Transfer Learning

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Outline

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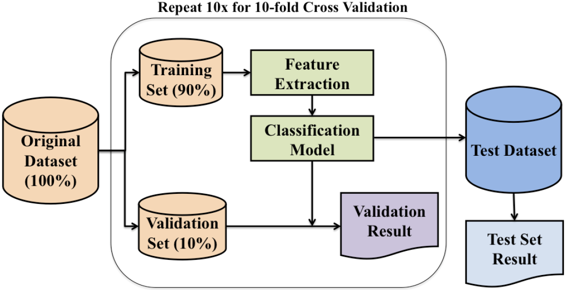
Standard Supervised Learning Task



Standard Supervised Learning Task

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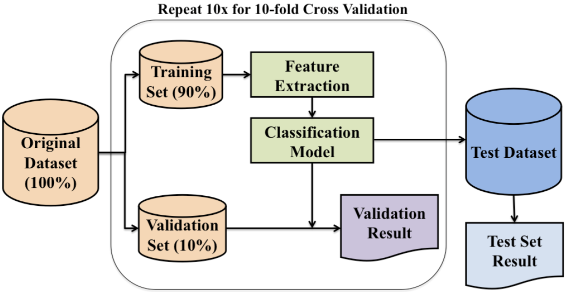

- Most ML tasks assume the training/test data are drawn from the same data space and the same distribution

NLP tasks: POS, NER, Category labelling

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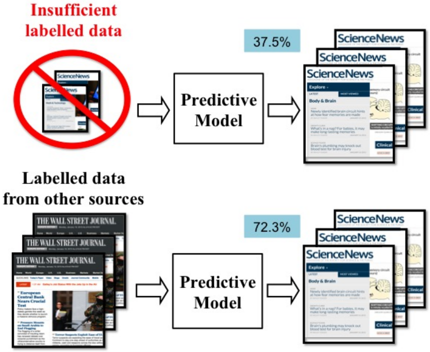
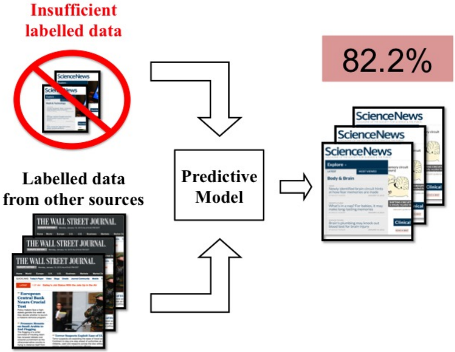


Modified from Gao et al.'s presentation in KDD '08

Combine and get better result

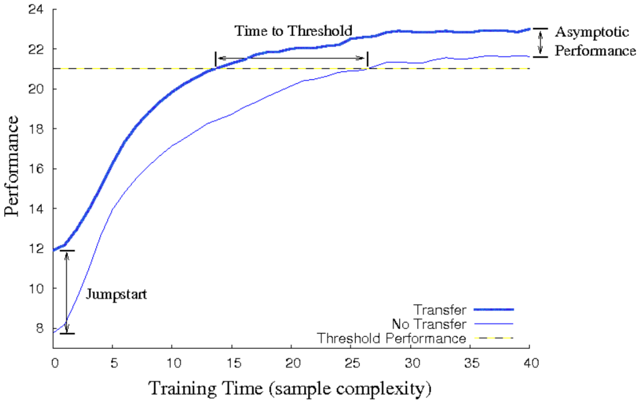


Modified from Gao et al.'s presentation in KDD '08

Motivation

- Traditional ML tasks assume the training/test data are drawn from the same data space and the same distribution
- Insufficient labelled data result in poor prediction performance
  - Lots of (un-)related existing data from various sources
- Start from scratch is always time-consuming
- Transfer knowledge from other sources may help!

Motivation (Taylor et.al JMLR '09)



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Psychology and Education

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- In 1901, Thorndike and Woodworth explored how individuals transfer similar characteristics shared by different contexts

Psychology and Education

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Psychology and Education

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- In 1901, Thorndike and Woodworth explored how individuals transfer similar characteristics shared by different contexts
- In 1992, Perkins and Salomon published "Transfer of Learning" which defined different types of transfer
- examples:
  - Skill learning: $C/C++ \rightarrow Python$
  - Language acquisition: $German \rightarrow English$

Machine Learning

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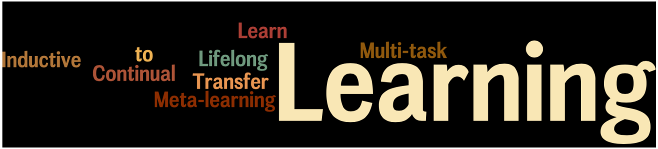

Machine Learning

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- Explanation-Based Neural Network Learning: A Lifelong Learning Approach [Thrun PhD '95, NIPS '96]

Machine Learning

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- Multitask Learning [Caruana ICML '93 & '96, PhD '97]

Machine Learning

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- Explanation-Based Neural Network Learning: A Lifelong Learning Approach [Thrun PhD '95, NIPS '96]
- Multitask Learning [Caruana ICML '93 & '96, PhD '97]
- Workshops
  - Learning to Learn: Knowledge Consolidation and Transfer in Inductive Systems [NIPS '95]
  - Inductive Transfer: 10 Years Later [NIPS '05]
  - Structural Knowledge Transfer for Machine Learning [ICML '06]
  - Transfer Learning for Complex Tasks [AAAI '08]
  - Lifelong Learning [AAAI '11]
  - Theoretically Grounded Transfer Learning [ICML '13]
  - Workshop: Second Workshop on Transfer and Multi-Task Learning: Theory meets Practice [NIPS '14]
  - ...

Outline

Definition

Notations

- Domain $\mathcal{D}$
  1. Data space $\mathcal{X}$
  2. Marginal distribution $P(X)$, where $X \in \mathcal{X}$
- Task $\mathcal{T}$ (Given $\mathcal{D} = \{\mathcal{X}, P(X)\}$)
  1. Label space $\mathcal{Y}$
  2. Learn a $f : X \rightarrow Y$ to approach the underlying $P(Y|X)$, where $X \in \mathcal{X}$ and $Y \in \mathcal{Y}$

Definition

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Assume we have only one source S and one target T:

Definition

Transfer Learning (TL): Given a source domain $\mathcal{D}_S$ and learning task $\mathcal{T}_S$, a target domain $\mathcal{D}_T$ and learning task $\mathcal{T}_T$, transfer learning aims to help improve the learning of the target predictive function $f_T(\cdot)$ in $\mathcal{D}_T$ using the knowledge in $\mathcal{D}_S$ and $\mathcal{T}_S$, where

$$\mathcal{D}_S \neq \mathcal{D}_T \quad (\textit{either } \mathcal{X}_S \neq \mathcal{X}_T \textit{ or } P_S(X) \neq P_T(X))$$

$$\text{or } \mathcal{T}_S \neq \mathcal{T}_T \quad (\textit{either } \mathcal{Y}_S \neq \mathcal{Y}_T \textit{ or } P(Y_S|X_S) \neq P(Y_T|X_T))$$

Example: Category labelling

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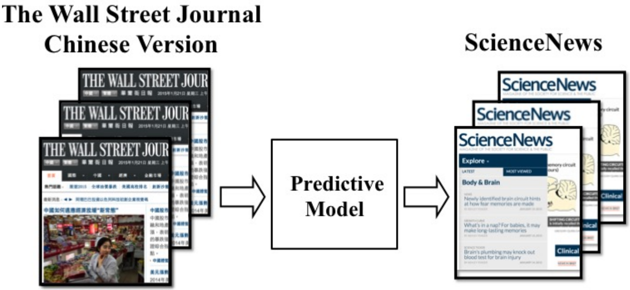

Example: Category labelling

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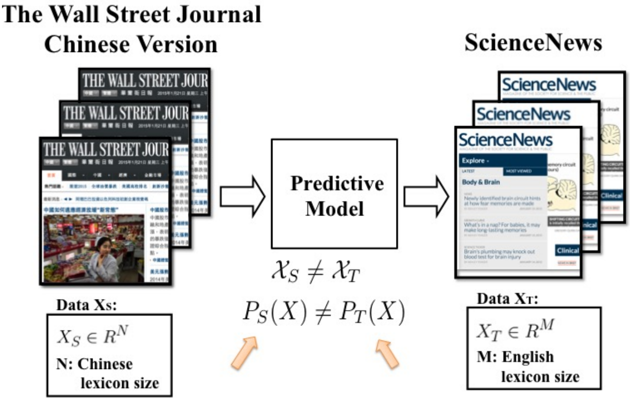
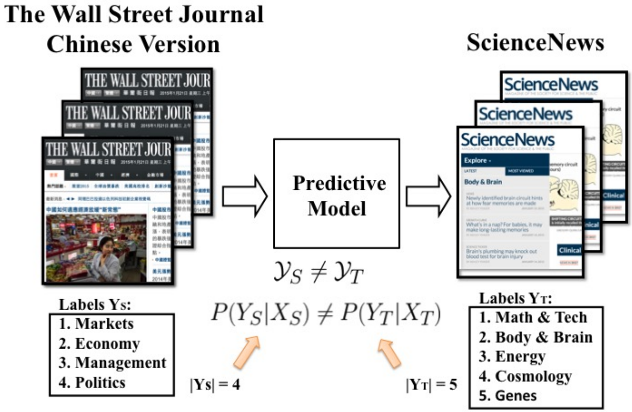
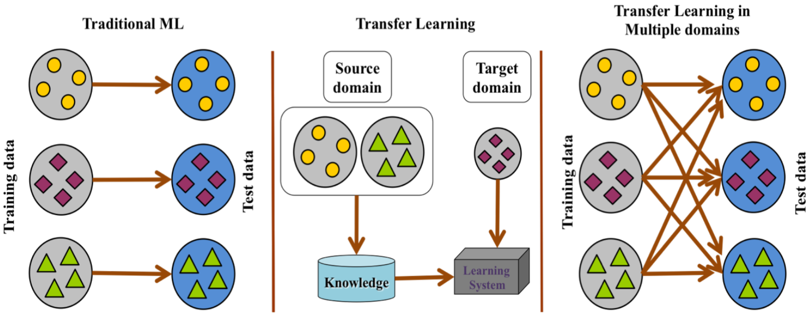


Example: Category labelling



ML v.s. TL (Langley '06, Yang et al. '13)



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Transfer in practice

The rest of the talk will give you an intuition, with examples, on:

- **when** to transfer
- **what** to transfer
- and **how** to transfer

When to transfer: Domain relatedness

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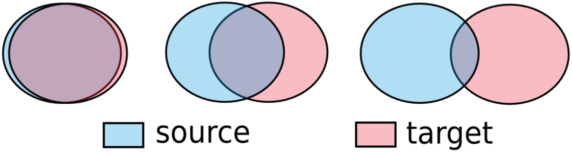
Transfer learning is applicable when there exists relatedness



- Standard machine learning assume source = target
- Transferring knowledge from unrelated domain can be harmful
  - Negative transfer [Rosenstein et al NIPS-05 Workshop]
- (Ben-David et al.) proposed a bound of target domain error

Reference

Ben-David et al. Analysis of Representation for Domain Adaptation. NIPS '06

When to transfer (Ben-David et al.)

In standard binary classification supervised learning task:

- Given $X, Y = \{0, 1\}$ and samples from $P(x, y)$, we aim to learn $f : X \rightarrow [0, 1]$ which captures $P(y|x)$
- Often we decompose the problem into:
  1. determine a feature mapping $\Phi : X \rightarrow Z$
  2. learn a hypothesis $h : Z \rightarrow \{0, 1\}$ on dataset $\{\Phi(x), y\}$

In transfer learning scenario:

Theorem (Simplified version of Thm. 1&2)

Given $X = X_S = X_T$ and $P_S(x), P_T(x)$ the distributions of the source and target domain. Let $\Phi : X \rightarrow Z$ be a fixed mapping function and $\mathcal{H}$ be a hypothesis space. For any hypothesis $h \in \mathcal{H}$ trained on source domain:

$$\epsilon_T(h) \leq \epsilon_S(h) + d_{\mathcal{H}}(\tilde{P}_S, \tilde{P}_T) + \epsilon_S(h^*) + \epsilon_T(h^*)$$

where $\tilde{P}_S$, $\tilde{P}_T$ are induced distributions on Z wrt. P_S and P_T, $h^* = \arg\min_{h \in \mathcal{H}}(\epsilon_S(h) + \epsilon_T(h))$ is the best hypothesis by joint training.

Domain adaptation

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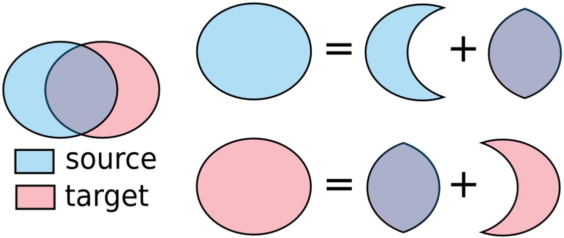
Approach 1: mixture of general & specific component



- Can we learn hypotheses for both the general and specific components?

Reference:
Daume III. Frustratingly easy domain adaptation. ACL '07
Daume III et al. Co-regularization Based Semi-supervised Domain Adaptation. NIPS '10

EasyAdapt (Daume III)

Binary classification problem:

- $X_S = X_T \subset \mathcal{R}^d$, $Y_S = Y_T = \{-1, +1\}$
- Goal: obtain classifier $f_T : X_T \to Y_T$
- in SVM context: learn a hypothesis $h_T \in \mathcal{R}^d$

However:

- too little training data available on (X_T, Y_T) for robust training
- also $P(x_S) \neq P(x_T)$ and $P(x_S, y_T) \neq P(x_S, y_T)$
- ...so directly apply a trained hypothesis h_s returns bad results

How to use $x_S, y_S \sim P(x_S, y_S)$ to improve learning of h_T?

EasyAdapt (Daume III)

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EasyAdapt algorithm

- define two mappings $\Phi_S, \Phi_T : \mathcal{R}^d \to \mathcal{R}^{3d}$:

$$\Phi_S(x_S) = (x_S, x_S, 0), \quad \Phi_t(x_T) = (x_T, 0, x_T)$$

- training: learn a hypothesis $h = (w^g, w^s, w^t) \in \mathcal{R}^{3d}$ on transformed dataset $\{(\Phi_S(x_S), y_S)\} \cup \{(\Phi_T(x_T), y_T)\}$
- test: apply $h_T = w^g + w^t$ on x_T
- (also $h_S = w^g + w^s$)

EA++ (Daume III et al.)

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Use unlabelled data to improve training:

- want h_S and h_T to agree on unlabelled data x_U:

$$h_S \cdot x_U = h_T \cdot x_U \Leftrightarrow w^s \cdot x_U = w^t \cdot x_U \Leftrightarrow h \cdot (0, x_U, -x_U) = 0$$

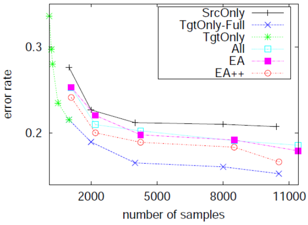
- so we define mapping $\Phi_U : \mathcal{R}^d \to \mathcal{R}^{3d}$ for unlabelled data

$$\Phi_U(x_U) = (0, x_U, -x_U) \tag{1}$$

- and train the hypothesis h on augmented and transformed dataset $\{(\Phi_S(x_S), y_S)\} \cup \{(\Phi_T(x_T), y_T)\} \cup \{(\Phi_U(x_U), 0)\}$

EA++ (Daume III et al.)

(a) DVD → BOOKS (proxy A-distance=0.7616),
(b) KITCHEN → APPAREL (proxy A-distance=0.0459).



(a) (b)

- SOURCE/TARGETONLY(-FULL): trained on source/target (full) labelled samples
- ALL: trained on combined labelled samples
- EA/EA++: trained in augmented feature space (and unlabelled target data)

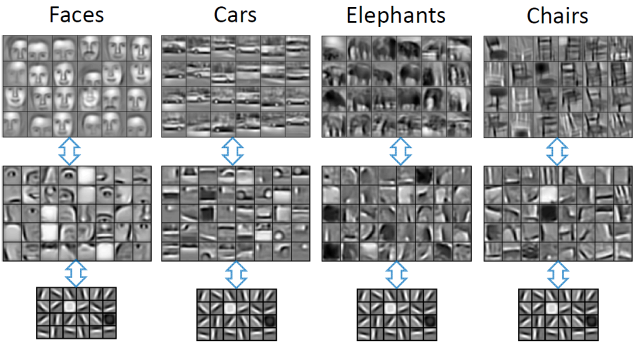
Feature transfer

Approach 2: shared lower-level features

- DNN first layer learns Gabor filters or color blobs when trained on images
- instances in source/target domain share the same lower-level features?

Reference:
Yosinski et al. How transferable are features in deep neural networks? NIPS '14.

Feature transfer[1]



Lee et al. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. ICML '09

[1] adapt from Ruslan Salakhutdinov's tutorial in MLSS'14 Beijing

Feature transfer (Yosinski et al.)

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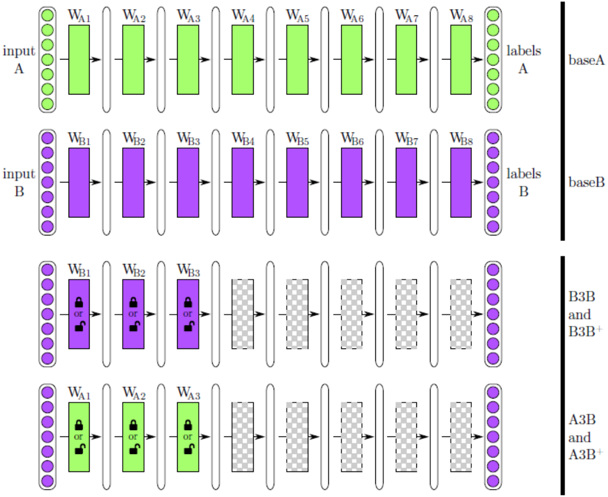
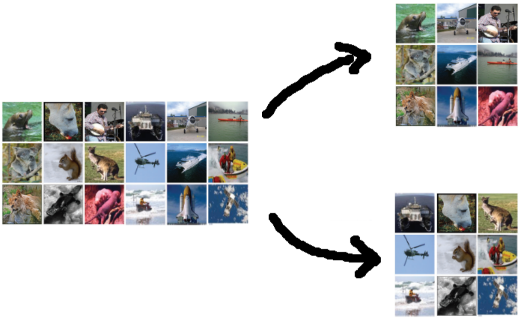


Feature transfer (Yosinski et al.)

Test 1 (similar datasets): random A/B splits of the ImageNet dataset



(similar source and target domain training/testing instances)

Feature transfer (Yosinski et al.)

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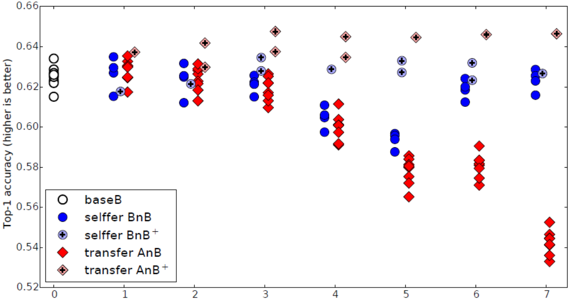

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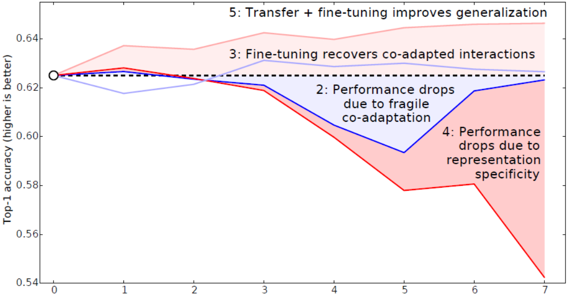
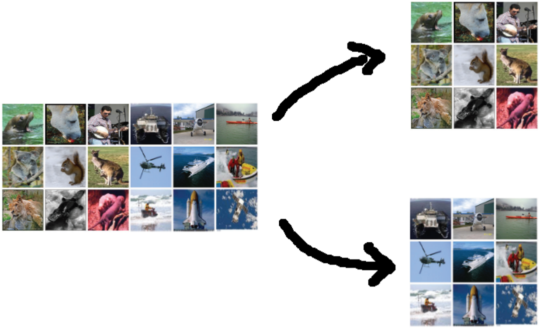


(similar source and target domain training/testing instances)

Feature transfer (Yosinski et al.)

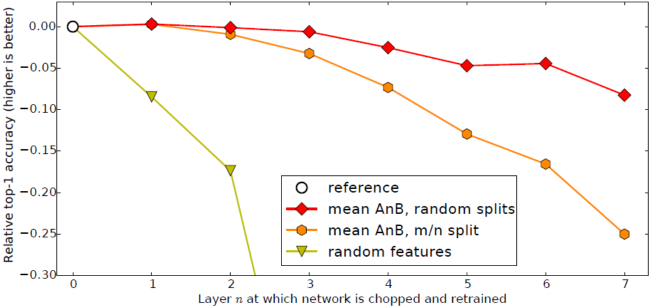
Test 2 (very different datasets): man-made/natural object split



(dissimilar source and target domain training/testing instances)

Feature transfer (Yosinski et al.)

Test 2 (very different datasets): man-made/natural object split



(dissimilar source and target domain training/testing instances)

Joint representation

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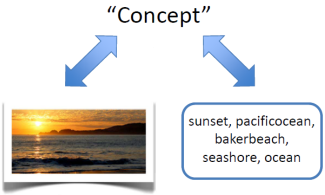
Approach 3: joint feature representation



- data has many domain specific characteristics
- however might be related in high level?
- our brain might work like this as well

Reference:

Srivastava and Salakhutdinov. Multimodal Learning with Deep Boltzmann Machines. NIPS '12, JMLR 15 (2014).

Joint representation (Srivastava et al.)

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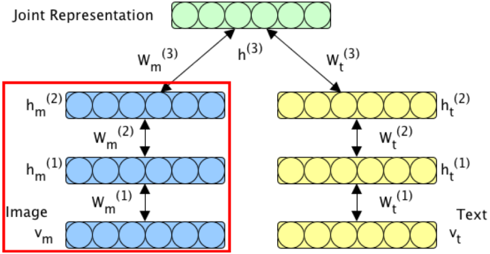
MIR Flickr Dataset `http://press.liacs.nl/mirflickr/`

Classes	baby, female, people, portrait	plant life, river, water	clouds, sea, sky, transport, water	animals, dog, food	clouds, sky, structures
Images					
Tags	claudia	⟨ no text ⟩	barco, pesca, boattosail, navegação	watermelon, hilarious, chihuahua, dog	colors, cores, centro, comercial, building

- For images
  - 1M datapoints, 25K labelled instances in 38 classes, 10K for training, 5K for validation and 10K for testing
  - inputs are the concatenation of PHOW and MPEG-7 features
- For texts
  - use word count vectors on 2K frequently used tags (very sparse)
  - 18% training images have missing texts

Joint representation (Srivastava et al.)

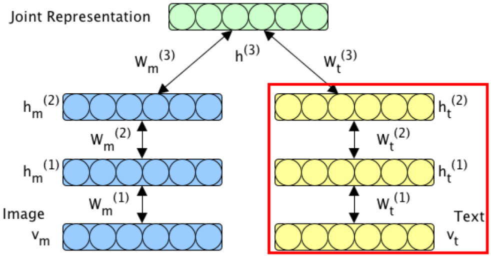


for images: 2-layer deep Boltzmann machine (DBM) with Gaussian input units ($v_{mi} \in \mathbb{R}$, abbrev. $W_m^{(k)}(i,j)$ as $W_{ij}^{(k)}$)

$$P(v_m, h_m^{(1)}, h_m^{(2)}) \propto$$

$$\exp\left(-\sum_i \frac{(v_{mi}-b_i)^2}{2\sigma_i^2} + \sum_{i,j} \frac{v_{mi}}{\sigma_i} W_{ij}^{(1)} h_{mj}^{(1)} + \sum_{j,l} h_{mj}^{(1)} W_{jl}^{(2)} h_{ml}^{(2)}\right)$$

Joint representation (Srivastava et al.)

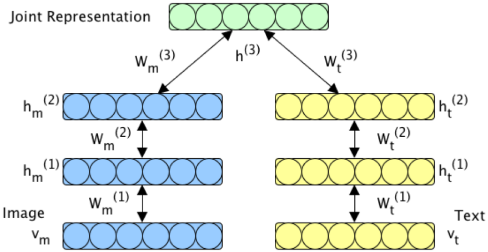


for texts: 2-layer DBM with replicated softmax model (v_{ti} counts the occurrence of word i, abbrev. $W_t^{(k)}(i,j)$ as $W_{ij}^{(k)}$)

$$P(v_t, h_t^{(1)}, h_t^{(2)}) \propto$$

$$\exp\left(-\sum_{i=1} v_{ti} b_i + \sum_{i,j} v_{ti} W_{ij}^{(1)} h_{mj}^{(1)} + \sum_{j,l} h_{tj}^{(1)} W_{jl}^{(2)} h_{tl}^{(2)}\right)$$

Joint representation (Srivastava et al.)



combining domain specific models to a multimodal DBM:

$$P(v_m, v_t, h; \theta) \propto$$
$$\exp\left(-E(h_m^{(2)}, h_t^{(2)}, h^{(3)}) - E(v_m, h_m^{(1)}, h_m^{(2)}) - E(v_t, h_t^{(1)}, h_t^{(2)})\right)$$

Joint representation (Srivastava et al.)

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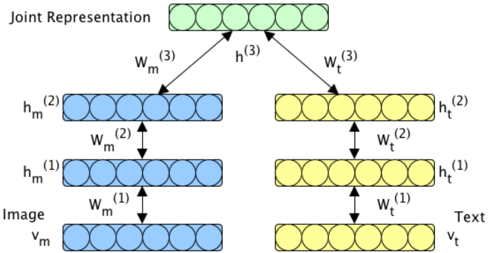

- first pre-train domain specific DBMs with CD, then co-train the joint model with PCD
- use mean-field variational approximation when computing hidden unit moments driven by data

Joint representation (Srivastava et al.)

Results:

Model	**MAP**	**Prec@50**
Random	0.124	0.124
SVM (Huiskes et al., 2010)	0.475	0.758
LDA (Huiskes et al., 2010)	0.492	0.754
DBM	0.526 ± 0.007	0.791 ± 0.008
DBM (using unlabelled data)	$\mathbf{0.585} \pm 0.004$	$\mathbf{0.836} \pm 0.004$

Figure: Classification with data from both image and text domain

Model	MAP	Prec@50
Image LDA (Huiskes et al., 2010)	0.315	-
Image SVM (Huiskes et al., 2010)	0.375	-
Image DBN	0.463 ± 0.004	0.801 ± 0.005
Image DBM	0.469 ± 0.005	0.803 ± 0.005
Multimodal DBM (generated text)	$\mathbf{0.531 \pm 0.005}$	$\mathbf{0.832 \pm 0.004}$

Figure: Classification with data from image domain only

Joint representation (Srivastava et al.)

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Results:

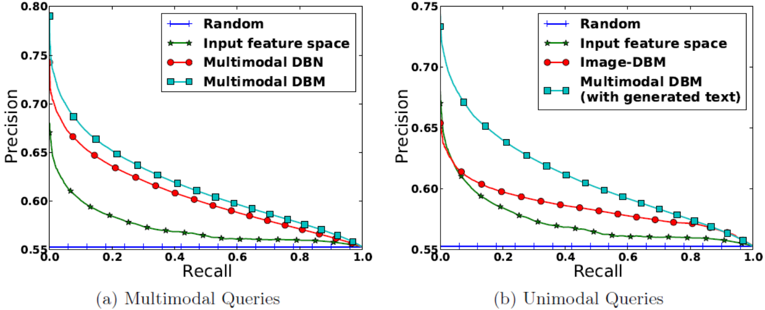

Figure: Retrieval results for multi/image domain queries

Conclusions

In this talk, we showed that

- transfer learning adapts knowledge from other sources to improve target task performance
- domains related to each other in different ways

In the future:

- manage large scale data that do not lack in size but may lack in quality
- manage data which may continuously change over time

Open Questions[2]

- what are the limits of existing multi-task learning methods when the number of tasks grows while each task is described by only a small bunch of samples ("big T, small n")?
- what is the right way to leverage over noisy data gathered from the Internet as reference for a new task?
- how can an automatic system process a continuous stream of information in time and progressively adapt for life-long learning?
- can deep learning help to learn the right representation (e.g., task similarity matrix) in kernel-based transfer and multi-task learning?
- How can similarities across languages help us adapt to different domains in natural language processing tasks?
- ...

[2] nips.cc/Conferences/2014/Program/event.php?ID=4282

Thank you

Reference

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12. Lee et al. Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. ICML 2009