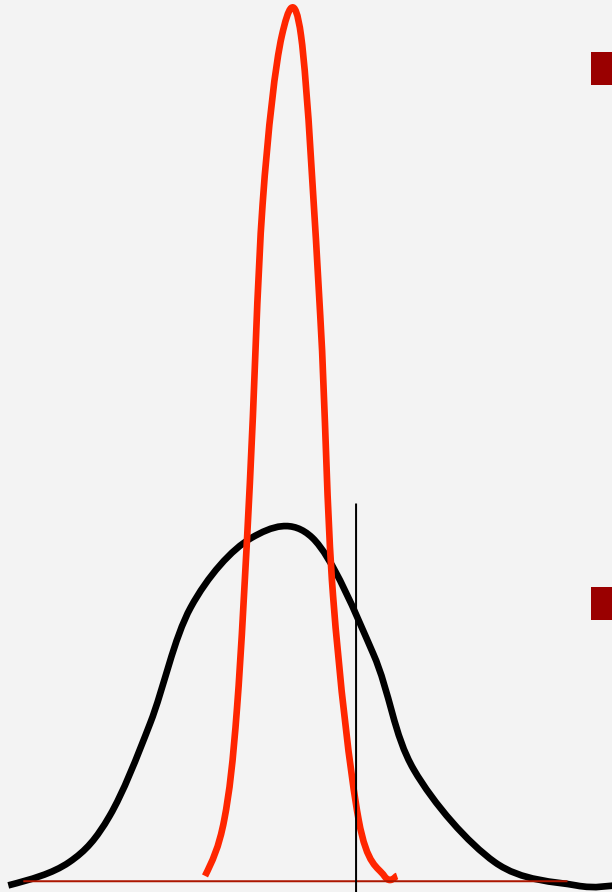
- Edgeworth (1888)
- Hundreds of papers
- Many approaches
  - statistical, NN, classification, clustering, information theoretic, spectral
- Excellent surveys
  - Markou&Singh (SP 2003, statistical, neural)
  - Hodge&Austin (AI Review 2004)
  - Agymang&Barker&Alhajj (Int Data Anal 2006)
  - Chandola&Banerjee&Kumar (ACM Surveys 2010)
  - Saligrama&Konrad&Vodoin (SPM2010, video)

# Classical model and its critique (re machine perception)

- Multiple models
- Discriminative classifiers
- Ambiguity of interpretation
- Contextual reasoning
- Hierarchical representation
- Data quality
- Model pruning



# Data quality/ decision confidence



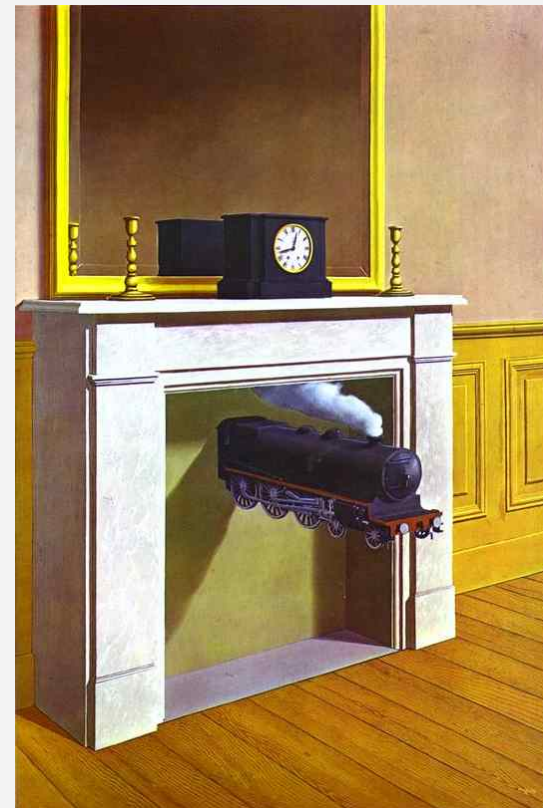
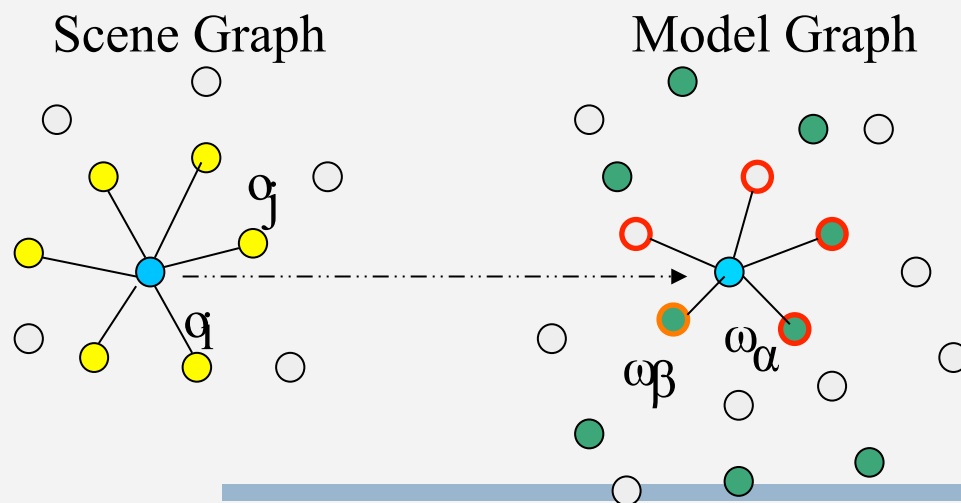
- Data quality
  - effect of noise on the notion of normality
  - need to measure data quality
  - notion of data quality and its dependence on context
- Confidence in classifier output

$$\Delta_c(x) = \frac{P(\omega_i|x) - e_i}{1 - 2e_i}$$



# Incongruence/unexpected event

- Magritte's La duree poignard
- Model base pruning
  - Computational efficiency
- Hierarchical representation



# Different aspects of anomaly



# Different aspects of anomaly



- Distribution drift
- Novelty detection

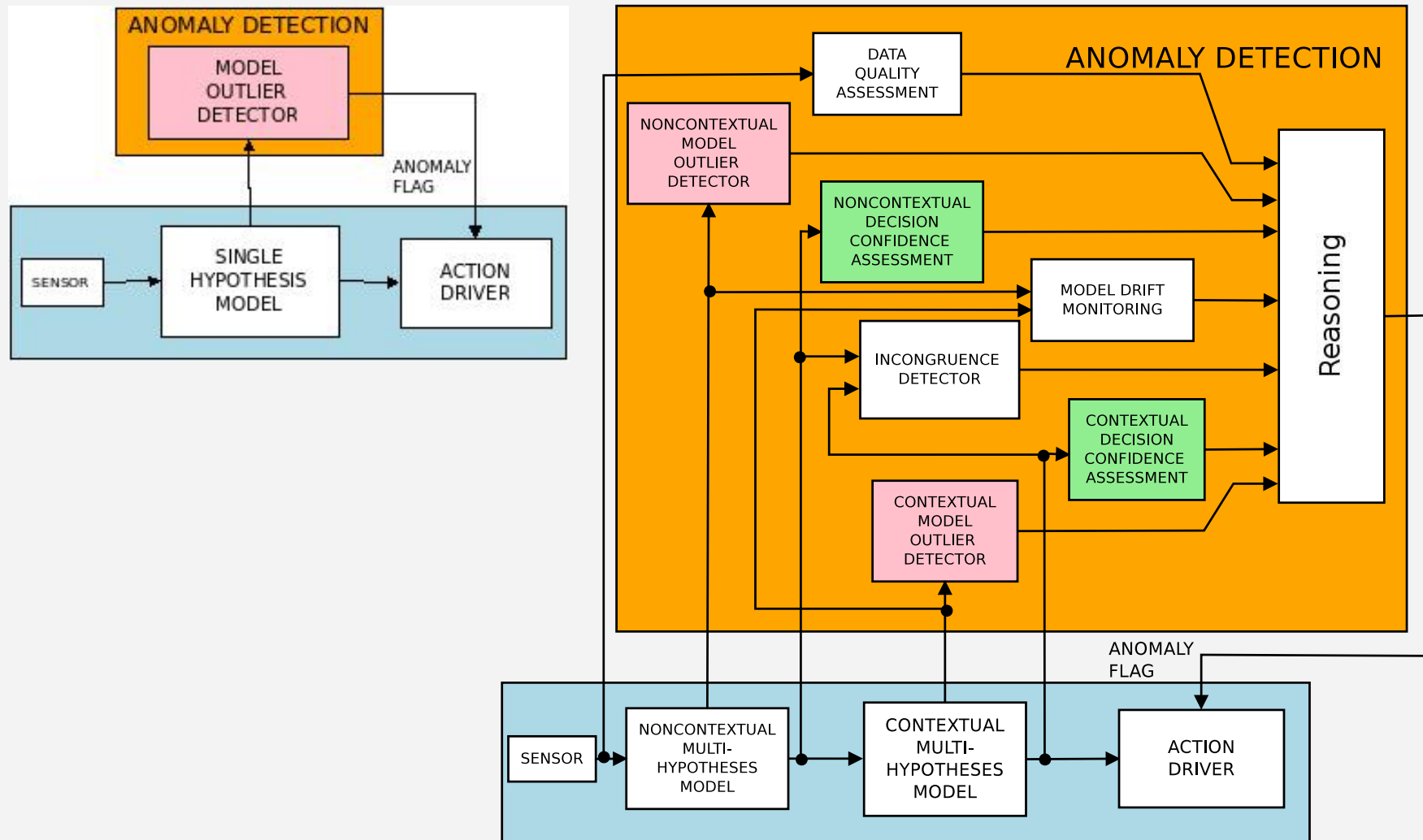
# Data quality



# Data quality



# Proposed anomaly detection system



# Nuances of anomaly

- No anomaly
- Noisy measurement
- Unknown object
- Corrupted measurement
- Congruent labelling
- Unknown structure
- Spurious measurement errors
- Unexpected structural component
- Unexpected structural component & structure
- Measurement model drift

# Incongruence detection

- Detecting differences between observations and expectations (anomaly, rare event, incongruence)
- Basic principle – comparison of outputs of weak and strong classifiers (Ketabdard et al 2007)
- Dirac Project (Burget et al 2008, Weinshall et al [2009-2012])
- Exemplified by out-of-vocabulary word detection
  - Phoneme recognizer (weak classifier)
  - HMM speech recognizer (strong, contextual classifier)

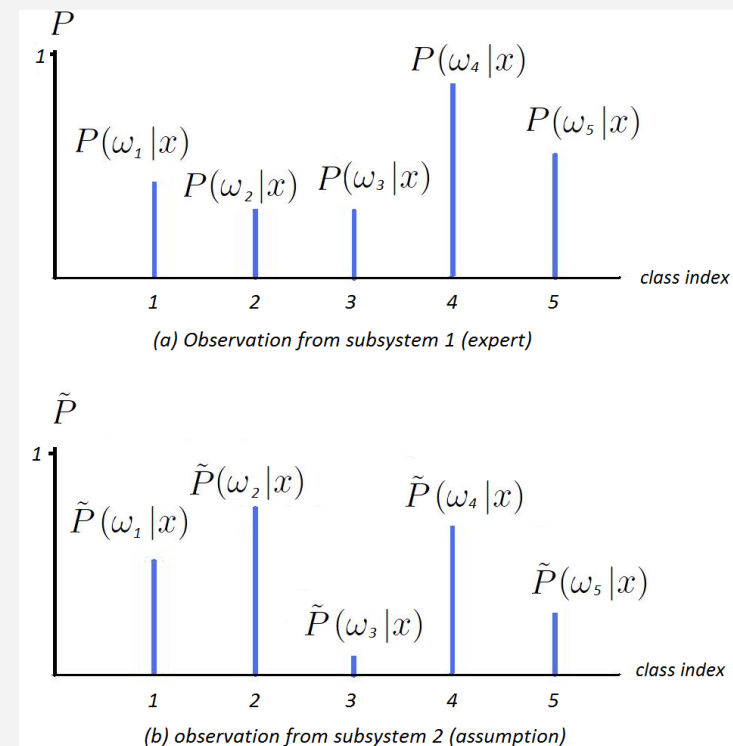


# Classifier incongruence

- Testing for incongruence
  - need an incongruence measure
  - understand its properties
  - sensitivity to noise
- Bayesian surprise

$$\Delta_{BS} = \sum_{j=1}^r \tilde{P}(\omega_j|x) \log \frac{\tilde{P}(\omega_j|x)}{P(\omega_j|x)}$$

$P(\omega_j|x)$  classifier 1 output  
 $\tilde{P}(\omega_j|x)$  classifier 2 output



# Novel surprise measure

- Bayesian surprise has undesirable properties
  - Decision agnostic
  - Values from  $[0, \infty]$
  - Difficult to set confidence level threshold
  - Complex dependence on errors
- Modified measure of surprise

$$\Delta_{max} = \frac{1}{2} [|\tilde{P}(\tilde{\mu}|x) - P(\tilde{\mu}|x)| + |\tilde{P}(\mu|x) - P(\mu|x)|]$$

- Sensitivity to estimation errors investigated

# Estimation errors

- Class probabilities corrupted by noise

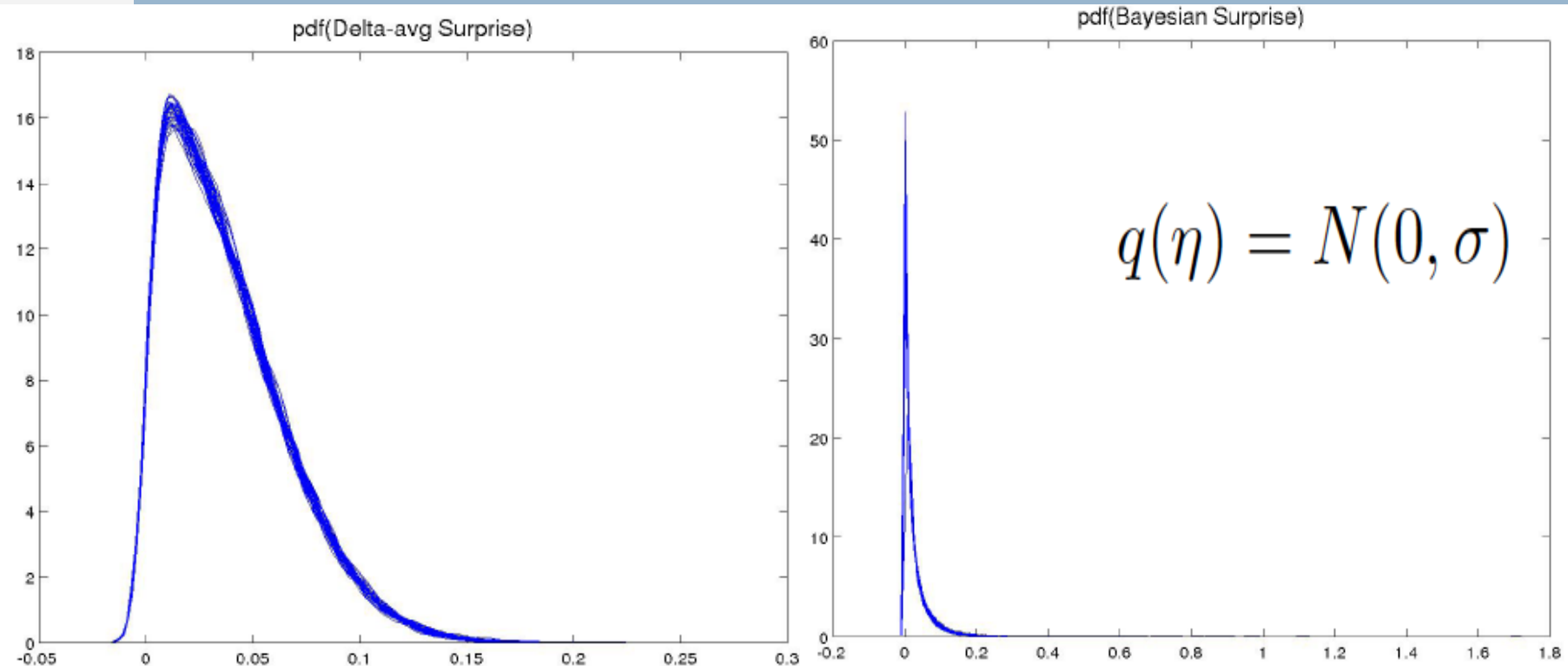
$$\hat{P}(\omega|\mathbf{x}) = P(\omega|\mathbf{x}) + \eta_{\omega}(\mathbf{x})$$

- satisfying

$$\sum_i^m \eta_{\omega}(\mathbf{x}) = 0$$

$$0 \leq \eta_{\omega}(\mathbf{x}) + P(\omega|\mathbf{x}) \leq 1$$

# Error sensitivity of incongruence measures

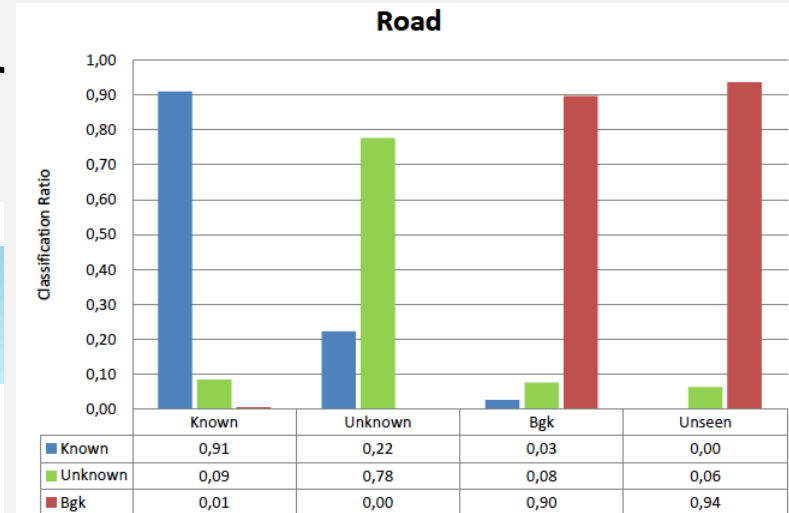
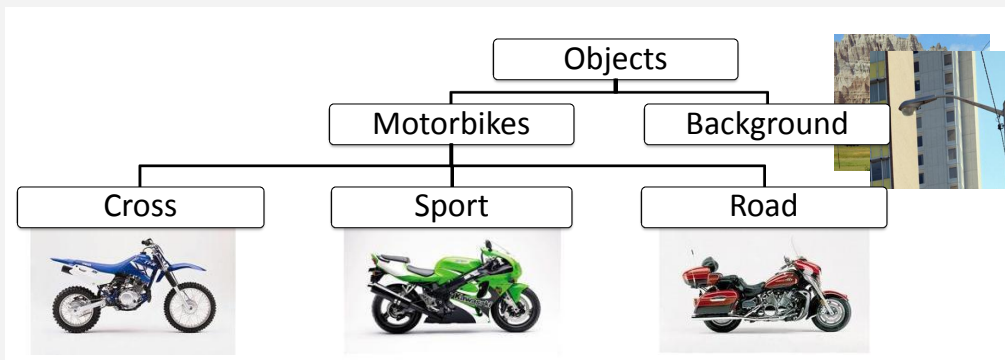
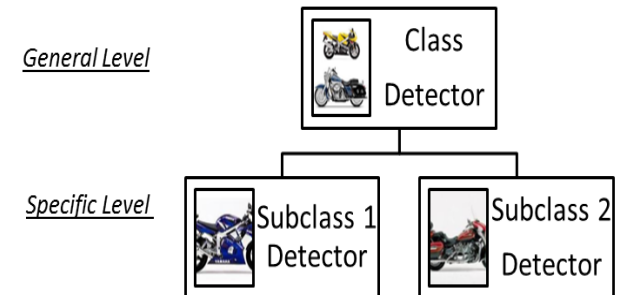


## Scenario

- Identical class probabilities
- Estimation error st.dev 0.05

# New object class detection

- Works well in biometrics
- Hierarchical object category representation (Weinshall PAMI 2012)
- Detection based on incongruence between general and specific classifier outputs



# New object class detection

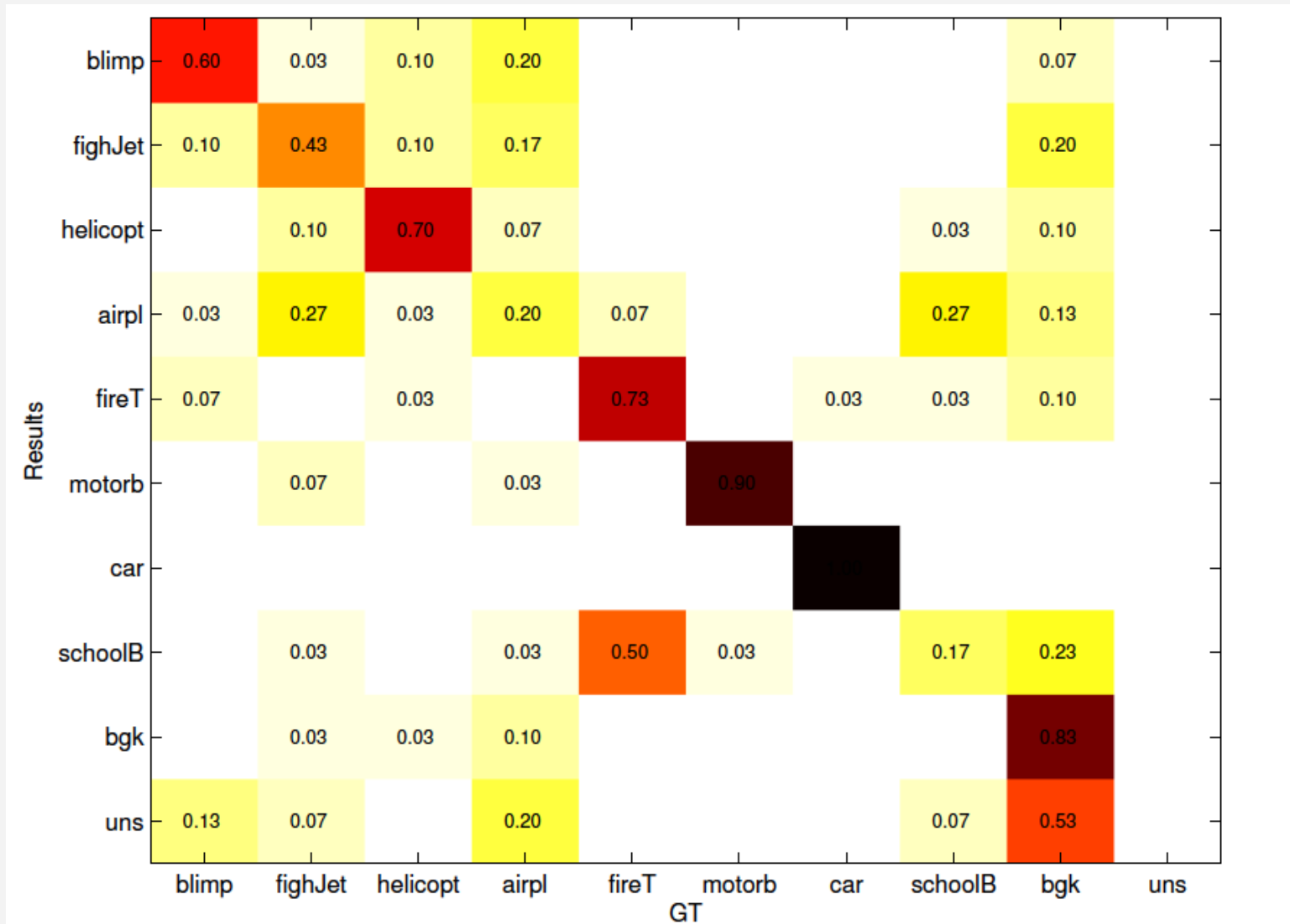
- Abstract vehicle hierarchy versus visual hierarchy
- Road transport



## Air transport



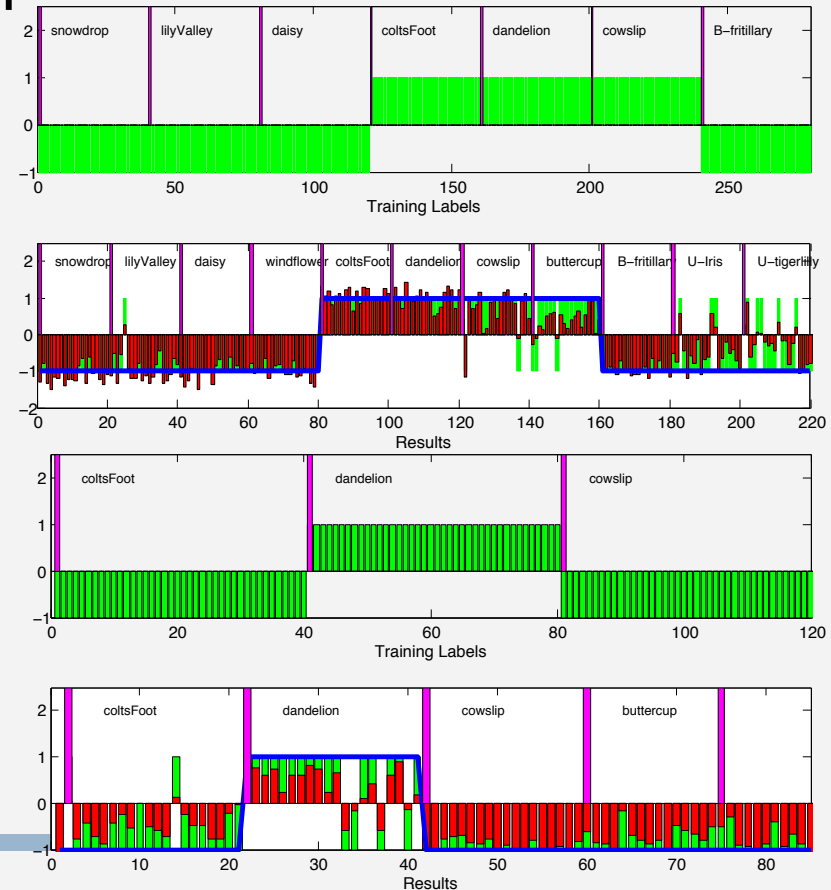
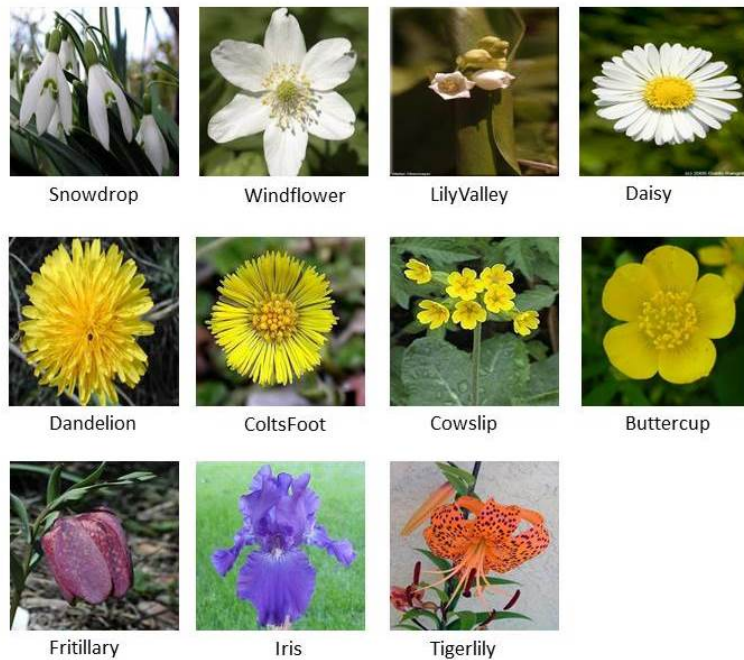
# Transport vehicle confusion matrix





# Visual object hierarchy

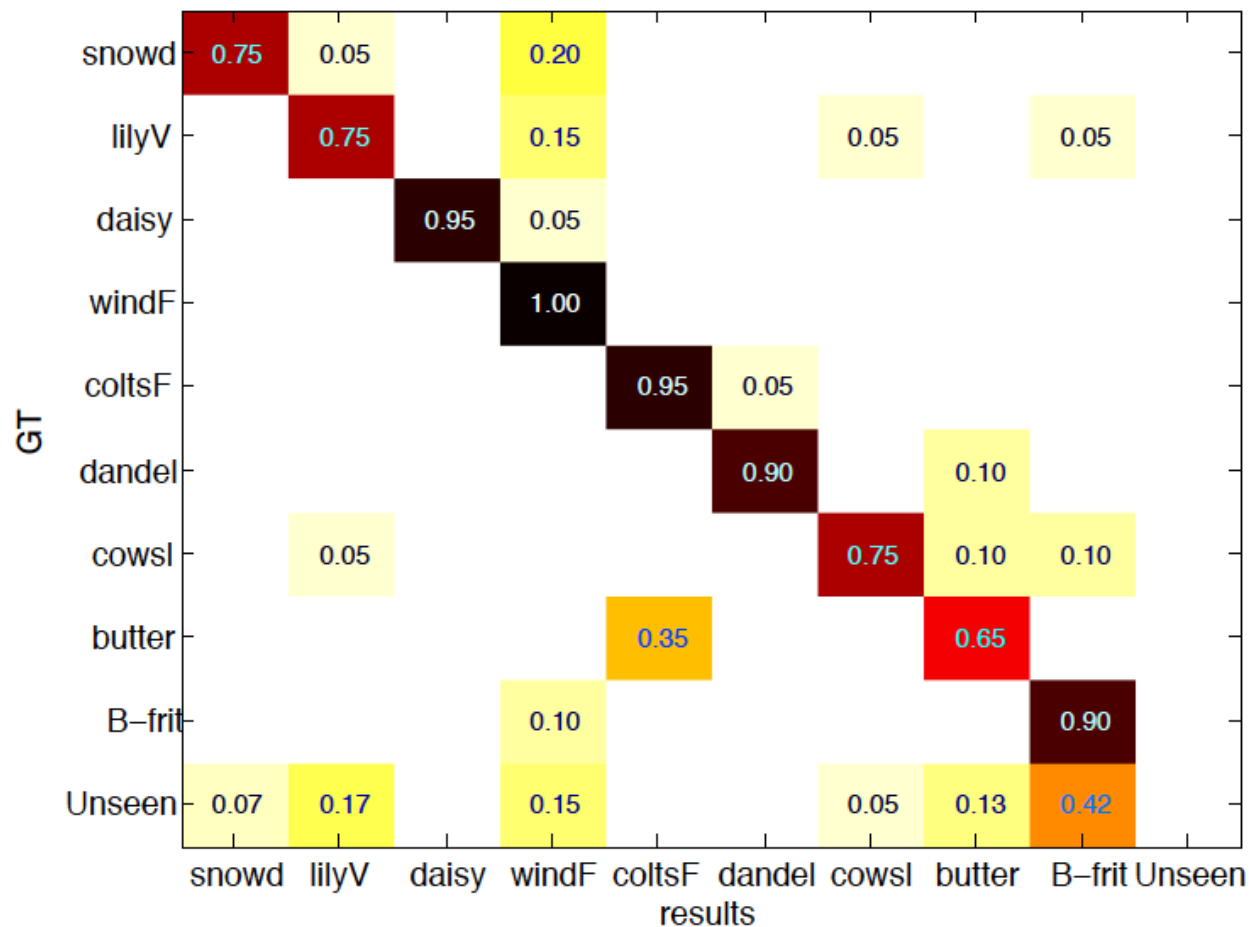
- Oxford flower data set
- General classifier based on spectral properties
- SIFT descriptor class specific classifiers





# Flower confusion matrix

## ■ Specific classifier performance

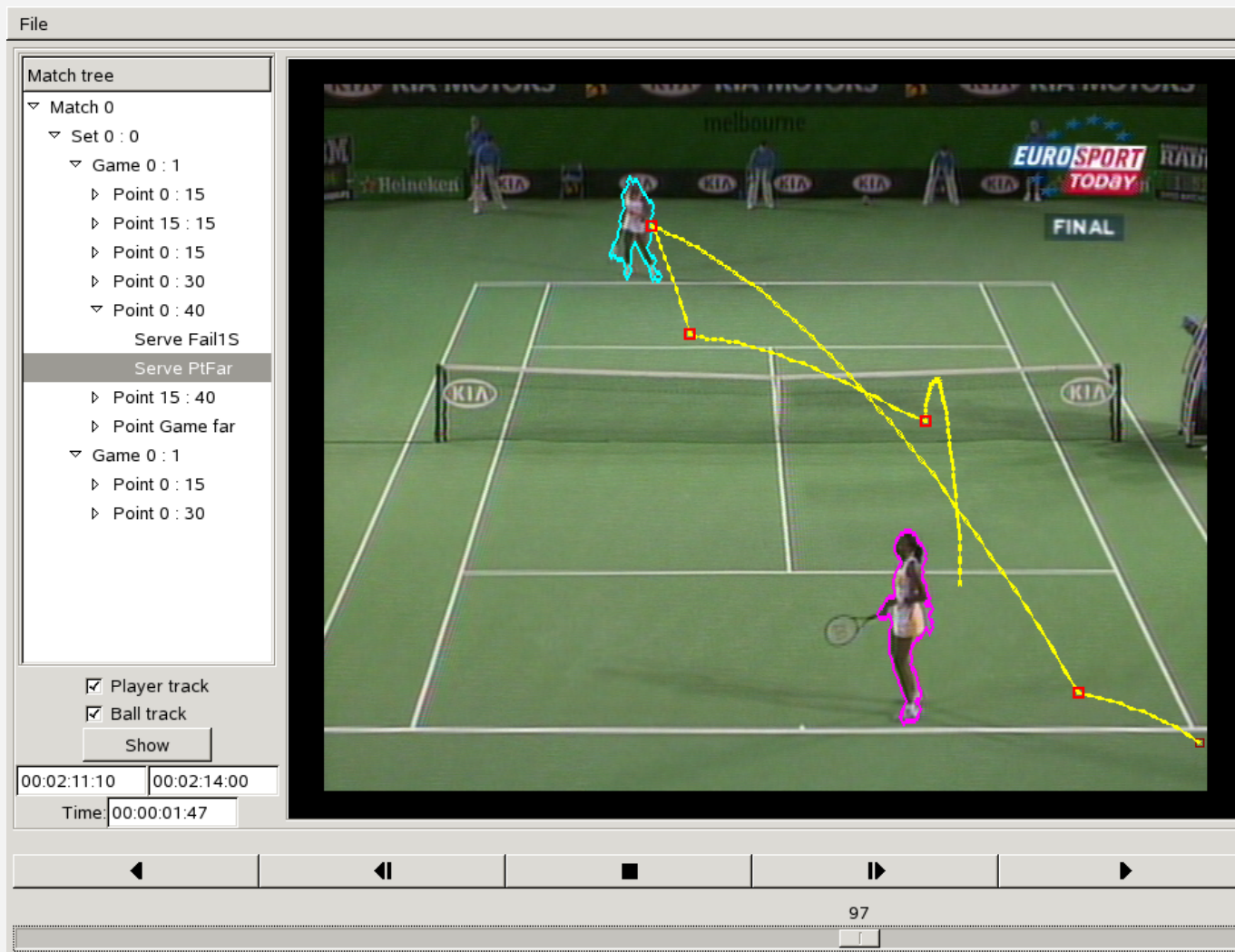


## Application to sports video annotation

- Aim is to interpret tennis video from the observed visual events
- The states are:
  - 1st serve
  - 2<sup>nd</sup> serve
  - Ace
  - Rally
  - Point award

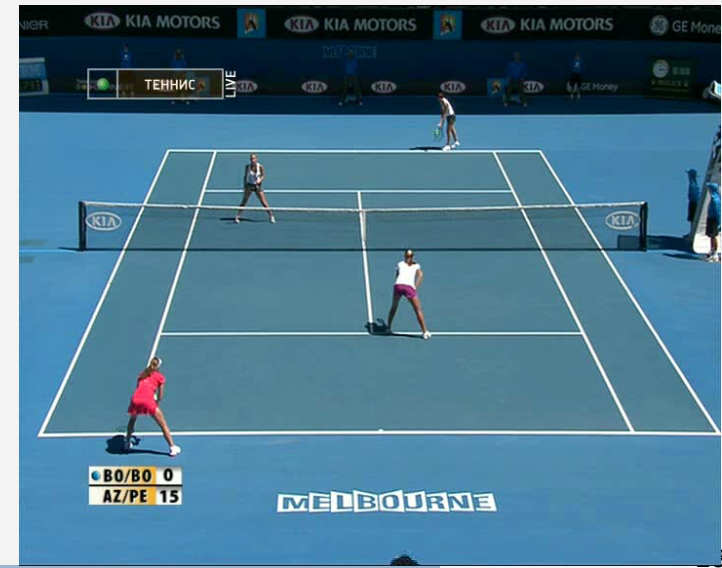


# The tennis annotation system



# Testing on tennis doubles

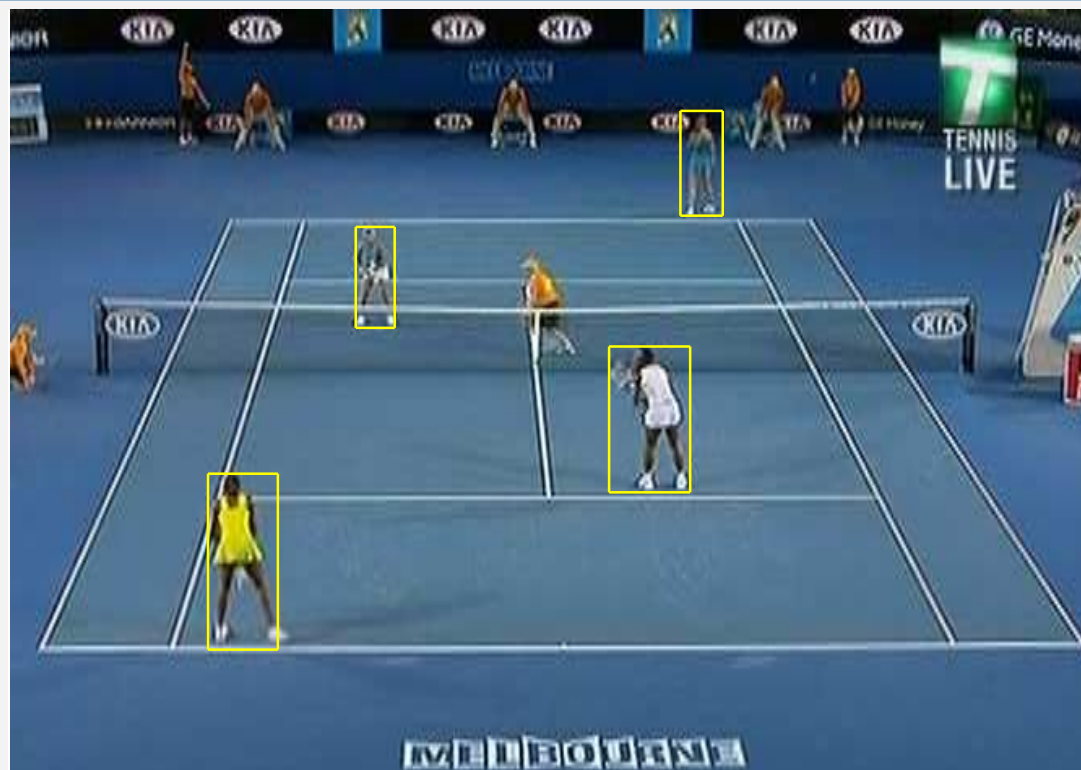
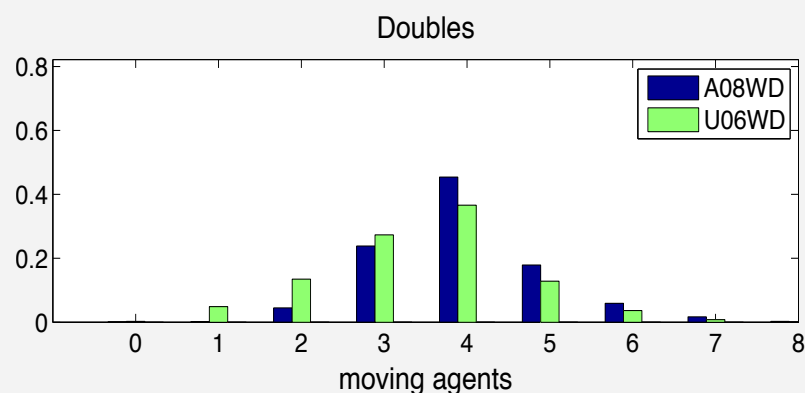
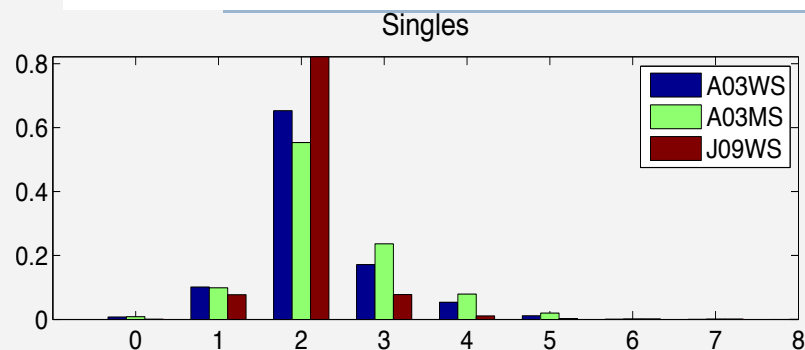
- Transfer learning – mechanisms
  - Anomaly detection
  - Visual event – anomaly association
  - Model adaptation
  - Context classifier



- Mechanisms needed for system competence extension
  - Anomaly detection
  - Visual event – anomaly association
  - Model adaptation
  - Context classifier

# #players detection

$$MD(p(x), \hat{p}(x)) = \arg \max_x p(x) - \arg \max_x \hat{p}(x)$$



TENNIS VIDEOS USED IN EXPERIMENTS AND THEIR DURATION

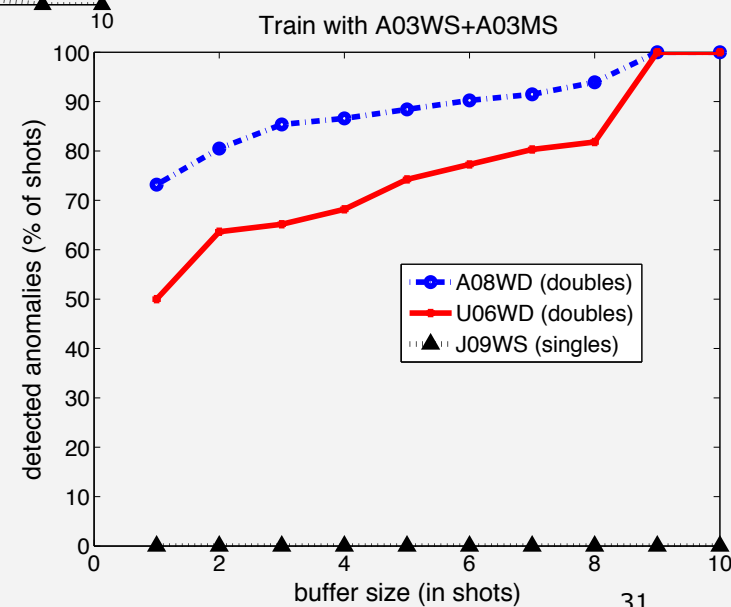
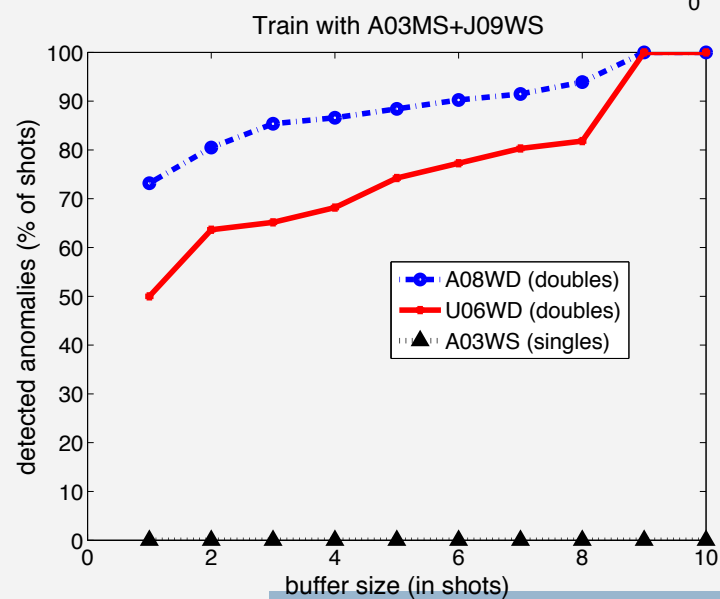
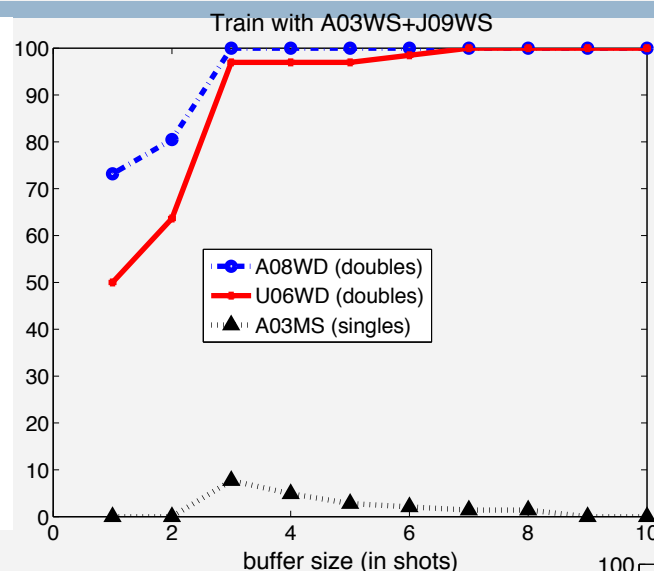
Label	Tennis match	Duration (minutes)	# play shots
A03WS	Australia03 Women's Singles	35	76
A03MS	Australia03 Men's Singles	65	143
J09WS	Japan09 Women's Singles	60	100
A08WD	Australia08 Women's Doubles	122	164
U06WD	USA06 Women's Doubles	47	66



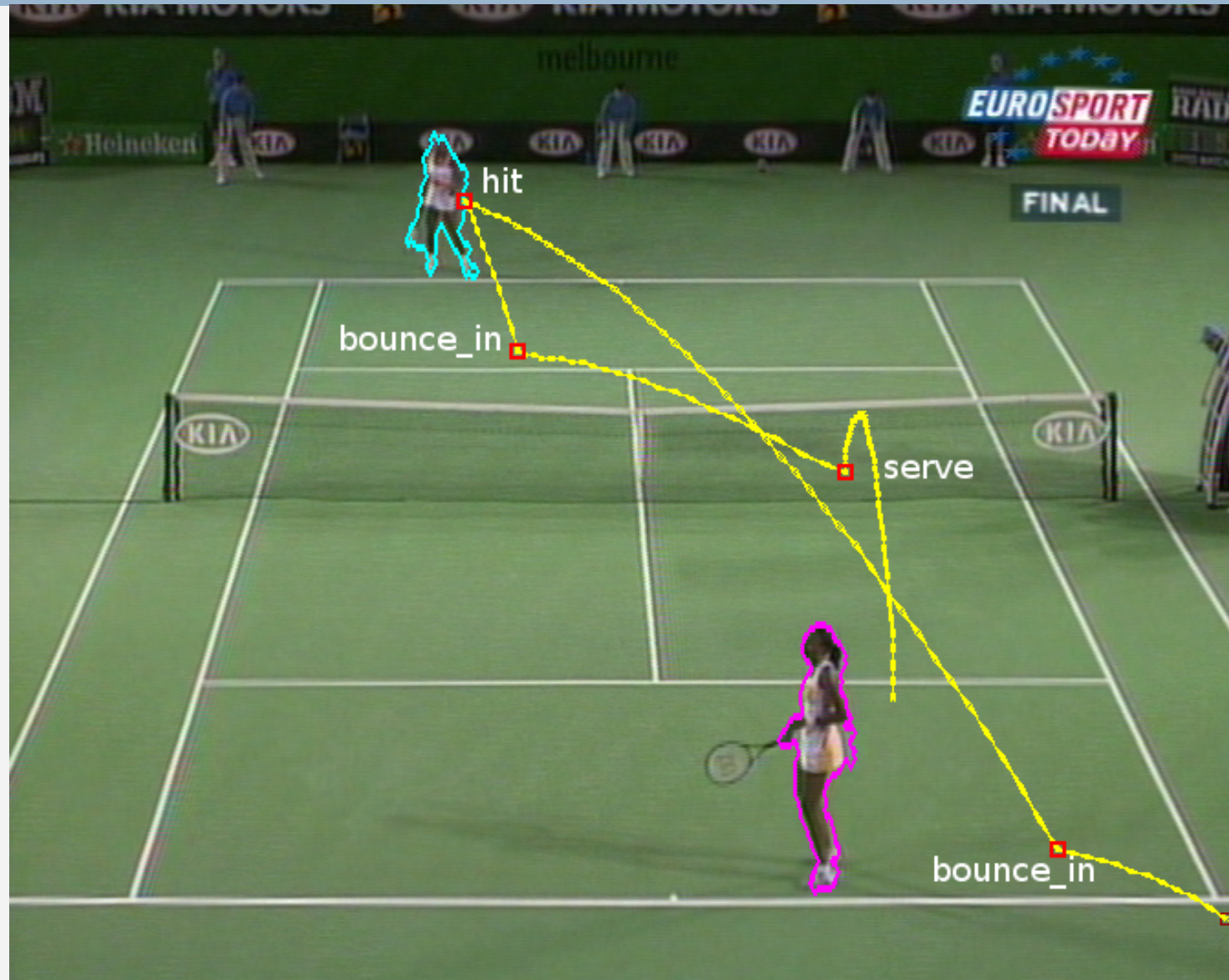
# # player anomaly detection

## NOISE STATISTICS

Video	mean $\pm$ std
A03WS	$1.9 \pm 0.1$
A03MS	$3.1 \pm 2.3$
J09WS	$1.6 \pm 0.5$
A08WD	$1.3 \pm 1.0$
U06WD	$1.5 \pm 1.9$



# Out-of-play anomaly detection





# Out-of-play anomaly detection

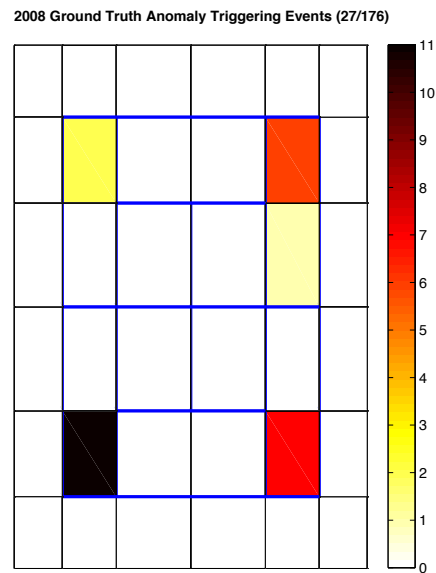
Notation	Event type
$\text{hit}_A$	ball hit by player $_A$
$\text{bounce\_in}_A$	ball bounces in play area $_A$
$\text{bounce\_out}_A$	ball bounces outside play area $_A$
$\text{net}_A$	ball played by player $_A$ hitting the net
$\text{serve}_A$	serve delivered by player $_A$

- 
- ТЕННИС LIVE
- B0/B0 0  
AZ/PE 15
- MELBOURNE



- The proposed measure of surprise in a two class case

$$\Delta_{max} = |P(\theta_i = \omega | \mathbf{x}_i, \theta_{i-1}) - P(\theta_i = \omega | \mathbf{x}_{i+1}, \dots, \mathbf{x}_{i+4})|$$



# Conclusions

- Novel anomaly detection system
  - Incongruence detector
  - Decision confidence filter
  - Data quality assessment
  - Computationally efficient outlier detector
- Proposed novel decision incongruence measure
- Applied to
  - novel object class detection
  - anomaly detection in tennis video analysis

# Acknowledgements

- Kittler, Christmas, de Campos, Windridge, Yan, Illingworth and Osman, 2013. Domain anomaly detection in machine perception: A system architecture and taxonomy, IEEE PAMI 2014

<http://doi.ieeecomputersociety.org/10.1109/TPAMI.2013.209>

- Other contributors
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