Learning Better Object Models using Video Data Patrick Li, Inmar Givoni, Brendan Frey

Motivation

Training on a collection of static monocular images is unnatural.

Labelled Training Images are hard to get. And the lack of is becoming a problem.

There is a wealth of video data available.

First Attempt: Learning Bags of Features Models for Image Classification

Goal:

Represent Objects as Bags of SIFT Features

Use unsupervised learning to learn models of objects

Use learned models for image classification

Image Classification

INPUT:



OUTPUT:



TRAINING:



"Boat"

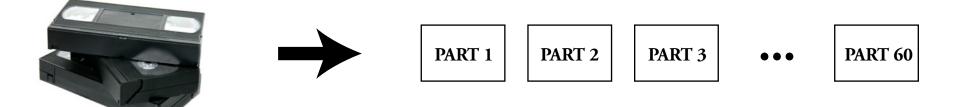
"Car"

"Sofa"

•••

Overview of the Technique

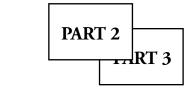
Unsupervised Training from Video



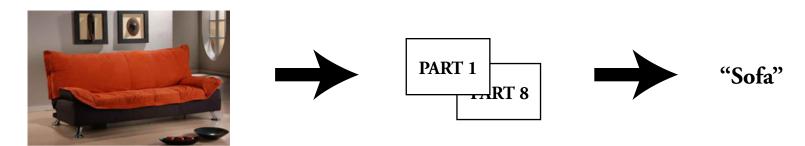
Supervised Training on Labelled Images



"Cow"

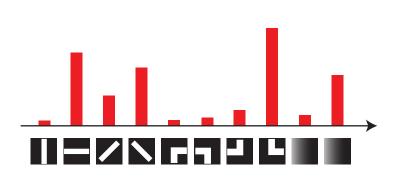


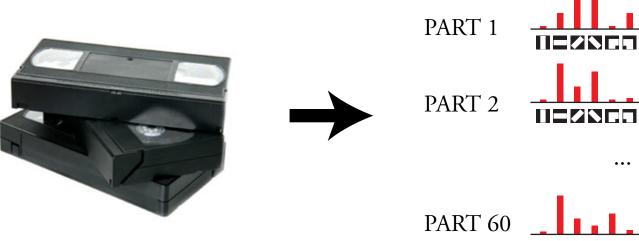
Testing



Bags of Features Models

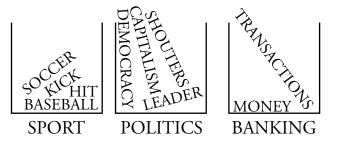








Latent Dirichlet Allocation for Topic Modelling



Convex Clustering with Exemplar-Based Models

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Abstract

Clustering is often formulated as the maximum likelihood estimation of a mixture model that ceptains the data. The bid appendix models used to solve the resulting optimization problem is inherently a gradient-descert method and is sensitive to initialization. The resulting solution is a local optimum in the neighborhood of the initial geness. This sensitivity to initialization presents a significant challenge in clustering inguing data sets into maxary clusters. In this spent, we present a dif-ferent approach to approximate mixture fitting for clustering. We introduce an exemption-based likelihood function that approximate the exact likelihood. This formulation leads to a convergence to the globally optimal models. The resulting clust-wich guaranteed more minimization problem and an efficient algorithm with guaranteed process prove the globally optimal models. The resulting clust-ecomplies that minimizes the vergat distance and the information-theoretic cost of mapping. We present experimently results likelihood to mixe model clustering. ring is often formulated as the maximum likelihood estimation of a mixture

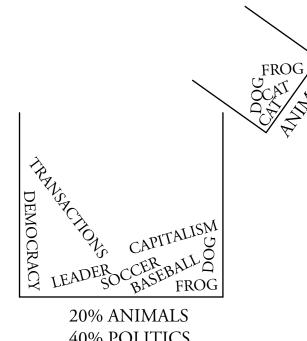
1 Introduction

1 Introduction Clustering is one of the most basic problems of unsupervised learning with applications in a wide variety of fields. The input is either vectorial data, that is, vectors of data points in the feature space, are protouving data, the pairwise animitary or dissimity values between the data points. The determines the resulting clustering [1]. Intuitively, most methods seek, compare clusters of data points, namely, clusters with relatively small intra-cluster and high inter-cluster distances. Often approaches, such a Spectral Clustering [2], loak for clusters of more complex shapes bying on some low dimensional annialduk in the fratem space. These methods typically transform the data such set of the statement of the statement of the statement of the statement of the origin of the statement of the data statement of the statement is the statement of the statement of

on one remove one neero are encount compact-conservating teconiques such as e-means. The widely used 6th "emenses method is an instance of maximum likelihood fitting of a mixture model through the LM algorithm. Although this approach yields satisfactory results for problems with a small another of clastera at on a treatively task. Its use of a gradient descent algorithm for the scatch space grows, that is, the number of data points or clusters increases, it becomes harder the scatch space grows, that is, the number of data points or clusters increases, it becomes harder to large biological data sets such as gene-expression. Typically, one runs the algorithm many times with different random initializations and selects the best soution. More synderized initialization alloss of clustering for the different random initialization and selects the best soution. More synderizated initialization initialization and selects the best soution. More synderizated initialization alloss of the series of the seri methods have been proposed to improve the results but the challenge of finding go for EM algorithm remains [4].

We aim to circumvent the initialization procedure by designing a convex problem whose global optimum can be found with a simple algorithm. It has been shown that mixture modeling can

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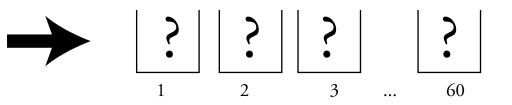


40% POLITICS 39% BANKING **1% SPORTS**

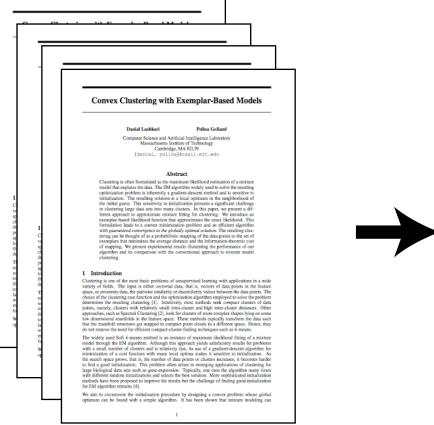
Latent Dirichlet Allocation for Topic Modelling

	Convex Clustering with Exemplar-Based Models
	Danial Lashkari Pelina Golland Computer Science and Artificial Intelligence Laboratory Massachuseth Institute of Technology Cambridge, MA 02159 {danial, polina}@cosail.mit.edu
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	The widely used Soft Avagants method is an instance of maximum likelihood fining of a mininte model through the IM algorithm. Albraugh this specific products further methods methods with a small number of clusters and is relatively fast, in use of a gradient-descent algorithm for minimization of a cost fraction with many local optimum makes it sensitive to initialization. As the search space grows, that is, the number of data points or clusters increases, in becomes harder to find a good initialization. This problem often annus in emerging applications of clustering for large biological data sets such as gene-expression. Typically, one trans the algorithm many times methods have been reproved to improve the results but the challenge off finding good initialization.

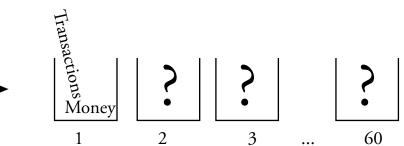
Corpus of Documents



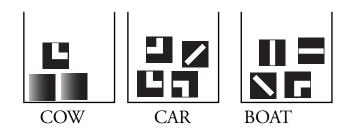
Latent Dirichlet Allocation for Topic Modelling

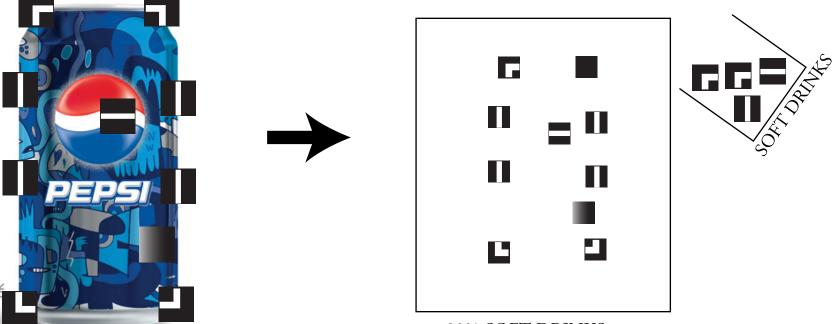


Corpus of Documents



Latent Dirichlet Allocation for Object Modelling





90% SOFT DRINKS **10% CORPORATE LOGOS**



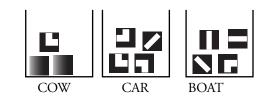
Single Image

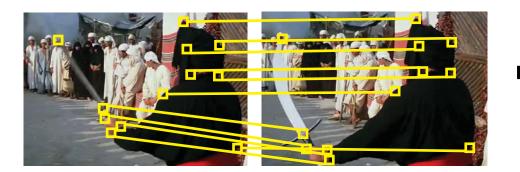
Latent Dirichlet Allocation for Object Modelling



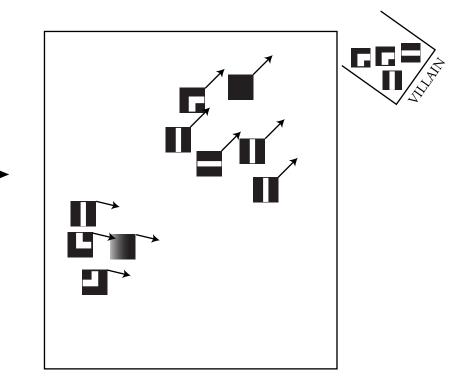
Image Collection

Flow-LDA for Motion Modelling



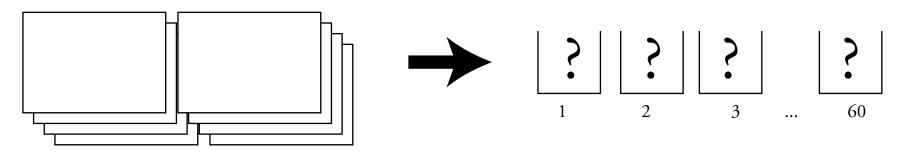


Pair of Consecutive Frame Pairs



50% SWORD 50% VILLAIN

Flow-LDA for Motion Modelling



Frame Pair Collection

Flow-LDA for Motion Modelling

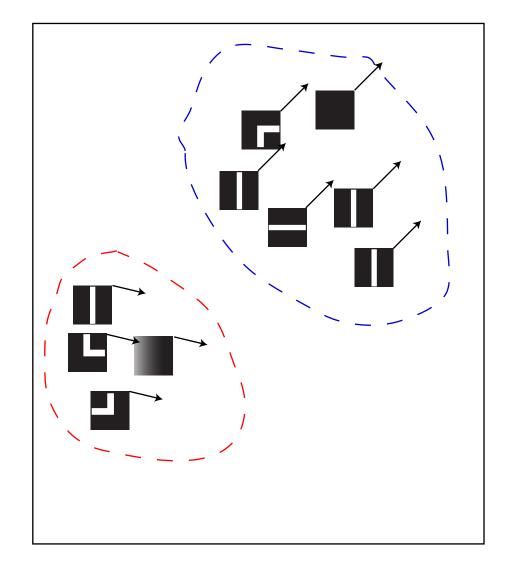
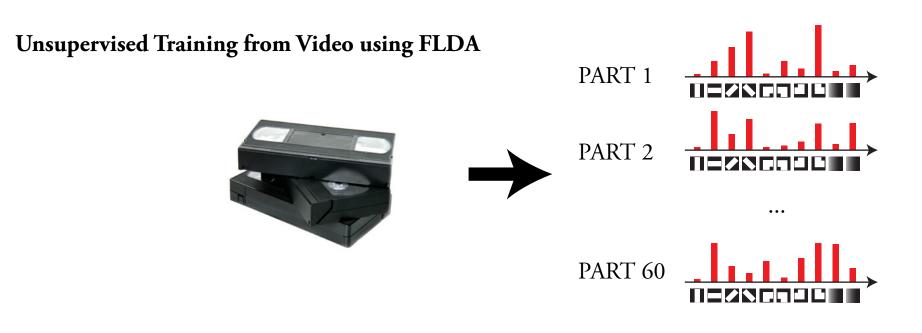
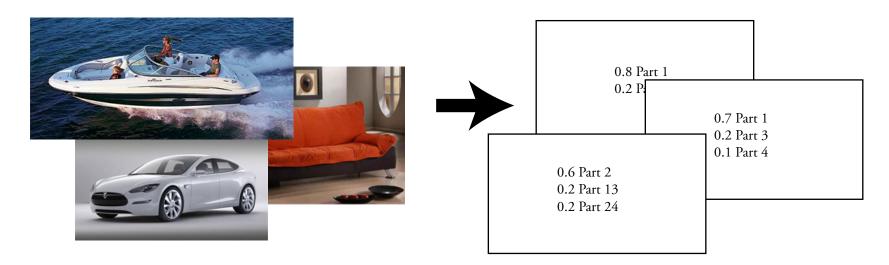


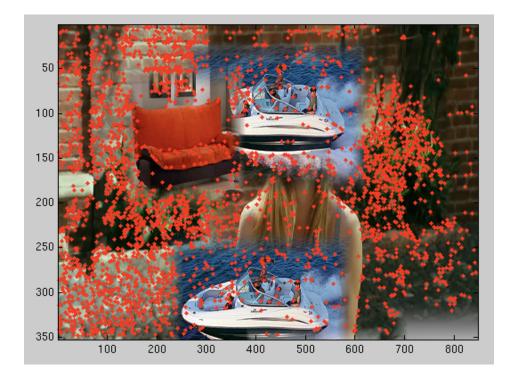
Image Recognition



Training And Testing Images



Initial Results



Naive Guesser: 8.6% Error SVM trained on SIFT histograms directly: 8.6% Error SVM trained using LDA model (no motion): 5.6% Error SVM trained using FLDA model (motion): 3.7% Error

... to continue

Experiment on Real Dataset

Go beyond Bags of Features models -Hierarchical Models -Account for Spatial Relations -Account for temporal relations between more than 2 frames

Thank you!