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Intelligent Product Retrieval System

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***Abstract*:** It is desired (especially for young people) to shop for the same or similar products shown in the multimedia contents (such as online TV programs). This indicates an urgent demand for improving the experience of TV-to-Online (T2O). In this paper, a transfer learning approach as well as a prototype system for effortless T2O experience is developed. In this paper, a novel manifold regularized heterogeneous multitask metric learning framework is proposed, in which each domain is treated equally. The proposed approach allows us to simultaneously exploit the information from other domains and the unlabelled. In the system, a key component is high-precision product search, which is to fulfil exact matching between a query item and the database ones. The matching performance primarily relies on distance estimation, but the data characteristics cannot be well modelled and exploited by a simple Euclidean distance**.**

Keywords: TV-to-Online, distance metric learning, transfer learning, heterogeneous domains, manifold regularization, ranking-based loss.

I. INTRODUCTION

The way that multimedia contents (such as photographs and videos) are consumed has been transformed by the current era of Mobile Internet due to the growing popularity of the smart mobile devices (e.g., smartphone and laptop). Specifically, the experience of consuming video contents in the main screen (e.g., TV) and having access to the companion contents in a second device (e.g., smartphone and tablet) has become widely appreciated for viewers. Such a multi-screen video experience has in turn led to an emerging business model, TV-to-Online (T2O). It bridges the gap between video contents and online merchants. With the help of T2O systems, the video viewers are able to quickly locate the desired products, which is same or similar with the item displayed on video program. Inspired by this emerging market trend and based on the highly touted multi-screen social TV system, we developed an effortless T2O subsystem. In our system, people are allowed to buy the desired items via online merchants. Particularly, this purchase behaviour can be done simultaneously while watching video contents on the web or TV. The T2O system is composed of several modules, and product search (or retrieval) is among the most significant ones. After capturing the desired product from the video scene, the search function aims to match the queried item with the online merchant list. Two major stages are involved in the search (or retrieval) problem:
1) both the features of the query item and reference items (such as products) in the database (e.g., merchant list) are extracted;
2) the similarity or distance of each pair of items (the query item versus each item listed in the database) are calculated. Hence, an appropriate distance estimation strategy plays a critical role in achieving satisfactory performance.

In this paper, each feature space or modality is regarded as a domain, and a novel manifold regularized heterogeneous MTML (MRHMTML) framework is developed for improving the product search in our T2O system by effectively utilizing the side information from each domain. We also assume there are abundant multi-domain unlabelled samples, each of them has representations in all domains. Specifically, metrics of all different domains are learned in a single optimization problem, where the empirical loss with respect to each domain is minimized. Meanwhile, the metric learning is reformulated as learning feature transformation. Our algorithm is superior to other related methods. For example, transformations of multiple heterogeneous domains are also learned together. However, these approaches only explore the statistics (correlation information) between pairs of representations in either one-vs-one, or centralized way. Thus, the high-order statistics are ignored, which can only be obtained by examining all domains simultaneously.

Our approach outperforms them in that:
1) More information is utilized to learn the metrics since the high-order correlations of all domains are exploited, which may contribute to better performance;

2) The unlabelled data are well exploited by enabling knowledge transfer across domain and preserving topology in each domain;
3) The ranking based loss is adopted to learn metrics, which elegantly supports product search

II. RELATED WORKS

The one of the important features of the project is designing the system. The design part provides the different elements of the system such as, architecture and components. System design solves the problem by splitting the components of the complex system into smaller components and will perform and operate on each individual component. The framework configuration prepare develops general structure building outline. Programming diagram incorporates addressing the item system works in a shape that might be changed into at least one anticipates. The essential demonstrated by the end customer must be placed in a systematically way. Diagram is a creative system; an extraordinary design is the best approach to reasonable structure. The structure "Layout" is portrayed as "The methodology of applying distinctive frameworks and guidelines with the ultimate objective of describing a strategy or a system in sufficient purpose important to permit its physical affirmation". Diverse design segments are taken after to add to the system. The design detail depicts the segments of the system, the sections or segments of the structure and their appearance to end-customers

In the existing DML methods, the side information (such as the similar/dissimilar constraints or relevance/irrelevance judgements) in the target domain is leveraged. These methods may fail due to limited side information. This issue can be alleviated by utilizing transfer metric learning (TML) to exploit information from other related domains.

Disadvantage**:**
The data samples of different domains lie in the same feature space, and so DML approaches cannot handle heterogeneous features.

HTL is limited in that only the pair wise correlations (between each latent representation and the shared representation).

The explanation behind the plan is to orchestrate the course of action of the issue dictated by the necessities report. This stage is the underlying stage in moving from issue to the game plan space. All things considered, start with what is obliged; diagram takes us to work towards how to satisfy those necessities. The design of the system is perhaps the most essential segment affecting the way of the item and note worthily affects the later stages, particularly testing and upkeep. System diagram delineates all the huge data structure, report game plan, yield and genuine modules in the system and their Specification is picked

OBJECTIVES
• Learning the definitions of the concepts.
• Access to latest approaches, methods and theories.
• Discovering research topics based on the existing research
• Concentrate on your own field of expertise– Even if another field uses the same words, they usually mean completely
• It improves the quality of the literature survey to exclude side tracks– Remember to explicate what is excluded Before building our android application the following system is taken into consideration Literature survey describes about the existing work on the given project. It deals with the problem associated with the existing system and also gives user a clear knowledge on how to deal with the existing problems and how to provide solution to the existing problems .different thing.

III. METHODOLOGY

The structural setup methodology is worried with working up a fundamental\ essential framework for a system. It incorporates perceiving the genuine parts of the structure and exchanges between these fragments. The starting design technique of perceiving these subsystems and working up a structure for subsystem control and correspondence is called development demonstrating plot and the yield of this framework method is a depiction of the item basic arranging. The proposed design for this framework is given beneath. It demonstrates the way this framework is outlined and brief working of the framework.

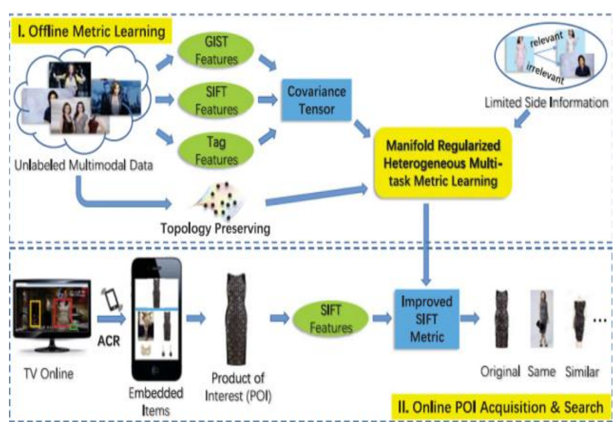


Fig.: Architecture diagram

System Requirement Specification (SRS) is a central report, which frames the establishment of the product advancement process. It records the necessities of a framework as well as has a depiction of its significant highlight. A SRS is essentially an association's seeing (in composing) of a client or potential customer's frame work necessities and conditions at a specific point in time (generally) before any genuine configuration or improvement work. It's a two-way protection approach that guarantees that both the customer and the association comprehend alternate's necessities from that viewpoint at a given point in time.

The composition of programming necessity detail lessens advancement exertion, as watchful audit of the report can uncover oversights, mistaken assumptions, and irregularities ahead of schedule in the improvement cycle when these issues are less demanding to right. The SRS talks about the item however not the venture that created it, consequently the SRS serves as a premise for later improvement of the completed item

Modules: Distance Metric Learning

The goal of distance metric learning (DML) is to learn an appropriate distance function over the input space, so that the relationships between data are appropriately reflected. Most conventional metric learning methods, which are often called "Mahalanobis metric learning", can be regarded as learning a linear transformation of the input data. These algorithms are developed for clustering and classification. To learn metric for information

retrieval, some ranking based metric learning approaches have been proposed. A ranking based loss is designed to address this problem by separating distances between query and relevant samples from distances between query and irrelevant samples. Ranking SVM was extended to learn distance metric and a scalable DML algorithm that optimizes ranking measure via stochastic gradient descent (SGD) is proposed to handle large datasets. Here, we propose a novel manifold regularized heterogeneous MTML

(MRHMTML) inspired by manifold regularization, ranking based DML and heterogeneous transfer learning.

Heterogeneous Transfer Learning

Most HDA methods only incur two domains, i.e., one source and one target domain. The main idea in these methods is to either map the heterogeneous data into a common feature space by learning a feature mapping for each domain or map the data from the source domain to the target domain by learning an asymmetric transformation. The former is equivalent to Mahalanob is metric learning since each learned mapping could be used to derive a metric directly. Compared with HDA, there are much fewer works on HMTL, and one representative approach is the multi-task discriminate analysis (MTDA),which extends linear discriminate analysis (LDA) to learn multiple tasks simultaneously by assuming a common intermediate structure is shared by the learned latent representations of different domains. MTDA can deal with more than two domains, but is limited in that only the pairwise correlations (between each latent representation and the shared representation) are exploited. Therefore, the high-order correlations between all domains are ignored in MTDA. This shortcoming is rectified in the proposed MRHMTML framework. It is noted that heterogeneous multi-task DML method is different from multi-view DML [35], which is also used to deal with heterogeneous data. The goal of heterogenous multi-task DML method is to improve the performance of each DML task by utilizing the information of all different tasks, where the utilized features are different. However, multi-view (or multimodal) DML is to learn an integrated distance metric by using all different features. In heterogeneous multi-task DML, the final prediction is performed in each domain based on the improved distance metric, where only a single type of feature is available. Distinctly in multi-view DML, features of all different domains should be provided in the prediction.

Scale-invariant feature transform (SIFT)

In this paper sift is used, is a kind of computer vision algorithm used to detect and describe Local characteristics in images. It finds extreme points in scale-space and gets its coordinate, scale, orientation, which in final come into being a descriptor. This paper studied the theory of SIFT matching, use Euclid distance as similarity measurement of key points and use RANSAC to eliminate mismatches. The result shows that SIFT algorithm is invariant on rotations, translations and scaling and SIFT features have strong matching robustness for radiation transformation, perspective changes, illumination changes and noises. This paper also compare different results obtained by different ratio threshold and finally set 0.6 as the best value considering the balance number of matched points and matching accuracy. It is important to image recognition application.

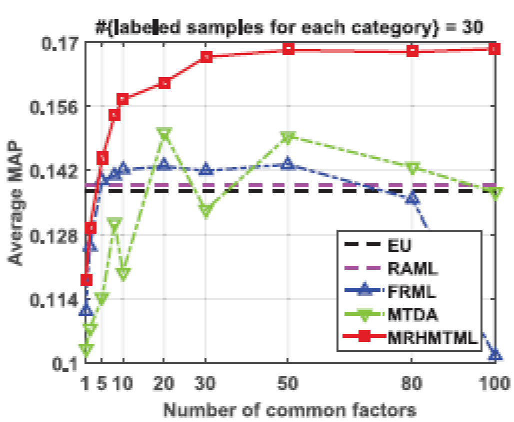
IV. RESULTS AND DISCUSSION

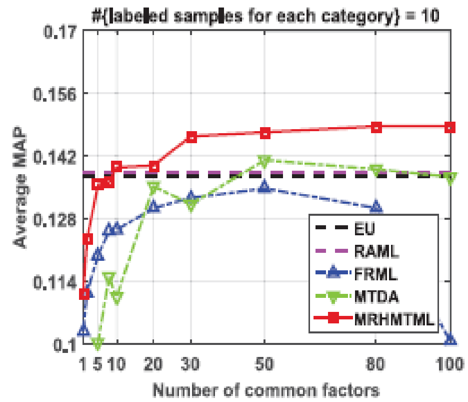
Proposed System:

In the proposed system, people are allowed to buy the desired items via online merchants. Particularly, this purchase behaviour can be done simultaneously while watching video contents on the web or TV. The T2O system is composed of several modules, and product search (or retrieval) is among the most significant ones. After capturing the desired product from the video scene, the search function aims to match the queried item with the online merchant list. To improve the user experience of the T2O system, an appropriate distance estimation algorithm is required. In this paper, each feature space or modality is regarded as a domain, and a novel manifold regularized heterogeneous MTML (MRHMTML) framework is developed for improving the product search in our T2O system by effectively utilizing the side information from each domain. We also assume there are abundant multi-domain unlabelled samples, each of them has representations in all domains. Specifically, metrics of all different domains are learned in a single optimization problem, where the empirical loss with respect to each domain is minimized. Meanwhile, the metric learning is reformulated as learning feature transformation. We project the different representations of the given unlabelled samples into a common subspace and maximize their high-order covariance in the subspace. This results in improved feature transformations since the side information of all domains are utilized to learn the shared subspace. Intuitively, the common subspace bridges different domains so that information can be successfully transferred. The learned metrics are thus more reliable than learning them separately. This is particularly beneficial when the side information is limited. Moreover, a manifold regularization term is added to make full use of the unlabelled information in each domain by exploring the geometric structure of the data.

Advantage:
Is developed for improving the product search in our T2O system by effectively utilizing the side information from each domain.

Help people to buy the desired items via online merchants as a result they can save their time.
Is efficient and reliable. The implementation phase involves the actual materialization of the ideas, which are expressed in the analysis document and developed in the design phase. Implementation should be perfect mapping of the design document in a suitable programming language in order to achieve the necessary final product. Often the product is ruined due to incorrect programming language chosen for implementation or unsuitable method of programming. It is better for the coding phase to be directly linked to the design phase in the sense if the design is in terms of object oriented terms then implementation should be preferably carried out in a object oriented way.





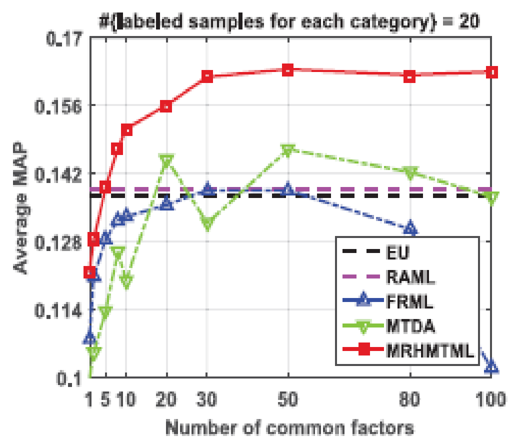


Fig:Average MAP of all domains versus number of the common factors on the VOC dataset.

The implementation involves:

1. Careful planning.
2. Investigation of the current system and the constraints on implementation.
3. Training of staff in the newly developed system.

Implementation of any software is always preceded by important decisions regarding selection of the platform, the language used, etc. these decisions are often influenced by several factors such as real environment in which the system works, the speed that is required, the security concerns, and other implementation specific details. There are three major implementation decisions that have been made before the implementation of this project. They are as follows:

1. Selection of the platform (Operating System).
2. Selection of the programming language for development of the application.
3. Coding guideline to be followed.

The GUI is developed using Android Studio, which is the client side. Android Studio is the official integrated development environment (IDE) for the Android platform. The server side of the implementation is done using NetBeans. NetBeans is a software development platform written in Java. The NetBeans Platform allows applications to be developed from a set of modular software components called modules. Applications based on the NetBeans Platform, including the NetBeans integrated development environment (IDE), can be extended by third party developers. The NetBeans IDE is primarily intended for development in Java, but also supports other languages, in particular PHP, C/C++ and HTML5.The protocol implemented in this project is Light Weight Anonymous Authentication Protocol. This protocol aims at providing Data Freshness, Authentication, Secure Localization and Maintains Anonymity.

V. CONCLUSION AND FUTUREWORK

An effective TV-to-Online (T2O) system aims to make it easier for people to shop online while watching TV. This paper introduces a novel transfer distance metric learning algorithm to address the distance estimation problem, which plays a vital role in products matching module of a T2O system. The proposed method takes full advantage of multiple domains (feature spaces) by analysing their feature covariance tensor. In addition, we exploit the geometric structure of the data to make full use of the unlabelled data and employ ranking-based loss to make the learned metric especially appropriate and feasible to match similar products. The main conclusions of the experiments on two challenging and popular datasets are: 1) a separate metric learning for each domain may degrade performance if the side information is given insufficiently. Meanwhile, the deficiency problem of labelled data can be alleviated if the metrics of multiple heterogeneous domains are learned simultaneously. This result is consistent with description in the literatures for multi-task learning; 2) transfer learning methods can exploit the shared knowledge across different domains. The high-order statistics (correlation information) play a critical role in discovering appropriate common factors, which can benefit each domain;3) the ranking-based loss is adopted to help learn an efficient metric for products matching.

Future Work

In the future, we intend to design some algorithm for such case that only one domain is provided with the side information. There exist some approaches that can annotate products in videos or learn concept (e.g., product) relationships for visual search. Incorporate these techniques into our system may further improve our product search performance.

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