Adaptive Ensembling: Unsupervised Domain Adaptation for Political Document Analysis

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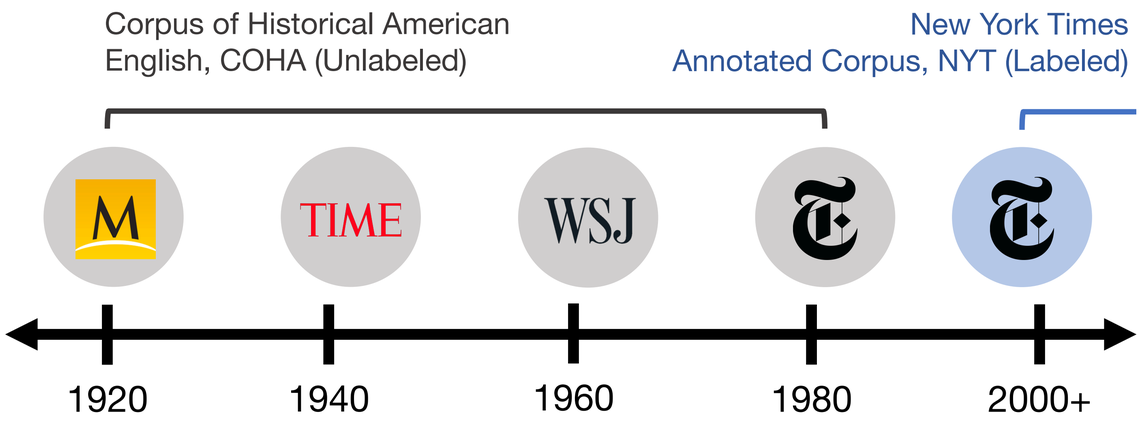
Problem

Topic 1: like, day, would
Topic 2: two, samour, family
Topic 3: would, hospital, also

Figure 1: LDA model topics from the full COHA corpus.

Topic 1: vietnam, hanoi, south
Topic 2: court, justice, law
Topic 3: coal, union, strike

Figure 2: LDA model topics from a COHA political subcorpus.



What is our goal?

> We would like to study latent variables in political science (e.g., polarization) using a **diachronic corpus** consisting of **multiple news sources**

What are our challenges?

> COHA is a **multi-source** corpus spanning **multiple decades**, but it is **unlabeled**; in contrast, NYT is a **single-source** corpus spanning **one decade**, but it is **labeled**

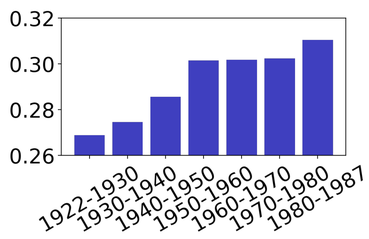
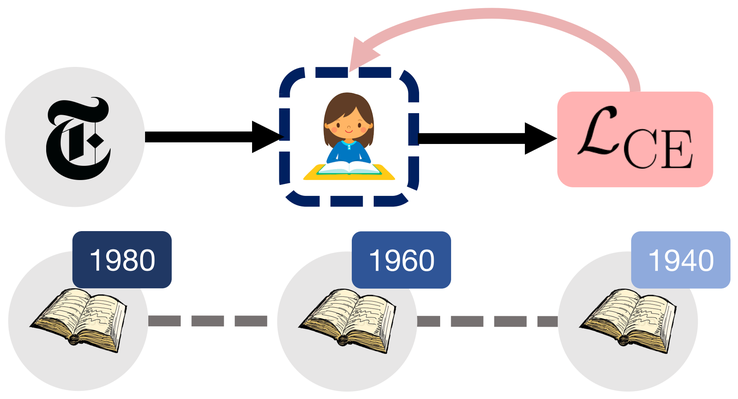


Figure 3: The percentage vocabulary overlap (y-axis) between COHA and NYT increases over the decades (x-axis), providing motivation for a domain adaptation setup; more modern COHA documents are *closer* in feature space to NYT documents.

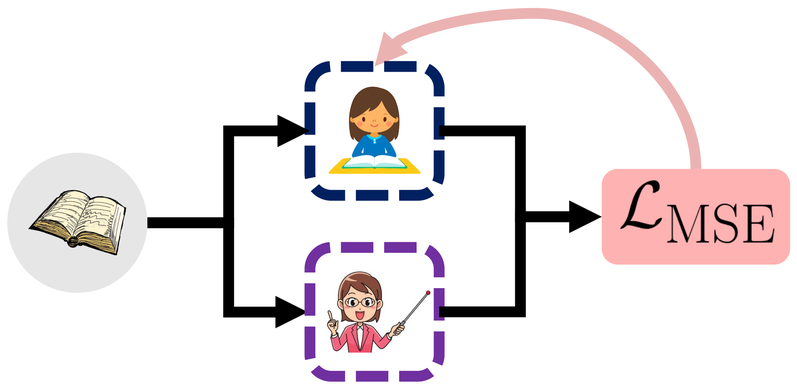
Solution: Domain Adaptation

> We present **adaptive ensembling**—an unsupervised domain adaptation framework that uses supervision from a *source* domain (e.g., NYT) to provide labels for a *target* domain (e.g., COHA)
> Our method iteratively updates a **student model** and **teacher model** (both identically initialized CNNs) with the following steps:

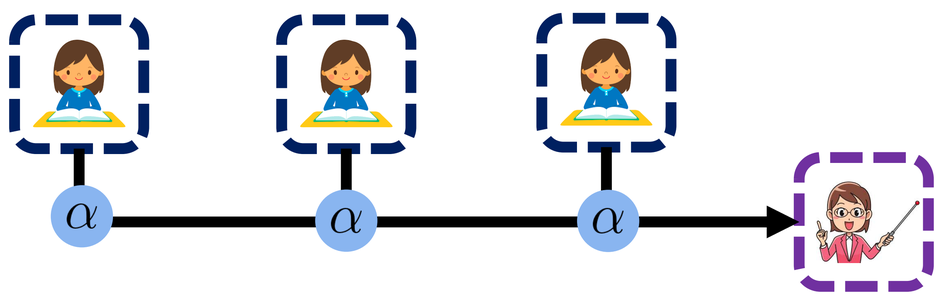
1 **Student model** learns features from source domain; **temporally order** target domain samples from modern to old



2 **Both models** maintain consistent predictions when given samples from the target domain; backprop on student



3 **Teacher model** updated via exponential average of **student model's parameters** over time (i.e., in each iteration)



4 The exponential averaging smoothing rates are **adaptive**; this leads to **smoother training** in comparison to previous methods

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \odot \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix}$$

Adaptive constants matrix — Teacher model parameter matrix

Experiments

> We experiment with a **binary task** (Political, Non-Political) and a **multi-label task** (American Government, Political Economy, International Relations)

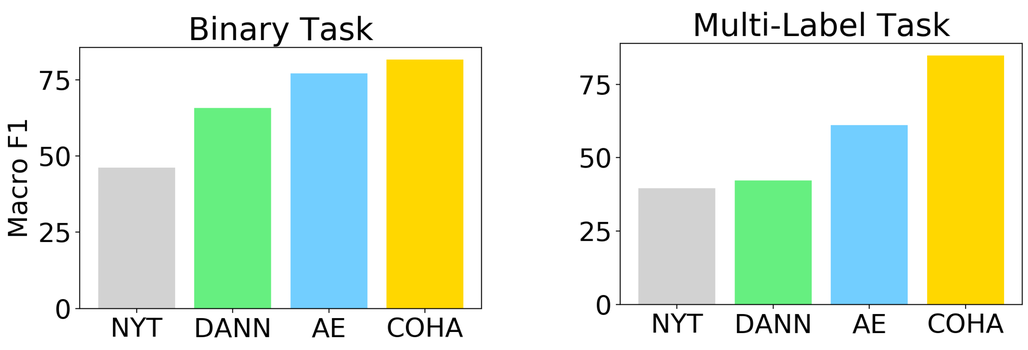
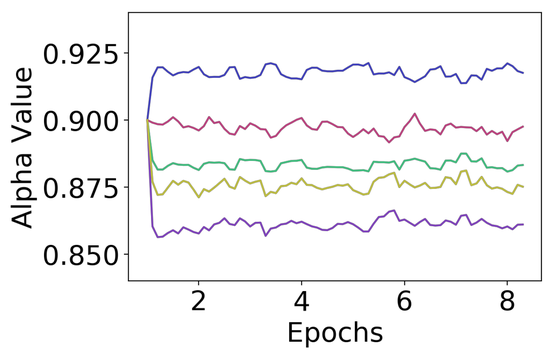
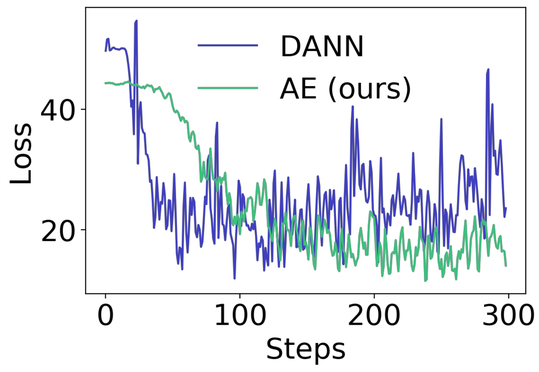


Figure 4: Macro F1 scores compared between **NYT only** (source domain, lower bound), **adaptive ensembling (AE)**, **domain adversarial neural networks (DANN)** and **COHA only** (target domain, upper bound).

Analysis



> The adaptive constants in our framework sharply converge to **different values**, showing how different parameters need their **own smoothing rates**



> Our framework (AE) is significantly than domain adversarial neural networks (DANN)—the training process **highly unstable** and **fails to converge**