Natural Language Processing (CSE 517): Text Classification (II)

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Quick Review: Text Classification

Input: a piece of text $\boldsymbol{x} \in \mathcal{V}^\dagger$, usually a document (r.v. $\boldsymbol{X}$)
Output: a label from a finite set $\mathcal{L}$ (r.v. L)

Standard line of attack:

1. Human experts label some data.
2. Feed the data to a supervised machine learning algorithm that constructs an automatic classifier $\text{classify} : \mathcal{V}^\dagger \rightarrow \mathcal{L}$
3. Apply classify to as much data as you want!

We covered naïve Bayes, reviewed multinomial logistic regression, and, briefly, the perceptron.

Multinomial Logistic Regression as "Log Loss"

$$p(L = \ell \mid \boldsymbol{x}) = \frac{\exp \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell)}{\sum_{\ell' \in \mathcal{L}} \exp \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell')}$$

MLE can be rewritten as a minimization problem:

$$\hat{\mathbf{w}} = \operatorname*{argmin}_{\mathbf{w}} \sum_{i=1}^{n} \underbrace{\log \sum_{\ell' \in \mathcal{L}} \exp \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}_i, \ell')}_{\text{fear}} - \underbrace{\mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}_i, \ell_i)}_{\text{hope}}$$

Recall from lecture 3:

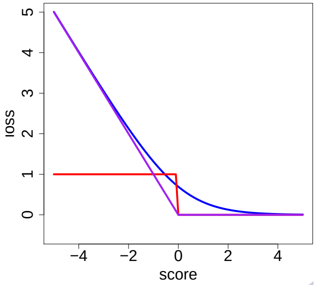
- Be wise and regularize!
- Solve with batch or stochastic gradient methods.
- w_j has an interpretation.

Log Loss and Hinge Loss for $(\boldsymbol{x}, \ell)$

$$\text{log loss:} \quad \left(\log \sum_{\ell' \in \mathcal{L}} \exp \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell') \right) - \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell)$$

$$\text{hinge loss:} \quad \left(\max_{\ell' \in \mathcal{L}} \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell') \right) - \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell)$$

In the binary case, where "score" is the linear score of the correct label:



Minimizing Hinge Loss: Perceptron

$$\min_{\mathbf{w}} \sum_{i=1}^{n} \left(\max_{\ell' \in \mathcal{L}} \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}_i, \ell') \right) - \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}_i, \ell_i)$$

Stochastic subgradient descent on the above is called the **perceptron** algorithm.

- For $t \in \{1, \ldots, T\}$:
  - Pick i_t uniformly at random from $\{1, \ldots, n\}$.
  - $\hat{\ell}_{i_t} \leftarrow \mathrm{argmax}_{\ell \in \mathcal{L}} \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}_{i_t}, \ell)$
  - $\mathbf{w} \leftarrow \mathbf{w} - \alpha \left(\boldsymbol{\phi}(\boldsymbol{x}_{i_t}, \hat{\ell}_{i_t}) - \boldsymbol{\phi}(\boldsymbol{x}_{i_t}, \ell_{i_t}) \right)$

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E.g., false positives vs. false negatives in spam detection.

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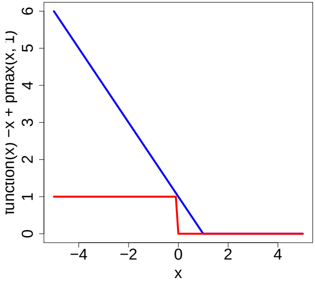
Intuition: estimate the scoring function so that

$$\mathrm{score}(\ell_i) - \mathrm{score}(\hat{\ell}) \propto \mathrm{cost}(\ell_i, \hat{\ell})$$

General Hinge Loss for $(\boldsymbol{x}, \ell)$

$$\left(\max_{\ell' \in \mathcal{L}} \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell') + \mathrm{cost}(\ell, \ell') \right) - \mathbf{w} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell)$$

In the binary case, with $\mathrm{cost}(-1, 1) = 1$:



In blue is the general hinge loss; in red is the "zero-one" loss (error).

Support Vector Machines

A different motivation for the generalized hinge:

$$\hat{\mathbf{w}} = \sum_{i=1}^{n} \sum_{\ell \in \mathcal{L}} \alpha_{i,\ell} \cdot \boldsymbol{\phi}(\boldsymbol{x}_i, \ell)$$

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Those $\boldsymbol{\phi}(\boldsymbol{x}_i, \ell)$ are called "support vectors" because they "support" the decision boundary.

$$\hat{\mathbf{w}} \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell') = \sum_{(i,\ell) \in \mathcal{S}} \alpha_{i,\ell} \cdot \boldsymbol{\phi}(\boldsymbol{x}_i, \ell) \cdot \boldsymbol{\phi}(\boldsymbol{x}, \ell')$$

See Crammer and Singer (2001) for the multiclass version.

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Really good tool: SVM*light*, `http://svmlight.joachims.org`

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- Regularization is critical; squared ℓ_2 is most common, and often used in (yet another) motivation around the idea of "maximizing margin" around the hyperplane separator.
- Often, instead of linear models that explicitly calculate $\mathbf{w} \cdot \boldsymbol{\phi}$, these methods are "kernelized" and rearrange all calculations to involve inner-products between $\boldsymbol{\phi}$ vectors.
  - Example:

$$K_{\text{linear}}(\mathbf{v}, \mathbf{w}) = \mathbf{v} \cdot \mathbf{w}$$
$$K_{\text{polynomial}}(\mathbf{v}, \mathbf{w}) = (\mathbf{v} \cdot \mathbf{w} + 1)^p$$
$$K_{\text{Gaussian}}(\mathbf{v}, \mathbf{w}) = \exp - \frac{\|\mathbf{v} - \mathbf{w}\|_2^2}{2\sigma^2}$$

  - Linear kernels are most common in NLP.

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- Rumor: random forests are widely used in industry when performance matters more than interpretability.
- Lots of papers about neural networks, but with hyperparameter tuning applied fairly to linear models, the advantage is not clear (Yogatama et al., 2015).

Readings and Reminders

- Jurafsky and Martin (2015); Collins (2011)
- Submit a suggestion for an exam question by Friday at 5pm.

References I

Michael Collins. The naive Bayes model, maximum-likelihood estimation, and the EM algorithm, 2011. URL http://www.cs.columbia.edu/~mcollins/em.pdf.

Koby Crammer and Yoram Singer. On the algorithmic implementation of multiclass kernel-based vector machines. *Journal of Machine Learning Research*, 2(5): 265–292, 2001.

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Dani Yogatama, Lingpeng Kong, and Noah A. Smith. Bayesian optimization of text representations. In *Proc. of EMNLP*, 2015. URL http://www.aclweb.org/anthology/D/D15/D15-1251.pdf.