Big ideas

- Straightforward discriminative methods are powerful
- Spot locally discriminative properties
  - skin
  - faces
  - motion
- Pool these for detection
- Reason about relations
Finding skin

- Skin has a very small range of (intensity independent) colours, and little texture
  - Compute an intensity-independent colour measure, check if colour is in this range, check if there is little texture (median filter)
  - See this as a classifier - we can set up the tests by hand, or learn them.
Histogram based classifiers

- Represent class-conditional densities with histogram
- Advantage:
  - estimates become quite good
  - (with enough data!)
- Disadvantage:
  - Histogram becomes big with high dimension
  - but maybe we can assume feature independence?
Histogram classifier for skin

\[ \frac{P(\text{rgb} \mid \text{skin})}{P(\text{rgb} \mid \neg \text{skin})} \geq \Theta \]

Figure from Jones+Rehg, 2002
Curse of dimension - I

- This won’t work for many features
  - try R, G, B, and some texture features
  - too many histogram buckets
Finding faces

• Faces “look like” templates (at least when they’re frontal).
• General strategy:
  • search image windows at a range of scales
  • Correct for illumination
  • Present corrected window to classifier
• Issues
  • How corrected?
  • What features?
  • What classifier?
  • what about lateral views?
The Thatcher Illusion
Figures by Henry Rowley,
http://www.cs.cmu.edu/~har/puzzle.html
The Thatcher Illusion
Figures by Henry Rowley,
http://www.cs.cmu.edu/~har/puzzle.html
Naive Bayes

• Previously, we detected with a likelihood ratio test

\[
\frac{P(\text{features}|\text{event})}{P(\text{features}|\text{not event})} > \text{threshold}
\]

• Now assume that features are conditionally independent given event

\[
P(f_0, f_1, f_2, \ldots, f_n|\text{event}) = P(f_0|\text{event})P(f_1|\text{event})P(f_2|\text{event}) \ldots P(f_n|\text{event})
\]
Naive Bayes

- (not necessarily perjorative)
- Histogram doesn’t work when there are too many features
  - the curse of dimension, first version
  - assume they’re independent conditioned on the class, cross fingers
  - reduction in degrees of freedom
  - very effective for face finders
    - relations may not be all that important
  - very effective for high dimensional problems
    - bias vs. variance
Work by Schneiderman and Kanade,
http://www.cs.cmu.edu/afs/cs.cmu.edu/user/hws/www/hws.html
Work by Schneiderman and Kanade,
http://www.cs.cmu.edu/afs/cs.cmu.edu/user/hws/www/hws.html

Many more face finders on the face detection home page
http://home.t-online.de/home/Robert.Frischholz/face.htm
From “Gender Classification with Support Vector Machines”  
Baback Moghaddam  
Ming-Hsuan Yang, MERL TR
Figure 7. Top five human misclassifications
Neural networks

- Logistic regression heavily generalized

\[
g(x) \approx f(x) = [\phi(w_{21} \cdot y), \phi(w_{22} \cdot y), \ldots \phi(w_{2n} \cdot y)]
\]

\[
y(z) = [\phi(w_{11} \cdot z), \phi(w_{12} \cdot z), \ldots \phi(w_{1m} \cdot z), 1]
\]

\[
z(x) = [x_1, x_2, \ldots, x_p, 1]
\]
Figure 22.14. On the left, a series of squashing functions obtained using $\phi(x; \nu) = \frac{e^{x/\nu}}{1 + e^{x/\nu}}$, for different values of $\nu$ indicated on the figure. On the right, a series of squashing functions obtained using $\phi(x; \nu, A) = A \tanh (x/\nu)$ for different values of $\nu$ indicated on the figure. Generally, for $x$ close to the center of the range, the squashing function is linear; for $x$ small or large, it is strongly non-linear.
Training

- Choose parameters to minimize error on training set

\[ Error(p) = \left( \frac{1}{2} \right) \sum_{e} |n(x^e; p) - o^e|^2 \]

- Stochastic gradient descent, computing gradient using trick (backpropagation, aka the chain rule)
- Stop when error is low, and hasn’t changed much
Rowley-Baluja-Kanade face finder (1)

Figure from “Rotation invariant neural-network based face detection,”
Figure from “Rotation invariant neural-network based face detection,”
Pedestrian detection with an SVM

Dalal+Triggs 05
Features

Dalal+Triggs 05
Performance

DET – different descriptors on INRIA database

Dalal+Triggs 05
Face Recognition

• Whose face is this? (perhaps in a mugshot)
• Issue:
  • What differences are important and what not?
  • Reduce the dimension of the images, while maintaining the “important” differences.
• One strategy:
  • Principal components analysis, then nearest neighbours
  • Many face recognition strategies at http://www.cs.rug.nl/users/peterkr/FACE/face.html
Curse of dimension-II

- General phenomenon of high dimensions
  - volume is concentrated at the boundary
- Parameter estimation is hard for high dimensional distributions
  - even Gaussians
    - where probability is concentrated further and further from the mean
    - and covariance has too many parameters
      - dodge: assume covariance is diagonal
- Idea: reduce the dimension of the feature set
  - Principal components
  - Linear discriminants
Linear discriminant analysis

• Principal components do not preserve discrimination
  • so we could have features that don’t distinguish, see picture
• Assume (pretend) class conditional densities are normal, with the same covariance
  • Choose linear features so that
    • between class variation is big compared to within class variation
      • between class variation
        • covariance of class means
      • within class variation
        • class covariance
First two canonical variates for well known image collection
More complex template matching

- Encode an object as a set of patches
  - centered on interest points
  - match by
    - voting
    - spatially censored voting
    - inference on a spatial model
- Patches are small
  - even if they’re on a curved surface, we can think of them as being plane
View variation for a plane patch

- Plane patches look different in different views
Pinhole camera (F+P, p31)

Orthographic camera (F+P, p33)
Views of plane patches in perspective cameras induce homographies.
Views of plane patches in orthographic cameras induce a special subset of homographies.
Interest points and local descriptions

• Find localizable points in the image
  • e.g. corners - established technology,
    • eg find image windows where there tend to be strong edges going in several different directions
• Build at each point
  • a local, canonical coordinate frame
    • Euclidean+scale
    • Affine
  • Do this by searching for a coordinate frame within which some predicate applies
    • E.g. Rotation frame from orientation of gradients
    • E.g. Rotation + scale orientation of gradients, maximum filter response
  • a representation of the image within that coordinate frame
    • this representation is invariant because frame is covariant
Example: Lowe, 99

- Find localizable points in the image
  - find maxima, minima of response to difference of gaussians
    - over space
    - over scale
    - using pyramid
- Build at each point
  - a Euclidean + scale coordinate frame
    - scale from scale of strongest response
    - rotation from peak of orientation histogram within window
- Representation
  - SIFT features
Lowe’s SIFT features

Fig 7 from:
Distinctive image features from scale-invariant keypoints
From Lowe, 99, *Object Recognition from Local Scale-Invariant Features*
Mikolaczyk/Schmid coordinate frames
Matching objects with point features

- Voting
  - each point feature votes for every object that contains it
  - object with most votes wins
  - Startlingly effective (see figures)
Employ spatial relations

Figure from "Local grayvalue invariants for image retrieval," by C. Schmid and R. Mohr, IEEE Trans. Pattern Analysis and Machine Intelligence, 1997 c 1997, IEEE as used in Forsyth + Ponce, p 609
ASL translation
ASL

- Notice:
  - intra-class variation (timing, role of hands)
  - carefully dressed narrator
  - low resolution
- Would like to spot words in text

Grandma

Grandpa
Wordspotting allows translations
Wordspotting

- **Difficulties**
  - building a discriminative word model for a large vocabulary is hard
    - need lots of examples of each word
  - building a generative word model is hard, too
    - no widely available pronunciation dictionary
  - very large number of features
    - next slide

- **Strategy**
  - build spotters for some words (base words)
  - now use the output of those spotters as features for other words
    - uses less training data
    - because features are discriminative
Features

SIFT features

image locations

+ \((x,y)\)

+ \((x,y)\)

+ \((x,y)\)

+ image distances

\(f_i\) (image feature vector for frame \(i\))
ASL translation
Logistic Regression

- Build a parametric model of the posterior,
  - \( p(\text{class|information}) \)
- For a 2-class problem, assume that
  - \( \log(P(1|data)) - \log(P(0|data)) = \text{linear expression in data} \)
- Training
  - maximum likelihood on examples
  - problem is convex
- Classifier boundary
  - linear
Multiclass classification

- **Many strategies**
  - 1-vs-all
    - for each class, construct a two class classifier comparing it to all other classes
    - take the class with best output
      - if output is greater than some value
  - Multiclass
    - $\log(P(\text{ilfeatures})) - \log(P(\text{klfeatures})) = \text{(linear expression)}$
    - many more parameters
    - harder to train with maximum likelihood
    - still convex
One-vs-All classifier outputs for vocabulary

Classify words

One-vs-All classifier outputs for base words (30 features, all rather discriminative)

Compare to base words

High Dimensional Input Features
Grandma? What is it? What's wrong with grandpa?
your grandpa is very sick, littlefoot.
il? he'll be cured, won't he?
I don't know, littlefoot. some dinosaurs cure, and some don't.
I've seen this sickness many times in my life. No dinosaur ever cure, unless--
Unless what?
Unless they eat the golden petals of the night flower.
The night flower? did you hear that? the night flower?
Yes, golden petals. sick dinosaurs eat them and are cured, if they eat them in time.
Grandma, we have to get the night flower for grandpa.
Old one, where can I find the night flower?
In the land we came from, the land of mists.
The land of mists.
Cousins, who will take me to the night flower?
Not me. I'm not going back there.
The land has changed too much. Long necks are not welcome there.
Pose consistency

- A match between an image structure and an object structure implies a pose
  - we can vote on poses, objects
From Lowe, 99, *Object Recognition from Local Scale-Invariant Features*
From Lowe, 99, *Object Recognition from Local Scale-Invariant Features*
Kinematic grouping

• Assemble a set of features to present to a classifier
  • which tests
    • appearance
    • configuration
    • whatever

• Classifier could be
  • handwritten rules (e.g. Fleck-Forsyth-Bregler 96)
  • learned classifier (e.g. Ioffe-Forsyth 99)
  • likelihood (e.g. Felzenszwalb-Huttenlocher 00)
  • likelihood ratio test (e.g. Leung-Burl-Perona 95; Fergus-Perona-Zisserman 03)
Pictorial structures

• For models with the right form, one can test “everything”
  • model is a set of cylindrical segments linked into a tree structure
    • model should be thought of as a 2D template
      • segments are cylinders, so no aspect issue there
      • 3D segment kinematics implicitly encoded in 2D relations
      • easy to build in occlusion
    • putative image segments are quantized
  • => dynamic programming to search all matches
  • What to add next? (DP deals with this)
  • Pruning? (Irrelevant)
  • Can one stop?
    • (Use a mixture of tree models, with missing segments marginalized out)
  • Known segment colour - Felzenszwalb-Huttenlocher 00
  • Learned models of colour, layout, texture - Ramanan Forsyth 03, 04
Constellations of parts

Fischler & Elschlager 1973
Yuille ‘91
Brunelli & Poggio ‘93
Lades, v.d. Malsburg et al. ‘93
Cootes, Lanitis, Taylor et al. ‘95
Amit & Geman ‘95, ‘99
Agarwal & Roth ‘02
Generative model for plane templates (Constellation model)

<table>
<thead>
<tr>
<th>Foreground model</th>
<th>based on Burl, Weber et al. [ECCV ’98, ’00]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian shape pdf</td>
<td>Gaussian part appearance pdf</td>
</tr>
<tr>
<td><img src="image1.png" alt="Gaussian shape pdf" /></td>
<td><img src="image2.png" alt="Gaussian part appearance pdf" /></td>
</tr>
<tr>
<td>Clutter model</td>
<td></td>
</tr>
<tr>
<td>Uniform shape pdf</td>
<td>Gaussian background appearance pdf</td>
</tr>
<tr>
<td><img src="image3.png" alt="Uniform shape pdf" /></td>
<td><img src="image4.png" alt="Gaussian background appearance pdf" /></td>
</tr>
</tbody>
</table>

- Gaussian relative scale pdf
  - ![Gaussian relative scale pdf](image5.png)
  - Prob. of detection: 0.8, 0.75, 0.9

- Uniform relative scale pdf
  - ![Uniform relative scale pdf](image6.png)
  - Poisson pdf on # detections

Figure after Fergus et al, 03; see also Fergus et al, 04
Star-shaped models

- Features generated at parts
  - at image points that are conditionally independent given part location
  - with appearance that is conditionally independent given part type
- Part locations are conditioned on root
- Easy to deal with
  - very like a pictorial structure
  - inference is dynamic programming
  - localization easy

![Diagram of star-shaped model]
Other types of model

- We’ve already seen a tree-structured model!
  - (pictorial structure)
- Complete models are much more difficult to work with
  - because there is no conditional independence
  - means fewer features

Root
(which may not be observed)
Constellation models

- **Learning model**
  - on data set consisting of instances, not manually segmented
  - choose number of features in model
  - run point feature detector
  - each response is from either one “slot” in the model, or bg
    - this known, easy to estimate parameters
    - parameters known, this is easy to estimate
  - missing variable problem -> EM

- **Detecting instance**
  - search for allocation of feature instances to slots that maximizes likelihood ratio
  - detect with likelihood ratio test
Typical models

Motorbikes

Spotted cats

Figure after Fergus et al, 03; see also Fergus et al, 04
## Summary of results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Fixed scale experiment</th>
<th>Scale invariant experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motorbikes</td>
<td>7.5</td>
<td>6.7</td>
</tr>
<tr>
<td>Faces</td>
<td>4.6</td>
<td>4.6</td>
</tr>
<tr>
<td>Airplanes</td>
<td>9.8</td>
<td>7.0</td>
</tr>
<tr>
<td>Cars (Rear)</td>
<td>15.2</td>
<td>9.7</td>
</tr>
<tr>
<td>Spotted cats</td>
<td>10.0</td>
<td>10.0</td>
</tr>
</tbody>
</table>

% equal error rate

Note: Within each series, same settings used for all datasets

Figure after Fergus et al, 03; see also Fergus et al, 04

Caution: dataset is known to have some quirky features
LOTS of BIG collections of images

<table>
<thead>
<tr>
<th>Collection</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corel Image Data</td>
<td>40,000 images</td>
</tr>
<tr>
<td>Fine Arts Museum of San Francisco</td>
<td>83,000 images online</td>
</tr>
<tr>
<td>Cal-flora</td>
<td>20,000 images, species information</td>
</tr>
<tr>
<td>News photos with captions (yahoo.com)</td>
<td>1,500 images per day available from yahoo.com</td>
</tr>
<tr>
<td>Hulton Archive</td>
<td>40,000,000 images (only 230,000 online)</td>
</tr>
<tr>
<td>internet.archive.org</td>
<td>1,000 movies with no copyright</td>
</tr>
<tr>
<td>TV news archives (televisionarchive.org, informedia.cs.cmu.edu)</td>
<td>Several terabytes already available</td>
</tr>
<tr>
<td>Google Image Crawl</td>
<td>&gt;330,000,000 images (with nearby text)</td>
</tr>
<tr>
<td>Satellite images (terrarserver.com, nasa.gov, usgs.gov)</td>
<td>(And associated demographic information)</td>
</tr>
<tr>
<td>Medial images</td>
<td>(And associated with clinical information)</td>
</tr>
</tbody>
</table>

* and the BBC is releasing its video archive, too;
and we collected 500,000 captioned news images;
and it’s easy to get scanned mediaeval manuscripts;
etc., etc.,
Imposing order

- Iconic matching
  - child abuse prosecution
  - managing copyright (BayTSP)
- Clustering
  - Browsing for:
    - web presence for museums (Barnard et al, 01)
    - home picture, video collections
    - selling pictures
- Searching
  - scanned writing (Manmatha, 02)
  - collections of insects
- Building world knowledge
  - a face gazetteer (Miller et al, 04)
Search is well studied

- Metadata indexing
  - keywords, date of photo, place, etc.
- Content based retrieval
  - query by example with
    - global features
      - (e.g. Flickner et al. 95, Carson et al. 99, Wang 00, various entire conferences)
    - local features
      - (e.g. Photobook - Pentland et al 96; Blobworld - Carson et al, 98)
  - relevance feedback
    - (e.g. Cox et al 00; Santini 00; Schettini 02; etc.)
  - query by class
    - naughty pictures
      - (eg Forsyth et al. 96, 99; Wang et al. 98; Chan et al 99)
What will users pay for?

- Work by Peter Enser and colleagues on the use of photograph movie collections
  (Enser McGregor 92; Ornager 96; Armitage Enser 97; Markkula Sormunen 00; Frost et al 00; Enser 00)
- Typical queries:
  
  “… smoking of kippers…”
  “The depiction of vanity in painting, the depiction of the female figure looking in the mirror, etc.”
  “Cheetahs running on a greyhound course in Haringey in 1932”
Annotation results in complementary words and pictures

Query on

“Rose”

Example from Berkeley Blobworld system
Annotation results in complementary words and pictures

Query on

Example from Berkeley Blobworld system
Annotation results in complementary words and pictures

Query on

“Rose”

and

Example from Berkeley Blobworld system
Cluster found using only text
Cluster found using only blob features
Adjacent clusters found using both text and blob features
“This is a picture of the sun setting over the sea with waves in the foreground”

Each blob is a large vector of features
- Region size
- Position
- Colour
- Oriented energy (12 filters)
- Simple shape features

* Thanks to Blobworld team [Carson, Belongie, Greenspan, Malik], N-cuts team [Shi, Tal, Malik]
Web number: 4359202410830012

Title: Le Matin

Primary class: Print

Artist: Tissot

Description: serving woman stands in a dressing room, in front of vanity with chair, mirror and mantle, holding a tray with tea and toast

Display date: 1886

Country: France

83,000 images online, we clustered 8000
Searching

Compute \( P(\text{document} \mid \text{query\_items}) \)

query\_items can be words, features, or both

Natural way to express “soft queries”

Related retrieval work: Cascia, Sethi, and Sclaroff, 98; Berger and Lafferty, 98; Papadimitriou et al., 98
Query: “river tiger” from 5,000 Corel images
(The words never occur together.)

Retrieved items: rank order P(document | query)
Search
Compute $P(\text{document} \mid \text{query\_items})$
Related retrieval work: Cascia, Sethi, and Sclaroff, 98; Berger and Lafferty, 98; Papadimitriou et al., 98

Query: “water sky cloud”
Retrieved items:
“The large importance attached to the harpooneer’s vocation is evinced by the fact, that originally in the old Dutch Fishery, two centuries and more ago, the command of a whale-ship ...“
Auto-annotation

- Predict words from pictures
  - Obstacle:
    - Hoffman’s model uses document specific level probabilities
  - Dodge
    - smooth these empirically

- Attractions:
  - easy to score
  - large scale performance measures (how good is the segmenter?)
  - possibly simplify retrieval (Li+Wang, 03)
Keywords
GRASS TIGER CAT FOREST
Predicted Words (rank order)
tiger cat grass people water bengal buildings ocean forest reef

Keywords
HIPPO BULL mouth walk
Predicted Words (rank order)
water hippos rhino river grass reflection one-horned head plain sand

Keywords
FLOWER coralberry LEAVES PLANT
Predicted Words (rank order)
fish reef church wall people water landscape coral sand trees
Train a system of svm classifiers, one per word but penalize that matrix for rank, after Rennie+Srebro 05

The latent space reveals scenes because it is good at word prediction and takes appearance into account.

Loeff Farhadi Forsyth??
It was there and we didn’t

sky, sun, clouds, sea, waves, birds, water

tree, people, sand, road, stone, statue, temple, sculpture, pillar

tree, birds, snow, fly

sky, water, tree, plane, elephant, herd

mountain, sky, water, clouds, tree

It was there and we predicted it

sky, sun, jet, plane

mountain, sky, water, tree, grass, plane, ground, giraffe

water, people, pool, swimmers

It wasn’t and we did

tree, people, shadows, road, stone, statue, sculpture, pillar

people, buildings, stone, temple, sculpture, pillar, mosque
News dataset

- Approx 5e5 news images, with captions
  - Easily collected by script from Yahoo over the last 18 months or so
- Mainly people
  - politicians, actors, sportsplayers
  - long, long tails distribution
- Face pictures captured “in the wild”
- Correspondence problem
  - some images have many (resp. few) faces, few (resp. many) names (cf. Srihari 95)
President George W. Bush makes a statement in the Rose Garden while Secretary of Defense Donald Rumsfeld looks on, July 23, 2003. Rumsfeld said the United States would release graphic photographs of the dead sons of Saddam Hussein to prove they were killed by American troops. Photo by Larry Downing/Reuters
Data examples

Doctor Nikola shows a fork that was removed from an Israeli woman who swallowed it while trying to catch a bug that flew into her mouth, in Poriah Hospital northern Israel July 10, 2003. Doctors performed emergency surgery and removed the fork. (Reuters)

President George W. Bush waves as he leaves the White House for a day trip to North Carolina, July 25, 2002. A White House spokesman said that Bush would be compelled to veto Senate legislation creating a new department of homeland security unless changes are made. (Kevin Lamarque/Reuters)
Process

- Extract proper names
  - rather crudely, at present
- Detect faces
  - with Cordelia Schmid’s face detector, (Vogelhuber Schmid 00)
- Rectify faces
  - by finding eye, nose, mouth patches, affine transformation
- Kernel PCA rectified faces
- Estimate linear discriminants
- Now have (face vector; name_1, ..., name_k)

Scale

- 44773 big face responses
- 34623 properly rectified
- 27742 for $k \leq 4$
Rectification

• SVM based local feature detectors, affine transformation
Kernel PCA

• Find principal components - high variance features - in an abstract feature space by computing eigenvectors of the kernel matrix

• Problems:
  • kernel matrix dimension (number of data items, approx 40,000)
  • can’t compute all, many kernel matrix entries
  • incomplete cholesky no help
    • (column operations involve touching every face)
  • Nystrom approximation works, because matrix has very low rank

\[ K = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix} \]

Approximate C as:

\[ C' = B^T A^{-1} B \]
Building a face dictionary

• Compute linear discriminants
  • using single name, single face data items
  • we now have a set of clusters

• Now break correspondence with modified k-means
  • assign face to cluster with closest center,
    • chosen from associated names
  • recompute centers, iterate
  • using distance in LD space

• Now recompute discriminants, recluster with modified k-means
US President George W. Bush (L) makes remarks while Secretary of State Colin Powell (R) listens before signing the US Leadership Against HIV/AIDS, Tuberculosis and Malaria Act of 2003 at the Department of State in Washington, DC. The five-year plan is designed to help prevent and treat AIDS, especially in more than a dozen African and Caribbean nations (AFP/Luke Frazza)

German supermodel Claudia Schiffer gave birth to a baby boy by Caesarian section January 30, 2003, her spokeswoman said. The baby is the first child for both Schiffer, 32, and her husband, British film producer Matthew Vaughn, who was at her side for the birth. Schiffer is seen on the German television show 'Bet It...?!' ('Wetten Dass...?!') in Braunschweig, on January 26, 2002. (Alexandra Winkler/Reuters)

British director Sam Mendes and his partner actress Kate Winslet arrive at the London premiere of 'The Road to Perdition', September 18, 2002. The films stars Tom Hanks as a Chicago hit man who has a separate family life and co-stars Paul Newman and Jude Law. REUTERS/Dan Chung
and yields a useful little NLP module, too

IN Pete Sampras IN of the U.S. celebrates his victory over Denmark’s OUT Kristian Pless OUT at the OUT U.S. Open OUT at Flushing Meadows August 30, 2002. Sampras won the match 6-3 7- 5 6-4. REUTERS/Keith Lamarque

Germany’s IN Chancellor Gerhard Schroeder IN, left, in discussion with France’s IN President Jacques Chirac IN on the second day of the EU summit at the European Council headquarters in Brussels, Friday Oct. 25, 2002. EU leaders are to close a deal Friday on finalizing entry talks with 10 candidate countries after a surprise breakthrough agreement on Thursday between France and Germany regarding farm spending. (AP Photo/European Commission/HO)

‘The Right Stuff’ cast members IN Pamela Reed IN, (L) poses with fellow cast member IN Veronica Cartwright IN at the 20th anniversary of the film in Hollywood, June 9, 2003. The women played wives of astronauts in the film about early United States test pilots and the space program. The film directed by OUT Philip Kaufman OUT, is celebrating its 20th anniversary and is being released on DVD. REUTERS/Fred Prouser

Kraft Foods Inc., the largest U.S. food company, on July 1, 2003 said it would take steps, like capping portion sizes and providing more nutrition information, as it and other companies face growing concern and even lawsuits due to rising obesity rates. In May of this year, San Francisco attorney OUT Stephen Joseph OUT, shown above, sought to ban Oreo cookies in California – a suit that was withdrawn less than two weeks later. Photo by Tim Wimborne/Reuters

<table>
<thead>
<tr>
<th>Classifier</th>
<th>labels correct</th>
<th>IN correct</th>
<th>OUT correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>67%</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>EM Labeling with Language Model</td>
<td>76%</td>
<td>95%</td>
<td>56%</td>
</tr>
<tr>
<td>MM Labeling with Language Model</td>
<td>84%</td>
<td>87%</td>
<td>76%</td>
</tr>
</tbody>
</table>
successful of all the invertebrate groups. They have exploited an incredible array of habitats and because of their small size (some are truly microscopic) most go totally unnoticed. Many live freely in the soil, but there is also a vast array of species that live as parasites on plants or animals. This SEM image of a Peacock mite shows an animal less than 0.5 mm long.

Photo credit: Betsvill ARC (http://emu.arsusda.gov/default.html) USDA