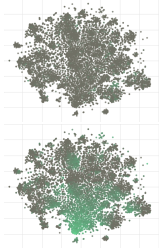
SAP-sLDA: An Interpretable Interface for Exploring Unstructured Text

Charumathi Badrinath, Weiwei Pan, Finale Doshi-Velez

Exploring Text Corpora

Low-dimensional projections are a common way to explore text corpora; ideally, thematically similar documents are clustered together in projected space.

Problem: Popular algorithms for dimensionality reduction of text corpora, like Latent Dirichlet Allocation (LDA), do not produce *useful* projections.



Topic 17 (top) has top 5 words *mindfulness, wisdom, develop, quality* and *concentration*. Topic 36 (bottom) has top 5 words *get, see, let, want* and *know*. More green = higher concentration of that topic.

Contributions

We propose **S**emantically **A**ligned **P**rojection (focused) supervised **LDA** (**SAP-sLDA**) – a flexible LDA-based framework for learning topic models with human-in-the-loop feedback to produce useful low-dimensional projections of corpora. Our method has the explicit objectives of ensuring **semantic alignment** and **robustness** in projections.

We perform a **feasibility analysis** of our method on various synthetic corpora. We also perform preliminary experiments on a **real corpus** from *Dharma Seed*.

The SAP-sLDA Objective

SAP-sLDA objective = LDA ELBO + **regularizer**.

Documents with **same label** pushed **closer** in projected space, documents with **different labels** to pulled **farther**. Projected space = PCA-transformed.

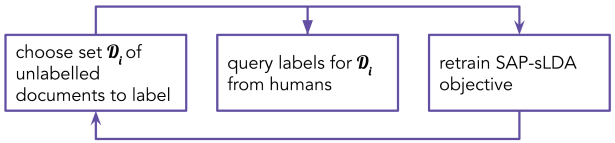
$$\sum_{\ell=1}^{L}\sum_{\ell'=1}^{L}\mathbb{I}(\ell \neq \ell')\cdot\lambda_1\text{dist}(S_\ell, S_{\ell'}, \lambda_2)$$

$$-\mathbb{I}(\ell = \ell')\cdot\lambda_3\text{dist}(S_\ell, S_{\ell'}, \lambda_4)$$

$$\text{dist}(S_\ell, S_{\ell'}, \lambda) = \sum_{x\in S_\ell}\sum_{x'\in S_{\ell'}} ||f(x) - f(x')||_\lambda$$

The SAP-sLDA Algorithm

SAP-sLDA iterates the following steps until projections are stable across random restarts:

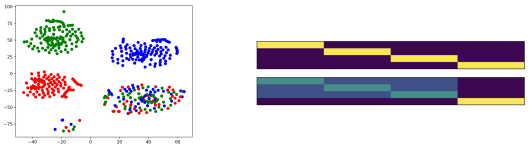


The learned topics for each document are then plotted in 2-D after applying t-SNE.

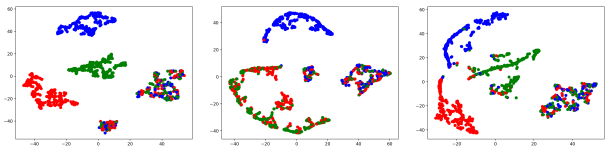
1) How to choose $\mathcal{D}_i$?
2) What sort of **label class** to choose?

Recovering Ground-Truth Data Structure

Synthetic data generated with varying settings of document-topic distribution θ and word-topic distribution β. One example below:



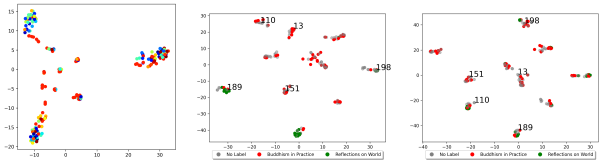
Finding 1: SAP-sLDA consistently **recovers ground truth clusters** while preserving local features for identifiable (left) and non-identifiable β (middle). LDA fails for non-identifiable β (right).

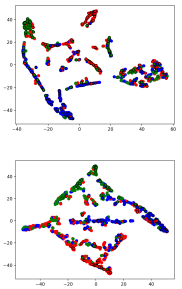


Finding 2: When SAP-sLDA learns a faithful $\hat{\theta}$, the **learned $\hat{\beta}$ is also close to the ground truth**.

Factors Influencing Clustering Quality

Finding 3: The class of labels provided matters. Tested label classes with varying levels of signal: *random*, labelling by *author* (left), labelling by *binary theme* (right two). More semantically-aligned, stable clusters when using binary theme as label class.





Finding 4: Which documents are labelled matters. Tested *random* (top) and *variance-based* (bottom) active learning schemes. Variance-based achieves interpretable clustering with fewer labels (15%) than naive alternative (25%).

Future Work

1) More exploration into label classes; labeling schemes.
2) Tuning hyperparameters and adding further components to regularizer (e.g. topic sparsity; orthogonality).
3) Human studies to investigate whether projection is practically useful for navigating corpus.

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