CS 4650/7650
Semi-Supervised Learning[1]

Jacob Eisenstein

November 13, 2014

[1] With slides borrowed from John Blitzer, Mingwei Chang, Hal Daume III, Xiaojin Zhu, and everyone they borrowed slides from...

Frameworks for learning

- So far, we have focused on learning a function f from labeled examples $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell}$.
- What if you don't have labeled data for a domain or task you want to solve?
  - You can use labeled data from another domain.
    This rarely works well.
  - You can label data yourself.
    This is a lot of work.

Examples

Phonetic transcription[2]

- "Switchboard" dataset of telephone conversations
- Annotations from word to phoneme sequence:
  - film $\rightarrow$ F IH_N UH_GL_N M
  - be all $\rightarrow$ BCL B IY IY_TR AO_TR AO L_DL

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- **400 hours** annotation time per hour of speech!

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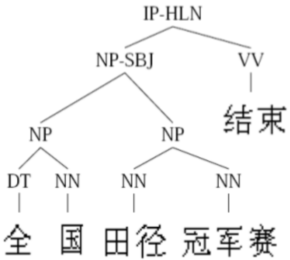
Natural language parsing[3]

- Penn Chinese Treebank
- Annotations from word sequences to parse trees



"The National Track and Field Championship has finished."

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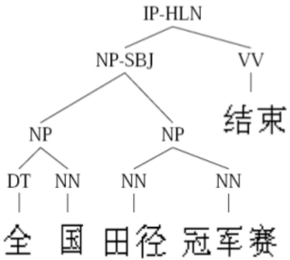

"The National Track and Field Championship has finished."

- **2 years** annotation time for 4000 sentences

[3]Examples from Xiaojin "Jerry" Zhu

How can we learn with less annotation effort?

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- **Semisupervised learning**
  - $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell}$: labeled examples
  - $\{(\mathbf{x}_i)\}_{i=\ell+1}^{\ell+u}$: unlabeled examples
  - often $u \gg \ell$

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- **Domain adaptation**
  - $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell_S} \sim \mathcal{D}_S$: labeled examples in *source* domain
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  - possibly some unlabeled data in target and possibly source domain
  - evaluate in the target domain

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  - evaluate in the target domain
- **Active learning**: model can query annotator for labels

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Let's learn to do sentiment analysis in French.

- labeled data
  - ☺ émouvant avec grâce et style
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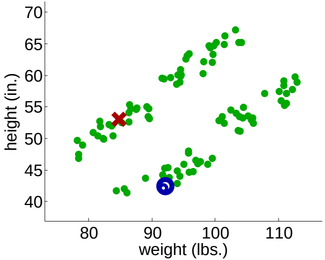
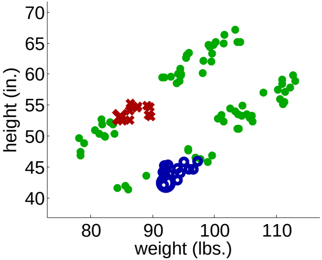
By propagating training labels to unlabeled data, we learn the sentiment value of many more words.

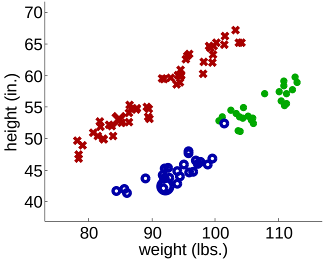
Propagating 1-Nearest-Neighbor: now it works



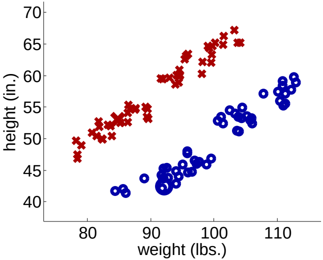
(a) Iteration 1



(b) Iteration 25



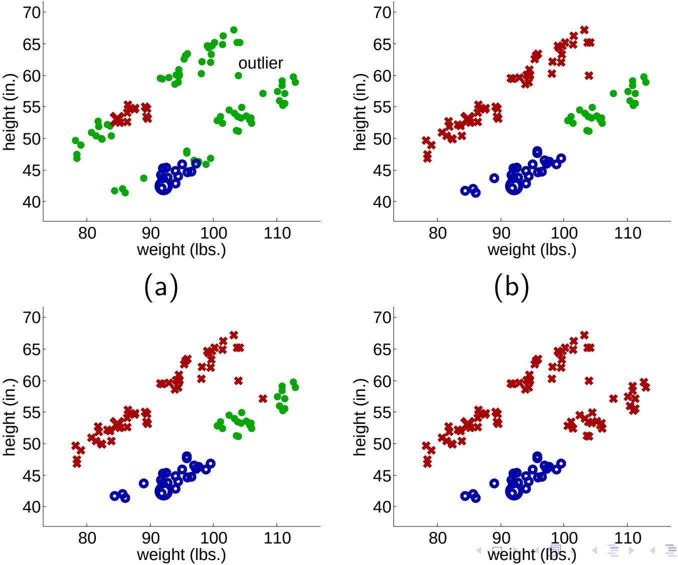
(c) Iteration 74



(d) Final labeling of all instances

Propagating 1-Nearest-Neighbor: now it doesn't

But with a single outlier...



When does bootstrapping work? “Folk wisdom”

- Better for generative models (e.g., Naive Bayes) than for discriminative models (e.g., perceptron)
- Better when the Naive Bayes assumption is stronger.
  - Suppose we want to classify NEs as PERSON or LOCATION
  - Features: string and context, e.g.
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$$P(x_1 = \text{street}, x_2 = \text{on} | \textsc{loc}) \approx P(x_1 = \text{street} | \textsc{loc}) P(x_2 = \text{on} | \textsc{loc})$$

Two views and co-training

- **Co-training** makes bootstrapping folk wisdom explicit.
  - Assume two, **conditionally independent**, views of a problem.
  - Assume each view is sufficient to do good classification.

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- Sketch of learning algorithm:
  - On labeled data, minimize error.
  - On unlabeled data, constrain the models from different views to agree with each other.

Co-training example

	$\mathbf{x}^{(1)}$	$\mathbf{x}^{(2)}$	y
1.	Peachtree Street	located on	LOC
2.	Dr. Walker	said	PER
3.	Zanzibar	located in	?
4.	Zanzibar	flew to	?
5.	Dr. Robert	recommended	?
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Algorithm

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- Use classifier 1 to label example 5.
- Use classifier 2 to label example 3.

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- Retrain both classifiers, using newly labeled data.

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Algorithm

- Use classifier 1 to label example 5.
- Use classifier 2 to label example 3.
- Retrain both classifiers, using newly labeled data.
- Use classifier 1 to label example 4.
- Use classifier 2 to label example 6.

Building a graph of related instances

Back to sentiment analysis in French...

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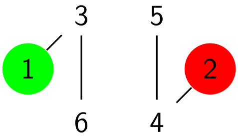

- We can view this data as a **graph**, with edges between similar instances.
- Unlabeled instances propagate information through the graph.

Graphs over instances

- Often we compute similarity from features,

$$\mathrm{sim}(i,j) = \exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right)$$

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  and build an edge between i and j when $\text{sim}(i,j) > \tau$
- But sometimes there is a natural similarity metric.
  - For example, Pang and Lee (2004) use proximity in the document for subjectivity analysis.
  - The idea is that adjacent sentences are more likely to have the same subjectivity status.

Minimum cuts

Pang and Lee use **minimum cuts** to assign subjectivity in a proximity graph of sentences.

$$
\begin{aligned}
y_i &\in \{0, 1\} \\
\text{Fix } Y_l &= \{y_1, y_2, \ldots y_\ell\} \\
\text{Solve for } Y_u &= \{y_{\ell+1}, \ldots, y_{\ell+m}\} \\
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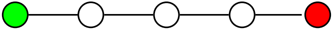
- This looks like a combinatorial problem...
- But assuming $w_{ij} \geq 0$, it can be solved with maximum-flow.

Problems with minimum cuts

- Mincuts may have several possible solutions:
  - Initial graph 

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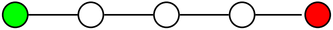
  - Initial graph 
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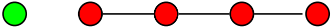
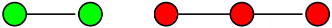
    - 
    - 
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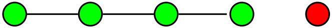
    - 

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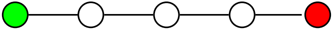
  - Initial graph 
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    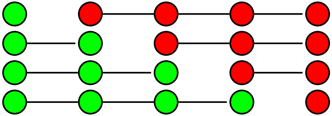
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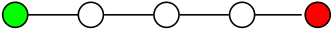
  - Initial graph 
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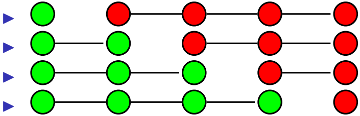

- Another problem is that mincuts doesn't distinguish high confidence predictions.
- One solution is randomized mincuts (Blum et al, 2004)
  - Add random noise to adjacency matrix.
  - Rerun mincuts multiple times.
  - Deduce the final classification by voting.

Label propagation

- Relax y_i from $\{0, 1\}$ to $\mathbb{R}$
- Minimize $\sum_{i,j} w_{ij}(y_i - y_j)^2$
- Advantages:
  - unique global optimum
  - natural notion of confidence: distance of y_i from 0.5

Label propagation on the graph Laplacian

- Let $\mathbf{W}$ be the $n \times n$ weight matrix.
- Let $\mathbf{D}$ be the **degree matrix**, $d_{ii} = \sum_j w_{ij}$. $\mathbf{D}$ is diagonal.
- The unnormalized **graph Laplacian** is $\mathbf{L} = \mathbf{D} - \mathbf{W}$
- We want to minimize the energy $\sum_i w_{ij}(y_i - y_j)^2 = \mathbf{y}^\mathsf{T}\mathbf{L}\mathbf{y}$, subject to the constraint that we can't change $\mathbf{y}_\ell$.

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- Solution:
  - Partition the Laplacian $\mathbf{L} = \begin{bmatrix} \mathbf{L}_{\ell\ell} & \mathbf{L}_{\ell u} \\ \mathbf{L}_{u\ell} & \mathbf{L}_{uu} \end{bmatrix}$
  - Then the closed form solution is $\mathbf{y}_u = -\mathbf{L}_{uu}^{-1}\mathbf{L}_{u\ell}\mathbf{y}_\ell$
  - This is great ... if we can invert $\mathbf{L}_{uu}$.

Iterative label propagation

- $\mathbf{L}_{u,u}$ is huge, so we can't invert it unless it has special structure.
- Iterative solution from Zhu and Ghahramani (2002):
  - Let $\mathbf{T}_{ij} = \frac{w_{ij}}{\sum_k w_{kj}}$, row-normalizing $\mathbf{W}$.
  - Let $\mathbf{Y}$ be an $n \times C$ matrix of labels, where C is the number of classes. In the R&R reading, a special "default" label is used for the unlabeled nodes.
  - Until tired,
    - Set $\mathbf{Y} = \mathbf{TY}$
    - Row-normalize $\mathbf{Y}$
    - Clamp the seed examples in $\mathbf{Y}$ to their original values

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    - correct on the labeled data
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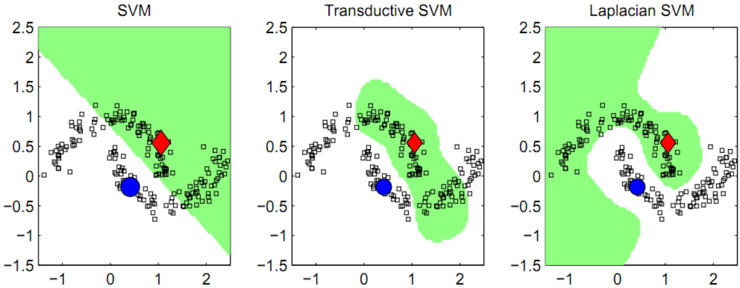
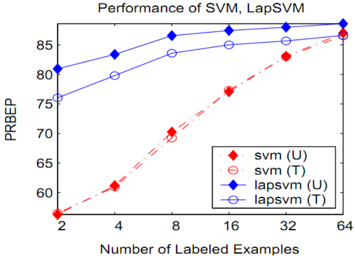
Manifold regularization: synthetic data



Manifold regularization: text classification

- Text classification: mac versus $\mathrm{windows}$
- Each document is represented by its TF-IDF vector
- The graph W is constructed from 15-nearest-neighbors (in TF-IDF space)



How can we learn with less annotation effort?

- **Semisupervised learning**
  - $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell}$: labeled examples
  - $\{(\mathbf{x}_i)\}_{i=\ell+1}^{\ell+u}$: unlabeled examples
  - often $u \gg \ell$

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  - often $u \gg \ell$

- **Domain adaptation**
  - $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell_S} \sim \mathcal{D}_S$: labeled examples in *source* domain
  - $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell_T} \sim \mathcal{D}_T$: labeled examples in *target* domain
  - possibly some unlabeled data in target and possibly source domain
  - evaluate in the target domain

The current status of NER

Quote from Wikipedia

"State-of-the-art NER systems produce near-human performance. For example, the best system entering MUC-7 scored 93.39% of f-measure while human annotators scored 97.60% and 96.95%"

The current status of NER

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The current status of NER

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Wow, that is so cool! At the end, we finally solved something!

Truth: The NER problem is still not solved. Why?

The problem: domain over-fitting

- The issues of supervised machine learning algorithms:
  Need Labeled Data
- What people have done: Labeled large amount of data on news corpus
- However, it is still not enough.....
- The Web contains all kind of data....
  - Blogs, Novels, Biomedical Documents, . . .
  - Many domains!
- We might do a good job on news domain, but not on other domains...

Domain Adaptation

- Many NLP tasks are cast into classification problems
- Lack of training data in new domains
- Domain adaptation:
  - POS: WSJ → biomedical text
  - NER: news → blog, speech
  - Spam filtering: public email corpus → personal inboxes
- Domain overfitting

NER Task	Train → Test	F1
to find PER, LOC, ORG from news text	NYT → NYT	0.855
	Reuters → NYT	0.641
to find gene/protein from biomedical literature	mouse → mouse	0.541
	fly → mouse	0.281

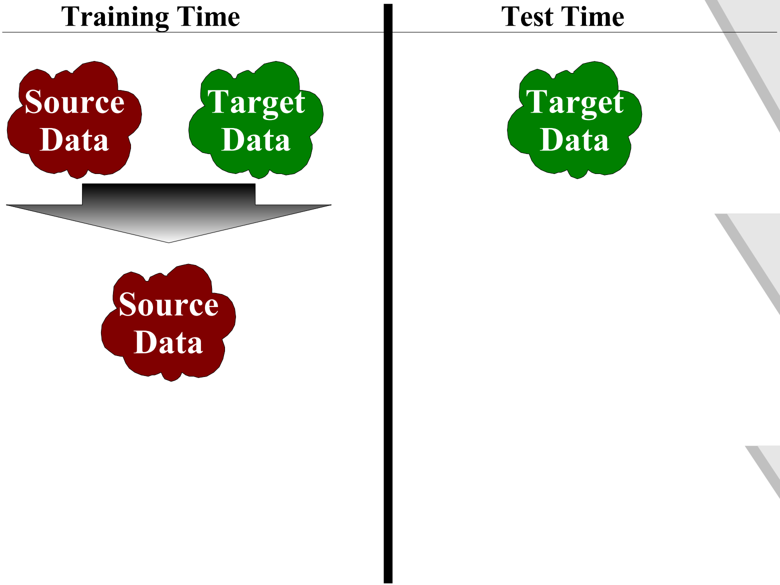
Supervised domain adaptation

In supervised domain adaptation, we have:

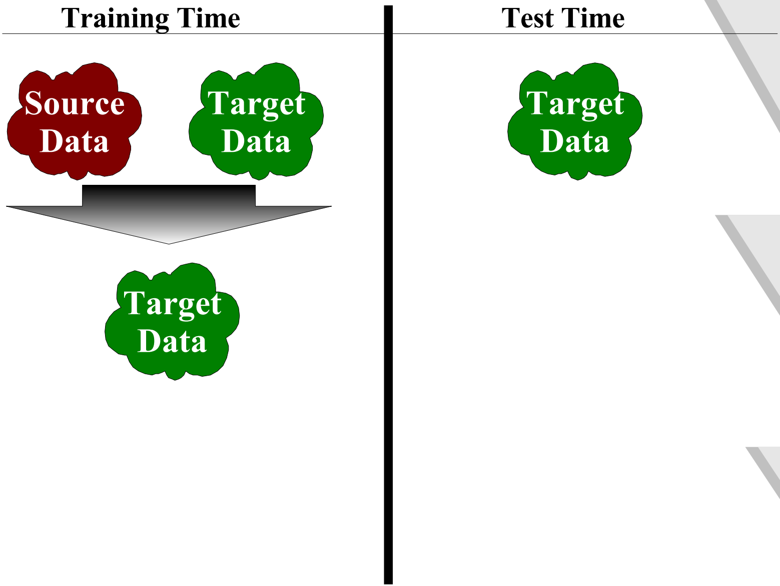
- Lots of labeled data in a "source" domain, $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell_S} \sim \mathcal{D}_S$ (e.g., reviews of restaurants)

- A little labeled data in a "target" domain, $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell_T} \sim \mathcal{D}_T$ (e.g., reviews of chess stores)

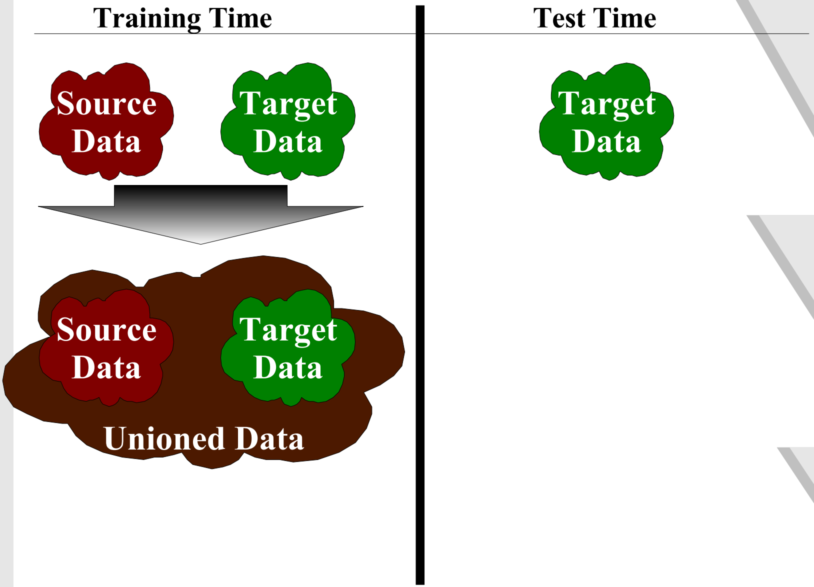
Obvious Approach 1: SrcOnly



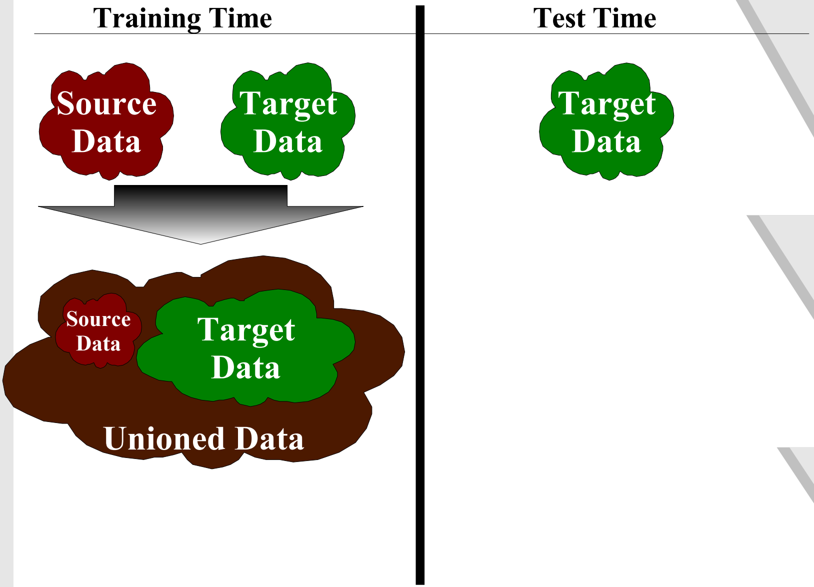
Obvious Approach 2: TgtOnly



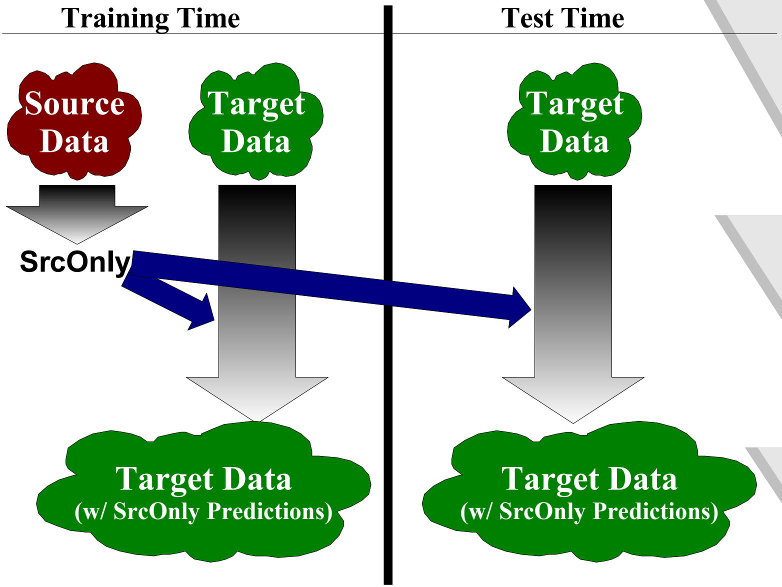
Obvious Approach 3: All



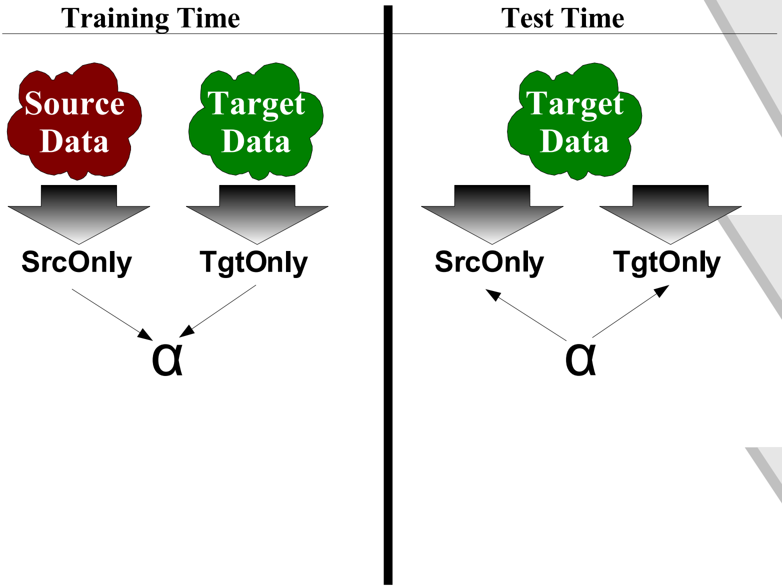
Obvious Approach 4: Weighted



Obvious Approach 5: Pred



Obvious Approach 6: LinInt



Less obvious approaches

- **Priors** (Chelba and Acero 2004)
  - Let $\mathbf{w}^{(S)}$ be the optimal weights in the source domain.
  - Design a prior distribution $P(\mathbf{w}^{(T)}|\mathbf{w}^{(S)})$
  - Solve $\mathbf{w}^{(T)} = \arg\max_{\mathbf{w}} \log P(\mathbf{y}^{(T)}|\mathbf{x}^{(T)}) + \log P(\mathbf{w}^{(T)}|\mathbf{w}^{(S)})$

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- **Feature augmentation** (Daume III 2007)

"MONITOR" versus "THE"

News domain:
"MONITOR" is a **verb**
"THE" is a **determiner**

Technical domain:
"MONITOR" is a **noun**
"THE" is a **determiner**

Key Idea:
Share some features ("the")
Don't share others ("monitor")

(and let the *learner* decide which are which)

Feature Augmentation

	We	monitor	the	traffic	The	monitor	is	heavy
	N	**V**	**D**	**N**	**D**	**N**	**V**	**R**
Original Features		W:monitor P:we N:the C:a+	W:the P:monitor N:traffic C:a+		W:the P:<s> N:monitor C:Aa+	W:monitor P:the N:is C:a+		
Augmented Features		SW:monitor SP:we SN:the SC:a+	SW:the SP:monitor SN:traffic SC:a+		TW:the TP:<s>	TW:monitor TP:the		

Why should this work?

In feature-vector lingo:

$\Phi(x) \rightarrow \langle \Phi(x), \Phi(x), 0 \rangle$ (for source domain)

$\Phi(x) \rightarrow \langle \Phi(x), 0, \Phi(x) \rangle$ (for target domain)

Results – Error Rates

Task	Dom	SrcOnly	TgtOnly	Baseline	Prior	Augment
ACE-NER	bn	4.98	2.37	2.11 (pred)	2.06	**1.98**
	bc	4.54	4.07	3.53 (weight)	**3.47**	**3.47**
	nw	4.78	3.71	3.56 (pred)	3.68	**3.39**
	wl	2.45	2.45	**2.12** (all)	2.41	**2.12**
	un	3.67	2.46	2.10 (linint)	2.03	**1.91**
	cts	2.08	0.46	0.40 (all)	**0.34**	**0.32**
CoNLL	tgt	2.49	2.95	**1.75** (wgt/li)	1.89	**1.76**
PubMed	tgt	12.02	4.15	3.95 (linint)	3.99	**3.61**
CNN	tgt	10.29	3.82	3.44 (linint)	**3.35**	**3.37**
Tree bank-Chunk	wsj	6.63	4.35	4.30 (weight)	4.27	**4.11**
	swbd3	15.90	4.15	4.09 (linint)	3.60	**3.51**
	br-cf	5.16	6.27	**4.72** (linint)	5.22	5.15
	br-cg	4.32	5.36	**4.15** (all)	4.25	4.90
	br-ck	5.05	6.32	**5.01** (prd/li)	5.27	5.41
	br-cl	5.66	6.60	**5.39** (wgt/prd)	5.99	5.73
	br-cm	3.57	6.59	**3.11** (all)	4.08	4.89
	br-cn	4.60	5.56	**4.19** (prd/li)	4.48	4.42
	br-cp	4.82	5.62	**4.55** (wgt/prd/li)	4.87	4.78
	br-cr	5.78	9.13	**5.15** (linint)	6.71	6.30
Treebank-	brown	6.35	5.75	4.72 (linint)	4.72	**4.65**

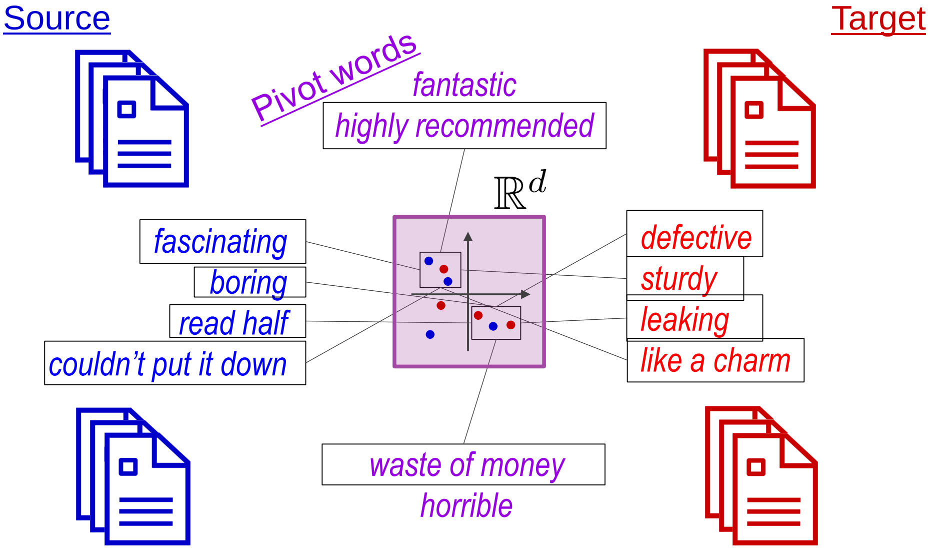
Unsupervised domain adaptation

In unsupervised domain adaptation, we have:

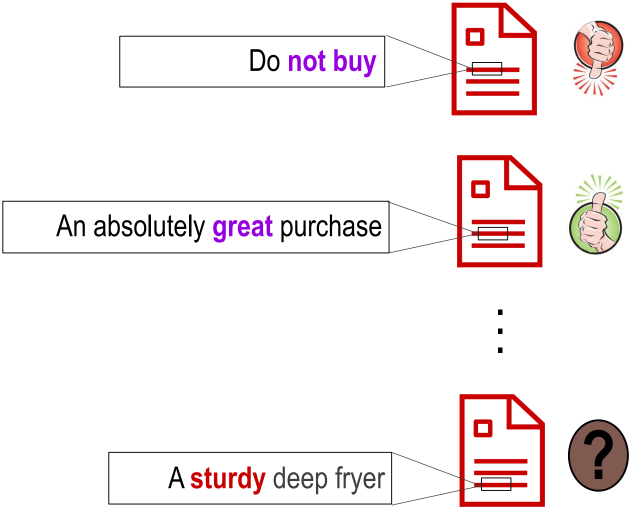
- Lots of labeled data in a "source" domain, $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{\ell_S} \sim \mathcal{D}_S$ (e.g., reviews of restaurants)

- Lots of unlabeled data in a "target" domain, $\{(\mathbf{x}_i)\}_{i=1}^{\ell_T} \sim \mathcal{D}_T$ (e.g., reviews of chess stores)

Learning Representations: Pivots



Predicting pivot word presence



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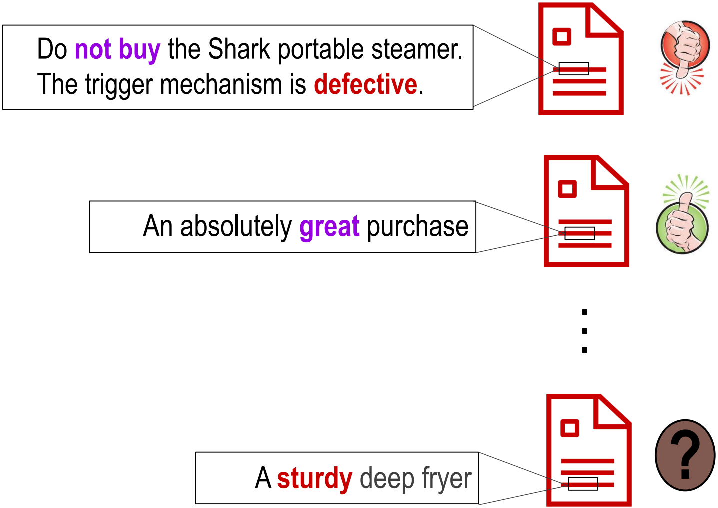
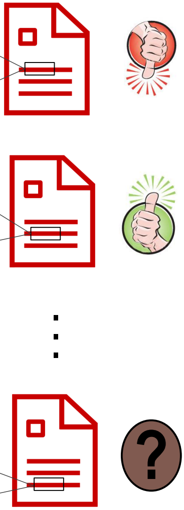


Predicting pivot word presence

Do **not buy** the Shark portable steamer. The trigger mechanism is **defective**.

An absolutely **great** purchase. . . . This blender is incredibly **sturdy**.



Predict presence of pivot words

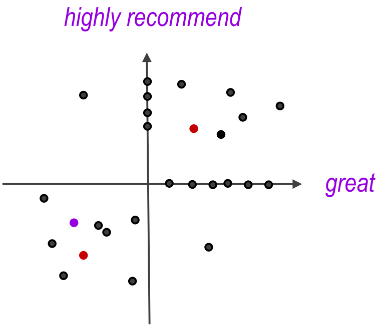
$$p_{w(\textit{great})}(\textit{great}\,|\,x) \propto \exp\{\langle x, w(\textit{great})\rangle\}$$

A **sturdy** deep fryer

Finding a shared sentiment subspace

$$W = \begin{bmatrix} | & & | & & | \\ w_1 & \dots & w(\textit{highly recommend}) & \dots & w_N \\ | & & | & & | \end{bmatrix}$$

- $p_W(\textit{pivots}|x)$ generates N new features
- $p_{w(\textit{highly recommend})}(\textit{highly recommend}|x)$: “Did *highly recommend* appear?”
- Sometimes predictors capture non-sentiment information



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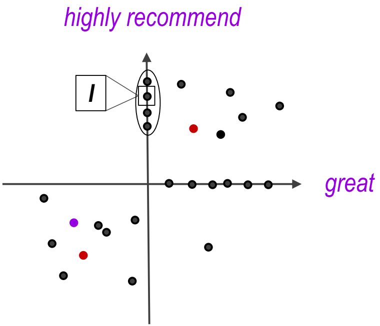

Finding a shared sentiment subspace

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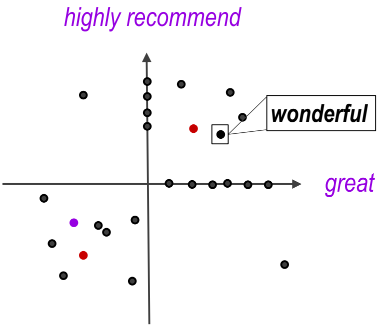

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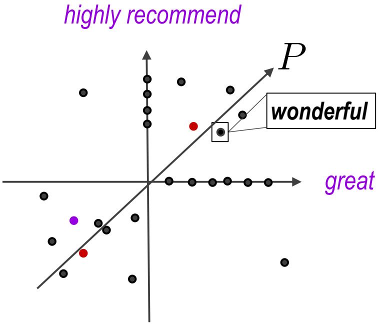

Finding a shared sentiment subspace

$$W = \begin{bmatrix} | & & | & & | \\ w_1 & \dots & w(\textit{highly recommend}) & \dots & w_N \\ | & & | & & | \end{bmatrix}$$

- Let P be a basis for the subspace of best fit to W
- P captures sentiment variance in W

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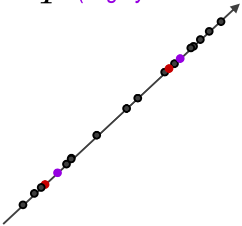
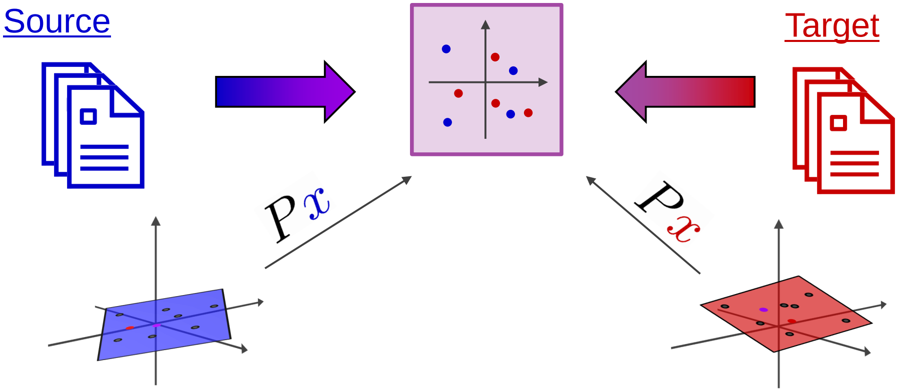
- $p_{w(\textit{highly recommend})}(\textit{highly recommend}|x)$: "Did *highly recommend* appear?"
- Sometimes predictors capture non-sentiment information

P (*highly recommend, great*)

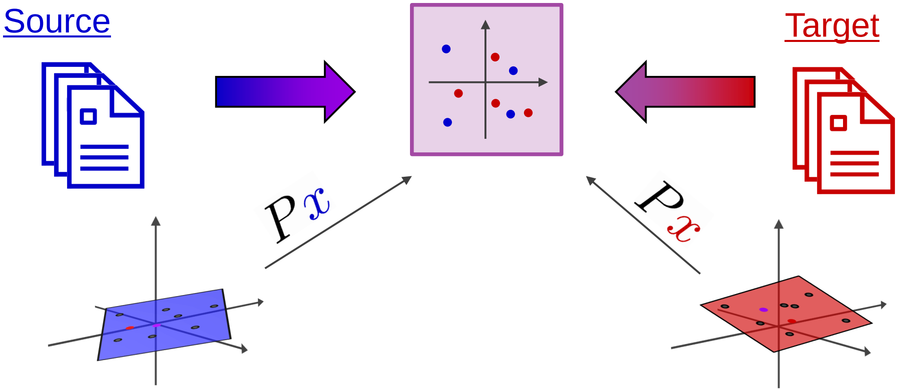


P projects onto shared subspace



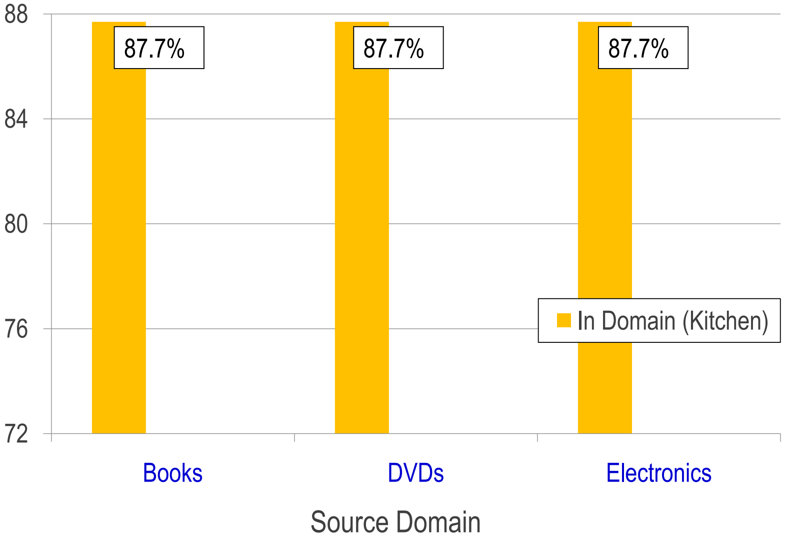
$$p_{\tilde{\theta}}(\quad|x) \propto \exp\left\{\langle \phi(\quad, Px), \tilde{\theta}\rangle\right\}$$

P projects onto shared subspace



$$h(x) = \mathrm{sgn}\left(\theta^\top P x\right)$$

Target Accuracy: Kitchen Appliances



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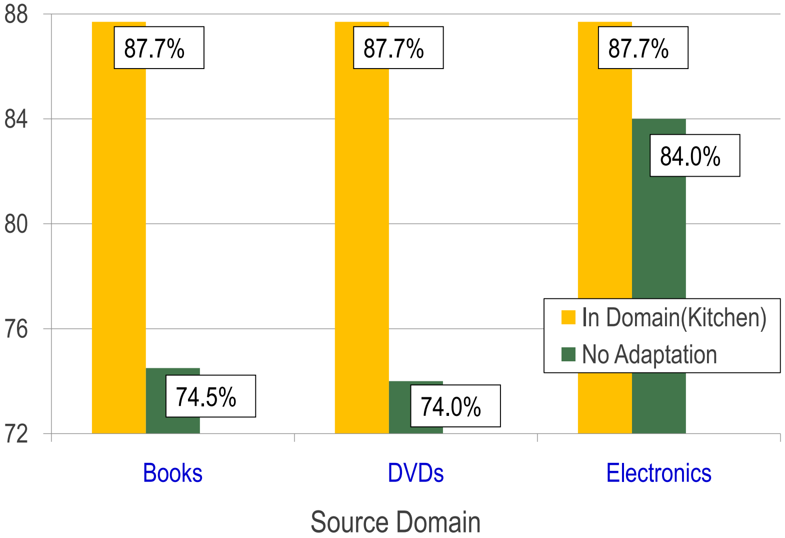
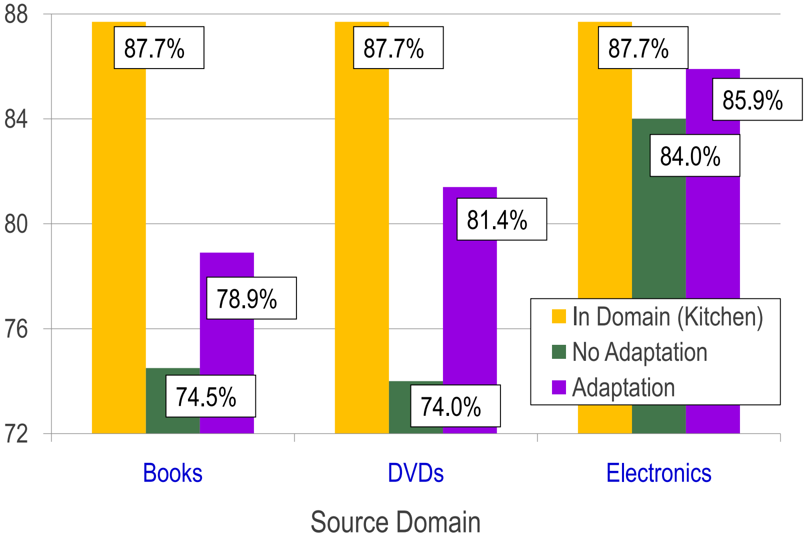
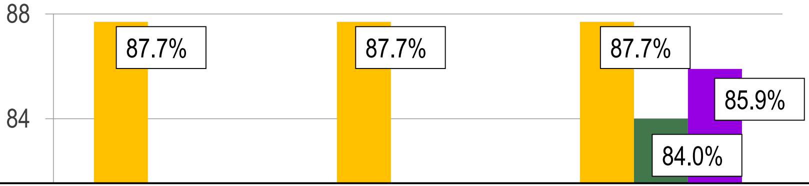


Target Accuracy: Kitchen Appliances



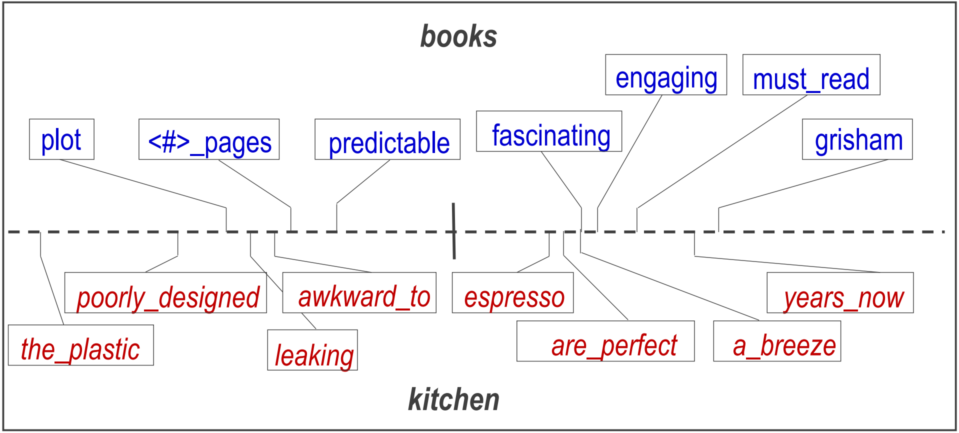
Adaptation Error Reduction



<u>36% reduction in error due to adaptation</u>

Visualizing P (books & kitchen)

negative vs. positive

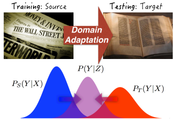


Fast Easy Unsupervised Domain Adaptation with Marginalized Structured Dropout

Yi Yang and Jacob Eisenstein

Georgia Tech

Domain Adaptation



Example: Part-of-speech Tagging

Source:

And God said, Let …
CC NNP VBD, VB …

Features:

- Mid_said source spec
- Prev_God cross domain
- Next_Let source spec
- …

Target:

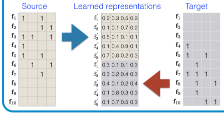
And God seide, Liyt …
CC NNP VBD, VB …

Features:

- Mid_seide target spec
- Prev_God cross domain
- Next_Liyt target spec
- …

Representation Learning

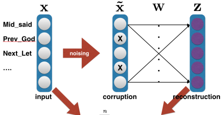
Learn new sets of dense features:



Representation learning for domain adaptation:

- *Pivots*: Structural Corresponding Learning (SCL) [1]
- *Clustering*: Brown Clustering
- *Latent Variable Models*: Topic Model, Hidden Markov Model
- *Deep Learning*: (marginalized) Stacked Denoising Autoencoders (SDA/mSDA) [2,3]

Denoising Autoencoders



$$\mathcal{L} = \sum_{i=1}^{n} ||\mathbf{x}_i - \mathbf{W}\tilde{\mathbf{x}}_i||^2$$

Reconstruct 'pivots': $\mathcal{L} = \sum_{i=1}^{n} ||\mathbf{x}_i^{pivot} - \mathbf{W}\tilde{\mathbf{x}}_i||^2$

Closed-form solution: $\mathbf{W} = \mathbf{P}\mathbf{Q}^{-1}$, with $\mathbf{P} = \sum_{i=1}^{n} \mathbf{x}_i\tilde{\mathbf{x}}_i^\top$ and $\mathbf{Q} = \sum_{i=1}^{n} \tilde{\mathbf{x}}_i\tilde{\mathbf{x}}_i^\top$

Marginalized Denoising Autoencoders []: $\mathbf{P} = \sum_{i=1}^{n} E[\mathbf{x}_i\tilde{\mathbf{x}}_i^\top]$, and $\mathbf{Q} = \sum_{i=1}^{n} E[\tilde{\mathbf{x}}_i\tilde{\mathbf{x}}_i^\top]$

Learned representations: $\tanh(\mathbf{W}\mathbf{X})$

Compute P and Q under dropout noise: For each feature of an instance, remove it with probability p.

$$\mathbf{Q}_{\alpha,\beta} = \begin{cases} (1-p)^2\mathbf{S}_{\alpha,\beta} & \text{if } \alpha \neq \beta \\ (1-p)\mathbf{S}_{\alpha,\beta} & \text{if } \alpha = \beta \end{cases},$$

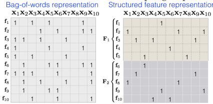
$$\mathbf{P}_{\alpha,\beta} = (1-p)\mathbf{S}_{\alpha,\beta},$$

where $\mathbf{S} = \sum_{i=1}^{n} \mathbf{x}_i\mathbf{x}_i^\top$ is the scatter matrix, α and β index two features.

Structured Dropout

Bag-of-words (BoW) vs. structured feature representations:

- *Bag-of-words*: features fire anywhere.
- *Structured*: one feature fires per group.



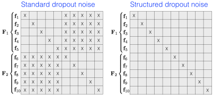
Compute P and Q under structured dropout: Randomly choose one active feature (type) to keep, dropout all other features.

$$\mathbf{Q}_{\alpha,\beta} = \begin{cases} 0 & \text{if } \alpha \neq \beta \\ \frac{1}{K}\mathbf{S}_{\alpha,\beta} & \text{if } \alpha = \beta \end{cases}$$

$$\mathbf{P}_{\alpha,\beta} = \frac{1}{K}\mathbf{S}_{\alpha,\beta},$$

where K is the number of feature types. There is no free hyperparameter.

Shape of Q under different noises:



Evaluation

Datasets: Tycho Brahe corpus (historical Portuguese texts with 383 tags)

Dataset	# of Tokens				
	Total	Narrative	Letters	Dissertation	Theatre
1800-1849	125719	91582	34137	0	0
1750-1799	202346	57477	84465	0	60404
1700-1749	278846	0	130327	148519	0
1650-1699	248194	83938	115062	49194	0
1600-1649	295154	117515	115252	62387	0
1550-1599	148061	148061	0	0	0
1500-1549	182208	126516	0	55692	0
Overall	1480528	625089	479243	315792	60404

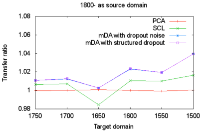
Experiment setup:

- *CRF tagger*: 16 feature types, 372,902 features, and 1572 pivots.
- *Methods*: baseline, PCA, SCL
- *Parameters*: decided with development data on the training set.

Representation learning time:

Method	PCA	SCL	mDA	
			dropout	structured
Time (sec)	7,779	38,849	8,939	**339**

Results:



Task	baseline	PCA	SCL	mDA	
				dropout	structured
from 1800-1849					
→ 1750	89.12	89.09	89.69	**90.08**	**90.08**
→ 1700	90.43	90.43	91.06	91.56	**91.57**
→ 1650	88.45	88.52	87.09	88.69	**88.70**
→ 1600	87.56	87.58	88.47	89.60	**89.61**
→ 1550	89.66	89.61	90.57	**91.39**	**91.39**
→ 1500	85.58	85.63	86.99	**88.96**	88.95
from 1750-1849					
→ 1700	94.64	94.62	94.81	**95.08**	**95.08**
→ 1650	**91.98**	90.97	90.37	90.83	90.84
→ 1600	92.95	92.91	93.17	**93.78**	**93.78**
→ 1550	93.27	93.21	93.75	**94.06**	94.05
→ 1500	89.80	89.75	90.59	**91.71**	**91.71**

References

[1] John Blitzer et al. Domain Adaptation with Structural Correspondence Learning. In *EMNLP'06*.

[2] Xavier Glorot et al. Domain Adaptation for Large-Scale Sentiment ClassiñĄcation: A Deep Learning Approach. In *ICML '11*

[3] Minmin Chen et al. Marginalized Denoising Autoencoders for Domain Adaptation. In *ICML '12*

Acknowledgments

This research was supported by National Science Foundation award 1349837. The first author was also supported by National Science Foundation ACL travel award.

Recap

- In application settings,
  - You rarely have all the labeled data you want.
  - You often have lots of unlabeled data.
- Semi-supervised learning learns from unlabeled data too:
  - Bootstrapping (or self-training) works best when you have multiple orthogonal views: for example, string and context.
  - Probabilistic methods *impute* the labels of unseen data.
  - Graph-based methods encourage similar instances or types to have similar labels.

Alternative frameworks

- **Semisupervised learning**
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- **Feature labeling**
  - Provide prototypes of each label (Haghighi and Klein 2006)
  - Give rough probabilistic constraints, e.g. $\mathrm{Mr.}$ preceeds a person name at least 90% of the time (Druck et al 2008)