Cross-Modal Retrieval: A Pairwise Classification Approach

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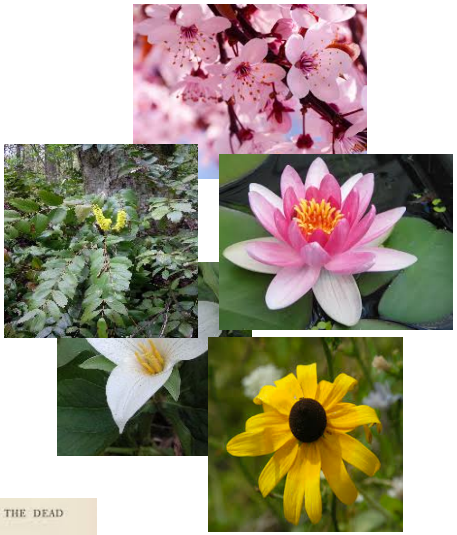
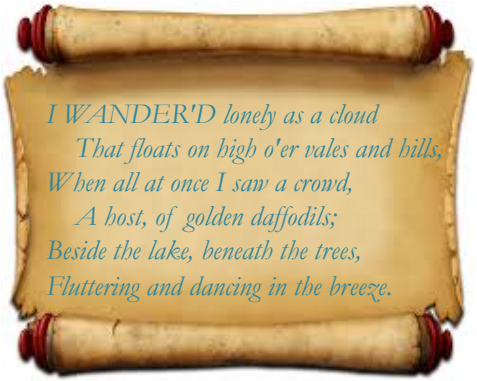
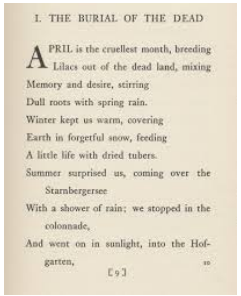
Overview of talk

Background

Content is increasingly available in multiple modalities (images, text, videos, ...)





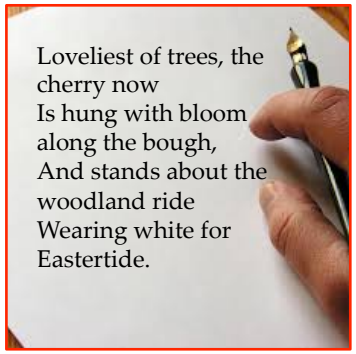


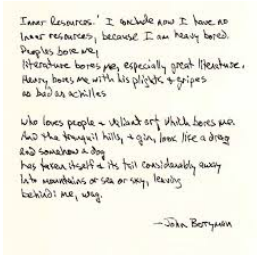
Cross-modal retrieval: informally

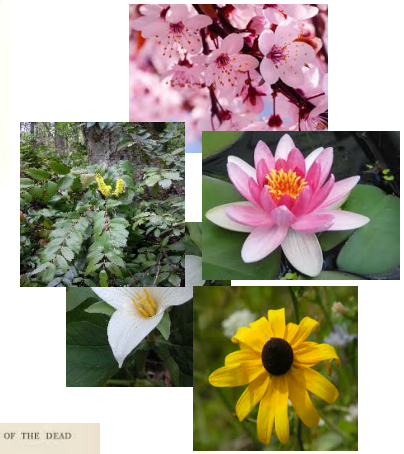
Given the representation of an entity in one modality, find its best representation in all other modalities

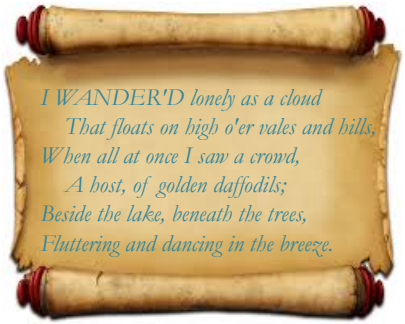
Cross-modal retrieval: informally

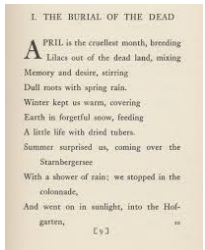
e.g. Given a piece of text, what is the image that best accompanies it?











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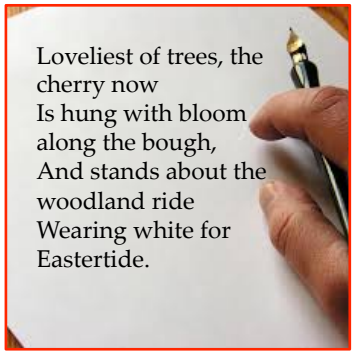
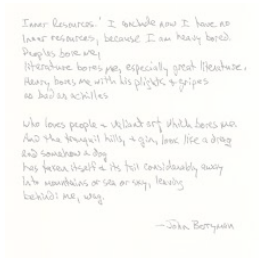
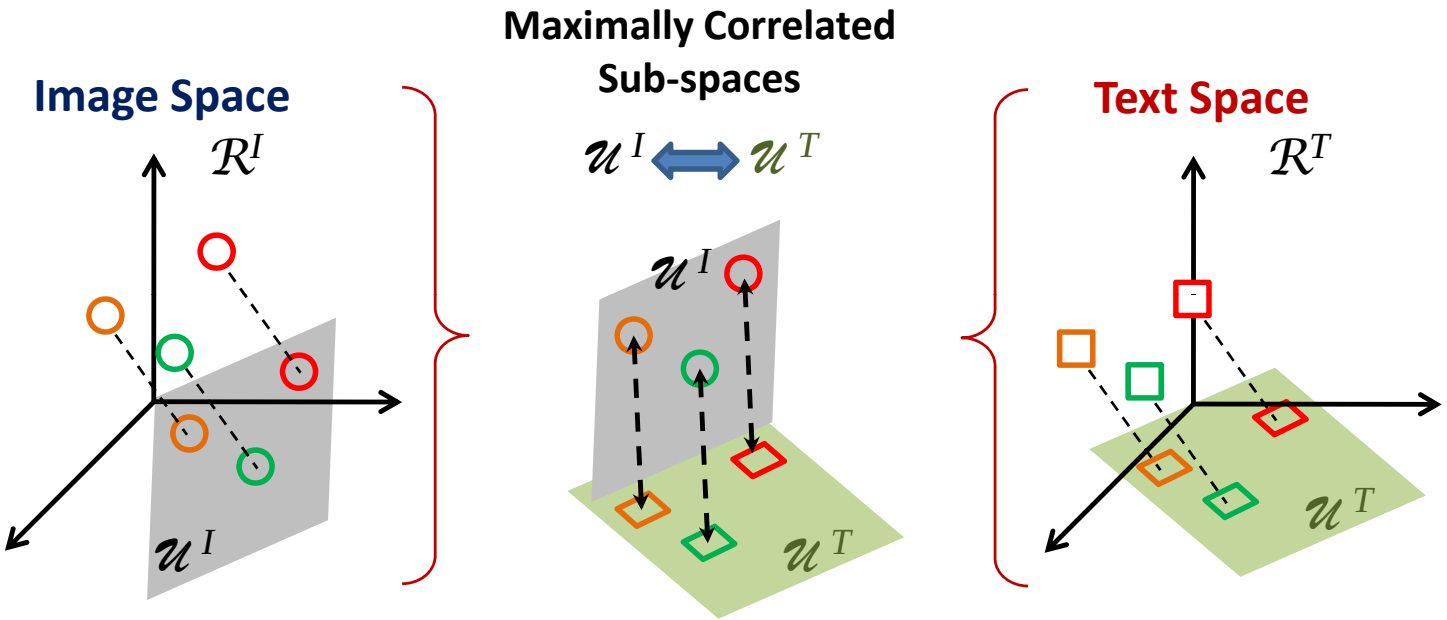




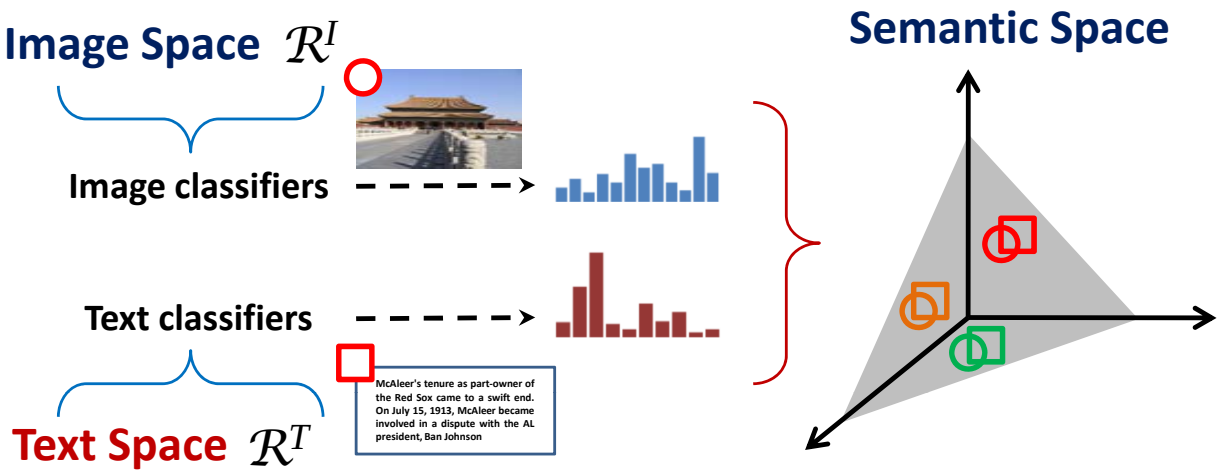
Prior work: CCA

Canonical Correlation Analysis (CCA): project both modalities onto a latent subspace where they exhibit maximum correlation



Prior work: SM

Semantic Matching (SM): project both modalities into a rich supervised subspace



This paper

A pairwise classification perspective on cross-modal retrieval

- Goal is to score pairs of instances based on affinity

Seamlessly study scenarios with and without ground-truth annotation

- Essentially, reduction to logistic regression on pairs of instances
- Unification of the CCA and SM approaches

Good empirical performance on real-world retrieval tasks

Overview of talk

(Unsupervised) Cross-modal retrieval: training set

Training examples: $\mathcal{D} = \{(a^{(i)}, b^{(i)})\}_{i=1}^{n}$

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- Set of suitable pairings of entities across two modalities
- $(a^{(i)}, b^{(i)}) \in \mathcal{A} \times \mathcal{B}$, $\mathcal{A} \subseteq \mathbb{R}^{d_a}$ and $\mathcal{B} \subseteq \mathbb{R}^{d_b}$ the modality representations

Cross-modal retrieval: goal

Goal: Learn retrieval mappings $f : \mathcal{A} \to \mathcal{B}$ and $g : \mathcal{B} \to \mathcal{A}$

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- *e.g.* Given a piece of text, what is the best accompanying image?

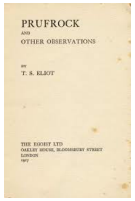
f :

They call me 'The Wild Rose'
But my name was Elisa Day
Why they call me it, I do not know
For my name was Elisa Day

Assumption: ground-truth annotations

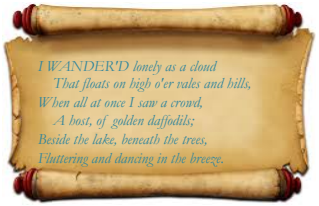
We assume there is a set of ground-truth annotations for each entity

- For our purposes, a label from some set $\mathcal{Y} = \{1, 2, \ldots, K\}$



Arts

Nature



Nature

History

Politics

Science

These annotations may be unobserved

- But are still used for evaluation

(Supervised) Cross-modal retrieval: training set

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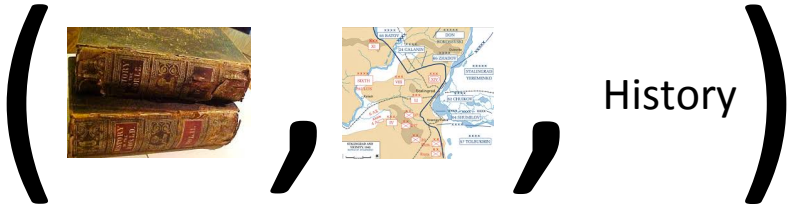
- $y^{(i)} \in \mathcal{Y}$ are the annotations



Goal is as before

Overview of talk

Latent map approach

Popular approach: learn latent maps $\psi_{\mathcal{A}} : \mathcal{A} \to \mathbb{R}^k$, $\psi_{\mathcal{B}} : \mathcal{B} \to \mathbb{R}^k$

- $k \in \mathbb{N}_+$ is the dimensionality of some latent subspace

Compute retrieval maps

$$f : a \mapsto \operatorname*{argmin}_{b \in \mathcal{B}} d(\psi_{\mathcal{A}}(a), \psi_{\mathcal{B}}(b))$$

$$g : b \mapsto \operatorname*{argmin}_{a \in \mathcal{A}} d(\psi_{\mathcal{A}}(a), \psi_{\mathcal{B}}(b)),$$

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e.g.: In CCA, we learn linear projections

$$\psi_{\mathcal{A}} : a \mapsto Ua$$

$$\psi_{\mathcal{B}} : a \mapsto Vb,$$

and use Euclidean distance for retrieval

Similarity function approach

Our approach: learn a similarity function, $s : \mathcal{A} \times \mathcal{B} \to \mathbb{R}$

- Assigns a high score when the given pair are related to each other

Compute retrieval maps

$$f : a \mapsto \operatorname*{argmax}_{b \in \mathcal{B}} s(a, b)$$

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- But what is a good similarity?

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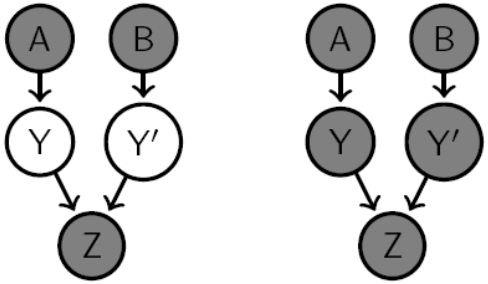

A: random variable over $\mathcal{A}$ (1^{st} modality)
B: random variable over $\mathcal{B}$ (2^{nd} modality)
Y: random variable over $\mathcal{Y}$ (annotation for A)
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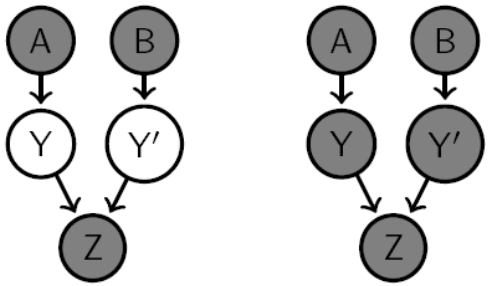

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Here, $\mathsf{Z} := 2[\![\mathsf{Y} = \mathsf{Y}']\!] - 1 \in \{\pm 1\}$

- whether or not the two annotations agree

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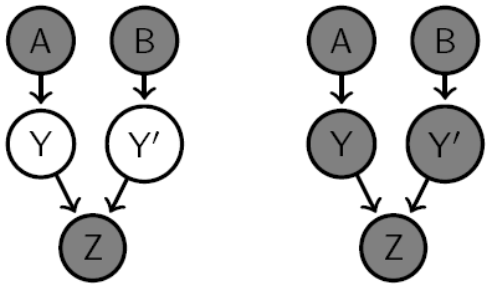

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Judge s according to probability of incorrectly assessing compatible pairs:

$$\mathbb{L}(s) = \mathbb{P}_{\mathsf{A},\mathsf{B},\mathsf{Z}}(s(\mathsf{A}, \mathsf{B}) \cdot \mathsf{Z} < 0).$$

- sign of s should indicate whether the ground truths align

Reduction to pairwise classification

We can view Z as a binary label on the instance pair (A, B)

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More effort is needed depending on whether or not we have ground-truth annotations

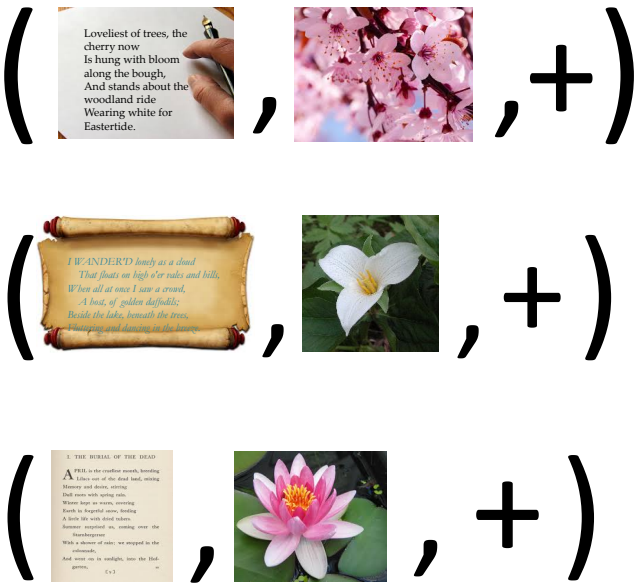
Overview of talk

Learning without annotations

Without ground-truth annotations, we only observe pairs that are linked

- We do not observe pairs that do not link

Training set: $\mathcal{D}' = \{((a^{(i)}, b^{(i)}), z^{(i)})\}$ where all labels $z^{(i)} = +1$



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- Learning from positive only data
- Cannot apply standard binary classifier!

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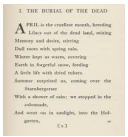
(

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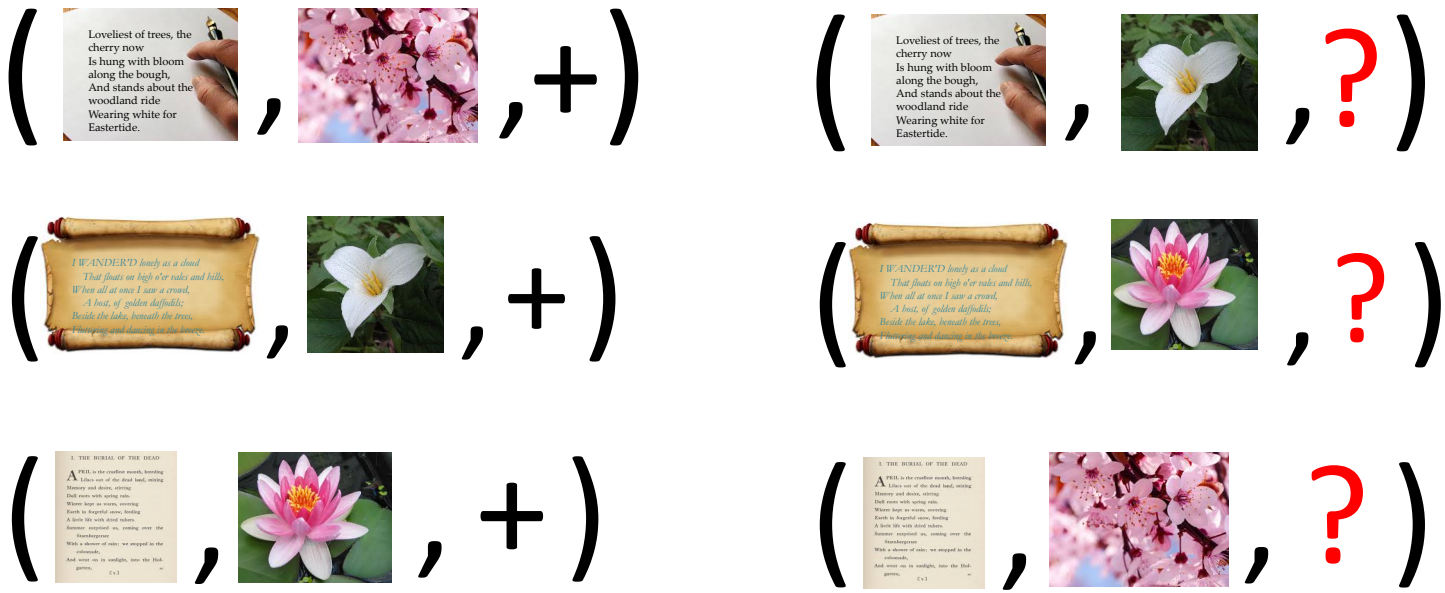
Reduction to positive and unlabelled learning

Basic idea: Construct all pairs of instances from each modality

$$\mathcal{D}'' = \{((a^{(i)}, b^{(j)}), z^{(i,j)})\}_{i,j=1}^{n}$$

We know $z^{(i,i)} = 1$, **but** $z^{(i,j)}$ **unknown** for $i \neq j$



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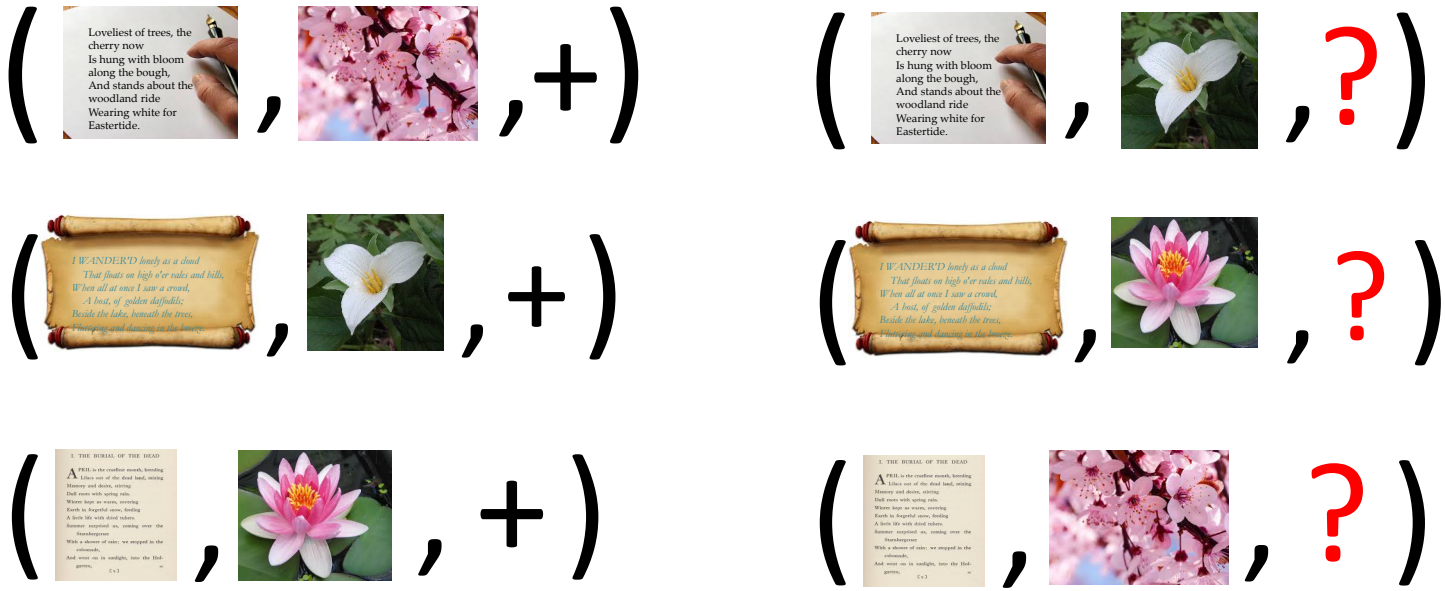
- Learning from positive and unlabelled data
- Aims to better discriminate linked and unlinked pairs



Reduction to binary classification

Simple recipe for positive and unlabelled learning [Elkan and Noto, 2008]:

- Treat unlabelled instances as negatives
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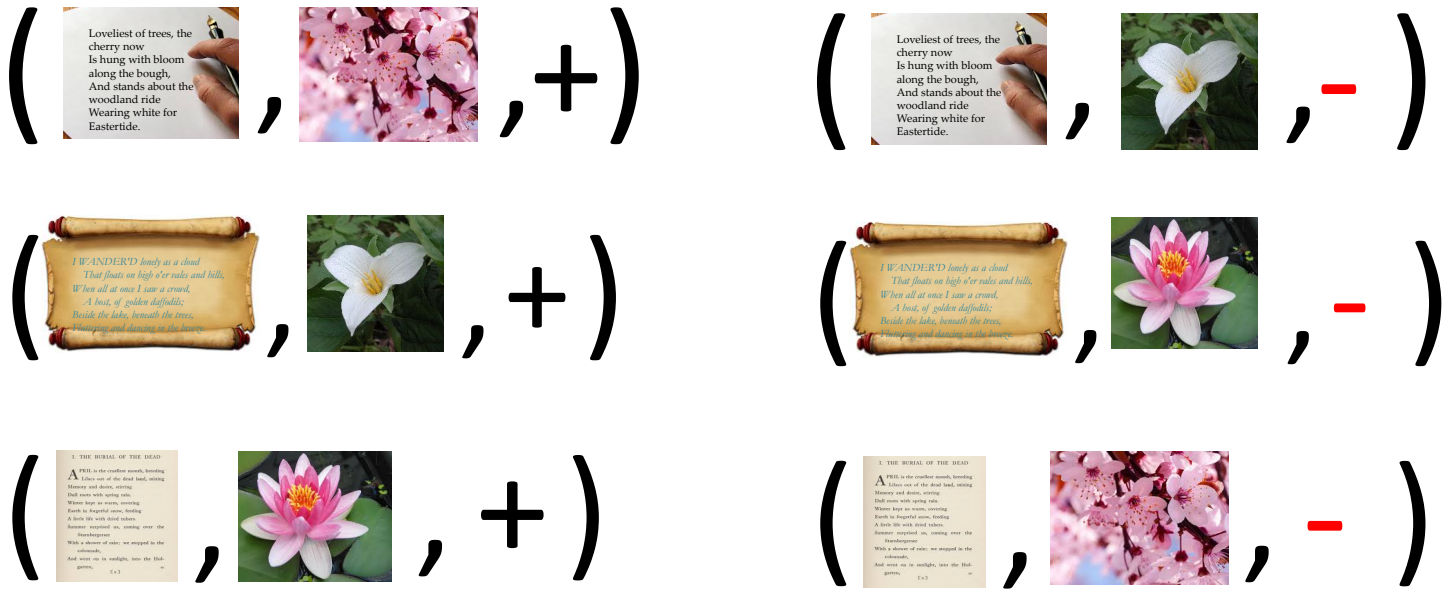
Thus, we can perform logistic regression on the labelled instances

$$\mathcal{D}'' = \{((a^{(i)}, b^{(j)}), (2[\![i = j]\!] - 1))\}_{i,j=1}^{n}$$



Choice of feature mapping

We consider ℓ_2 regularised logistic regression with some linear scorer:

$$\min_w \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \log(1 + e^{-z^{(i,j)} \cdot s(a^{(i)}, b^{(j)}; w)}) + \frac{\lambda}{2} ||w||_2^2$$

where

$$s(a, b; w) = \langle w, \Phi(a, b) \rangle$$

for some feature mapping Φ

Simplest Φ is concatenation:

$$\Phi(a, b) = \begin{bmatrix} a & b \end{bmatrix}$$

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Problem: Induces the same ranking over $b \in \mathcal{B}$ for any $a \in \mathcal{A}$!

Choice of feature mapping

Better Φ:

$$\Phi(a, b) = \left[a_d \cdot b_{d'}\right]_{d,d'}$$

i.e. consider the cross-product of features

The similarity function is equivalently:

$$s(a, b; w) = \langle w, \Phi(a, b) \rangle = a^T W b$$

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Learn, for each pair of features across the modalities, their predictive power in determining affinity

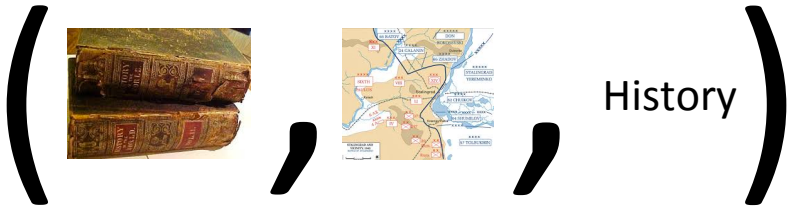
Overview of talk

Learning with annotations

With ground-truth annotations, we still only observe pairs that are linked

Training set: $\mathcal{D}' = \{((a^{(i)}, b^{(i)}), y^{(i)})\}_{i=1}^{n}$

- $y^{(i)} \in \mathcal{Y}$ is the category for the ith entity



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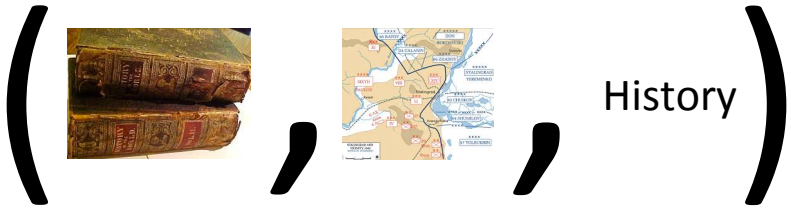

However, using annotations, we can more accurately infer whether other pairs should be linked or not

Pairwise classification approach

Basic idea: Construct all pairs of instances from each modality

$$\mathcal{D}'' = \{((a^{(i)}, b^{(j)}), z^{(i,j)})\}_{i,j=1}^{n}$$

where $z^{(i,j)} = 2[\![y^{(i)} = y^{(j)}]\!] - 1$

- Link a pair iff ground-truth annotation coincides

Now learn logistic regression model as in the case without annotations

- Only changing the labelling procedure

An alternate approach

There is a simpler approach to learning with annotations

If well-specified, logistic regression will learn a transformation of

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$$\begin{aligned}\mathbb{P}(\mathsf{Z}=1|\mathsf{A}=a,\mathsf{B}=b) &= \mathbb{P}(\mathsf{Y}=\mathsf{Y}'|\mathsf{A}=a,\mathsf{B}=b)\\ &= \sum_{k=1}^{K}\mathbb{P}(\mathsf{Y}=k|\mathsf{A}=a)\cdot\mathbb{P}(\mathsf{Y}=k'|\mathsf{B}=b)\\ &= \langle\eta_{\mathcal{A}}(a),\eta_{\mathcal{B}}(b)\rangle,\end{aligned}$$

where $\eta_{\mathcal{A}}$ and $\eta_{\mathcal{B}}$ are vectors of instance-conditional distributions over labels

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Why not just directly learn $\eta_{\mathcal{A}}, \eta_{\mathcal{B}}$?

Marginal approach

Basic idea: Learn independent models for $\eta_{\mathcal{A}}$ and $\eta_{\mathcal{B}}$

- *e.g.* using multi-class logistic regression on $\{(a^{(i)}, y^{(i)})\}$ and $\{(b^{(i)}, y^{(i)})\}$

Use their dot-product as the similarity function

- c.f. use of cosine similarity in SM method

While individual probability models are linear, final similarity function will be nonlinear in the inputs

Overview of talk

Overview of experiments

Experiments on three datasets:

- WIKIPEDIA: 2,173 training, 693 test pairs; 10 semantic categories.
- PASCAL: 700 training, 300 test pairs; 20 semantic categories.
- TVGRAZ: 1,558 training, 500 testing pairs; 10 semantic categories.

Feature representations:

- **Text**: LDA topic assignment distributions
- **Images**: SIFT features

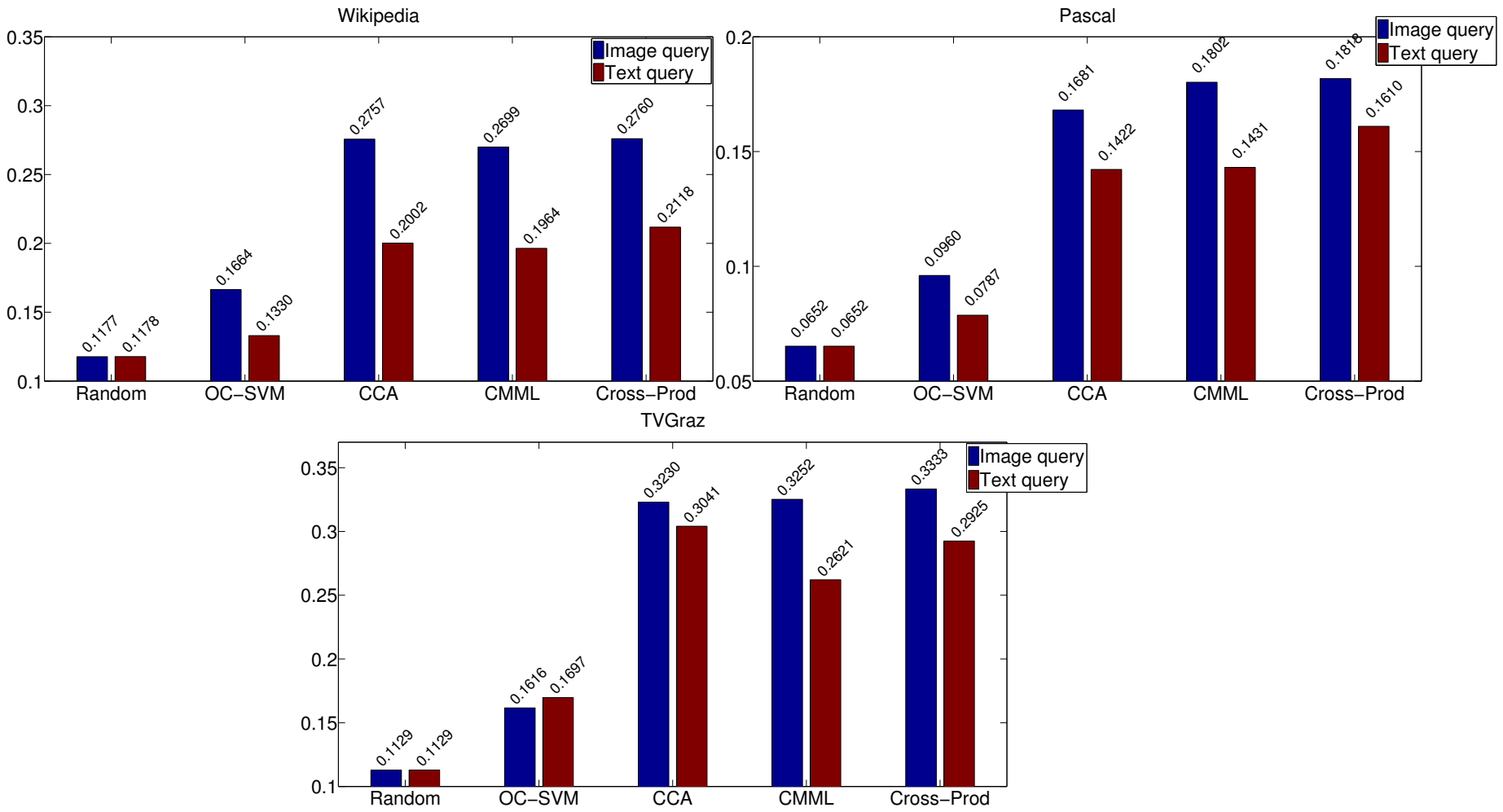
Methods compared

Baselines:

- Random predictor
- OC-SVM
- CCA
- SM, SCM
- Cross-modal metric learning (CMML)

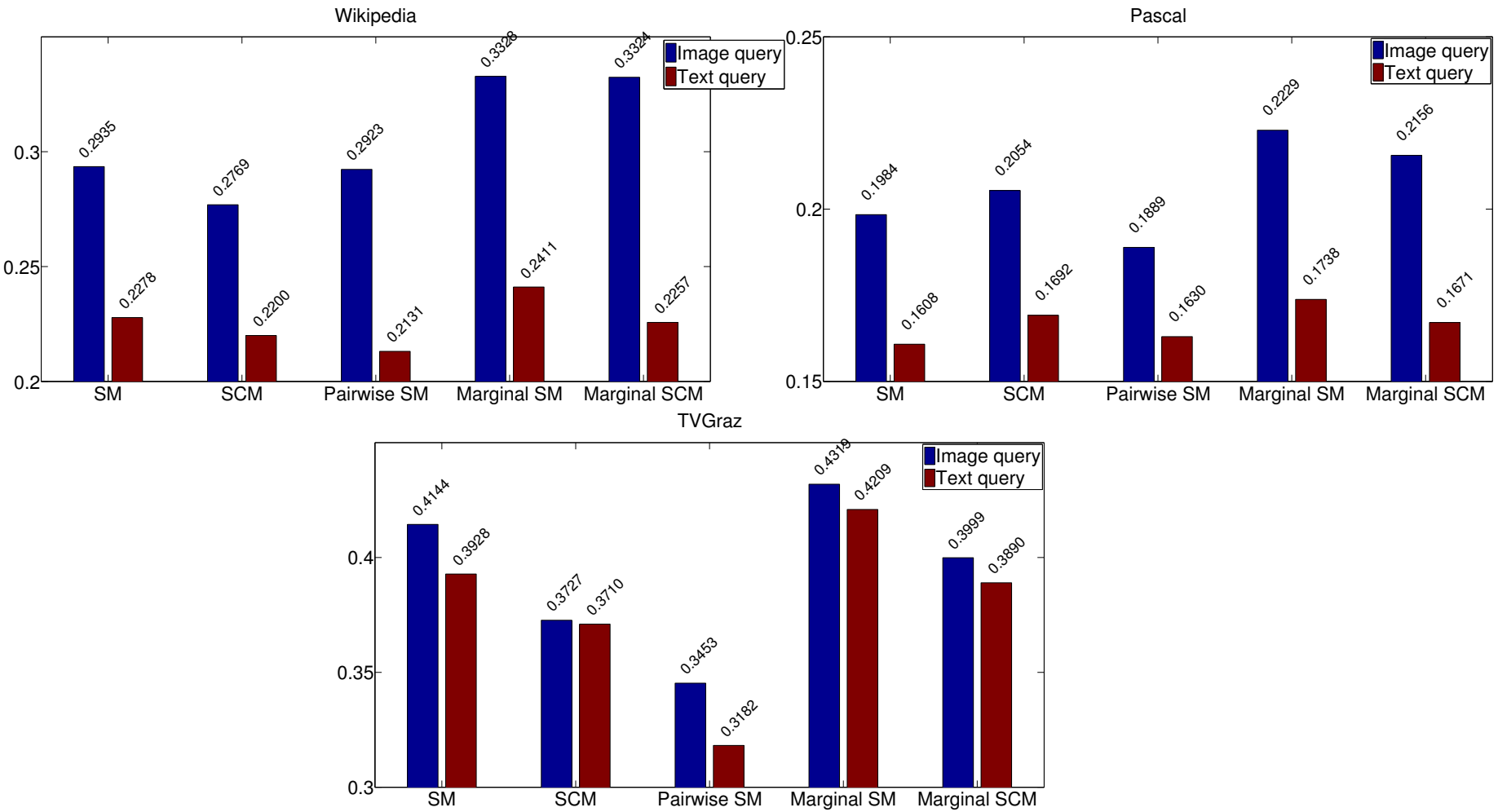
Measure performance based on mean average precision (MAP)

Results without annotation



MAP score improvements to CCA: ∼2% on WIKIPEDIA, ∼10% on PASCAL, and ∼3% on TVGRAZ.

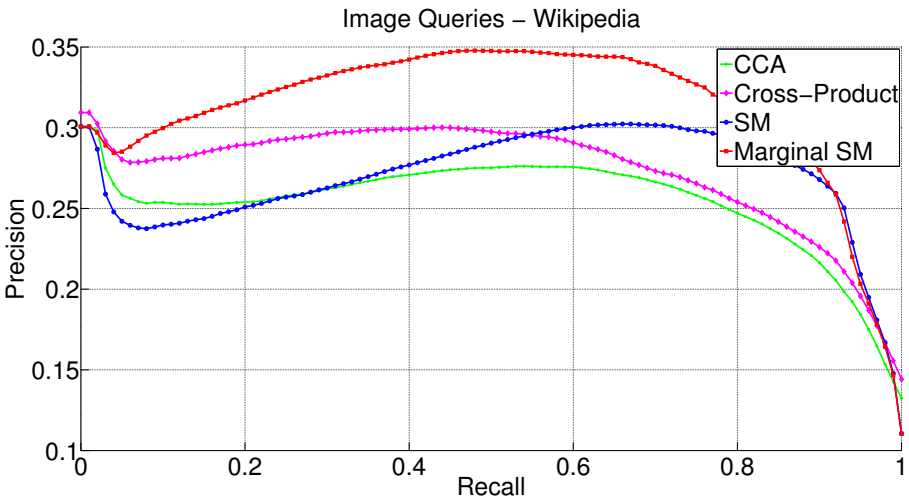
Results with annotation

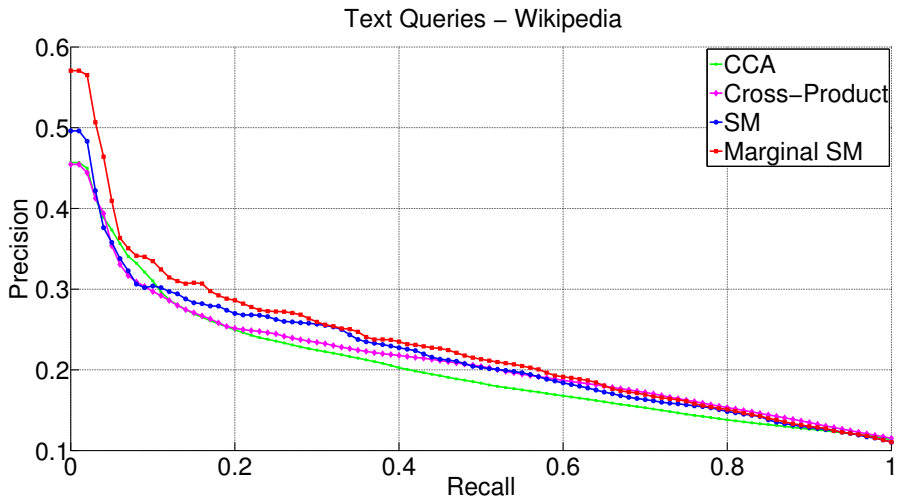


MAP score improvements to SM: ∼10% on WIKIPEDIA, ∼10% on PASCAL, and ∼5% on TVGRAZ.

Precision-recall curves on WIKIPEDIA

Consistent dominance of cross-product method over CCA, marginal over SM





Case study: text query

Given a text, find images

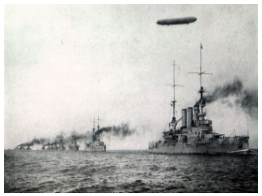
TEXT QUERY

Cobby was a member of the RAAF Reserve (also known as the Citizen Air Force) during his time with the Civil Aviation Board, and rejoined the Permanent Air Force following the outbreak of World War II ...

Warfare

Image Results

Cross-product



Warfare

Warfare

Warfare

Warfare

CCA

Warfare

Warfare

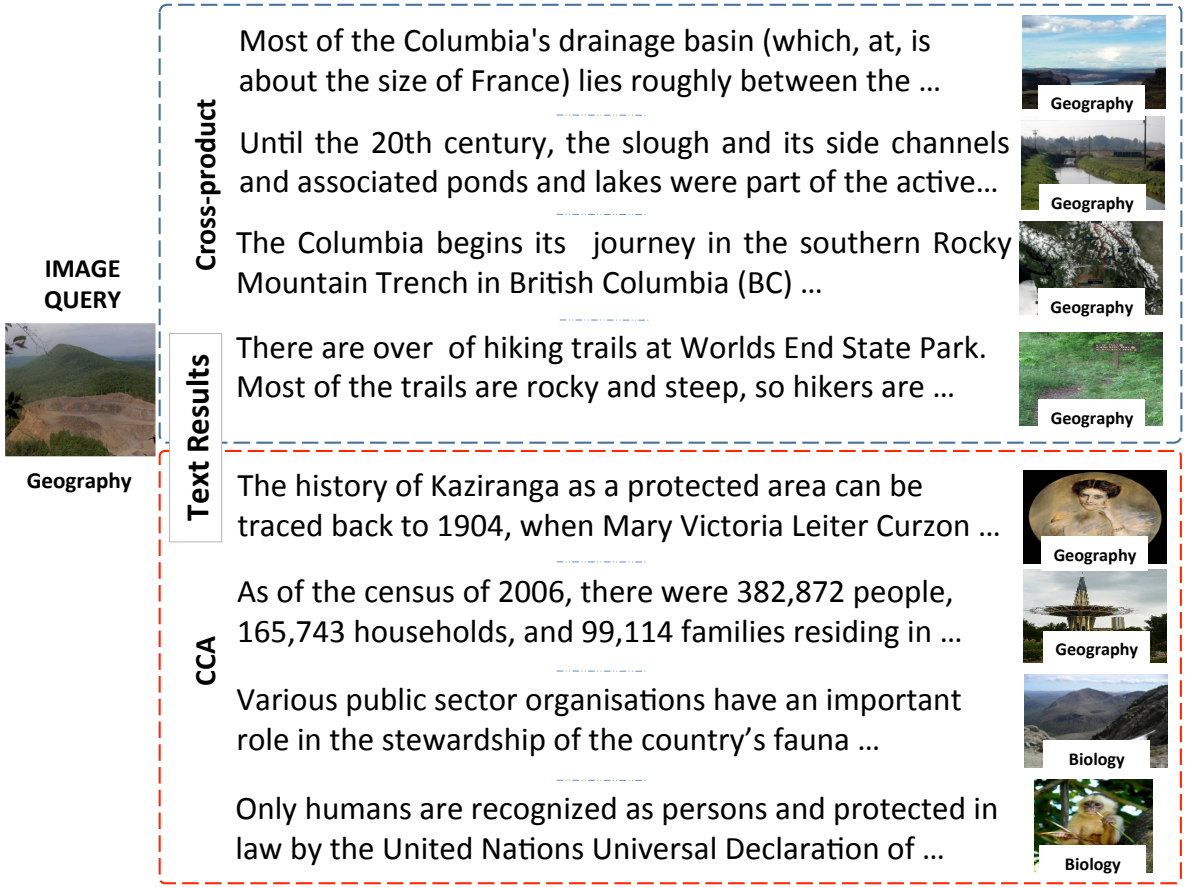
Geography

Music

CCA suffers from not considering negative links

Case study: image query

Given an image (top), find texts



Overview of talk

Conclusion

Pairwise classification perspective on cross-modal retrieval

- Unified perspective in the presence and absence of ground truth annotations

Logistic regression approach for learning without and with annotations

- **Without**: reduction to positive and unlabelled learning
- **With**: learn probability distributions for each modality

Good empirical performance

Questions?