Convex Experimental Design Using Manifold Structure for Image Retrieval

Lijun Zhang[1] zljzju@zju.edu.cn

Chun Chen[1] chenc@zju.edu.cn

Wei Chen[1] chenw@zju.edu.cn

Jiajun Bu[1] bjj@zju.edu.cn

Deng Cai[2] dengcai@cad.zju.edu.cn

Xiaofei He[2] xiaofeihe@cad.zju.edu.cn

[1]Zhejiang Key Laboratory of Service Robot, College of Computer Science, Zhejiang University, Hangzhou, China
[2]State Key Lab of CAD&CG, College of Computer Science, Zhejiang University, Hangzhou, China

ABSTRACT

Content B sed I ge Retriev CBIR h s eco e one of the ost ctive rese rch re s in co puter science Re ev nce feed ck is often used in CBIR syste s to ridge the se ntic g p Typic y users re sked to ke re ev nce judge ents on so e query re su ts nd the feed ck infor tion is then used to re r nk the i ges in the d t se An effective re ev nce feed ck gorith ust provide the users ith the ost infor tive i ges ith re spect to the r nking function In this p per e propose nove ctive e rning gorith c ed Conve L p ci n Regu rized I opti Design CL pRID for re ev nce feed ck i ge retriev Our gorith is sed on regression ode hich ini izes the e st squ re error on the e ed i ges nd si u t neous y pre serves the intrinsic geo etric structure of the i ge sp ce It se ects the ost infor tive i ges hich ini ize the ver ge predictive v ri nce The opti iz tion pro e of CL pRID c n e c st s se ide nite progr ing SDP pro e nd so ved vi interior point ethods E peri ent resu ts on COREL d t se h ve de onstr te the effectiveness of the proposed gorith for re ev nce feed ck i ge retriev

Categories and Subject Descriptors

H **Information storage and retrieval** Infor tion se rch nd retriev *Re e nce feed c* G **Mathematics of Computing** Pro i ity nd St tistics *E peri ent design*

General Terms

A gorith s Perfor nce Theory

Keywords

I ge retriev ctive e rning conve opti iz tion re ev nce feed ck se ide nite progr ing

1. INTRODUCTION

ith the r pid incre se in the vo u e of e ectronic y rchived i ge nd video teri s Content B sed I ge Retriev CBIR h s eco e one of the ost ctive rese rch re s for the st fe dec des Query y e p e QBE is the tr dition type of query in CBIR In this environ ent users for u te query y e ns of giving n e p e i ge 2 CBIR syste s use the o eve visu fe tures ost y co or te ture nd sh pe to represent n i ge s content nd re ev nt i ges re retrieved sed on the si i rity of their visu fe tures A though CBIR h s een e ten sive y studied the se ntic g p et een o eve i ge fe tures nd high eve se ntic concepts i its its perfor nce rge y

To n rro do n the se ntic g p re ev nce feed ck is intro duced into CBIR Typic y users re sked to ke re ev nce judge ents on the top i ges returned y the syste nd their preference is used to tr in c ssi er to sep r te i ges th t tch the query concept fro those th t do not Ho ever in gener the top returned i ges y not e the ost infor tive ones In the orst c se the top i ges e ed y the user y e positive nd thus the st nd rd c ssi c tion techniques c n not e pp ied due to the ck of neg tive e p es The key pro e then e co es ho to se ect the ost infor tive s p es fro the i ge d t se In chine e rning this pro e is c ed ctive e rn ing hich studies the pheno enon of e rner se ecting ctions or king queries th t i uence h t d t re dded to its tr ining set

Active e rning gorith is high y corre ted ith the under ying r nking ech nis The ost popu r ctive e rning tech niques inc ude Support ector M chine ctive e rning S M_{active} 2 nd regression sed ctive e rning 2 2 2 S M_{active} sks the user to e those i ges hich re c osest to the S M ound ry The r tion e is th t the c oser to the S M ound ry n i ge is the ess re i e its c ssi c tion is One of the jor dis dv nt ges of S M_{active} is th t the esti ted ound ry y not e ccur te enough especi y hen the nu er of e ed i ge is s Moreover S M_{active} c n not e pp ied t the rst round of the retriev hen there is no feed ck i ges

In st tistics the pro e of se ecting s p es to e is usu y referred to s e peri ent design The study of Opti u E peri ent Design OED 2 is concerned ith the design of e peri ents th t re e pected to ini ize v ri nce of p r e terized ode There re t o types of se ection criteri of OED One type is to choose points to ini ize the con dence region for the esti ted ode p r eters hich resu ts in D A nd E opti Design The other is to ini ize the v ri nce of the pre diction v ue hich resu ts in I nd G opti Design Recent y Yu et propose n ctive e rning for u tion c ed Tr nsduc tive E peri ent Design TED 2 TED se ects d t points to ini ize the ver ge predictive v ri nce of the e rned function on so e pre given d t set It is so for u ted into conve opti

TED is then for u ted s the fo o ing opti iz tion pro e

$$\begin{array}{ll} \min & \mathrm{Tr}(X^T(ZZ^T+\gamma I)^{-1}X) \\ \mathrm{s\ t} & \{\mathbf{z}_1,\cdots,\mathbf{z}_k\}\subseteq\mathcal{X} \end{array}$$

ith v ri e $Z=[\mathbf{z}_1,\cdots,\mathbf{z}_k]$ After so e the tic deriv tion the ove pro e c n e for u ted s n equiv ent opti iz tion pro e s fo o s

$$\begin{array}{ll} \mathrm{in} & \sum_{i=1}^m \|\mathbf{x}_i - Z\boldsymbol{\alpha}_i\|^2+\gamma\|\boldsymbol{\alpha}_i\|^2 \\ \mathrm{s\ t} & \{\mathbf{z}_1,\cdots,\mathbf{z}_k\}\subseteq\mathcal{X} \end{array}$$

here the v ri es re $Z=[\mathbf{z}_1,\cdots,\mathbf{z}_k]$ nd $\boldsymbol{\alpha}_i\in\mathbb{R}^k, i=1,\cdots,m$

The ove pro e is NP h rd Yu et h ve proposed sequen ti greedy gorith 2 nd conve re tion 42 to so ve it The conve re tion CovTED is sho n s fo o s

$$\begin{array}{ll} \mathrm{in} & \sum_{i=1}^m \left(\|\mathbf{x}_i - X\boldsymbol{\alpha}_i\|^2+\sum_{j=1}^m \frac{\alpha_{i,j}^2}{\beta_j}\right)+\gamma\|\boldsymbol{\beta}\|_1 \\ \mathrm{s\ t} & \beta_j\geq 0, j=1,\cdots,m \end{array}$$

here the v ri es re $\boldsymbol{\beta}\in\mathbb{R}^m$ nd $\boldsymbol{\alpha}_i\in\mathbb{R}^m, i=1,\cdots,m$ Here $\|\boldsymbol{\beta}\|_1$ is the ℓ_1 nor of $\boldsymbol{\beta}$ hich is used to enforce so e e e ents of $\boldsymbol{\beta}$ to e zero An iter tive gorith is proposed to so ve it 42

3. CONVEX LAPLACIAN REGULARIZED I-OPTIMAL DESIGN

Tr dition ctive e rning gorith s such s S M$_{active}$ nd OED re sed on supervised e rning gorith s S M or ine r regression These ppro ches on y consider the e ed d t points hi e neg ecting the rge ount of un e d t points hich y p y essenti ru es in se ecting infor tive s p es e introduce in this section nove ctive e rning gorith hich is sed on one se i supervised e rning gorith e i rst introduce the ine r gorith nd then gener ize it to the non ine r c se y pp ying kerne tricks Our gorith is fund ent y sed on L p ci n Regu rized Le st Squ res L pRLS nd otiv ted y recent progress in e peri ent design 24 2 42

3.1 Laplacian Regularized Least Squares

L p ci n Regu rized Le st Squ res L pRLS kes use of oth e ed nd un e ed points to discover the intrinsic geo etric structure in the d t It ssu es th t if t o points $\mathbf{x}_i$ nd $\mathbf{x}_j$ re c ose then their e sure ents $f(\mathbf{x}_i)$ nd $f(\mathbf{x}_j)$ re c ose s e Speci c y L pRLS dds ne oc ity preserving regu r izer into the oss function of ridge regression Eq4 Let W e si i rity tri the ne oss function is de ned s fo o s

$$J_L(\mathbf{w})=\sum_i^k(f(\mathbf{z}_i)-y_i)^2+\frac{\alpha}{2}\sum_{i,j=1}^m(f(\mathbf{x}_i)-f(\mathbf{x}_j))^2W_{ij}+\beta\|\mathbf{w}\|^2 \quad 2$$

here $\alpha\geq 0$ nd $\beta\geq 0$ re the regu riz tion p r eters The second ter of the right h nd side in the cost function is the oc ity preserving regu rizer hich incurs he vy pen ty if neigh oring points $\mathbf{x}_i$ nd $\mathbf{x}_j$ re pped f r p rt

There re ny choices of si i rity tri W A si p e de nition is s fo o s

$$W_{ij}=\begin{cases}1, & \text{if } \mathbf{x}_i \text{ is ong the } p \text{ ne rest neigh ors of } \mathbf{x}_j \\ & \text{or } \mathbf{x}_j \text{ is ong the } p \text{ ne rest neigh ors of } \mathbf{x}_i \\ 0, & \text{other ise}\end{cases}$$

Let D e di gon tri ith $D_{ii}=\sum_{j=1}^m W_{ij}$ nd $L=D-W$ The tri L is c ed *Gr ph L p ci n* in spectr gr ph theory 8 The so ution to ini ize equ tion 2 is given s fo o s

$$\widehat{\mathbf{w}}_L=(ZZ^T+\alpha XLX^T+\beta I)^{-1}Z\mathbf{y} \quad 4$$

Let $H=ZZ^T+\alpha XLX^T+\beta I$ the cov ri nce tri of $\widehat{\mathbf{w}}_L$ is

$$\begin{aligned}\mathrm{Cov}(\widehat{\mathbf{w}}_L)=&H^{-1}Z\,\mathrm{Cov}(\mathbf{y})Z^TH^{-1}\\ =&\sigma^2H^{-1}ZZ^TH^{-1}\\ =&\sigma^2H^{-1}(H-\alpha XLX^T+\beta I)H^{-1}\\ =&\sigma^2H^{-1}-\sigma^2H^{-1}(\alpha XLX^T+\beta I)H^{-1}\end{aligned}$$

Since the regu riz tion p r eters α nd β re usu y set to e very s e h ve

$$\mathrm{Cov}(\widehat{\mathbf{w}}_L)\approx\sigma^2H^{-1}=\sigma^2(ZZ^T+\alpha XLX^T+\beta I)^{-1}$$

3.2 Convex Laplacian Regularized I-optimal Design

Through king use of oth e ed nd un e ed d t L pRLS esti tes ine r tting function $f(\mathbf{x})=\widehat{\mathbf{w}}_L^T\mathbf{x}$ th t respects the intrinsic geo etric structure in the d t sp ce An ide design ou d choose su set $\mathcal{Z}\subseteq\mathcal{X}$ hich si u t neous y ini izes the con dence region for $\widehat{\mathbf{w}}_L^T$ nd the predictive v ri nce of $f(\mathbf{x})$ Ho ever usu y choice h s to e de et een these desider t 2 In i ge retriev e i t e rning regression function hich c n distinguish the re ev nt i ges fro irre ev nt ones It is n tur to require th t the predictions of the e rned function on the i ge d t se re s st e s possi e Thus e use the I opti design criterion to se ect those i ges hich c n ini ize the ver ge predictive v ri nce of e rned regression function

Here e consider set $\mathcal{V}=\{\mathbf{v}_1,\cdots,\mathbf{v}_l\}$ of test d t points esides c ndid tes in $\mathcal{X}=\{\mathbf{x}_1,\cdots,\mathbf{x}_m\}$ In speci c ses $\mathcal{V}$ nd $\mathcal{X}$ c n e the s e set Given test point $\mathbf{v}$ its prediction v ue is $f(\mathbf{v})=\widehat{\mathbf{w}}_L^T\mathbf{v}$ ith v ri nce $\mathrm{Var}(f(\mathbf{v}))=\mathbf{v}^T\mathrm{Cov}(\widehat{\mathbf{w}}_L)\mathbf{v}$ Let $V=[\mathbf{v}_1,\cdots,\mathbf{v}_l]$ the ver ge predictive v ri nce on $\mathcal{V}$ is

$$\begin{aligned}&\frac{1}{l}\sum_{i=1}^l\mathbf{v}_i^T\mathrm{Cov}(\widehat{\mathbf{w}}_L)\mathbf{v}_i\\ \approx&\frac{\sigma^2}{l}\sum_{i=1}^l\mathbf{v}_i^T(ZZ^T+\alpha XLX^T+\beta I)^{-1}\mathbf{v}_i\\ =&\frac{\sigma^2}{l}\mathrm{Tr}(V^T(ZZ^T+\alpha XLX^T+\beta I)^{-1}V)\end{aligned}$$

Then our pro e is to nd su set $\mathcal{Z}\subseteq\mathcal{X}$ to ini ize equ tion A si p e sequenti greedy ppro ch s suggested to se ect $\mathbf{z}_i$'s one fter nother in 4

By introducing m indic tor v ri es $\{\lambda_i\}_{i=1}^m\in\{0,1\}$ here λ_i indic tes hether or not point $\mathbf{x}_i$ is chosen nding su set $\mathcal{Z}$ to ini ize equ tion is equiv ent to the fo o ing opti iz tion pro e

$$\begin{array}{ll} \mathrm{in} & \mathrm{Tr}(V^T(\sum_{i=1}^m\lambda_i\mathbf{x}_i\mathbf{x}_i^T+\alpha XLX^T+\beta I)^{-1}V) \\ \mathrm{s\ t} & \{\lambda_i\}_{i=1}^m\in\{0,1\},\ \sum_{i=1}^m\lambda_i=k \end{array} \quad 8$$

here the v ri es re $\{\lambda_i\}_{i=1}^m$ nd k is the nu er of d t points to e chosen To si p ify our present tion e use vector $\boldsymbol{\lambda}=[\lambda_1,\cdots,\lambda_m]$ to denote the m v ri es The v ri e vector $\boldsymbol{\lambda}$ is sp rse nd h s on y k non zero entries nonneg tive v ues Then the v ue of λ_i indic tes ho signif ic nt y $\mathbf{x}_i$ contri utes to the ini iz tion in pro e 8 The sp rseness of $\boldsymbol{\lambda}$ c n e contro ed through ini izing the ℓ_1 nor of $\boldsymbol{\lambda}$ hich is very popu r technique in regression 4

Fo o ing the convention in the e d of opti iz tion e use $\boldsymbol{\lambda} \succeq 0$ to denote th t the e e ents in $\boldsymbol{\lambda}$ shou d e nonneg tive And ec use the e e ents of $\boldsymbol{\lambda}$ re nonneg tive $\|\boldsymbol{\lambda}\|_1$ is equ to $\mathbf{1}^T\boldsymbol{\lambda}$ here $\mathbf{1}$ is co u n vector cont ining ones Fin y our opti iz tion pro e eco es

De nition Conve L p ci n Regu rized I opti Design CL pRID

in $\mathrm{Tr}(V^T(\sum_{i=1}^{m} \lambda_i \mathbf{x}_i\mathbf{x}_i^T + \alpha XLX^T + \beta I)^{-1}V) + \gamma \mathbf{1}^T\boldsymbol{\lambda}$

s t $\boldsymbol{\lambda} \succeq 0$

here the v ri e is $\boldsymbol{\lambda} \in \mathbb{R}^m$ nd $\gamma \geq 0$ is the tr de off p r eter for sp rsity

THEOREM *Pro e 9 is con e opti iz tion pro e ith ri e $\boldsymbol{\lambda} \in \mathbb{R}^m$*

PROOF Let $g(X) = \mathrm{Tr}(V^T X^{-1} V) = \sum_{j=1}^{l} \mathbf{v}_j^T X^{-1} \mathbf{v}_j$ nd $h(\boldsymbol{\lambda}) = \sum_{i=1}^{m} \lambda_i \mathbf{x}_i\mathbf{x}_i^T + \alpha XLX^T + \beta I$ e kno th t tri fr ction function $f_1(X) = \mathbf{v}^T X^{-1}\mathbf{v}$ is conve function of X 4 Since nonneg tive eighted su preserves conve ity $g(X)$ is so conve function of X e de ne

$$g \circ h(\boldsymbol{\lambda}) = \mathrm{Tr}(V^T(\sum_{i=1}^{m} \lambda_i \mathbf{x}_i\mathbf{x}_i^T + \alpha XLX^T + \beta I)^{-1}V)$$

Bec use $h(\boldsymbol{\lambda})$ is n f ne function of $\boldsymbol{\lambda}$ nd co position ith n f ne function preserves conve ity $g \circ h$ is conve function of $\boldsymbol{\lambda}$ Since $f_2(\boldsymbol{\lambda}) = \gamma\mathbf{1}^T\boldsymbol{\lambda}$ is conve function of λ the o jective function of pro e $g \circ h(\boldsymbol{\lambda})$ $f_2(\boldsymbol{\lambda})$ is so conve

Bec use the o jective function is conve the inequ ity con str int function $-\boldsymbol{\lambda}$ is conve pro e is conve opti iz tion pro e ith v ri e $\boldsymbol{\lambda} \in \mathbb{R}^m$ 4 □

3.3 Optimization Scheme

The success of Se ide nite progr ing SDP in v rious p p ic tions otiv tes us to for u te nd so ve CL pRID s n SDP pro e Se ide nite progr ing h s een the ost e citing the tic deve op ent in the tic progr ing It h s pp ic tions in tr dition conve constr ined opti iz tion s e s in such diverse do ins s contro theory nd co in tori op ti iz tion 2 Moreover the po erfu interior point ethods for ine r progr ing h ve een e tended to SDP

By introducing ne v ri e $P \in \mathbb{R}^{l\times l}$ opti iz tion pro e c n e equiv ent y re rote s

in $\mathrm{Tr}(P) + \gamma\mathbf{1}^T\boldsymbol{\lambda}$

s t $P \succeq_{\mathbb{S}_l^+} V^T(\sum_{i=1}^{m} \lambda_i \mathbf{x}_i\mathbf{x}_i^T + \alpha XLX^T + \beta I)^{-1}V$ 2

$\boldsymbol{\lambda} \succeq 0$

ith v ri es $P \in \mathbb{R}^{l\times l}$ nd $\boldsymbol{\lambda} \in \mathbb{R}^m$ Here $\mathbb{S}_l^+$ denotes the set of sy etric positive se ide nite $l \times l$ trices hich is c ed positive se ide nite cone in the e d of opti iz tion The sso ci ted gener ized inequ ity $\succeq_{\mathbb{S}_l^+}$ is the usu tri inequ ity $A \succeq_{\mathbb{S}_l^+} B$ e ns $A - B$ is positive se ide nite $l \times l$ tri 4

THEOREM 2 *Pro e 9 is equi ent to pro e 2*

PROOF Let $\boldsymbol{\lambda}_a^*$ e the opti so ution of pro e nd P^* $\boldsymbol{\lambda}_b^*$ e the opti so utions of pro e 2 Then $\boldsymbol{\lambda}_a^*$ $\boldsymbol{\lambda}_b^*$ is suf cient condition for Theore 2Let $f(\boldsymbol{\lambda}) = T^T(\sum_{i=1}^{m} \lambda_i \mathbf{x}_i\mathbf{x}_i^T + \alpha XLX^T + \beta I)^{-1}T$

Assu e $\boldsymbol{\lambda}_a^* \neq \boldsymbol{\lambda}_b^*$ Since $\boldsymbol{\lambda}_a^*$ ini izes pro e e ust h ve $\mathrm{Tr}\, f(\boldsymbol{\lambda}_a^*) + \gamma\mathbf{1}^T\boldsymbol{\lambda}_a^* < \mathrm{Tr}\, f(\boldsymbol{\lambda}_b^*) + \gamma\mathbf{1}^T\boldsymbol{\lambda}_b^*$ Bec use P^* $\boldsymbol{\lambda}_b^*$ s tis es the constr ints in pro e 2 e h ve

$$\begin{aligned} P^* \succeq_{\mathbb{S}_l^+} f(\boldsymbol{\lambda}_b^*) &\Leftrightarrow P^* - f(\boldsymbol{\lambda}_b^*) \in \mathbb{S}_l^+ \\ &\Rightarrow \mathrm{Tr}(P^* - f(\boldsymbol{\lambda}_b^*)) \geq 0 \\ &\Rightarrow \mathrm{Tr}(P^*) \geq \mathrm{Tr}\, f(\boldsymbol{\lambda}_b^*) \\ &\Rightarrow \mathrm{Tr}(P^*) + \gamma\mathbf{1}^T\boldsymbol{\lambda}_b^* \geq \mathrm{Tr}\, f(\boldsymbol{\lambda}_b^*) + \gamma\mathbf{1}^T\boldsymbol{\lambda}_b^* \\ &\Rightarrow \mathrm{Tr}(P^*) + \gamma\mathbf{1}^T\boldsymbol{\lambda}_b^* > \mathrm{Tr}\, f(\boldsymbol{\lambda}_a^*) + \gamma\mathbf{1}^T\boldsymbol{\lambda}_a^* \end{aligned}$$

It is c e r th t $(f(\boldsymbol{\lambda}_a^*), \boldsymbol{\lambda}_a^*)$ s tis es the constr ints in pro e 2 Then for pro e 2 $(f(\boldsymbol{\lambda}_a^*), \boldsymbol{\lambda}_a^*)$ is ore opti th n P^* $\boldsymbol{\lambda}_b^*$ hich contr dicts our ssu ptions So e ush h ve $\boldsymbol{\lambda}_a^* = \boldsymbol{\lambda}_b^*$ □

Pro e 2 c n e c st s n SDP using the Schur co p e ent theore 4 Given sy etric tri X p rtitioned s

$$X = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix}$$

If A is inverti e the tri $S = C - B^T A^{-1} B$ is c ed the Schur co p e ent of A in X Schur co p e ent theore st tes th t if A is positive de nite then X is positive se ide nite if nd on y if S is positive se ide nite

According to this theore pro e 2 is equiv ent to the fo o ing se ide nite progr ing SDP

in $\mathrm{Tr}(P) + \gamma\mathbf{1}^T\boldsymbol{\lambda}$

s t $\begin{bmatrix} \sum_{i=1}^{m} \lambda_i \mathbf{x}_i\mathbf{x}_i^T + \alpha XLX^T + \beta I & V \\ V^T & P \end{bmatrix} \succeq_{\mathbb{S}_{n+l}^+} 0$ 2

$\boldsymbol{\lambda} \succeq 0$

ith v ri es $P \in \mathbb{R}^{l\times l}$ nd $\boldsymbol{\lambda} \in \mathbb{R}^m$ As e p ined previous y $A \succeq_{\mathbb{S}_{n+l}^+} 0$ e ns A is positive se ide nite $(n+l)\times(n+l)$ tri e c n so ve this pro e e ct y vi interior point ethods 4 After o t ining the opti so ution $\boldsymbol{\lambda}^*$ e se ect k points ith the rgest signi c nt indic tors λ_i^* s for user to e

4. CONVEX KERNEL LAPLACIAN REGULARIZED I-OPTIMAL DESIGN

Tr dition e peri ent design on y considers ine r functions hen the d t is high y non ine r distri uted the ine r function ight not e e to t the d t e In this Section e e tend CL pRID to h nd e non ine r c ses y perfor ing e peri en t design in the Reproducing erne Hi ert Sp ce R HS e egin ith rief description of erne L p ci n Regu rized Le st Squ res

4.1 Kernel Laplacian Regularized Least Squares

Let K e positive de nite ercer kerne $K: \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ nd $\mathcal{H}_K$ e the corresponding Reproducing erne Hi ert Sp ce R SH Consider the opti iz tion pro e 2in R HS Then e seek function $f \in \mathcal{H}_K$ such th t the fo o ing o jective func tion is ini ized

$$J_L(f) = \sum_{i=1}^{k}(y_i - f(\mathbf{z}_i))^2 + \frac{\alpha}{2}\sum_{i,j=1}^{m}(f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 W_{ij} + \beta\|f\|_{\mathcal{H}_K}^2$$

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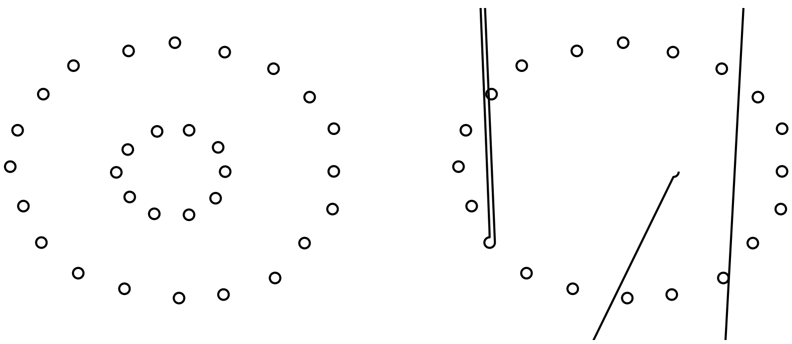
The Representer Theore c n e used to sho th t the so u tion is n e p nsion of kerne functions over oth the e ed nd the un e ed d t

$$\widehat{f}(\mathbf{x}) = \sum_{i=1}^{m} \widehat{\alpha}_i K(\mathbf{x},$$



D t set

precision-scope cur e

e e peri ent design e o

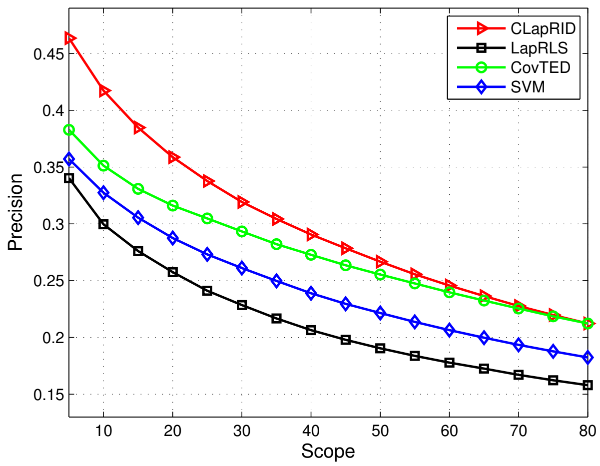
ithms. The numbers beside the selected points denote their o

o p r isons ith other gorith s e

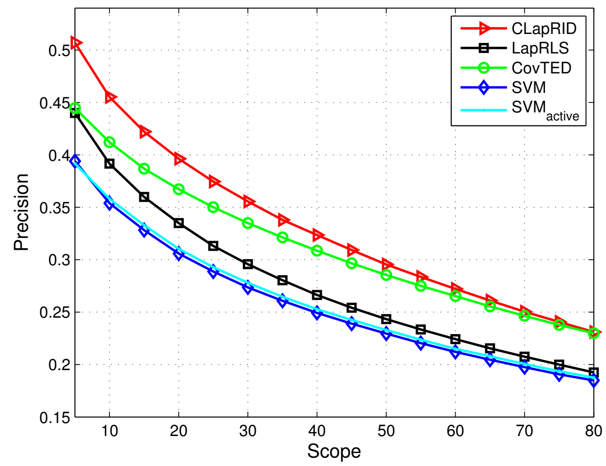
c Disdnomhiscue2: Sample imagesfrom 1: Data selected by different active learning algor using our gorith e need re i e y of ev u ting the retriev pe

Table 1: Precision at top 20 returns of the five algorithms after the second feedback iteration. The highest precision is in bold for each category.

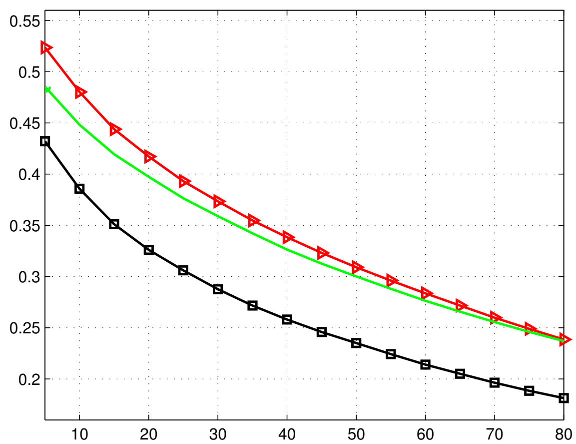
C tegory	S M	L pRLS	S M$_{active}$	CovTED	CL pRID	C tegory	S M	L pRLS	S M$_{active}$	CovTED	CL pRID
Ante ope	2				**0.21**	Horse	[illegible]	8 [illegible]	2	**0.92**	
Antique		[illegible] 8		[illegible] 2	**0.62**	Indoor decor te			2		**0.57**
Aqu re e	[illegible]		[illegible]		**0.18**	Je e ry	[illegible]			**0.10**	
B oon	[illegible]2	2	2	[illegible]	**0.41**	ungfu	88	[illegible]	8	8	**0.89**
Be ch			[illegible]	[illegible]	**0.15**	Leop rd	2	22	2	[illegible]2	**0.32**
Be d	[illegible]	2	[illegible]	**0.23**	2	Lighthouse		[illegible]		**0.11**	
Bird			[illegible]	**0.07**	[illegible]	Lion	8	8	2	2	**0.31**
Bo s ed	22	2	2		**0.34**	Liz rd	8		[illegible]	22	**0.29**
Bons i	22	8	2	8	**0.46**	M r e	2	8	8	**0.35**	2
Bui ding	8		8	2	**0.13**	M sk	2	[illegible]	2	[illegible]	**0.57**
Bus		[illegible]			**0.44**	Men	2		**0.12**		
Butte y		[illegible]			**0.45**	Mode			2		**0.16**
C ctus	2		[illegible]	**0.15**	**0.15**	Mos ic	[illegible]	[illegible]2		**0.72**	[illegible]
C nv s		2	2	**0.39**		Mount in	2	8	2		**0.40**
C rds	88	**0.94**	8			O d C r	[illegible]		8	[illegible]	**0.45**
C st e	**0.17**	[illegible]	[redacted]								



First Iter tion



Second Iter tion



r te even decre ses fter the second feed ck iter tion This pheno enon v id tes th t the top i ges y not e the ost infor tive ones

6. CONCLUSIONS

In this p per e propose nove ctive e rning gorith c ed Conve L p ci n Regu rized I opti Design CL pRID for re ev nce feed ck i ge retriev Our gorith is fund en t y sed on L p ci n Regu rized Le st Squ res L pRLS nd otiv ted y ny recent dv nces in e peri ent design 2 2 2 CL pRID kes use of oth e ed nd un e ed points to discover the intrinsic geo etric structure in the d t It se ects i ges to ini ize ver ge v ri nce of prediction v ue nd c n e so ved vi se ide nite progr ing E peri ent resu ts on COREL d t se sho th t the proposed ppro ch outperfor s Support ector M chines L p ci n Regu rized Le st Squ res Support ector M chine Active Le rning 2 Conve Tr ns ductive E peri ent Design 2

In this p per e use I opti design criterion Ho ever other c ssic opti criteri such s D A E nd G opti designs c n so e refor u ted under this fr e ork to re ect the under ing geo etric structure

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