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

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Quick Review: Text Classification

Input: a piece of text \( x \in \mathcal{V}^\dagger \), usually a document (r.v. \( X \))
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 \( \text{classify} : \mathcal{V}^\dagger \to \mathcal{L} \)
3. Apply \( \text{classify} \) 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”

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

MLE can be rewritten as a minimization problem:

\[ \hat{\mathbf{w}} = \arg\min_{\mathbf{w}} \sum_{i=1}^{n} \log \sum_{\ell' \in \mathcal{L}} \exp \mathbf{w} \cdot \phi(\mathbf{x}_i, \ell') - \mathbf{w} \cdot \phi(\mathbf{x}_i, \ell_i) \]

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 \((x, \ell)\)

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

\[
\text{hinge loss: } \left( \max_{\ell' \in \mathcal{L}} w \cdot \phi(x, \ell') \right) - w \cdot \phi(x, \ell)
\]

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

![Graph showing log loss, hinge loss, and zero-one loss.](image)
Minimizing Hinge Loss: Perceptron

\[
\min_w \sum_{i=1}^n \left( \max_{\ell' \in \mathcal{L}} w \cdot \phi(x_i, \ell') \right) - w \cdot \phi(x_i, \ell_i)
\]

Stochastic subgradient descent on the above is called the \textbf{perceptron} algorithm.

- For \( t \in \{1, \ldots, T\} \):
  - Pick \( i_t \) uniformly at random from \( \{1, \ldots, n\} \).
  - \( \hat{\ell}_{it} \leftarrow \arg\max_{\ell \in \mathcal{L}} w \cdot \phi(x_{it}, \ell) \)
  - \( w \leftarrow w - \alpha \left( \phi(x_{it}, \hat{\ell}_{it}) - \phi(x_{it}, \ell_{it}) \right) \)
Error Costs

Suppose that not all mistakes are equally bad.

E.g., false positives vs. false negatives in spam detection.
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Intuition: estimate the scoring function so that

\[
\text{score}(\ell_i) - \text{score}(\hat{\ell}) \propto \text{cost}(\ell_i, \hat{\ell})
\]
General Hinge Loss for \((x, \ell)\)

\[
\left( \max_{\ell' \in \mathcal{L}} w \cdot \phi(x, \ell') + \text{cost}(\ell, \ell') \right) - w \cdot \phi(x, \ell)
\]

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

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:

\[ \hat{\mathbf{w}} = \sum_{i=1}^{n} \sum_{\ell \in \mathcal{L}} \alpha_{i,\ell} \cdot \phi(x_i, \ell) \]

where most only a small number of \( \alpha_{i,\ell} \) are nonzero.
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\[ \hat{w} = \sum_{i=1}^{n} \sum_{\ell \in L} \alpha_{i,\ell} \cdot \phi(x_i, \ell) \]

where most only a small number of \( \alpha_{i,\ell} \) are nonzero.

Those \( \phi(x_i, \ell) \) are called “support vectors” because they “support” the decision boundary.

\[ \hat{w} \cdot \phi(x, \ell') = \sum_{(i,\ell) \in S} \alpha_{i,\ell} \cdot \phi(x_i, \ell) \cdot \phi(x, \ell') \]

See Crammer and Singer (2001) for the multiclass version.
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Really good tool: SVM\textsuperscript{light}, http://svmlight.joachims.org
Support Vector Machines: Remarks

- Regularization is critical; squared $\ell_2$ is most common, and often used in (yet another) motivation around the idea of “maximizing margin” around the hyperplane separator.
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- Often, instead of linear models that explicitly calculate $w \cdot \phi$, these methods are “kernelized” and rearrange all calculations to involve inner-products between $\phi$ vectors.
  - Example:

\[
K_{\text{linear}}(v, w) = v \cdot w \\
K_{\text{polynomial}}(v, w) = (v \cdot w + 1)^p \\
K_{\text{Gaussian}}(v, w) = \exp\left(-\frac{||v - w||^2}{2\sigma^2}\right)
\]

- Linear kernels are most common in NLP.
General Remarks

- Text classification: many problems, all solved with supervised learners.
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- 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


